# How does multi-modal feedback systems affect the learning rate of an abstract skill such as Motor Imagery Brain-Computer Interfacing?

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# Table of Contents


**Specific Aims**

Specific Aim

**Background and Significance**

Background

Motor imagery Brain-Computer Interfaces (MI-BCIs)

Meaningful Feedback

Multimodal Feedback

Task design

Significance

**Research Design and Methods**

Data collection

Design and Procedure

Analysis

Limitations

Future Development

Run length

Closed loop decoder and training paradigm

BCAPI

## Specific Aims

Recent progress in cognitive neuroscience and brain imaging technologies has paved the way for a human technology revolution, spawning a rapid redefining of the the possibilities of Brain-Computer Interfaces (BCIs) as well as pushing the barrier what what was thought to be possible. Specifically a particular type of BCI based on motor imagery enabled the rehabilitation and replacement of people with motor disabilities. Motor-imagery BCIs (MI-BCIs) rely on both machine learning algorithms that classify particular brain states into classes in addition to training-interfaces that enable the learning of motor imagery abstract skills, namely mental simulation of kinesthetic movements (Hwang, Kwon & Im, 2008).

Despite the huge potential of this technology, BCIs are scarcely used outside academic settings due to their lack of robustness. Motor imagery skills have a steep learning curve given its current academic and abstract nature. Thus, because of the difficulty of this learning process, it has been estimated that 15 to 30% of users that attempt to learn MI-BCI skills are unable to comprehend its immensity, a phenomenon commonly known as 'BCI illiteracy' (Vidaurre & Blankertz, 2009). For this research, robustness will be defined as the consistency, accuracy and reliability of the classification of EEG signals.

Recent studies have shown the importance of appropriate training interfaces. If users are not able to volitionally produce stable EEG patterns, then no matter how reliable the classification algorithm is, brain states can not be accurately classified (Xia et al, 201. With the aforementioned limitations of MI-BCI, we propose a set of studies to address the following specific aims:

**Specific Aim**

Compare the effect of different feedback modalities on the learning rate of users. Visual, auditory and haptic feedback will be individually tested as well as in combination (multimodal feedback) with each other. Building on previous work on BCI training interfaces, our studies will address the following hypotheses:

(a) Multimodal feedback improves the learning rate of abstract skills compared to individual feedback modalities.

(b) Virtual reality (3D) provides immersive and tangible feedback which can improve BCI performance.

(c) Proprioceptive feedback enhances learning over observation of movement.

# Background and Significance

## Background

BCIs allow for direct communication and control channels between the human brain and external devices (Alimardani, Nishio & Ishiguro, 2014). This revolutionary emerging technology has a wide range of applications - one of them being the its use in restorative therapies for people with disabilities (Osborn & Carmena, 2013). However, despite the immense potential of this technology, BCIs have been barely explored outside research settings primarily due to the difficulty of implementing robust BCIs.

### Motor imagery Brain-Computer Interfaces (MI-BCIs)

When a person imagines moving their left or right hand, event related desynchronization (ERD) is detected in the contralateral sensorimotor cortex. ERDs are spatio-spectrally specific power decreases in oscillatory brain electrical activity. (Faller et al. 2014). Using motor imagery, ERDs have been shown to provide reliable features for BCIs as they can produce consistent EEG patterns provided proper training paradigms are employed. This offers a major advantage of ERD based MI-BCIs being the contralateral localization of left and right motor imagery.

### Meaningful Feedback

However, learning to correctly control a BCI is a daunting challenge. This control requires movement imagination without execution. Thus, feedback is an invaluable tool for accelerating the learning of users trying to comprehend not only the abstract, but a myriad of other skills (Lotte et al., 2013). Studies have proven that a pragmatic and naturalistic display of feedback, such as a grasping hand, has a positive learning effect on MI-BCIs. Moreover, it is also proven that proprioceptive feedback promotes a subject self evaluation of performance which optimizes motor imagery skills. (Alimardani et al., 2014). Comparing different imagery of motor actions has shown that kinesthetic experiences improves MI-BCI performance by overusing visual representations of actions (Neuper, Scherer, Reiner & Pfurtscheller, 2005). Motivation has also been found to be a consequential factor in BCI performance. Positive emotion-inducing and supportive feedback is particularly vital to provide users a sense of competence in their tasks (Lotte et al., 2013). Poor-performing users may be benefited from positive biasing, however consequences have been found where users with better performance may be negatively affected by this biasing. Therefore, optimal feedback design in BCIs should take into account the subject's current performance and modulate its biasing (Barbero & Grosse-Wentrup, 2010).

