Human Computer Interaction for Brain Computer Interfaces

1. Introduction

A brain-computer interface (BCI) is a hardware-software complex that functionally establishes a direct connection between a computational or digital control system and the brain [1]. In tandem with robotics, BCI holds potential for future development in various fields including rehabilitation, prosthetics, entertainment, and augmentation [2-4]. The central premise of BCI-robotic systems is that the user is given a specific task designed to elicit a task-specific brain activation pattern, which is then identified by the data acquisition system. BCIs can use a variety of neuroimaging techniques including functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG) and functional near-infrared spectroscopy (fNIRS) [5-7]. The primary technique used by BCI systems, however, is electroencephalography (EEG), given its benefits of being non-invasive and portable, and having sufficient spatial and temporal resolution for BCI systems depending on quality and number of electrodes. EEG-BCI systems are typically configured to detect specific neurophysiological input which non-exhaustively includes slow cortical potential, sensorimotor rhythms, and evoked potentials [8].

Most current EEG-BCI systems include measures of mental (cognitive) workload, the amount of mental resources engaged in a task, and/or mental fatigue, reduced alertness from growing time-on-task (TOT) [9]. Moreover, measures of usability which typically encompass effectiveness, efficiency, satisfaction, and/or learnability are utilized to evaluate the system [10-11]. This literature review focuses primarily on exploring human-computer interaction within EEG-BCI systems from training to use, with the central purpose of understanding interaction for a navigation task.

2. BCI Training Sequence

Applying EEG-BCI systems as proposed poses several challenges, especially regarding acceptance by users. Zander et al. (2010) presents the following five stages for structuring a BCI session [12]:

1. User Training: User gets familiarized with the task of the next stage (Machine Training).
2. Machine Training: User is guided to generate prototypes of brain activity which can be used as input for the EEG-BCI system. All artifacts should be controlled, and the outcome should be a detector system that is able to distinguish the intended navigation commands (front, back, left, right).
3. Confluence: EEG-BCI system should have the ability to be controlled by the previously defined detector. Parameters may be adjusted and the user can learn how to interact with the system.
4. Validation: The first test of the EEG-BCI system, with an outcome of a performance estimate of the defined detector.
5. Application: The defined and validated detector is applied for generating input to the EEG-BCI system resulting from brain activity of the user.

Furthermore, Mladenović et al. (2018) in [13] emphasize that to assist users in producing clear EEG patterns is to assist their learning, given that one's capacity to create distinct EEG patterns is dependent on psychological components. These psychological components include motivation, mood, skills, and personality traits [13-15]. BCI output is thus adapted by considering a spectrum of users' psychological components to maintain motivation and performance, and to be efficient and effective–assisting in better EEG-BCI feedback design and task adaptation. In this way, EEG patterns are regulated, suggesting that there is a direct relationship from user learning to machine learning.

3. Cognitive Load and User Demands

Cognitive Load Theory (CLT) suggests that performance degrades at excessively low and excessively high cognitive loads; under these conditions, learners may cease to effectively learn [16-17]. Given the previously established relationship between user learning and machine learning in an EEG-BCI system, it is thus prudent to measure cognitive load to ensure the effectiveness of the system. One such method is to estimate cognitive load using EEG signals which are then classified using deep learning architectures, which has been observed to out-perform traditional machine learning (ML) classifiers such as support vector machine (SVM), k-nearest neighbors (KNN), and linear discriminant analysis (LDA) [18-19]. Authors in [18] propose two models, 1) stacked denoising autoencoder (SDAE) followed by a multilayer perceptron (MLP) and 2) long term short memory (LSTM) followed by an MLP, in which SDAE and LSTM are used for feature extraction and MLP is used for classification of cognitive load data. It was observed that SDAE followed by MLP out-performed LSTM followed by MLP, although both out-performed traditional ML techniques.

