Challenges for Brain-Computer Interface Research for Human-Computer Interaction Applications

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ABSTRACT
Electro-encephalography (EEG) is unique among functional brain imaging methods in that it promises a means of providing a cost-efficient, safe, portable and easy to use brain-computer interface (BCI) for both healthy users and the disabled. While an already extensive corpus of EEG-BCI experimental work has demonstrated that, to a degree, a person's mental states can be detected in single-trials using sophisticated mathematical tools, clear challenges for the use in human-computer interaction applications have also been outlined. He we discuss challenges, which are relevant for the use of BCIs in wider range of applications beyond rehabilitation.

1. INTRODUCTION
The proof-of-concept of Brain-Computer Interface (BCI) systems ([12, 22, 17]) was given decades ago (e.g.[13]), and machine learning based approaches (e.g.[15, 1, 11, 2]) have contributed substantially to improve the information transfer rates. Nevertheless several major challenges are still to be faced. Here we discuss two of those challenges, which are relevant for the use of BCIs in wider range of applications beyond rehabilitation. To present, the use of machine learning based EEG-BCI systems involves two time-consuming preparational steps at the beginning of every new session. The first one, the montage of an EEG cap, which can take up to one hour for 128-channel caps, and the second step is the recording of calibration data, which takes usually between 20 and 40 minutes. These issue will be discussed in this paper.

Another challenge is to develop BCI applications which take the specific characteristics of BCI communication into account (high bandwidth from the computer to the user, low bandwidth from the user's brain to the computer) is discussed in [7].

The Berlin Brain-Computer Interface (BBCI) is an EEG-based BCI system which operates on the spatio-spectral changes during different kinds of motor imagery. It uses machine learning techniques to adapt to the specific brain signatures of each user, thereby achieving high quality feedback already in the first session ([8, 2, 3]).

2. CHALLENGE EASY PREPARATION OF MEASUREMENT
The most elementary obstacle of EEG-BCI is that standard EEG practice involves the tedious application of conductive gel on EEG electrodes in order to provide for accurate measurements of the micro-volt level scalp potentials that constitute EEG signals. Without 'dry-cap' technology the proper set-up of BCI sessions in, say, a home environment, is too tedious, messy and therefore impractical. In [20] we present a novel dry EEG recording technology which does not need preparation with conductive gel, see Fig. 1. In the reported study with good BCI subjects, feedback performance was about 70% of the approach with conventional EEG caps. Notably, for several subjects the performance was at the same level, which indicates that the novel technology might be at the present state not flexible enough to fit optimally with various head shapes. Most dry-cap challenges remaining are of an engineering design nature, excluding perhaps the computational reduction of artifacts produced not by unrelated electro-physiological activity but by measured low-frequency voltage variations caused by the physical movement of the head.

Note that the system only uses 6 electrodes and can thus be miniaturized to run with a tiny EEG amplifier and a pocket PC.

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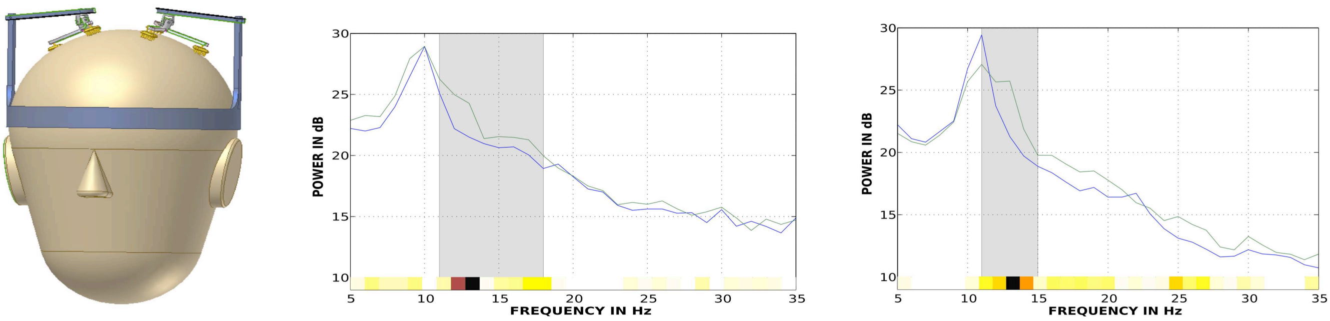

