Emotiv-Based Low-Cost Brain Computer Interfaces: A Survey

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Abstract Within the field of Brain Computer Interfacing (BCI), Electroencephalography (EEG) is the most widely applied modality. But most of the EEG based BCI applications use expensive sensors for capturing brain data. In order to make these systems accessible to end-user, it is quite necessary to have low-cost alternatives. The Emotiv EPOC is one of the inexpensive EEG devices that has been increasingly employed. Although the headset has limitations related to signal quality but it is gaining popularity in BCI researches. In this paper, a detailed review of Emotiv based BCI systems is presented along with its comparison with medical grade EEG devices. Classification algorithms and preprocessing techniques used with these systems are also discussed. Its performance is evaluated based on different factors including subjects, stimuli and specific nature of the application. The paper is concluded with the discussion of present challenges and future research possibilities for Emotiv based BCI applications.

Keywords Emotiv · Brain computer interfaces · Electroencephalography · Signal processing · Classification

1 Introduction

A brain-computer interface (BCI) is defined as a communication system for translating the signals from brain of a person into commands interpretable by a machine or a computer [1]. Within the field of BCI, electroencephalography

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Fig. 1 Emotiv EPOC headset [2]

(EEG) is the most widely applied modality. But most of the applications are designed using expensive EEG sensors. In order to make these BCI systems accessible to end-user for home use or outside the lab applications, it is quite necessary to have low-cost alternatives with increased portability. The Emotiv EPOC headset is one of the inexpensive EEG devices that has been increasingly employed in BCI applications based on consumer-grade sensors. Although the Emotiv headset does have limitations related to the signal quality and number of electrodes but it is gaining popularity in BCI researches that are focused towards low-cost and outside the lab applications (Fig. 1).

The paper summarizes the results of a survey of different BCI systems using Emotiv as main device for EEG signal acquisition. A detailed review of Emotiv based BCI systems is presented along with its comparison with medical grade EEG devices. The classification algorithms and preprocessing techniques used with these systems are also discussed. Its performance is evaluated based on different factors including subjects, stimuli and specific nature of the application.

2 Non-medical Applications

Because of its accessibility and portability to consumers and researchers, Emotiv EPOC has been employed in a variety of BCI applications. But due to its limited signal quality, the applications usually cover non-medical domain although few studies have been conducted for medical purposes as well. Following five categories of non-medical applications have been identified where Emotiv is used for capturing brain signals.

2.1 Device Control

One of the major reasons for conducting researches in BCI domain is desperate need to give patients or users who lack full control of their limbs access to control different devices and communication systems. Keeping these scenarios in consideration, such users may be facilitated from a device even it bears limited accuracy, efficiency or speed. Emotiv has been used in designing of such applications. Using emotive various device control applications have been designed including control of wheelchair for disabled persons [3, 4], any input device of computers [5], to control in-vehicle systems or drive a car [6, 7].

2.2 Gaming

Emotiv EPOC headset has been increasingly employed for gaming purpose as well. In such applications signals from user's brain are used to play the game and operate the controls. Sourina and Liu designed a gaming application based on Emotiv employing Steady State Visual Evoked Potential (SSVEP) as electrophysiological signal. Along with this, the performance of Emotiv is compared with the research grade EEG sensor and the study suggests that the satisfactory results are obtained from Emotiv [11].

Bernays and Mone have worked on an adaptable 3D video game named as Lost in the Dark: Emotion Adaption. It makes use of player's emotions as input to alter and adjust the gaming controls and environment. Emotiv headset is used here not only to record brain signals but facial expressions and head movement also [13]. Few gaming applications using Emotiv are mentioned in Table 1.

Table 1 List of Emotiv based studies categorized on the basis of type of application

Device control	Gaming	Emotion detection	User brain state detection	Robots
i. Controlling a Wheelchair Fattouh et al. [3], Li et al. [4] Chowdhury and Shakim [8] Bahri et al. [9] Abiyev et al. [10] ii. Controlling a computer input device Lievesley et al. [5] iii. Controlling an in-vehicle system Nisar et al. [6], Cernea et al. [7]	Sourina and Liu [11], Thomas et al. [12], Bernays et al. (2012) [13], Qiang, Sourina et al. [14]	Jatupaiboon et al. [15], Liu et al. [16], Pham and Tran [17], Aspinallet al. [18], Wang [19], Fattouh et al. [3]	Wang et al. [20], Purawijaya and Fitri [21], Ben Dkhil et al. [22], Ekanayake et al. [23]	Szafir and Signorile [24], Vourvopoulos and Liarokapis [25], Vourvopoulos and Liarokapis [26], Grude et al. [27], Guneysu and Akin [28]