**Multimodal Feedback**

Most BCI paradigms rely on visual unimodal feedback - in fact, research has been done on how multimodal feedback can enhance learning by providing multiple representations. Authors have investigated the use of haptic and visual feedback to alleviate cognitive fatigue by distributing visual workload among multiple sensory input channels (Leeb, Gwak, Kim, & del R. Millán, 2013). Ramos-Murguialday implemented a feedback system combining visual and tactile feedback and observed enhanced BCI performance to improve and enhance his abilities. However, poorly designed multimodal feedback may decrease BCI performance, so in order to achieve correct multimodal feedback, the different representations must share granularity, such as being all continuous instead of discrete (Ramos-Murguialday et al. 2012). Different feedback modalities must be redundant between each other so users are able to relate them with ease and interpret them with the same kind of mental analysis (Ainsworth, 2006).

**Task design**

The design of the task in research studies have perhaps been the most vital component of effective BCI learning. Engaging tasks and feedback such as gaming mechanisms are shown to promote learning (Lotte et al., 2013). The use of progressive and adaptive BCI tasks such as increasing mental tasks or difficulty overall are also shown to improve the learning rate of BCI and thus enhance overall performance (Ainsworth, 2006). In addition, giving autonomy to the participants to choose when they train (self-paced) has also been observed to enhance learning abilities due to the simple idea that different users learn at different paces. Also, variability in the tasks has proven to decrease cognitive fatigue and increase motivation, objectively promoting learning (Lotte et al, 20013).

## Significance

Despite recent advancements in assistive technologies, many people with mental and physical disabilities cannot effectively communicate with the world. BCIs are the most promising technology that enables people to interface more naturally and intuitively with computers and assistive technologies. The ability to control a computer using one's thoughts, without any physical movement, would virtually change the lives of the millions of physically disabled people. Many of the potential users of this technology are quadriplegics and paraplegics, locked-in patients, patients with Lou Gehrig's disease and stroke victims undergoing rehabilitation. BCIs can not only be used by disabled people but also by individuals wanting to extend their capabilities beyond human limits. MI-BCI provides a framework which enables the learning of new 'control' skills, allowing able and healthy humans to extend their output streams and abilities. Because the learning of BCI skills is a difficult process, we propose a new training paradigm using what we have learned from previous studies. Our goal is to create a robust MI-BCI learning protocol which will eradicate BCI illiteracy and create a new realm for exploration.

## Research Design and Methods

### Hypothesis

(a) **Multimodal feedback improves the learning rate of abstract skills compared to individual feedback modalities.**

Previous studies on instructional design depict improved learning rate by increasing the number of sensory stimuli. This contributes to the creation of feature rich images which have higher probability of being encoded into the neocortex. Recent studies on MI-BCI skill acquisition have utilized the combination of haptic and visual stimuli to provide more tangible feedback for effective learning.

**(b) Virtual reality (3D) provides immersive and tangible feedback which improves BCI performance.**

Research on task design has shown that engaging tasks and feedback promotes motivation which leads to more effective learning. Recent development on virtual reality (VR) headsets allows the development of virtual 3D environments. Implementing virtual tasks in these environments will permit a higher level of immersion which is thought to enhance learning.

**(c) Proprioceptive feedback enhances learning over observation of movement.**

Recent studies have explored utilizing proprioceptive feedback in comparison to observation of movement. By using such VR technology users are able to explore the virtual environment in a first-person point-of-view. Combining this feed with haptic feedback, an effect known as the body-ownership illusion, can be induced on users. This promotes an even further level of immersion which facilitates learning.

## Recording setup

Eight EEG channels are recorded using an OpenBCI 8-bit board, an open-source EEG with 24-bit channel data resolution. Cognionics Flexible Dry EEG Electrodes are placed on the primary motor cortex (M1), premotor area (PMA), supplementary motor area (SMA) and primary somatosensory cortex (S1) according to the International 10-20 System of Electrode Placement (FC3, FCz, FC4, C3, C4, CP3, CPz, CP4, see Figure 1). A reference electrode is mounted on the left earlobe and a ground electrode on the forehead (AFz). The signal is sampled at 256 Hz with a bandpass filter between 5 and 30 Hz.

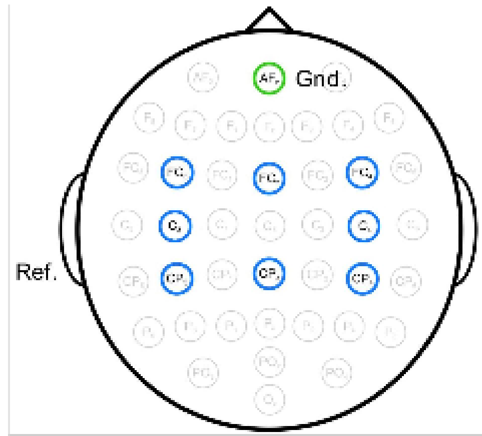


**Figure 1. Scalp electrode placement**
The blue circles indicate the position of the electrodes on the sensorimotor cortex. The green circle indicates the global ground and the left earlobe is used as a global reference (Faller et al. 2014).

