Usability and Cost-effectiveness in Brain-Computer Interaction: Is it User Throughput or Technology Related?

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ABSTRACT

In recent years, Brain-Computer Interfaces (BCIs) have been steadily gaining ground in the market, used either as an implicit or explicit input method in computers for accessibility, entertainment or rehabilitation. Past research in BCI has heavily neglected the human aspect in the loop, focusing mostly in the machine layer. Further, due to the high cost of current BCI systems, many studies rely on low-cost and low-quality equipment with difficulties to provide significant advancements in physiological computing. Open-Source projects are offered as alternatives to expensive medical equipment. Nevertheless, the effectiveness of such systems over their cost is still unclear, and whether they can deliver the same level of experience as their more expensive counterparts. In this paper, we demonstrate that effective BCI interaction in a Motor-Imagery BCI paradigm can be accomplished without requiring high-end/high-cost devices, by analyzing and comparing EEG systems ranging from open source devices to medically certified systems.

Author Keywords

Brain-Computer Interaction; EEG; Motor-Imagery; Cost-effectiveness; Usability

ACM Classification Keywords

Human-centered computing---Human computer interaction (HCI)---HCI design and evaluation methods---Usability testing

INTRODUCTION

Brain-computer interfaces (BCIs) are communication systems that aim at providing users with an alternative control input to computers. BCIs detect changes in brain signal modulation and translate them into control commands [34]. Currently, electroencephalography (EEG) is utilized as the main acquisition technology for BCI [29]. The acquired EEG signal represents a macroscopic measurement of neural activity of the brain, mediated by a layer of bone, tissue and fluid. For this reason, EEG has low spatial resolution and the signal acquisition by surface electrodes make EEG susceptible to interference from a variety of sources such as physical movement, power line noise, and other electronic equipment.

AH 2016, February 25 - 27, 2016, Geneva, Switzerland

ACM 978-1-4503-3680-2/16/02…$15.00
DOI: http://dx.doi.org/10.1145/2875194.2875244

The three main types of EEG based BCI paradigms include: (a) Steady State Visual Evoked Potentials (SSVEP), (b) P300 BCI and (c) Motor-Imagery (MI) BCI. SSVEP is caused by visual stimulation of flashing lights and are measured from the primary visual cortex of the brain [33]. P300 BCI is generated by measuring the brain evoked response 300ms after stimulus onset, of positive and negative deflections in the EEG signal [10]. Finally, ERS/ERD stands for event related synchronization/desynchronization through Motor imagery (MI) of limb movements, localized at the motor and somatosensory cortex of the brain [20].

Despite the increased attention that BCI technology had with the launch of low-cost commercial EEG devices in the last few years, BCIs are hardly used outside the laboratory environment [16]. This is mainly due to the fact that current BCI systems lack reliability and good performance in comparison to other types of interfaces [15]. For instance, MI-BCI requires long training trials per session and settings are subject specific. As consequence, these long and repetitive training sessions can result in user fatigue and declining performance over time. Moreover, prolonged training is problematic in generating EEG oscillatory rhythms modulated during MI, such as mu (μ) and beta (β) rhythms [28]. To solve these issues, past research in BCIs has investigated various methodologies to create new experimental designs [7], specialized algorithms [27] and signal processing techniques [19] that minimize current limitations of EEG-based BCIs.

In Human-Computer Interaction (HCI) research, there is an increased interest in working towards novel approaches for improving the communication bandwidth and quality of the loop using various BCI technologies [1,30]. Unfortunately, due to the cost and complexity, these brain sensing technologies have a set of disadvantages for HCI research [13]. Consequently, HCI is limited of such equipment compared with alternative user interfaces. In the past, researchers have explored brain-computer interfacing technology with low-cost alternatives [4,12], with reduced capabilities and black box algorithms. Due to the big cost of current equipment, a large portion of previous research has been done in the medical domain with high-end devices costing between 20,000-250,000 USD [e.g. Biosemi (Biosemi B.V., Amsterdam, Netherlands), g.tec (Guger Technologies, Graz, Austria) or EGI (Electrical Geodesics, Inc., Oregon, USA)]. Because of these limitations, advancements in HCI research for Brain-Computer Interaction have been hampered.

