Investigating alternative training protocols for spontaneous Brain-Computer Interfaces on BCI skill acquisition

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Author Note

This paper was made for the final assignment in Psych 122: Human Learning and Memory. The experiment wasn't actually carried out because the OpenBCI delivery was delayed so the results are simulated, but will be done over the course of this summer. The purpose of this paper is to formalize an idea I had. This is definitely the best class I've taken in Berkeley so far and thus recommend it to everyone. I've changed the way I learn and acquire knowledge: meta-learning. You are welcome to use this document for learning and research purposes, but at your own risk. I am still an undergraduate with little knowledge on the field so my conclusions are merely based on recent acquired knowledge.

Abstract

Brain-Computer Interfacing (BCI) is an emerging field that is quickly acquiring the attention of the scientific community as well as the general public. BCI applications are currently being developed for commercial EEG headsets. There have been numerous studies on the processing of EEG signals and machine-learning algorithms. Nevertheless, human training, a key component of the BCI loop, has been scarcely studied. In order for the user to produce stable and distinct EEG signals that are accurate enough to trigger a previously trained command, it is essential to have an appropriate training protocol. This study explores the use of a newly designed BCI training and feedback protocol to achieve more efficient BCI skill learning. Methods from psychology, neuroscience and instructional design were employed in the design of the BCI training protocol. The results show that the proposed BCI training and feedback protocol is a more suitable procedure for the acquisition of BCI skills *de novo*.

Keywords – BCI; skill learning; multimodal feedback; vibrotactile stimulation; instructional design; EEG; motor and kinesthetic imagery

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Brain-Computer Interfaces (BCIs) are communication pathways designed to translate brain activity signals into digital outputs that enable users to communicate with computers (McFarland & Wolpaw, 2011). This is usually done using Electroencephalography (EEG), a non-invasive technique that uses electrodes on the surface of the scalp to record brain electrical activity. BCI has been shown to have very high potential not only for communication and control of applications, but also for rehabilitation, human-computer interaction and entertainment (Lotte, Larrue, & Mühl, 2013). Nevertheless, this technology is barely used outside laboratories as it still lacks robustness.

Robustness of BCI

For this research, *robustness* will be defined as the consistency, accuracy and reliability of relevant data extracted from EEG signals. The BCI studied in this research will be based on spontaneous BCI, which involves training subjects to modulate their brain state to perform a desired command. Conversely, Event Related Potential (ERP) BCI does not require skill training. The lack of robustness in current BCI applications is due to flaws in two separate components of the BCI loop: machine processing and human training.

Machine Processing

Data extracted from the scalp is in the form of analog signals, which are processed using methods such as Fourier transform, and then machine learning is applied to recognize and classify EEG patterns. There are weaknesses in both the hardware and software that compose the BCI machine segment. In the hardware side, there is heavy interference due to noise sources that EEG designers haven't been able to eradicate. In the software flank, signal-processing algorithms are not yet reliable enough to produce accurate predictions. Combining these two segments, it is clear that performing unreliable signal processing on erratic data does not provide a high enough level of robustness for BCI applications (McFarland & Wolpaw, 2011).

Human Training

Most research on how to improve BCI robustness has been focused on its machine components. Nevertheless, it has been shown that how well the user masters the BCI skill is a key component. No matter how accurate the signal-processing and machine-learning algorithm are, if the user is not able to produce stable and distinct EEG patterns, the BCI user won't be able to trigger the desired mental commands. A recent study based on instructional design[1] has identified

[1] The development of instructional experiences that make the acquisition of knowledge and skill more efficient, effective, and appealing (Merrill, Drake, Lacy, & Pratt, 1996)

numerous flaws in the design of current spontaneous BCI training. Thus, it was concluded that current spontaneous BCI training procedures are suboptimal and hence hinders BCI skill learning. Consequently, it has been recognized the need of appropriate training to effectively use BCI applications (Lotte, Larrue, & Mühl, 2013).

BCI Training Protocols

There are two common training protocols, the operant conditioning and the machine learning approach. Both of these are built on top on the concept of neurofeedback, which consists in providing the users with real-time feedback about his/her own brain activity. The operant conditioning approach consists of a fixed EEG signal classifier, which is unknown to the user. The user is expected to learn how to modulate his/her brain activity to perform the desired mental commands. This method may require from two weeks to months for the user to correctly learn the BCI skill. On the other hand, there is the machine learning approach. The user performs the targeted mental tasks beforehand in a “training session”. Brain activity while performing such task is recorded and fed to the machine-learning algorithm. This is the most frequently used protocol as it reduces the training time to about 20 minutes for 2 classes. For the purpose of this research, only the machine learning approach will be studied, as it is the most efficient and commonly used. Despite being the ‘state-of-art’ in BCI training protocols, this method has been proven to contain many flaws, as aforementioned (Lotte, Larrue, & Mühl, 2013).

The purpose of this study was to test an improved spontaneous BCI training and feedback protocol designed by myself based on the flaws found on the current BCI training protocol and new research suggestions that are theoretically expected to improve the efficiency of BCI skill learning (Lotte, Larrue, & Mühl, 2013).

