Chapter #13

ATTENTIONAL VARIABLES AND BCI PERFORMANCE: COMPARING TWO STRATEGIES

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ABSTRACT
The objective of this chapter is to evaluate task factors and user factors affecting Motor Imagery Brain Computer Interfaces (MI-BCI) performance. Brain computer interface (BCI) technology has been under research for several decades. Nevertheless, its practical applications have been mostly ad hoc solutions for individual users. In order to become an alternative in clinical use BCI performance must be improved. In our experiment fifty subjects performed two different EEG based MI-BCI tasks. The participants controlled a BCI task with an action-action motor imagery strategy versus an action-relaxation strategy. BCI performance and subject attentional traits were evaluated for every user under both experimental conditions. Our results show a better performance when the task was controlled with an action-action strategy versus an action-relaxation strategy. Moreover, in the action-action strategy a constant performance improvement was achieved with short term training. It can be hypothesized that for most subjects it is easier to switch from an action strategy to another action strategy than to switch from an action strategy to a relaxation strategy. Regarding user factors, impulsivity seems to be inversely related to the ability to master the BCI-task. Processing speed and cognitive flexibility can also predict a better performance in MI-BCI based tasks.

Keywords: brain computer interfaces, motor imagery, instructions, attention.

1. INTRODUCTION

Brain Computer Interfaces (BCIs) are non-muscular communication and control systems that a person can use to communicate his/her intention and to act on the environment directly from brain activity measurements (Schalk, Brunner, Gerhardt, Bischof, & Wolpaw, 2008). BCIs consist of sensors that record brain activity and algorithms that process this information in order to use it to interact with the environment (Lotte, 2014). Looking for extensive clinical use we focus on EEG based BCI applications due to its non-invasive character and high temporal resolution.

The potential of BCI as assistive technology systems was the main motor for its development. Patients who can benefit most from this technology are those with limited communication and movement capabilities (Kranczioch, Zich, Schierlholz, & Sterr, 2014). Different user-oriented applications have been developed including communication protocols such as spellers (Placidi, Petracca, Spezialetti, & Iacoviello, 2016), control of robot arms and neuro-prosthesis (Iturrate, Chavarriaga, Montesano, Mínguez, & Millán, 2015), control of motorized wheelchairs (Iturrate, Antelis, Kübler, & Mínguez, 2009) and different home automation systems (Perego, Maggi, Parini, & Andreoni, 2008).

BCI technology has been under research for several decades. Despite its relevant medical potential, existing developments have been limited to ad hoc solutions for individual users. BCI is not yet a common technology in medical or rehabilitation protocols (Mihajlović, Grundlehner, Vullers, & Penders, 2015). Barriers that must be solved before BCI technology can become commercial or standard include customization of BCI applications for each subject, such as the necessity of an individual and recurrent calibration; standardization of protocols and procedures and convenience and comfort in use of registration systems (i.e. EEG electrodes and caps) (Lightbody, Galway, & McCullagh, 2014). It is currently intended to solve problems that prevent the extension from the research lab to medical or recreational extended BCI use (Tangermann, Lotte, & Van Erp, 2012). Success of BCI technology depends on its reliability and accuracy improvement, i.e. to achieve a high percentage in the number of times in which the system executes the intended action.

Motor imagery is one of the most common strategies applied to design BCIs. The motor imagery technique is based on the analysis of the EEG when the subject imagines or performs a movement. The thought or realization of a motor action modifies the characteristics of the EEG signal produced by the sensorimotor areas of the cerebral cortex. *Mu* rhythms and *beta* rhythms are modified not only by the execution of the action but also by its imagined realization. The imagination of motor actions usually involves a variation of the amplitude of the mu and beta rhythms in the sensory-motor cortex (Wolpaw & McFarland, 2004). These variations in the spectral content of the EEG signal associated with the thought of a given action can be employed by the subject to control a BCI system (Lotte, Congedo, Lécuyer, Lamarche, & Arnaldi, 2007). What motor imaginations allow for a better control remains an open issue.