BACKGROUND

In the last few years, low-cost commercial EEG devices and Open Source projects [36,37], are offered as alternatives to expensive medical equipment. However, results are mixed and it is not clear if they can deliver comparable user experiences as compared to medical grade EEG systems.

In a recent study, it was investigated the difference in comfort between the Emotiv EPOC headset and silver chloride scalp discs in a P300 paradigm [14]. It was found that the Emotiv EPOC was more uncomfortable than the attached disks and discomfort increased over time. Another comparative study between the Emotiv EPOC and a medical grade headset in a P300 paradigm reported that the Emotiv was a better in terms of price, setup process and intrusiveness. On the other hand, the ANT system was reported to be more comfortable, cheaper to maintain and more durable [6]. A usability comparison between four commercially oriented EEG systems: B-Alert, Emotiv EPOC, Biosemi's ActiveTwo and QUASAR's Dry Sensor Interface, revealed that overall in (i) the adaptability for different head sizes, (ii) comfort and preference, (iii) variance for the recording scalp locations for the recording electrodes , (iv) the stability of the electrical connection and (v) the integration between the EEG system and stimulus presentation, participants preferred the B-Alert system [5]. In MI, a new comparative study between the Emotiv EPOC and the Biosemi ActiveTwo system, showed that performance is comparable between the same number of sensors and sensor positions for a three class MI [17]. Many studies have investigated the usability of BCI applications as a whole. Nijboer et al, investigated the acquisition component and compared the usability of three different EEG headsets (Biosemi, Emotiv EPOC and g.Sahara) in a P300-paradigm including also classification score information [21].

Overall, most of the comparative studies have used the P300 paradigm but similar information between different headsets in SSVEP or MI is limited. MI-BCI training is based on visuo-motor imagination and together with other mental task imagination (e.g. mental subtraction, word association)[8] is the only paradigm of endogenous nature that does not require external stimulation but only the user's imaginative action. In addition, MI is considered the most important type of BCI paradigm for motor function restoration. Results from previous studies have proven mental practice of action to be useful in MI-BCI [25], and have shown beneficial effects of motor imagery practice during stroke recovery [24]. Unfortunately, an estimated 15-30% of people cannot use a BCI system, resulting in a big amount of BCI illiteracy in the user base [31].

In this paper, our main focus is on the MI-BCI paradigm because it is self-paced, and also because of its utilization in the health domain. Our target is to demonstrate that brain-computer interaction throughput in non-expert users is not technology related but user related and it can be accomplished without requiring such high-end and high-cost devices.

To this end we performed a (1) usability assessment following the same protocol as a previous study using the P300 paradigm [21] in order to have comparable results, and (2) by performing a cost-effectiveness analysis of all tested EEG systems from both BCI studies, in two different paradigms (P300 and MI). For that purpose, a pilot study with 8 non-expert participants using 3 different EEG systems, ranging from an open-source project, commercial system for gaming, to medical certified systems, and a total of 24 BCI training sessions, was conducted.

METHODOLOGY

Participants

8 users (mean age of 29 ± 4.9 years old, all male) were recruited as a voluntary sample, based on their motivation to participate in the study. All participants were right handed with no previous known neurological disorder, nor previous experience in BCIs. All participants were University students and academic staff. Finally, all participants provided their written informed consent before participating in the user-study.

Experimental Design

The experiment followed a within-subject design, with each participant taking part in overall three BCI training sessions, one per day, by using a different headset on each session in a randomized order. Before the first session, informed consent was obtained and demographical information was collected. At the beginning of each session, a BCI headset was applied by the experimenters, who logged the time (in minutes) it took from the conductive gel application to the moment that good EEG signals were achieved. Participants then were asked about their perceived setup time (in minutes) and to answer a set of usability questions before starting the experiment.

Experimental Setup

The experimental setup was composed by a desktop computer (OS: Windows 8.1, CPU: Intel® Core™ i5-4440 at 3.3 GHz, RAM: 8GB DDR3 1600MHZ, Graphics: Nvidia GT 630 1GB GDDR3), running the BCI training task. In addition the Vuzix iWear VR920 (Vuzix, NY, USA) head mounted display (HMD) was used by the participants in order to focus their attention on the training and prevent any external visual stimulation from the environment. The HMD is made of two 640x480 twin LCD displays, 32-degree field of view (FOV), 3/4" eye relief and 5/16" eye box.

