Bidirectional Feedback in Motor Imagery BCIs: Learn to Control a Drone within 5 Minutes

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Abstract
Brain Computer Interface systems rely on lengthy training phases that can last up to months due to the inherent variability in brainwave activity between users. We propose a BCI architecture based on the co-learning between the user and the system through different feedback strategies. Thus, we achieve an operational BCI within minutes. We apply our system to the piloting of an AR.Drone 2.0 quadricopter. We show that our architecture provides better task performance than traditional BCI paradigms within a shorter time frame. We further demonstrate the enthusiasm of users towards our BCI-based interaction modality and how they find it much more enjoyable than traditional interaction modalities.

Author Keywords
BCI; Co-learning; Feedback; Interaction; Motor Imagery; Games

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

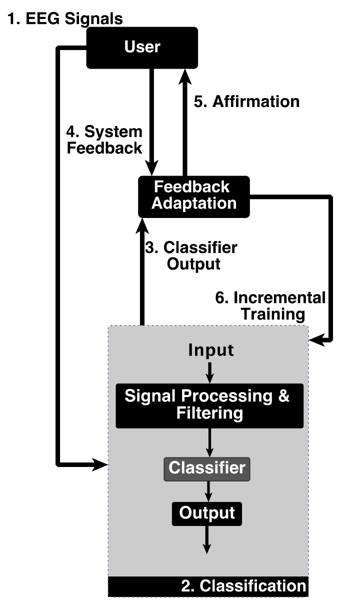

Figure 1. Overview of the architecture

Introduction

Current BCI systems are mostly grounded on a supervised machine-learning (ML) approach. This paradigm relies on lengthy training phases that can last a very long time until good performance is achieved. This limits the usage as an interaction modality for Human-Computer Interaction (HCI) [4], especially in terms of the operationalization. Furthermore, a supervised paradigm typically requires that the training phases as well as the interactive use of the system be done in a synchronous manner: the system tells the user when to perform an action. Alternatives to classical supervised systems are asynchronous BCI systems: the user is free to act at any time, but main challenge with such systems is that they are very difficult to develop and to evaluate [1].

We propose an architecture that minimizes the need for a synchronous training phase: it requires a few seconds of calibration data. The foundation of the architecture is our use of feedback: contrarily to simply using feedback from the system to the user (usual setting), we introduce feedback from the user to the system. In other words, we propose a co-learning based BCI system following the principles of [2]. We apply the system to the task of piloting an AR Drone in a task that involves taking off, flying in a straight line until a target is reached and landing the drone.

Audience & Relevance for CHI

The BCI based interaction modality we propose is aimed at making BCI interaction more ubiquitous and more practical to use in out-of-the-lab interactive tasks for everyone. Our modality retains the advantage of BCIs systems but makes them accessible to regular users easily by overcoming the main limitations of BCIs (see Challenges section for more details). Moreover, our goal is to make BCI systems fully usable as a new modality for HCI systems.

Challenges

We have identified several challenges regarding current BCI systems:

- (C1) Long training phases;
- (C2) High variability and noise/signal ratio;
- (C3) Training phases often disconnected from the actual tasks and are monotonous;
- (C4) A lot of emphasis on training the system but not on training the user. Training users could help them perform the tasks better;
- (C5) Minimal feedback strategies that tend to annoy users

Our system goes towards overcoming these challenges:

- Semi-supervised asynchronous BCI (minimizing training time – C1);
- ICA-based DSP techniques (reduce variability/SNR, extract better features – C2);
- Bidirectional feedback at the very center of the system. Incremental training model (training part of performing the task (C3), user training has equal importance (C4));
- More advanced and alternative forms of feedback (e.g. exploiting Electromyography (EMG)) (C5).

Design & Description

Figure 1 shows an overview of our system. The acquisition (1) is performed with 14 electrodes over the motor cortex. Then follows the classification stage (2)

Figure 2. Exhibit of our system in use

where signals a processed and filtered (Band Power, Independent Component Analysis). By using distance measures between current signals and calibration signals for each class and each channel, we can select the most likely by taking the class with a majority of shortest distances. The feedback from the system to the user (4) is the current classification result. The innovation in our architecture is the addition of affirmative feedback (was the classification correct?) from the user to the system (5) that allows adapting the classification step. The output of the classification step is what determines the action to trigger in specific applications.