## Participants

Fifty right-handed, healthy (no motor impairment) volunteers are recruited for the experiment (age 22 ± 4 (SD), 10 female). Verbal and written consent is required for volunteers to participate in the study. Participants are to be divided into experimental groups randomly. None of the participants have previous background knowledge or experience with BCIs. All participants are given a fully detailed summary of the experimental procedures and protocols prior to the experiment.

## Data collection

EEG data is recorded in runs of 36 trials each. A session is composed of five runs, one of one minute followed by four of six minutes each. The study is divided in eight sessions performed in eight consecutive days.

## Design and Procedure

This research is designed to measure learning rate as a function of the feedback modality given. The study is composed of 4 levels, each containing 2 sessions. The first level involves learning the 'up' MI-BCI command. The second encompasses learning the 'left' and 'right' MI-BCI skill. In the third session, users learn the 'up', 'left' and 'right' command. Finally, the fourth one involves learning 2D BCI: 'up', 'down', 'left' and 'right'.

Volunteers are instructed to sit on a comfortable armchair throughout the session. A session starts with a 1-minute 'non-control' run in which a white cross and an audible cue saying 'relax' is presented. Each of the next four runs (six-minute long) start with a two-second reference (non-control) period followed by 36 ten-second trials. In each trial, a random cue is presented depending on the session level.

Participants are divided into five groups. The first one receives haptic feedback only. Four sets of vibration motors are placed on each of these participants. Each set is composed of three vibration motor. Sets are placed on the left forearm, right forearm, back and chest of the participant.

The second group receives 2D visual feedback showing videos of a left/right grasping hand, feet moving forward/backward.

The third group receives immersive virtual reality feedback using an Oculus Rift and a platform developed in a 3D graphics engine (Unity). The virtual environment is perceived from a first-person point-of-view. When users imagine moving forward/backward, they walk in the virtual environment. When they perform the left/right MI command, they can perceive their respective arms moving up in virtual space. The fourth group is given 2D visual and haptic feedback. Finally, the fifth group is given proprioceptive feedback (immersive virtual reality + haptic).

## Analysis

The procedure is adapted from Hassan, Ali & Eladawy (2008). The code (not fully cleaned yet): https://github.com/Cognitive-Technology-Group/PyOBCI/blob/master/utilities/classify_data_better2.py. First, each group of signals (3 on the right, 3 on the left, and 2 in the middle) is averaged to obtain one signal for each side of the scalp. This helps reduce eye and muscle artifacts (EMG). We proceed to extract multiple features at each sample, from a sliding window going 125 samples back. The features are the magnitude and angle of the discrete fourier transform (DFT) of the original signal and of the signal convolved with complex Morlet wavelets of fundamental frequencies at 10Hz and 22Hz. 2250 features are obtained per sample and reduced to 15 using the Fisher criterion. Next, a neural network is trained to classify these features as left/right hand, up or down, using training data we gather for each subject. To generate a control signal, we classify each point from the 15 features we get from the 125 sample sliding window, then smooth out the classifications with a low-pass filter (otherwise the output varies too much). The output is either non-control, up, down, left or right.

# Discussion

## Limitations

We want to reduce BCI illiteracy not only for the motor impaired but also for healthy individuals, so we choose all participants to be healthy (non-impaired). This is of course assuming the depicted paradigm works effectively - an assumption that may not always be the case for the motor-impaired. It is thus reasonable to expect and perform further investigate then just the suggested training protocol using motor-impaired participants.

If the expected results are not achieved, we will adapt and learn from current flaws and improve the training protocol for further research, with the hope of decreasing the learning rate of abstract skill acquisition.

## Future Development

### Run length

We believe that reducing the runs' length will increase BCI performance and learning overall. Intuition comes from personal experience; performing a MI-BCI command is very cognitively extenuating. By reducing the length of single runs users will be able to produce more stable and discreet EEG signals. We are considering investigating the effect of run length on learning rate.

### Closed loop decoder and training paradigm

Recent studies on closed loop decoders and training paradigms have been proven to increase MI-BCI performance (Orsborn, Dangi, Moorman & Carmena, 2012; Faller et al., 2014). These training protocols rely on self-updating machine-learning algorithms which then provides real-time feedback on the best and most recent features. We plan on implementing this paradigm in the next two months.

**BCAPI**

We are developing an open-source high-level Brain-Computer Interface (BCI) API that encapsulates cognitive neuroscience, signal processing and machine learning in a black-box, enabling developers with no experience in these fields to create BCI applications with ease. Brain-Computer Interfacing for the people.

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