The BCI set up comprised of 3 EEG systems. The spatial distribution of the electrodes followed the 10-20 system configuration [35] with the following electrodes over the somatosensory and motor areas: Frontal-Central (FC5, FC6), Central (C1, C2, C3, C4), and Central-Parietal (CP5, CP6) as illustrated in Figure 1. All three headsets connected via bluetooth to the desktop computer for the EEG signal acquisition. Data filtering and classification was performed through the OpenVibe platform [26]. The RehabNetCP [32] software was used to mediate between the openBCI system and OpenVibe via the Lab Streaming Layer protocol (LSL). For all EEG data, a Common Spatial Patterns (CSP) filter was used, and the classification of motor-imagery actions from the extracted EEG features were determined through a Linear Discriminant Analysis (LDA).

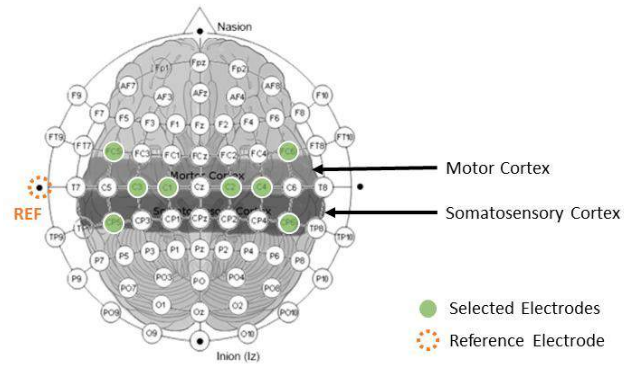

Figure 1. Electrode configuration used for the experiment based on the 10-20 system. Electrodes are placed over the motor and somatosensory cortices and reference electrode at the left ear lobe.

Open Source System

The Open-Source BCI system (see Figure 2a) is based on the ADS1299 Analog-to-Digital Converter (ADC) developed by Texas Instruments (TI, Dallas, Texas, United States) [38]. This system provides 8 EEG channels operating at sample rates between 250 and 16000 Hz, with a resolution of 24 bits per channel. The current prototype operated at 250 Hz. An ATmega328 Arduino UNO board was used to sample the ADC board, and for data transmission based on the first OpenBCI V1 data format. The cost for all components and electrodes for the complete system is calculated at 211 euro including VAT.

Enobio 8

Enobio (Neuroelectrics, Barcelona, Spain) is a wearable, wireless EEG sensor with 8 EEG channels and a triaxial accelerometer, for the recording and visualization of 24 bit EEG data at 500 Hz (see Figure 2 b). Enobio is a CE medically certified product and it is currently classified as an investigational device under US federal law [39]. The cost of the system including VAT is calculated at 6150 euro.

g.MOBIlab+

The g.MOBIlab+ biosignal amplifier (g.tec, Graz, Austria) is a wireless EEG system, composed of 8 active EEG electrodes (see Figure 2 c) equipped with a low-noise bio-signals amplifier and a 16-bit A/D converter at 256 Hz [9]. The cost including VAT is estimated at 9696 euro.

BCI Training

The BCI training was based on the Graz-BCI paradigm [23] with directional arrows feedback. When an arrow appears on the screen, the user has to perform a mental rehearsal of a motor task such as grasping, throwing or waving with the corresponding hand. The action selected for mental imagery needs to be constant during the whole duration of the training session in order to train a linear classifier to distinguish successfully left from right hand imagery. Each participant went through 3 complete training sessions followed by 3 online sessions (1 set per day for each headset) within one week. On each session, the participant had to perform 20 repetitions per class (left or right) of a 30 seconds baseline measurement followed by cue based motor-imagery training. The cue duration (using a unidirectional arrow) lasted for 4 seconds and was followed by 1.5 second pause. After the completion of the training session, a 5 minute rest was followed by an online MI-BCI session with the trained classifier. The classification performance of the offline session quantifies the ability of the classifier to distinguish the two classes (left and right hand imaginary) with cross-validation -based error estimation. In the online session, the