2.3 Emotion Detection

Human emotion refers to a complex psychological state comprised of three components i.e. user experience, his physiological response along with behavioral or expressive reaction [29]. Different categories of emotions are disgust, pride, satisfaction, anger etc. [30]. Various studies have been conducted to find how the EEG signals correlate to human emotions. Emotiv has also been used for this purpose. Pham, Duy et al. have used Emotiv to capture EEG data while users are watching movies to induce emotions. Oscillatory brain rhythms with different frequency bands filtered from the recorded brain signals are used as input to different machine learning classifiers [17].

2.4 User Brain State Detection

While performing any task, state of brain of user can be analyzed using BCI devices. Emotiv is used for this purpose also. Wang et al. developed a virtual driving mechanism to perform driving experiments for the collection of subjects' brain data for mental fatigue. Technique of Wavelet-packets transform (WPT) was applied for continuous feature extraction [20]. McMahan and Parberry compared three different engagement indices during various video game modalities using the Emotiv device. From the results, it is concluded that Emotiv can be used to measure a player's varying levels of engagement as they play a video game [31].

Drowsiness is one of the major reasons behind road accidents especially while driving on motorways and highways. Ben Dkhil, Neji et al. worked on a drowsiness detection system based not only eye blinking but physiological signals also. A smart video camera is used to capture face images and eye blinks and to record the brain signals Emotiv has been used [22].

2.5 Robots

One of the major application of BCI systems is to control robots by means of EEG brain signals. For this area also, Emotiv has successfully been employed. Vourvopoulos and Liarokapis worked on a project for controlling a robot in both the real and virtual world. The whole set up is performed with two prototypes based on the headset type used. One is the Neurosky headset that has been tested with 54 users. Other one is performed with Emotiv EPOC headset. Results indicate that using commercial grade headsets, robot can be navigated effectively [25].

Table 1 lists the studies and researches categorized on the basis of type of applications mentioned above.

Table 2 Signal processing algorithms considered in Emotiv based BCI applications

Signal processing algorithms	Research studies
PCA (principal component analysis)	Elsawy et al. [32], Turnip et al. [33]
ICA (independent component analysis)	Turnip et al. [33]
CSP (common spatial pattern)	Bialas and Milanowski [34]
Wavelet transform	Abdalsalam [35]

3 Signal-Processing Methods Used in Emotiv-Based BCIs

Signal processing algorithms are applied on EEG signals to remove artefacts. Emotiv based BCI systems have employed different approaches for pre-processing. In Table 2, we have categorized the research papers according to the signal processing techniques and algorithms used.

4 Feature Classification Algorithms Used in Emotiv-Based BCIs

In order to identify different brain activity patterns produced by a user during any BCI experiment, machine learning algorithms for classification are mostly applied. To achieve maximum performance, suitable algorithm must be selected so that it could aim at correct estimation of the class of data represented by the feature vector. Table 3 lists the classification algorithms used in design and development of Emotiv based BCI systems.

Table 3 Classification algorithms considered in Emotiv based BCI applications

Classification algorithms	Research studies
SVM (support vector machine)	Zhang et al. [36], Vamvakousis and Ramirez [37], Wang [19], Pham and Tran [17]
LDA (linear discriminant analysis)	Wang et al. [38], Duvinage et al. [39], Vamvakousis and Ramirez [37]
Decision tree	None (to the best of our knowledge)
KNN	Pham and Tran [17], Mampusti et al. [40]
Naïve bayes	Pham and Tran [17]
Ada boost	Pham and Tran [17]
Multi layer perceptron	Abdalsalam et al. [35]