Figure 1: Signal spectra and electrode placement. *Left:* Illustration of the dry cap. *Middle:* Typical signal spectrum from proposed dry electrode (each trace corresponds to averaged spectra for one motor imagery class). *Right:* Comparable signal from conventional electrode with electrolyte gel (same subject, same conditions). Figure taken from [20], `doi:10.1371/journal.pone.0000637.g001`**.**

3. CHALLENGE FAST CALIBRATION OF THE SYSTEM

One drawback of machine learning based BCI systems is the need to record calibration data at the beginning of each session [5]. In [16] we studied to what extent this calibration period can be omitted. In other words, is it possible to successfully transfer information from prior BCI sessions of the same subject that may have taken place days or even weeks ago? While this question is of high practical importance to the BCI field, it has so far only been addressed in [21] in the context of transfering channel selection results from subject to subject. In contrast to this prior approach, we will focus on the more general question of transfering whole classifiers, resp.individualized representations between sessions. Note that EEG patterns typically vary strongly from one session to another, due to different psychological pre-conditions of the subject. A subject might for example show different states of fatigue and attention, or use diverse strategies for movement imagination across sessions. A successful session to session transfer should thus capture generic 'invariant' discriminative features of the BCI task (see [6] for another view on this).

For this we first transform the EEG feature set from each prior session into a 'standard' format and normalize it. This allows to define a consistent measure that can quantify the distance between representations. We use CSP-based classifiers (see [10]) for the discrimination of brain states; note that the line of thought presented here can also be pursued for other feature sets resp.for classifiers. Once a distance function is established in CSP filter space, we can cluster existing CSP filters in order to obtain the most salient prototypical CSP-type filters for a subject across sessions, see Fig. 2. To this end, we use the IBICA algorithm [18, 19] for computing prototypes by a robust ICA decomposition. See [16] for more details and the demonstration that these new CSP prototypes are physiologically meaningful and furthermore are highly robust representations which are less easily distorted by noise artifacts. The demonstration of the feasibility of this approach for online BCI experiments will be given in a forthcoming paper.

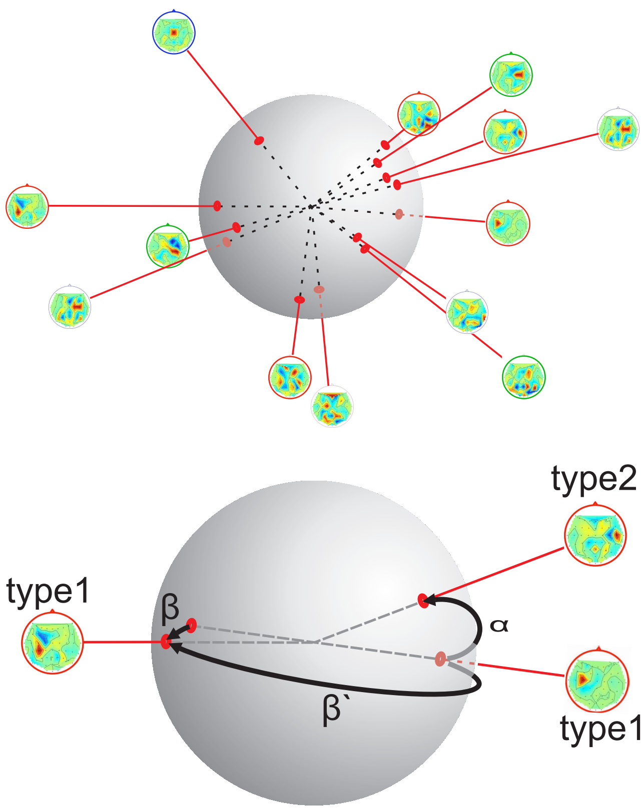

Figure 2: Clustering in the CSP space: The norm of the CSP filter vector is irrelevant as well as its sign.