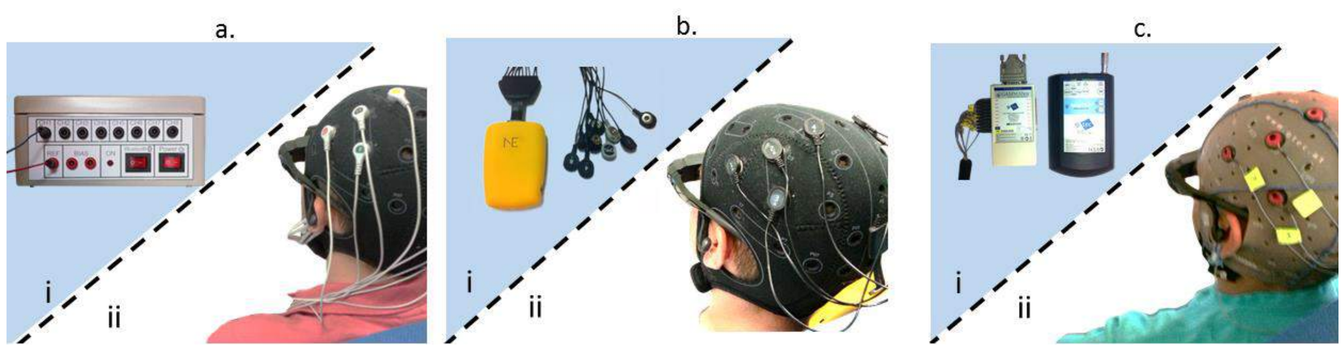

Figure 2. From left to right, the openBCI system (a.i) with snap-on type of electrodes using a neoprene cap (a,ii), the Enobio system (b.i) attached in the back of a neoprene cap (b.ii), and the gMOBIlab+ system (c.i) with active electrodes (c.ii)

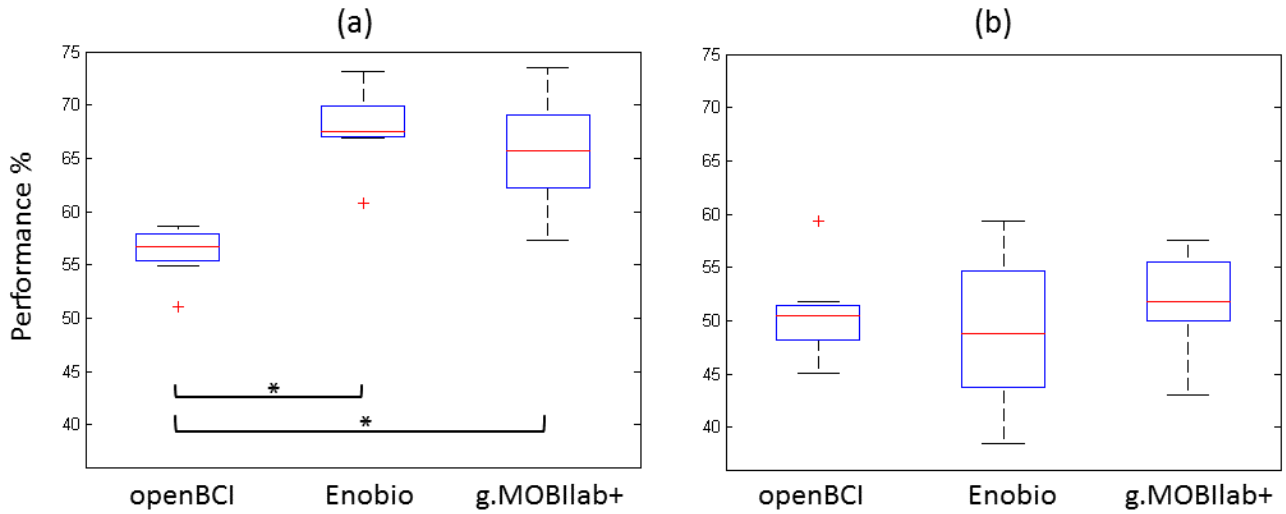

Figure 3. LDA classification performance. (a) Classification score between the two classes from the training data, (b) classification score of the two classes from a new dataset during the online session.

classifier needs to identify the two classes from a new stream of data that is acquired online by the user when trying to perform mental imagery within a specific time window. Finally, for all 3 sessions, from 8 participants, 24 EEG datasets were gathered and analyzed.