The study of Brain-Computer-Interfaces (BCI) requires deep knowledge of brain as well as processors' functioning. BCIs are biofeedback systems which transform EEG-waves into actions that can be performed by a machine. The term was coined by Jacques Vidal in 1973 (Vidal, 1973). BCIs may have interesting and possibly successful applications to therapeutic fields. It will be possible, for instance, developing exoskeletons that will allow those who have lost the ability to move their limbs just by using brain activity, as well as performing all sorts of home automation activities, or will facilitate the communication to those with severe speech disorders, among other possible utilities. Promising as it may look like, there are, however, a number of unknown aspects for which no solid explanations have been provided by now. A part of the future success of BCI-based therapeutic approaches relays on our ability to identify which variables affect the ability to interact with a machine by means of the mental activities that we can produce and control in highly variable conditions, as well as which are the conditions in which this ability can be most effectively acquired by learning (Vaadia & Birbaumer, 2009).

These facts have led many authors to investigate variables that affect BCI performance. (Jeunet, N'Kaoua, & Lotte, 2016) grouped the predictors of performance into three categories: (1) users' relationship with technology, (2) attention and (3) spatial abilities.

Concerning users' relationship with technology some authors have found a correlation between MI-BCI performance and variables such as locus of control related to technology (Burde & Blankertz, 2006). Jeunet, N'Kaoua, Subramanian, Hachet, & Lotte (2015) showed a positive correlation of MI-BCI performance with user tension and self-reliance.

Attention and motivation have been shown to positively correlate with MI-BCI performance (Daum, et al., 1993; Grosse-Wentrup, Schölkopf, & Hill, 2011; Grosse-Wentrup & Schölkopf, 2012; Neumann & Birbaumer, 2003; Nijboer, et al., 2008). Hammer, et al., (2012) also showed that attention span influenced MI-BCI control performance. When considering attention, it must be distinguished between the user's attentional abilities (trait) and attention level during the task (state). The latter can be influenced by parameters such as environmental factors, mood or motivation. Both these aspects of attention have been repeatedly suggested as being predictors of BCI performance (Jeunet et al, 2016).

Spatial abilities seem to play an important role in user BCI performance: Kinesthetic imagination, visual-motor imagination, mental rotation scores or abstractness abilities have been shown to affect user performance in MI-BCI tasks (Vuckovic & Osuagwu, 2013).

Other factors affecting BCI performance include demographic characteristics like gender and age and habits like playing a music instrument, practicing sports or playing video games.

Authors who have studied the problem agree on the need to carry out more research in order to identify variables that predict a good performance in BCI tasks. To go along those lines, we aim to study the strategies used by individuals having shown a high success at BCI tasks, since we have learned from previous studies that there are huge inter-individual differences in the ability to manipulate BCI devices (Jeunet et al, 2015). Some subjects display good performances, even after just a few trials, while others are almost unable to learn how to do it, a phenomenon that has been named 'BCI-illiteracy' and may affect an estimated 15 to 30% of the population aptly manage a BCI (Vidaurre & Blankertz, 2010; Allison & Neuper, 2010). Correctly identifying these skills could be a useful tool to predict 'BCI-literacy'. Additionally, we aim to ascertaining which kind of instruction may be more useful in order to facilitate learning to use a BCI-device.

2. OBJECTIVE

The objective of this chapter is to evaluate task variables and user variables affecting Motor Imagery Brain Computer Interfaces (MI-BCI) performance. We wanted to compare BCI performance with different motor imagery tasks. In particular, we compare actions instructions (imagining moving hands or feet) and non-action instructions (imagining quiet hands or feet). Regarding user variables, we evaluate the influence of attentional capabilities on BCI performance.

3. METHODS

3.1. Participants

A total of 50 second-year Psychology students (10 men and 40 women; age=20.18 ± 3.04) at the Universitat de València have participated in this study. None of them had previous experience with BCIs.

All procedures performed involving human participants were in accordance with the ethical standards of the Universitat de València research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants included in the study.

3.2. Instruments

The following instruments and materials were used:

- Initial questionnaire: Designed by ourselves to explore daily activities usually performed by the participants (physical exercise, video games, music training...) that had been hypothetically related to the ability to manage a BCI-device.