The current type of BCI the architecture supported in our implementation is Motor Imagery (MI) [4]. Motor imagery is the detection of imagined movements (hands, arms, legs, etc.) and is appreciated by users as shown in in Kosmyna & Tarpin-Bernard [3]. However the system is extensible to other BCI paradigms.

Performance

We performed a series of experiments with 25 users, to evaluate the performance of the architecture. We compared our system to a supervised system. Performance is better with an acclimation time shorter than supervised training. Users expressed enthusiasm for our system. We also evaluated the system with regard to the native tablet application. Although the performance of our system does not yet rival the touch-based piloting application, users found our BCI interaction more enjoyable.

Figure 2 illustrates our system in use.

Task & Installation

Setting. The task is intended to take place in a large room or space of roughly 6 meters long over 5 meters wide. All the processing for our system is performed on a Mac Book Pro that needs to be connected to a projector to display the feedback application. The experimental setting is illustrated in Figure 3.

There are two targets on the ground 4,67 m away (maximal length we managed to obtain in our initial setting). The first target is the starting location of the drone and is represented by a helipad sign on a black background. The second target is the landing target, on which the user has to land the drone. The size of the second target is 24 cm in width and 60 cm in length. The width of the target roughly corresponds to the width of the drone plus a small margin. The length corresponds to roughly three times the width of the drone.

Equipment. The equipment, experimenter and subject are located on the side of the room. A projection screen is placed in such a way as to allow the subject (seated at

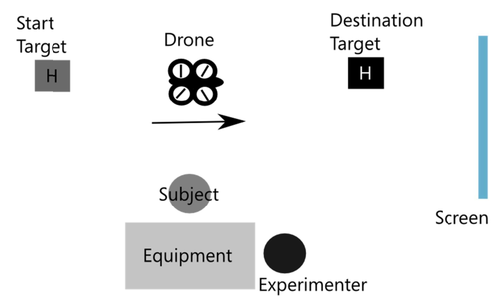

Figure 3. The experimental setting

Figure 4 The feedback GUI

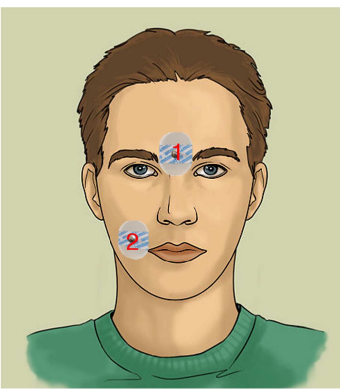

Figure 5. Position of the feedback electrodes

an angle) to see the drone and the screen with minimal movement. For the BCI interface, we use a g.tec USBAmp, 16 channel amplifier with a 16 electrode g.SAHARA dry active electrode system, mounted on a g.GAMMAcap.

Protocol. The subject first performs the calibration phase, where each of the imagined actions has to be performed for 20 seconds. Then follows an acclimation phase (2 min) where the subject can get used to the feedback on the screen and to giving feedback with facial gestures. Feedback is given until the subject feels confident in the degree of control.

Commands. We use three commands for the piloting task: taking off, going forward and landing. As we are in an asynchronous context, the state where no movement is imagined, or resting state, is most natural for the forward action (continuous over longer durations) when the drone is in the air and to no action when the drone is in a landed state (class 1). Then we respectively map left and right hand imagined movements (most common, adapted for spontaneous actions) to taking off and landing the drone.

User Feedback. We need users to give feedback to the system in order to train it, in a way that does not interfere with the motor imagery BCI. We cannot use touch-based feedback as the brain activity overlaps our left and right motor imagination classes. Our solution is to exploit EMG signals from face muscles as users perform light facial expressions. We use two disposable medical electrodes, one between the eyes and one on the left side of the lips. We instructed users to smile when the classification is correct and to frown otherwise: the first electrode (1) detects frowns and the second (2) detects smiling, as shown in Figure 4.

System Feedback. The feedback from the system to the user is displayed on a screen. The feedback consists in the currently detected state and the classification percentage of that state (text + progress bar), as well as the 4 previous classification results (Figure 5).

Conclusion

We proposed and asynchronous BCI system for control-related interactive tasks that reduces the need for uncomfortably long training phases and that makes the training process more engaging through co-learning. The system shows great enthusiasm in users and promising performance compared to standard BCI systems.

Acknowledgements

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