Questionnaires

Prior to the BCI training session, demographic data of the participants were collected together with a handedness assessment through the Edinburgh inventory [22]. After each setup, participants completed a usability questionnaire (used in a similar usability study [21]) for comparison. On this questionnaire, participants were asked to estimate the number of minutes it took for the headset to be setup (from the moment of electrode placement until the decision of the experimenter that signals were good). Then, they proceeded to rate on a 7-point Likert scale the 'speed of setup' (1 = very fast, 7 = very slow), level of 'comfort' of the headset (1 = very comfortable, 7 = very uncomfortable), and 'ease of setup' (1 = very easy, 7 = very difficult). Finally, the NASA Task Load Index (TLX) questionnaire [11] was used after each session in order to assess the perceived workload to use each EEG headset in terms of Mental Demand, Temporal Demand, Physical Demand, Performance, Effort and Frustration in a likert scale with 21 points (1 = very low, 21 = very high).

RESULTS

What is the Effectiveness of High-End EEG-based BCI devices?

In this study, effectiveness was measured in terms of performance - as objectively assessed by the classification accuracy during motor imagery task - and subjectively through the reported workload and the usability reports.

Performance

Classification Performance was computed as the success rate of the correct recognized classes of the training data and also the classifier performance during online task with the use of new data. Mean classification accuracy across participants and conditions was used for statistical analysis through a repeated measure ANOVA since the data was normally distributed as indicated by the Shapiro-Wilk Test.

Training

A statistically significant difference was found between the different headsets from the training data (*F(1.370, 9.590) = 21.112, p < 0.005*). Post hoc tests using the Bonferroni correction revealed that openBCI (M = 56.2, SD = 2.3) performed significantly worse (p<0.05) than Enobio (M = 67.8, SD = 3.4) and g.tec (M = 65.6, SD = 4.8) (Figure 3 a). Enobio and g.tec had no significant differences.

Task

We observed that the classifier performance with the new data acquired during the online task dropped for all headsets. We found no statistically significant main effect of BCI headset in performance (*F(1.997, 13.980) = 16.695, p = 0.563*). The highest mean performance was achieved by the g.MOBIlab+ system (*M* = 51.9 %, *SD* = 4.2%), followed by the openBCI system (*M* = 50.5%, *SD* = 4%), and finally the Enobio system (*M* = 49%, with the highest data variability *SD* = 6.6%) (Figure 3 b).

Workload

To assess how different headset technology may affect the perceived task workload required to perform the MI task we used the reports from the TLX questionnaire. We found again no significant main effect between the three conditions (*F(1.679, 11.756) = 0.694, p = 0.495*), nor in overall workload score as derived from the weighted sum of the TLX domains (Mental Demand, Temporal Demand, Physical Demand, Performance, Effort and Frustration). Nevertheless, the openBCI system had the highest score in Temporal Demand (*M = 8.8, SD = 4.7*), Performance (*M = 11, SD = 3.2*) and Frustration (*M = 8.4, SD = 5*). Enobio scored the highest in Mental (*M = 12.7, SD = 3.7*) and Physical Demand (*M = 6.7, SD = 2.9*). Finally, g.MOBIlab+ scored the highest in Effort (*M = 12.5, SD = 2.8*) (Figure 4).

Usability
Friedman's analysis showed no significant effect of type of headset in any of the usability questions (see Table 1). The scores obtained were the following: for speed of setup (1-7) the mean value was *M* = 5, for all headsets; for ease of setup (1-7) Enobio and g.tec scored higher (M = 6) than openBCI (*M* = 5); for comfort (1-7), g.MOBIlab+ was the highest (*M = 6*) over the other two (*M = 5*). Finally, on appearance (1-10), g. MOBIlab+ scored the lowest (*M = 3*) and openBCI and Enobio had a higher score (*M = 6*) (see Table 1 a).