- Virtual-Reality Test 'Aula Nesplora': Intended to evaluate sustained and selective attention to visual as well as auditive stimuli (Climent, Banterla, & Iriarte, 2011; Díaz-Orueta, et al., 2014). The participants are subjected to a variety of external distractors of both sensorial modalities, which allows an evaluation of their ability to inhibit the effect of distractions. The instrument also evaluates the ability to inhibit internal distractors, which has been considered as particularly relevant for our purposes (Zulueta, Iriarte, Díaz-Orueta, & Climent, 2013).

- CPT II Test: Provides an assessment of the general attentional capacities as well as concentration and alertness (Conners & MHS Staff, 2000). It offers, as well, a score of the participant's ability to inhibit a response.

- Enobio (8-channels): It is a BCI-device based on the recording of EEG-waves. It uses wireless technology. The dry electrodes make it easier and more comfortable for the participants and have shown similar levels of recording efficacy than the humid ones (Zander, et al., 2011). The signal was acquired through channels F3, F4, C3, Cz, C4, T7, T8 and Pz, according to the international system10/20, placed on sensory-motor areas in order to apply the BCI paradigm of motor imagery. To implement the system, BCI2000 software was employed because of its contrasted results (Schalk, McFarland, Hinterberger, Birbaumer, & Wolpaw, 2004).

- Cursor task: A cursor task, based on the modulation of Mu and Beta rhythms to control the position of a cursor on the computer screen, was selected to provide directions and feedback to the users (Renard, et al, 2010; Schalk, 2009). The participant's intentions should affect the cursor position by means of imagining motor actions. In our study, these actions have to follow the instructions received and are aimed to direct the cursor towards a bar that may appear in different parts of the screen. Being able to direct the cursor and to reach the bar is considered a successful attempt. The participant has to control the direction in which the cursor is moving, in order to reach the bar.

3.3. Experimental procedure

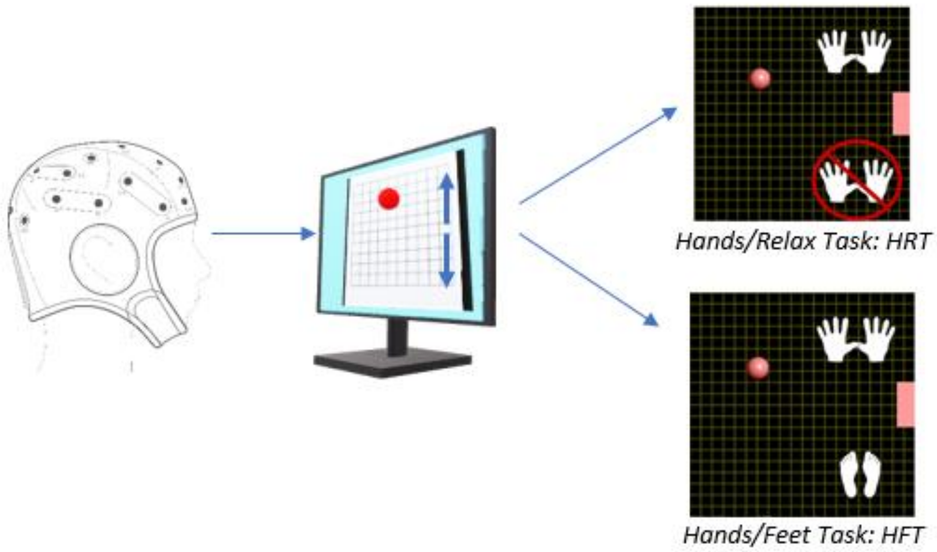
The whole experimental session in each session lasted for approximately 60 minutes and was organized in the following way: 10 minutes for preparation and information, 3 minutes for relaxation, 30 minutes for the MI-BCI tasks, 15 minutes for performing the attentional tests and 3 minutes for finishing.