Methods

Participants

Twelve healthy subjects (20 ± 3 years, 3 females) with no previous BCI skill training were chosen randomly from the University of California at Berkeley. It was explicitly stated that they must have no impaired learning or motor skills. They were told not to consume any type of drug that could either enhance or impair their performance in the study.

Measures/Materials

Participants were wired using an OpenBCI board with 8 channels. This EEG was used as it is open-sourced, offers laboratory-grade quality and is easy to program. Electrodes were placed according to the 10-20 system of electrode placement. The ground was placed on the center of the forehead, the reference electrode was split into two and placed in A1 and A2 (both earlobes) to ensure the reference is well balanced between both sides of the head. The 8 electrodes were placed in F_3, F_Z, F_4, C_3, C_4, P_3, P_2 and P_4. Using this electrode arrangement, recordings were focused on the Frontal and Parietal Lobe.

Design and Procedure

Proposed BCI training protocol

Feedback

Nine coin motors with a diameter of 10mm each and vibrational amplitude range of 0.5 to 1.8g each were placed on the back of the participant's neck. Six of them were attached in a horizontal array on the lower neck with a center point at the spine and about 2.5cm of inter-motor-spacing (Leeb, Gwak, Kim, & del R. Millán, 2013). The other three arrays were attached in a vertical array starting from the horizontal array center in an upward direction. Together, these two arrays represented an x and y plane. The output of the BCI was translated to different motors moving at different amplitudes to create spatiotemporal patterns. This method provided vibrotactile feedback that informed subjects about their current brain state. This feedback procedure works by assigning different amplitudes to the vibration of the motors. For example, if two motors were on at the same amplitude, the virtual sensation point would be in the middle of both. If the amplitude of the right motor was increased, the virtual sensation point would be further right (but still between the two motors).

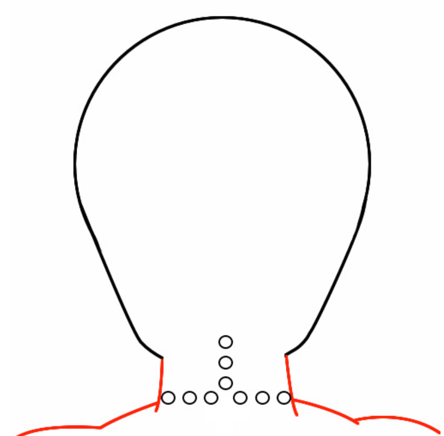

Fig. 1. Motor arrangement on the back of the neck

Instruction

A training interface was developed using python and pygame as the 2d graphics engine. Subjects were explained the purpose of the BCI training: to produce clear, specific and stable EEG patterns. BCI feedback was defined and explained to participants in non-technical ways and then instructed to imagine the movement associated with the chosen controlling electrode when presented with the cue. Participants were walked through the training interface and were making them feel comfortable. Kinesthetic animations were used to promote rich motor images when the user is imagining the task. In addition, distinct colors were used to increase the power of the images by increasing the number of cues. Finally, the modes the three commands were trained (up, left and right) were designed to be very different to assure a distinct and stable EEG pattern. For *left* and *right*, a clutching hand was animated. For up, a walking animation was displayed. Vibrotactile feedback was also incorporated to the training phase.

The study was divided in six sessions. A complete training session was defined as the completion of the training cycle: up, left and right. The participants were separated in two groups (six per group). Group 1 was provided with the common training protocol. Simple arrows were used as cues for training the three different directions. Group 2 was given the proposed BCI training protocol: visual + tactile training and feedback. EEG patterns were recorded while training and used as target data for the machine-learning algorithm.

After each complete training session, the participants were asked to perform each BCI skill ten times with a 2-minute rest between each attempt. The order of the three commands was chosen randomly. The fraction of successful trials was measured at each of the six sessions.

Results

The above chart shows the average task performance for each of the groups. The fraction of successful trials was recorded for each of the six runs. Each run was divided in 10 trials that were averaged. Each trial was measured from 0 to 1 in accordance to the ability shown by the participant to correctly perform the desired mental command.

Group 1 performed at a 0.4 success rate in the first run while Group 2 performed at 0.6. Both groups increased at a faster rate in the first three runs than in the last three, where performance reached a plateau. It is clear that Group 2 had a much higher performance, maintaining a difference of more than 0.2 throughout all the runs.

Discussion

Implications

The results showed that proposed BCI training and feedback protocol resulted in more efficient learning. The group that was trained using the designed interface was more successful at performing the desired command from the first attempt. This can be explained by the fact the proposed BCI training protocol was designed to promote the creation of rich kinesthetic and motor images that aid in the production of more stable and distinct EEG patterns. Furthermore, the proposed BCI training protocol offers multimodal feedback (visual + haptic) with some redundancy between them (left animation + left movement sensation).

Future Development

Because of time constraints, the BCI training and feedback protocol could not be developed completely, and thus a prototype version was employed for this experiment. The actual visual feedback could be improved even more using engaging feedback and environment. The development of a better interface is currently under development. The plan is to link this training interface to a ‘Bomberman’ pygame clone. In this way, the user is more motivated as gaming experiences produce positive emotions that are thought to enhance learning.

References and figures

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Figures

Training Interface