In regards to how EEG signals are collected in measuring cognitive load, medical grade EEG devices have often been used [20-21] yet are expensive and not user-friendly for regular use. However, the recent launch of low-cost wireless EEG headsets, namely Emotiv and Neurosky, have opened up the possibility for the commercialization of EEG-BCI [22]. Authors in [22] implemented cognitive load detection with criterion that differentiates a low cognitive task from a high-cognitive task; each of the trial epochs and the baseline epochs are S-transformed to decompose the non-stationary EEG signal in time-frequency domain for better precision and then the alpha band (7.5 to 12.5 Hz) and theta band (4 to 7.5 Hz) mean frequency and power for all trials and baselines are calculated separately for all EEG leads from N channels. Based on a performance index and a quality index, it was observed that Emotiv can provide superior results than Neurosky when measuring cognitive load as it can probe a larger part of the brain, hence carrying more information. Nevertheless, tradeoffs exist in that Neurosky is more user-friendly, and easier to set up and maintain, although its capacity for cognitive load detection is limited. For the navigation task presented previously, Emotiv is used to capture EEG signals.

Furthermore, Steady State Visually Evoked Potentials (SSVEP) is a cerebral pattern commonly used for EEG-BCIs. It is robust to external noise, requires limited training, and has relatively stable performance across users [23-24]. Authors in [24] assess the cognitive demand of the SSVEP paradigm and observe that little attention is needed from users to reach optimal accuracy whether visual or auditory attention is solicited. Given its low cognitive demands of, the SSVEP paradigm is thus encouraging for its use in complex interaction settings such as navigation tasks.

4. User Experience and Usability

To holistically evaluate BCI-controlled applications, the usability of the system with regard to its effectiveness, efficiency, and satisfaction can be measured. Effectiveness is defined as how accurately and frequently the intended output is achieved, and is measured in [25] by the relationship between successful selections and total number of attempted selections. Efficiency relates the costs invested by the user to effectiveness; it can be objectively measured by the information transferred per time unit (Information Transfer Rate) and subjectively measured by workload with the NASA Task Load Index (TLX) [25]. Satisfaction refers to perceptions of comfort and acceptance and is measured by authors in [25] with the Quebec User Evaluation of Satisfaction with Assistive Technology (QUEST 2.0) and additional BCI-specific items of reliability, speed, learnability, and aesthetic design.

While BCI systems are often designed for users with physical or mental impairments, its capabilities can be extended to users with other purposes such as entertainment. Using the ISO 9241-11 usability model, authors in [26] measured effectiveness, efficiency, and satisfaction for a gaming user population. Satisfaction was measured with the USE questionnaire [27], effectiveness was measured with the percentage of tasks completed successfully divided by the total number of tasks attempted, and overall relative efficiency [28] was calculated with the ratio of the time taken by users who have successfully completed the task in relation to the total time taken by all users. In [29], which similarly focuses on a gaming user population, usability is divided into learnability, memorability, efficiency, effectiveness, safety, and satisfaction. Authors in [29] found that training with neurofeedback can improve learnability, and that incorporating training in the game to increase motivation can improve memorability. [29] also introduces the possibility of error correction in BCI systems for safety, in which an error-related negativity potential is visible in brain activity and can be used to automatically undo actions. For satisfaction specific to gaming, it is presented that measures of user satisfaction can be customized and personalized by storyline, presentation or difficulty level according to the user's mental state.

Although satisfaction as part of usability is often measured through self-report questionnaires, such as in [28-30], authors in [31] detect user satisfaction level through brain activity, given that emotional states activate certain parts of the brain, particularly in the frontal lobe [32]. The feature vector is formed by taking the power spectral density of each EEG frequency band and the four largest Lyapunov exponents of each EEG signal. The Mann-Whitney-Wilcoxon test is then used to rank all the features, in which the highest ranked features are then selected to train a linear discriminant classifier (LDC) in order to determine the satisfaction level. There are thus various methods to obtain certain measures, depending on the central goal as well as availability of resources.

5. References

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