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Brendan Allison is a researcher at the University of Bremen's Institute of Automation. Contact him at allison@iat.uni-bremen.de.

Bernhard Graimann is a researcher at the University of Bremen's Institute of Automation. Contact him at graimann@iat.uni-bremen.de.

Computational Challenges for Noninvasive Brain Computer Interfaces

Florin Popescu, *Fraunhofer Institut für Rechnerarchitektur und Softwaretechnik (First) Berlin*
Benjamin Blankertz and Klaus-R. Müller, *Berlin Institute of Technology*

Electroencephalography (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. An already-extensive corpus of experimental work has demonstrated that, to a degree, EEG-based BCI can detect a person's mental state in single trials of mental imagination using sophisticated mathematical tools; but this work has also outlined clear challenges. The first challenge is the rather limited information transfer rate (ITR) achievable through EEG, which is—in the most optimistic of cases—about an order of magnitude lower than invasive BCI methods currently provide. That said, the potential benefits of brain implant-based BCI haven't yet proved worth the associated cost and risk in the most disabled patients, let alone healthy users.

EEG seems for now the only practical brain-machine interaction choice (cost and ITR limitations hamper other noninvasive methods). As such, we ask here not how further signal-processing and machine-learning improvements might increase the ITR.[1,2] BCI researchers already know that many complex technical problems remain: such problems have been the field's main concern up to now. Nor will we will discuss EEG-BCI applications. Instead, we concentrate on outlining the challenges that remain in adapting EEG-BCI from the laboratory to real-world use by healthy subjects.

Dry electrodes

The most elementary EEG-BCI challenge for healthy users isn't—at first glance—a computational one. Standard EEG practice involves the tedious application of conductive gel on EEG electrodes to provide accurate measurements of the microvolt-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 and messy to be practical. Some dry electrode designs that use a combination of EEG and electromyogram (EMG) have been announced for home entertainment use. The EMG originates from body and face muscles; in BCI studies, it's considered an artifact. Although EMG is stronger and easier to read than EEG, it doesn't truly constitute a mental interface. Our research group has developed an EEG-BCI dry-cap design and tested its performance (and the absence of muscle artifacts) in a controlled study.[3]

For ease-of-use and cost reasons, all foreseeable systems will use fewer electrodes than found on standard EEG caps today. The computational challenges we've addressed include optimal placement of the reduced number of electrodes and robustness of BCI algorithms to the smaller set of recording sites. With only six unipolar electrodes, we can achieve about 70 percent of full-gel-cap BCI performance at sites above the motor cortex, while being able to discount any potential influence of muscle and eye movement artifacts.

Most other remaining dry-cap challenges are of an engineering design nature, excluding perhaps the computational reduction of artifacts produced not by unrelated electrophysiological activity but by measured low-frequency voltage variations caused by the head's physical movement.

BCI illiteracy

A long-standing problem of BCI designs that detect EEG patterns related to a voluntarily produced brain state is that such paradigms work with varying success among different subjects or patients. We distinguish mental-task-based BCI, such as "movement imagination" BCI, from paradigms based on involuntary stimulus-related potentials such as P300. These stimulus-related potentials are limited to very specific applications, such as typing for locked-in patients, and they require constant focus on stimuli extraneous to the task at hand.

In a recent study, with 10 untrained users,[2] our research group took a close look at how fast the users achieved their best performance (by skill acquisition) during a small number of BCI sessions and how much this performance varied among subjects. We confirmed the results in a follow-up study with 13 novice subjects.[4] Although machine learning techniques allow use of minimal calibration data recording (< 20 minutes) before the BCI system is ready to use, the subjects' peak-performance plateaus, even after multiple sessions, varied greatly. Using this and other unreported data by many research groups, we estimate that

- about 20 percent of subjects don't show strong enough motor-related mu-rhythm variations for effective asynchronous motor-imagery BCI,
- another 30 percent exhibit slow performance (< 20 bits per minute), and
- up to 50 percent exhibit moderate to high performance (20–35 bits/min.).

It's 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 in terms of signal processing and machine learning algorithms. From internal investigations (as well as the results of BCI Competition II, data set Ib[5]), BCI illiteracy in a subject appears to depend not so much on the algorithm used but on a property inherent in the subject.