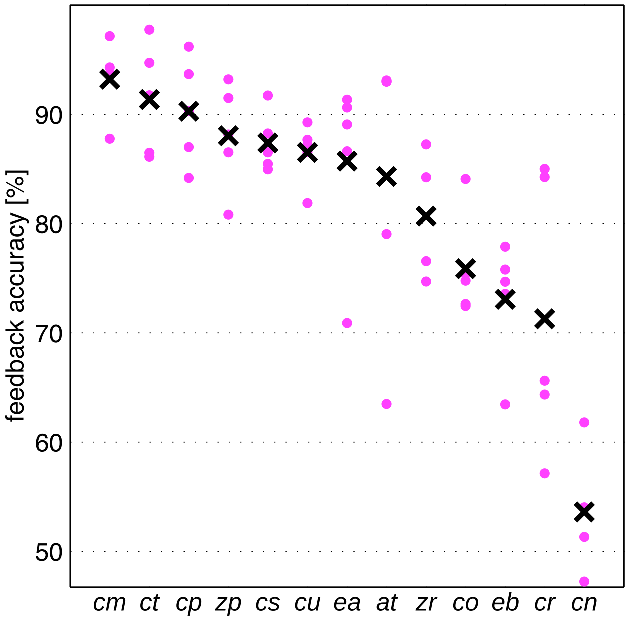

Figure 3: Results of a study with 14 naive BCI users. For 13 subjects a classifier could be trained on calibration data. Feedback accuracy of all 5 runs (magenta dots) and intra-subject averages (black crosses) for those 13 subjects are shown in the plot.

4. CHALLENGE BCI ILLITERACY

A long-standing problem of BCI designs which detect EEG patterns related to some voluntarily produced brain state is that such paradigms work with varying success among subjects/patients. We distinguish mental task based BCI such as 'movement imagination' BCI from paradigms based on exogenous stimulus related potentials such as P300 which are limited to very specific applications such as text entry and require constant focus on stimuli extraneous to the task at hand.

In a recent study, with 10 untrained users, we took a close look at how fast they achieved 'best' performance during a small number of BCI sessions (by skill acquisition) and how much this performance varied among subjects. Although machine learning techniques use calibration data (20–40 minutes of recording) before the BCI system can be used, the peak performance plateau, even after multiple sessions, varies greatly among subjects. Using this and other unreported data by many research groups, we estimate that about 20% of subjects do not show strong enough motor related mu-rhythm variations for effective asynchronous motor imagery BCI, that for another 30% performance is slow ($<$20 bits/min) and for up to 50% it is moderate to high (above 20 bits/min). See [14, 8] for two studies reporting the first-session preformance in a larger group of subjects.

It is still a matter of debate as to why BCI systems exhibit 'illiteracy' in a significant minority of subjects and what can be done about it. From internal investigations (as well as the results of BCI Competition II, data set Ib, [9]) it appears that 'BCI illiteracy' in a subject is not dependent so much on the algorithm used but is rather an inherent property of the subject. As EEG is sensitive to sources in cortical folds it may be that some motor imagery activity may not be readable in some subjects by EEG if the particular cortical region involved is tangential to the scalp. Consistent with this explanation, it has been observed that in certain subjects some 'classes' (types of imagined movements) are detectable and others not. Therefore calibration sessions should select subject specific classes along with frequency bands necessary for feature generation to minimize the illiteracy problem.

5. DISCUSSION

The prospective value of BCI research for rehabilitation is well known. In light of the work presented here we would advocate a further point. BCI provides stimulation to HCI researchers as an extreme example of the sort of interaction which is becoming more common: interaction with 'unconventional' computers in mobile phones, or with devices embedded in the environment. These have a number of shared attributes: high-dimensional, noisy inputs, which describe intrinsically low-dimensional content; data with content at multiple time-scales; and a significant uncontrolled variability. The mismatch in the bandwidth between the display and control channels (as explained in the introduction) and the slow, frustrating error correction motivate a more 'negotiated' style of interaction, where commitments are withheld until appropriate levels of evidence have been accumulated (i.e.the entropy of the beliefs inferred from the behavior of the joint human-computer system should change smoothly, limited by the maximum input bandwidth). The dynamics of a cursor, given such noisy inputs, should be stabilized by controllers which infer potential actions, as well as the structure of the variability in the sensed data. Hex-o-Spell demonstrates the potential of such intelligent stabilising dynamics in a noisy, but richly-sensed medium. The results suggest that the approach is a fruitful one, and one which creates the potential for incorporating sophisticated models without *ad hoc* modifications.

We envisage an EEG BCI scenario in which users purchase an affordable computer peripheral which is simply placed on the head and requires no gel. Novel users undergo a one-time calibration procedure which takes maximally 10 minutes, ideally even less. They then proceed to use the BCI system in a game environment, to control a robot or wheelchair, and the performance of the system slowly adapts to the users' brain patterns, reacting only when they intend to control it. At each repeated use, parameters from previous sessions are recalled and re-calibration is rarely, if ever, necessary. We strongly believe such a system, is achievable within the next few years. Still, some challenges are likely to only be partially met, such as the BCI illiteracy, but if this percentage is decreased further it should not prevent non-invasive BCI systems from reaching a large user population, healthy or disabled.

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