- Preparation: Participants completed the initial questionnaire. The Enobio helmet was properly placed on their heads following the standard procedure (Wilson, Schalk, Walton, & Williams, 2009). They listened at the instructions while the habituation period was going on.
- Relaxation: Immediately before starting the tests, participants performed a Jacobson's progressive facial relaxation procedure guided by recorded verbal instructions that lasted for 180 seconds. The role of this relaxation procedure was to induce a relaxed state in the participants. It was conducted because tension has been shown to correlate negatively with motor imagery BCI performance (Jeunet et al, 2016).
- BCI tasks: Each participant performed two cursor tasks that differed in the instructions to control the vertical movement of a cursor moving on the computer screen (Figure 1). Targets appear on the screen and participants were asked to imagine the instructed movements to move the cursor towards the targets. An action-relaxation instruction was compared with an action-action instruction. In the action-relaxation instruction (hands/relax task: HRT) subjects had to purport moving their hands to move the cursor up. If they wanted to move the cursor down, they were instructed to relax. In the action-

action task (hands/feet task: HFT) they had to purport moving their hands to direct the cursor up. If they wanted to move the cursor down, they were instructed to imagine that they were stretching their feet.

- Attentional tests: Subjects performed the virtual-reality test 'Aula Nesplora' and, after a five minutes-break, completed the CPT II computerized test.

Figure 1.
BCI cursor tasks.



Each participant performed a total of six tests (three for each type of task) lasting 150 seconds each and divided into 20-second trials. In each trial, the cursor was visible for a maximum 20 seconds during which they could achieve success (the cursor reaching the target) or fail (the cursor not reaching the target). In both cases, a new trial was subsequently initiated.

To analyze the results SPSS software v. 16.0 was used. T-tests for related samples as well as for paired samples, and univariate variance analyses have been performed.

4. RESULTS AND DISCUSSION

We have compared an action-action strategy (HFT) with an action-relaxation strategy (HRT) in the MI-BCI task. Figure 2 shows the individual task success comparing the HRT control strategy and HFT control strategy. In Figure 2 results for all subjects are ordered according to their performance in the HRT. Figure 3 shows the group performance averages in each strategy.

Figure 2.
Individual task performance in HRT vs HFT.

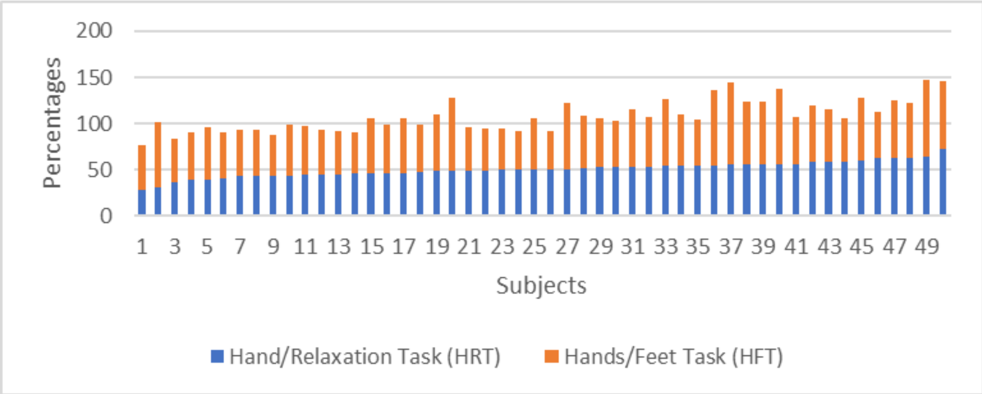
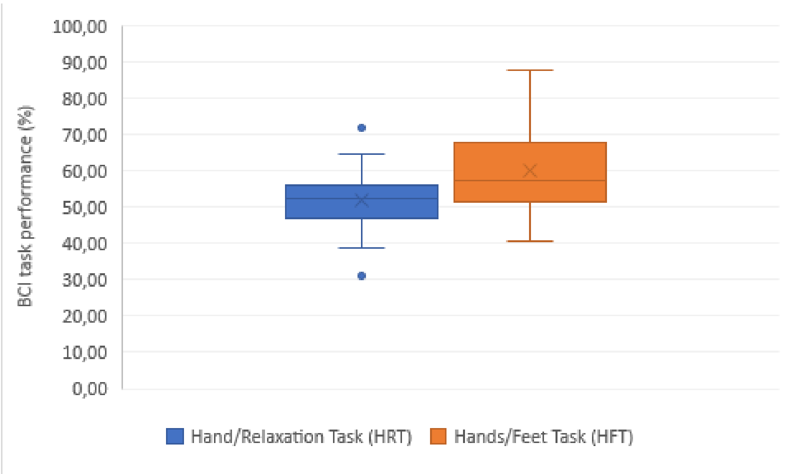