Cost-Effectiveness Analysis
The concept of cost-effectiveness is used in medical decision making and can be illustrated graphically on the cost-effectiveness (CE) plane [3]. The CE plane provides a geometrical interpretation of relative cost-effectiveness in terms of their assessed performance (see Figure 5). Typically, one or more new strategies are compared against an existing standard. Since there is no standard available for EEG systems, a within system comparison was performed with available data from the literature and the current study. One can visualize the results of such comparisons in CE plane (see Figure 5) in which both the MI and P300 effectiveness over cost is represented. For the sake of comparison, we only considered the offline classification

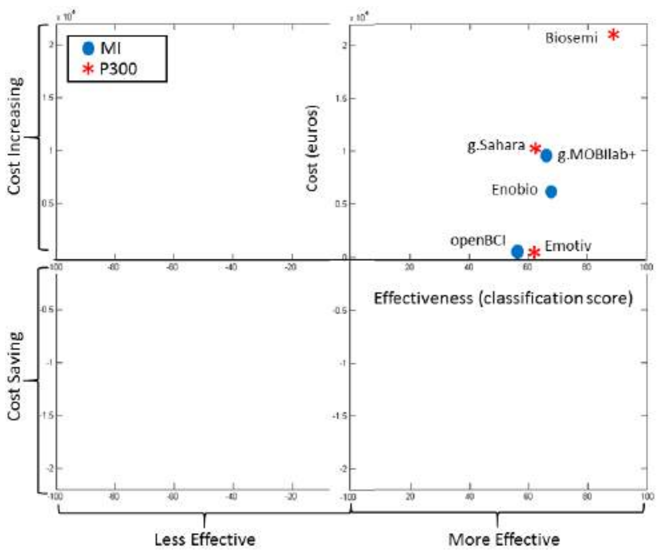

Figure 5. CE plane for cost (0-21000 euro) and effectiveness (1-100) for the offline classification on both studies. Systems that locate themselves further or closer from the origin (0,0) if they are more or less effective, and above or below the origin if they are more or less costly.

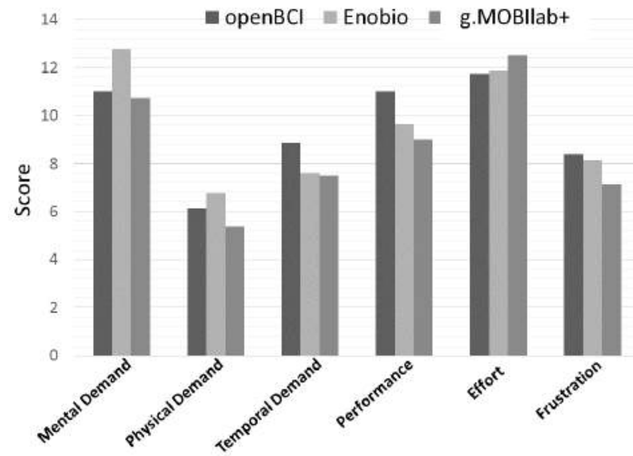

Figure 4. Sub-components of the NASA TLX questionnaire for obtaining task workload.

score from our study to match the available data from the previously mentioned P300 study [21]. Additionally, we estimated the cost of the devices reported in that study through online search. From the calculation of the cost-effectiveness ratios (CER) we found that the openBCI system was ranked first with the lowest CER (CER = 3.76), followed by Emotiv (CER = 6.48), Enobio (CER = 90.65), g.MOBIlab (CER = 147.83). The g.Sahara (CER = 159.49) and the Biosemi system (CER = 237.29) score the highest, CER ratio.

A repeated measures ANOVA with a Greenhouse-Geisser correction determined that mean CER differed statistically significantly between different BCI systems in both training ($F(1.209, 8.462) = 742.410$, $p < 0.001$) and online ($F(1.779, 12.456) = 339.260$, $p < 0.001$). Post hoc tests using the Bonferroni correction revealed that the openBCI system was statistically significantly better from Enobio and gMOBIlab+ systems as well as Enobio from gMOBIlab+.

