Drone, Your Brain, Ring Course – Accept the Challenge and Prevail!

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UbiComp'14 Adjunct, September 13-17, 2014, Seattle, WA, USA
ACM 978-1-4503-3047-3/14/09.
http://dx.doi.org/10.1145/2638728.2638785

Abstract
Brain Computer Interface systems (BCIs) 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 with a series of hoops delimiting an exciting circuit. 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.

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

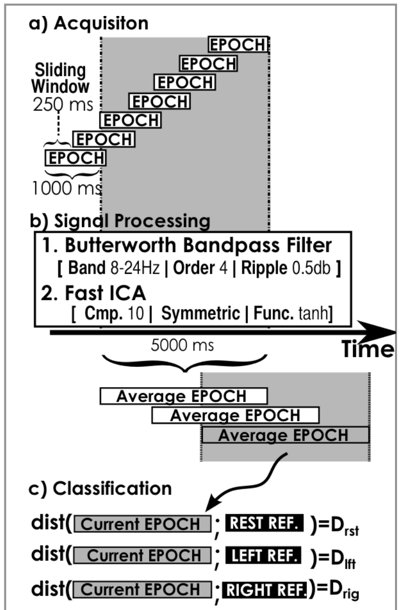

Figure 1. Overview of the architecture

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 Kosmyna et al. [2]. Subsequently to a simple piloting task[1] (take off, land, forward)[3], we propose a new control scheme that allows steering the drone through a circuit of hoops.

Audience & Relevance for UbiComp

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.

[1] http://research.kosmina.eu/sigchi-interactivity.html

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 on how to use a BCI system;
- (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. letting the user interactively adapt the classifier prior to a task session) (C5).

Design & Description

Figure 1 shows an overview of our system. The acquisition (a) is performed with 14 electrodes over the motor cortex. Then follows the signal processing stage (b) where signals a processed and filtered (Independent Component Analysis). Finally, in the classification stage (c), 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 interactive feedback allows to have users perform more calibrations for classes that were done badly. Moreover, a margin can be set for the minimum distance threshold. Thus, we can reduce noise in the classification or to increase the sensitivity of the classifier depending on the situation.

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

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 (a system trained from a set of several pre-recorded signals for each class of the BCI). Performance of our system is better than the performance of the supervised system after two sessions (0.49 task error less on average, 8s faster to complete the task) with an acclimation time shorter. After a single session, our system performance is similar to the supervised BCI. 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.

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 MacBook Pro. The experimental setting is illustrated in Figure 2.

There are two hoops (85 cm diameter) standing on each side of the room 5 m away. There is a target in the form of a helipad that corresponds to the take off/landing zone located equidistantly from the two hoops, 1 m upwards the axis formed by the hoops.

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

Protocol. The subject first performs the calibration

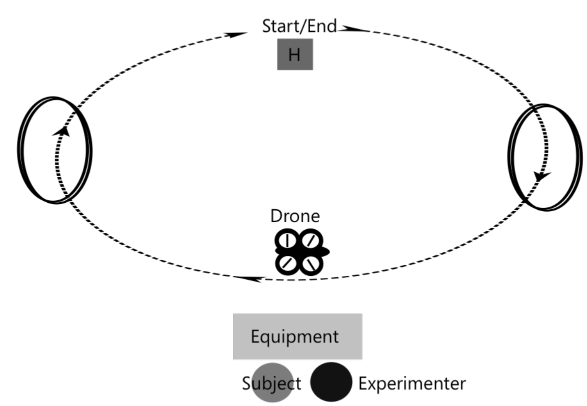

Figure 2. The experimental setting

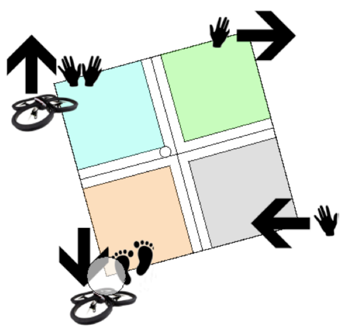

Figure 3. The feedback GUI

phase, where each of the imagined actions has to be performed for 20 seconds. Then follows an acclimation phase (2-5 min) where the subject can get used to the system feedback on the screen interactively adapting the classifier by giving his feedback. Feedback is given until the subject feels confident in the degree of control.

Commands. We use four commands for the piloting task: turn left (imagined left hand movement), turn right (imagined right hand movement), up/take off (both hands imagined movement, down/land (feet imagined movement). The drone automatically goes forward when it is in the air. The users only need to steer it.

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. In our interface we have a certain number of controls that allow customizing the classifier interactively for each user. To that end the operator must observe the performance of the user after calibration and adjust the parameters to what seems to yield the best classification results. The user is asked to say if they feel any improvements.

System Feedback. The feedback from the system to the user is displayed on a screen. The feedback is displayed graphically in a polygon whose corners represent the four classes; a point represents the current classification outcome (Figure 3).

Conclusion

Our semi-supervised asynchronous system was evaluated within the context of a quadricopter piloting task and compared with a standard supervised system implementation. We have demonstrated that there is an advantage towards reciprocal feedback in terms of the magnitude of the learning effect, which confirms previous findings in the more general setting of the incremental training of asynchronous BCI systems. We believe that our system as it is today is a step towards prototyping BCI systems for HCI interaction useable in future by grand public. Moreover, various EEG headsets are compatible (e.g. Emotiv EPOC[2], a cheap and market available EEG headset for consumer applications).

Acknowledgements

This research was funded by the Grenoble INP CA-ICO project.

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