Figure 3.
Task performance average in HRT vs HFT.



As shown in Figures 2 and 3, HFT resulted in a better performance, and 38 out of 50 subjects (76%) achieved better results with this task strategy than with HRT. We found a statistically significant difference between both strategies. Participants achieved significantly less control on HRT trials than on HFT: t (49)= -4.667, p<0.001.

It can be hypothesized that for most subjects it is easier to switch from one action strategy to another (switch from thinking of moving both hands to thinking of moving both feet) than to switch from an action strategy to a relaxation strategy (think about moving both hands vs. think about no movement at all).

Average task performance was low as expected for subjects without previous training in MI-BCI. For the HRT, no learning was observed among the participants, operationalized as an increase in the percentage of successful attempts between the first and the last trial: The difference between both attempts was not significant. For the HFT, though, an improvement was observed between the first and the third trial ($t=-2.425$; $p= .010$).

Regarding attentional variables, a significant correlation ($r= .654$; $p=.019$) was found between HFT performance and the variable Response-Time in mistakes at the Nesplora test, meaning that those who are quicker at emitting a mistaken response (impulsive style) are worse BCI-performers.

Similar results are found between the Hit Reaction Time Change variable that evaluates response time, from the CPT II-test, and BCI performance ($r=.450$, $p=.046$). Which means that those subjects that reflect more time on the response to target stimuli, that is, respond less impulsively, also perform better in the cursor task.

There is a significant correlation between learning and average Response-Time to the hyperestimulation task of the Nesplora test ($r=.705$; $p= 0.014$). For this task, the participant has to respond every time a stimulus is shown or a name is said out loud, except when it is the target-stimulus. This result means that subjects who are quicker at answering during high-concentration tasks and are better at performing inhibition, are the ones who perform better in the BCI tasks.

There is also a significant correlation between Detectability (a CPT II score) and learning of the BCI tasks ($r=.948$; $p=.008$). Detectability assesses the participant's ability to quickly switch the attentional focus. This result can be interpreted in the sense that individuals with a high cognitive flexibility will be more likely to learn to control the BCI task.

There is a significant correlation ($r=.692$; $p=0.051$) between the average Response-Time (Nesplora) when no distractors are present and performance: individuals displaying a more impulsive style and make mistakes because of that will be slower at learning the cursor task.

Finally, we had positive feedback from the participants. The use of dry electrodes and wireless EEG signal transmission made the experimental setup comfortable. Motor imagery is well accepted by users because it provides a sense of agency compared to other paradigms (such as evoked potentials).

5. FUTURE RESEARCH DIRECTIONS

Brain-computer interface technology has a great potential for communication and for the control of assistive systems. This technology could improve the lives of thousands of people with disabilities. It has been observed that the use and control of this type of technology requires some degree of training, which may be longer or shorter depending on the users' psychological and cognitive features and on the BCI characteristics themselves. Our future research focus on identifying user variables and task variables to enhance BCI performance.

6. CONCLUSION

Our results show a better performance in the cursor task with an action-action MI strategy versus an action-relaxation MI strategy. Moreover, a constant performance improvement was achieved with short-term training in the action-action strategy.

We can conclude that:

- Instructions based on Action/Relaxation constitute a worse strategy than Action/Action instructions in order to control a BCI-task.
- As it could be expected, increasing the number of training sessions produces better results.
- Impulsivity is inversely related to the ability to master the BCI-task.
- Processing speed and cognitive flexibility can predict a better performance in MI-BCI based tasks.

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