EEG is sensitive to sources in cortical folds, so it might not be able to read motor-imagery activity in some subjects because the particular cortical region involved is tangential to the scalp. An observation consistent with this explanation is that in certain subjects some *classes*—that is, types of imagined movements—are detectable and others not. Calibration sessions should therefore select subject-specific classes along with frequency bands necessary for feature generation to minimize the illiteracy problem.

Idle class

Most commonly, BCI controllers involve two classes, which can move a monitor-displayed cursor toward, say, left and right. Although these controllers can perform asynchronously—that is, at their own independent pace—useful cursor control is difficult. The user must either continuously imagine one of the two classes or lose control of the cursor.

Besides self-pacing, BCI would greatly benefit from integrating an "idle" or "rest" class with the BCI's active classes—that is, those corresponding to mentally imagining a particular task and implying the desire to transmit the activation of a corresponding command. This would keep the cursor from responding when no active class (from a set of two or more) is activated.

The idle state might take one of two forms: a relax state, where the subject stays still and tries to "think of nothing," or a state where the subject can do almost any mental task other than those belonging to the active classes. In the case of deliberate relaxation, usability is obviously limited, although signal processing is easier, given that relaxation tends to increase EEG power in the alpha band. For example, researchers have shown that alpha band modulation played a strong role in detecting relaxation when subjects closed their eyes during an idle state.[6]

Relying on alpha power modulation is complicated by the involuntary variation of background alpha in physiological as opposed to experimental conditions—for example, due to fatigue. Furthermore, relaxing itself induces drowsiness.

A neurofeedback-style, low-frequency modulation approach has shown promise as an idle-state paradigm, but it requires intensive subject training, exhibits limited ITR, and has only one active class.[7] The Graz group has begun work toward idle-state control with a relax cue,[8] but so far there is little hard data on idle-state duration and accuracy. This is important, because two-class classifier output (a noisy signal) is usually integrated until it hits a threshold (for example, left or right cursor movement). The level of this threshold offers a clear trade-off between high idle-class accuracy (that is, the thresholds are high) and fast speed of response or high ITR (the thresholds are low). Remaining challenges are to find a classifier that can induce a rest state without a relax cue and to optimize the relationship between classifier output and BCI command. Because of physiological variations in background EEG activity, where fatigue is a main factor, we believe an adaptive classifier and controller are necessary for maximal performance. Our group has undertaken some efforts toward optimizing a true idle-state BCI paradigm by balancing idle-class accuracy and ITR.[9]

Future challenges and implementations

While these three computational challenges are, we believe, the most urgent, other improvements might also be beneficial. Although 20 minutes of calibration for a novel subject isn't excessive, usability would benefit from knowing the minimal number of calibration trials needed to achieve moderate performance and rule out BCI illiteracy, such that a classifier can then adapt to the user during normal use. For applications such as gaming, or voluntary self-paced interaction with an unstructured environment, this adaptation should work even in cases where class labels aren't available (unsupervised adaptation).[10]

We envisage an EEG BCI scenario in which users purchase an affordable computer peripheral that is simply placed on the head and requires no gel. New users will undergo a one-time calibration procedure that takes maximally 10 minutes, ideally even less. They then proceed to use the BCI system in a game environment to, for example, control a robot or wheelchair. The system's performance slowly adapts to the user's brain patterns, reacting only when he or she intends to control it. At each repeated use, the system recalls parameters from previous sessions, so recalibration is rarely, if ever, necessary.

We strongly believe such a system, capable of an average performance of about 15 to 20 bits/min, is achievable within the next few years. Challenges such as BCI illiteracy are likely to be only partially met. Still, if this percentage decreases further, it shouldn't prevent noninvasive BCI systems from reaching a large user population, healthy or disabled.

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Florin Popescu is a research scientist at Fraunhofer FIRST's Intelligent Data Analysis Group. Contact him at florin.popescu@first.fraunhofer.de.

Benjamin Blankertz is a researcher in the Machine Learning Laboratory at the Berlin Institute of Technology and in the Intelligent Data Analysis group at Fraunhofer FIRST. Contact him at blanker@cs.tu-berlin.de.

Klaus-R. Müller is a professor and chair of the Machine Learning Department at the Berlin Institute of Technology and head of the Intelligent Data Analysis group at Fraunhofer FIRST. Contact him at krm@cs.tu-berlin.de.