5 Discussion

Emotiv offers a cost-effective solution for design and development of BCI applications. It is quite necessary while having the advantage of low cost, Emotiv based applications could not be compromised on performance and quality. To address this issue, researchers have conducted studies by comparing Emotiv with other medical or research grade devices. Badcock, Mousikou et al. tested if auditory Event Related Potentials (ERPs) measured using Emotiv are comparable to those by a medical grade widely-used EEG system from Neuroscan. The study suggests that the consumer grade EEG system may prove a valid alternative for medical grade Neuroscan system for recording late auditory ERPs over the frontal cortices [41]. Liu conducted a research based on SSVEP physiological signal using Emotiv headset. Based on video stimuli, SSVEP are recorded from Emotiv. In this study, canonical correlation analysis (CCA) is used for feature extraction. Furthermore, the performance of g.tec EEG equipment and Emotiv EPOC is also compared. The classification accuracy and Information transfer rate (ITR) of g.tec are $94.79 \pm 1.94\ \%$ and 35.66 ± 5.71 bits/min while for Emotiv, accuracy is $82.99 \pm 4.98\ \%$ and the ITR is 28.06 ± 6.45 bits/min [42]. Table 4 lists some of the studies with classification accuracies obtained with Emotiv based sensor. Some studies are conducted specifically for comparison of Emotiv with other devices. From the table, it is evident that the low cost Emotiv give satisfactory results as the classification accuracy is not significantly degraded using this equipment. Other than classification percentage, other performance parameters are also used for making such comparisons like reaction time, information transfer rate, *p*-value etc. Due to limitation of length, these parameters are not covered in this paper.

5.1 *Limitations for Emotiv Based BCI Applications*

BCI applications have general limitations like subject dependency, experiment scenario, research paradigm etc. for each type of EEG equipment whether consumer

Table 4 Classification accuracies obtained using Emotiv

Application	Classification accuracy with	
	Emotiv (%)	Other medical grade device (%)
Visual stimulator [42]	82.99	94.79 (gtec)
Controlling video game [43]	82–84	87–89 (IMEC)
P300 speller [32]	86.29	–
Diagnosis of major depressive disorder [38]	89.66	–
Emotion detection [15]	75	–
SSVEP visual stimulator [44]	76.6	–

or research grade. Therefore in case of Emotiv based BCIs, these limitations also exist. As in the study of Van Vilet in which it is observed that the tendency to control a game mainly depends on the subject rather than the device. During out of the lab public event, using EPOC headset, 36 % users achieved good accuracy for game control while 52 % found it difficult and challenging whereas 12 % users could not achieve any control [43]. Similarly, Lin et al. have worked on SSVEP based visual stimulator system such that subjects walking on the treadmill are provided with Emotiv EPOC headest to record their brain activity with different speeds of treadmill. Highest accuracy 76.7 % is achieved with standing position while accuracy decreases with increasing speed. This is the general limitation for BCI applications as the best results are produced when the subjects are in still position [44]. Jatupaiboon et al. found that using emotiv, pair of channels at temporal region produces better result than the other regions for the happiness detection system [15].

Liu et al. have implemented SSVEP based application using Emotiv EPOC. As per the research, to connect Matlab with Emotiv using existing software is difficult and to some extent little inconvenient. In future, extensive work could be performed to provide a better solution for a stable connection between Matlab and EPOC [42].

Hariston et al. worked on performance comparison of three wireless EEG sensors including B-Alert X10, EPOC and Quasar's dry sensor with conventional wired BioSemi's ActiveTwo EEG sensor. The study elicited that some subjects found lack of comfort with EPOC since the weight of electrodes is focused on certain locations of the scalp instead of being distributed all over the scalp surface. So, the problem for uneven weight distribution is observed in EPOC [45].

In order to compare Emotiv with other devices, one of the major issues arises due to inconsistency and difference of electrode placement using different sensors. In order to conduct true comparison, except the EEG sensor, all other parameters should ideally be uniform especially the electrode placement [45].

6 Conclusion

Major objective of this paper is to bring together pieces of information from research studies to summarize the situation and give beginners and researchers in this field a preliminary but clear and concise overview of where we are standing for Emotiv based BCI systems. In the paper, a detailed review of Emotiv based BCI systems is presented along with its comparison with medical grade EEG devices. The classification algorithms and preprocessing techniques used with these systems are also discussed. Its performance is compared based on classification accuracy. Five non-medical applications have been identified where Emotiv is being employed successfully. In a BCI context, the results they obtained, have been analysed and compared with other medical grade devices. Although limited number of studies are conducted so far to make this comparative analysis. One major difficulty that generally encountered in such comparative studies concerns the lack of published comparisons between algorithms, classifiers, devices etc. Ideally, to compare EEG sensors, the BCI experiments should be performed within the same context, that is with the same subjects, using the same feature detection technique and the same protocol for pre-processing.

The signal processing and classification techniques that are not applied so far in Emotiv based systems could be explored. Currently, this is one of the crucial problems for for BCI research and not specifically for Emotiv based systems. Based on the studies covered in this paper, it is concluded that although Emotiv does not perform as effectively as research grade equipment but it still offers the option to provide a user's brain wave signature.

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