DISCUSSION
From the technology side, the effect of intrinsic variability, low signal-to-noise ratio and non-stationarities of EEG signals [14] may explain the low classification accuracies obtained during task performance. The introduction of new EEG data combined with artifact contamination in the signals may have caused low performance of the LDA classifier as given by the hyperplane distance. From a user perspective, one of the biggest challenges in BCI research is to understand and solve the problem of "BCI Illiteracy" that is affecting an estimated 15 to 30% of the users [31]. Current limitations are based on the inability of many users to voluntarily modulate the amplitude of the sensory-motor rhythm in order to control the feedback application. Unfortunately, comparisons across different studies have been problematic since different groups use different performance thresholds [2]. To date, and to the best of our knowledge, there are no similar studies that investigate the

	(a)			(b)		
	Biosemi (32 channel)	**Emotiv (14 channel)**	**g.Sahara (8 channel)**	**openBCI (8 channel)**	**Enobio (8 channel)**	**g.MOBIlab (8 channel)**
Classification accuracy	88.5% (± 18.3)	61.7% (± 25.7)	62.7% (± 37.7)	56.2 (± 2.3)	67.8 (± 3.4)	65.6 (± 4.8)
Real time to setup	20.3 min (± 6.7)	6.9 min (± 3.3)	12.1 min (± 2.9)	6.7 min (± 2.4)	6.1 min (± 1)	4.8 min (± 0.6)
Participants' estimation of time to setup	14.4 min (± 5.2)	6.4 min (± 4.7)	9.7 min (± 2.9)	6.4 min (± 2.3)	5 min (± 1.5)	5.6 min (± 1.9)
Speed of setup	4	2	4	5	5	5
Ease of setup	6	3	3	5	6	6
Comfort	3	4	3	5	5	6
Appearance	6	6	4	6	6	3

Table 1. Overview of the usability scores and classification accuracy during training from this study (a) with openBCI, Enobio and g.MOBIlab, compared to a similar P300 study [21] with different headsets and number of electrodes and placement (b) using the Biosemi, Emotiv and g.Sahara systems.

ratio of cost effectiveness, a subjective measure through user experience, and an objective measure which is the classification score. From our current data, we can distinguish a trend in different dimensions concerning the classification performance, perceived workload, usability and cost-efficiency. From the P300 classification (Table 1 a), we can distinguish greater standard deviations compared with MI and also lower scores in usability.

Unfortunately, the small sample from both studies result in a low statistical power that may prevent capturing some effects. Nevertheless, the fusion of two studies, involving two BCI paradigms is a significant step towards understanding the technology transfer and acceptance of BCIs from non-expert users.

CONCLUSION

So far, we found no significant differences in the online performance among the 3 EEG headsets from the set of data derived from both subjective sources - through the questionnaires - as well as objective data - derived from the online performance. Given the current findings, devices seem to have similar effectiveness and we can conclude that there is no perceived difference in terms of comfort, appearance, speed/ease of setup and overall workload in the actual system performance. Hence, the low-cost openBCI open source system is the more cost-effective BCI solution as compared with its commercial medical grade counterparts.

The comparison in the P300 study [21] considered different electrode configurations across systems, and a different interaction paradigm (P300 vs MI). Although we cannot directly compare classification scores, we observed that regardless of the BCI paradigm, usability and CER analysis indicate that medical grade and more expensive systems do not necessarily add value on the experience level of the users. Therefore, we can conclude that brain-computer interaction performance/throughput, at least for the particular case of non-expert users, is not technology related and it can be accomplished without requiring high-end and high-cost devices. Current results provide useful pointers towards leveraging research of Brain-Computer Interaction for non-expert users and minimizing BCI illiteracy.

FUTURE WORK

In future work, it is important to consider the factors influencing not only user performance but also user experience for the advancement of physiological computing research. Future studies need to be based on similar protocols and experimental designs in order to be comparable, including system cost. Finally, based on our current findings, open-source EEG systems rather than commercial low-cost systems need to be further investigated because of their potential as they offer high CER and feasible and effective alternatives for BCI studies.

ACKNOWLEDGMENTS

This work is supported by the European Commission through the RehabNet project - Neuroscience Based Interactive Systems for Motor Rehabilitation - EC (303891 RehabNet FP7-PEOPLE-2011-CIG), by the Fundação para a Ciência e Tecnologia (Portuguese Foundation for Science and Technology) through SFRH/BD/97117/2013, and LARSyS (Laboratório de Robótica e Sistemas em Engenharia e Ciência) through UID/EEA/50009/2013.

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