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Brain-Computer Interfaces: from theory to practice

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Abstract. Brain-Computer Interfaces (BCI) are a new kind of human-machine interfaces emerging on the horizon. They form a communication pathway between the brain and a machine. This can be achieved by measuring brain signals and translate them directly into control commands. Such a system allows people with severe motor disabilities to manipulate their environment in an alternative way. However there's still a lot of work to be done to make it usable in daily life. In this contribution we give a tutorial overview of existing methods and possible applications.

1 Introduction

The development of brain-computer interfaces (BCI) is an active research domain that has as goal to help people, suffering from severe disabilities, to restore the communication with their environment through an alternative interface. Kamiya [1] was one of the first to use EEG (electroencephalography) signals in a feedback setup where subjects learned to control their alpha waves. Although this setup did not have direct clinical or other useful applications, the idea of brain-computer interfaces and neurofeedback was born. Since then different EEG signal features were used for feedback and for control of external devices (see [2] for a review and Figure 1 for a basic setup). At present, researchers also use other imaging devices like MEG (magnetoencephalgraphy, [3]), which measures magnetic fields produced by electrical brain activity, and NIRS (near-infrared spectroscopy, [4]), measuring blood flow in the brain. Even the use of invasive sensor technology, like ECoG (electrocorticography, [5]) and intracortical implants, is explored in monkeys [6] and humans [7]. To extract these different features in real-time, advanced signal processing and machine learning techniques are necessary. Therefore, a lot of research groups have been investigating the feasibility of a broad range of machine learning approaches and signal processing algorithms in the past few years. In [8] a taxonomy is given of the different feature extraction and translation methods used for BCI.
In this paper we only focus on the EEG-based BCI systems, because they are

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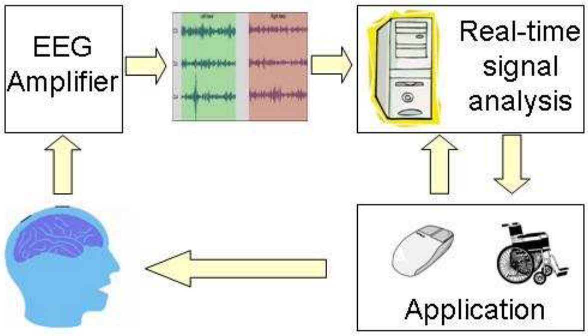

Fig. 1: To setup a BCI system you need an EEG amplifier and a computer to analyze the signals in real-time. After feature extraction and classification you can output commands for use in several applications. The application gives feedback to the user so he/she can correct for possible mistakes, but it can also give feedback directly to the analyzing software (for example through sensors on a wheelchair).

most frequently used. The most popular signal features used for BCI implementation are reviewed in Section 2. In Section 3 we shortly discuss the problem of adaptivity in feature translation and in Section 4 we present possible applications of BCI systems. In the last section we shed some light on possible future directions in BCI research.

2 Signal features

Current EEG devices measure potential differences on several electrodes placed on the head of the subject and digitize it for further analysis. In other words the EEG can be seen as a multivariate time series. Figure 2 shows the placement and naming conventions of the electrodes together with the corresponding regions of the brain.
BCI systems using these EEG signals, are subdivided in categories based on the signal features they use. Some of these features like the P300 and SSVEP (steady-state visual evoked potential) are elicited naturally by external stimuli while others like the SMR (sensorimotor rhythm) and SCP (slow cortical potential) need to be learned by the user through self-regulation and feedback.

2.1 P300

The P300 reflects the cognitive processing of events and is defined as a positive potential about 300ms after presentation of an infrequent stimulus amongst frequent ones. The oddball paradigm is a well-known task used to evoke this potential. The subject is instructed to listen to auditory stimuli. Most of these

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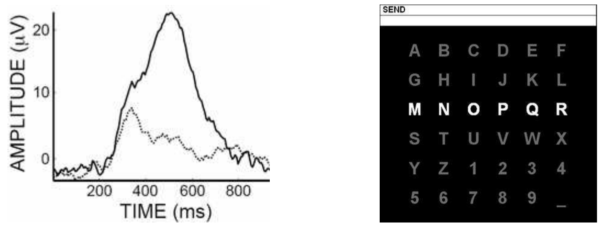
Fig. 2: *Left* The placement (and names) of the electrodes on the head according to the 10-20 international system. *Middle* The homunculus shows the mapping of the different body parts to the motor cortex. Notice that the hands occupy a large region. *Right* The different lobes of the brain. The motor cortex corresponds to the picture in the centre.

stimuli (about 80%) are low frequency tones while the other 20% are high frequency tones. Every time the subject hears a infrequent stimulus a P300 potential is clearly seen after averaging of the trials. This also works for visual stimuli. Depending on the user the P300 can differ somewhat in amplitude and latency (this is also related to the complexity of the stimulus) and is recorded best over parietal regions.
The first BCI system based on this feature was presented in [9] for use as a spelling device. The user faces a screen with a matrix of characters. Each row and column flashes several times per trial in a randomized order (see Figure 3 for a screen shot of the BCI2000 spelling interface [10]). The software computes the P300 of each character by averaging the responses of each row and column. The character, associated with the P300 best matching the one measured during calibration, is then selected for output on the screen. People are able to use this interface with only a small amount of calibration time, nevertheless reaching very high accuracy.
Although subject to a lot of research, there are still improvements being made to the P300 BCI. In [11] Rivet *et al.* propose a method to select the most relevant electrodes and to enhance the P300 potentials through spatial filtering.

2.2 Steady-State Visual Evoked Potential

SSVEPs receive increasingly more attention for use in BCI because of its high accuracy, very low training time and high transfer rates. It was employed by the Air Force Research Laboratory [12] for selection of two virtual buttons, both flickering at different frequencies. The SSVEP is a visual evoked potential that is characterized by increased amplitude at the frequency of the button the user is looking at. In [13] the authors show the same task can be performed through covert attention (selection of regions of visual space outside the central foveal



(a) (b)

Fig. 3: (a) The solid line represents the P300 potential associated with an infrequent stimulus. (b) The BCI2000 spelling interface shows the illumination of one row. The rows and columns flash repeatedly in a randomized order.

region). This leads to a setup completely independent of peripheral muscles and nerves because the user does not really need to direct his gaze to the target. In [14] researchers elaborate on this concept and apply it to robot control in a virtual environment.

2.3 Sensorimotor Rhythm

The cortical areas involved in motor function show a strong 8-12 Hz (or even 18-26 Hz) activity when the person is not performing any motor (imagery) task. However, when the person is engaged in a motor task the neural networks in the corresponding cortical areas are activated. This blocks the idle synchronized firing of the neurons and thus causes a measurable attenuation in the frequency range of 8-12Hz. This decrease in power is also called event-related desynchronization (ERD, see [15] and Figure 4), the opposite is event-related synchronization (ERS). The location (electrode) of this feature depends on the type of motor task. For example, if a person moves his left arm, the brain region contralateral to the movement (around electrode C4) will display this ERD feature, while the neurons in the ipsilateral cortical motor area continue to fire synchronously.

A commonly used method to extract this feature in single-trial EEG is the common spatial pattern (CSP) algorithm introduced by Koles [16] to detect abnormal EEG activity. Later, it was used for discrimination of imagined hand movement tasks [17]. Since then a lot of extensions were developed mainly by the Intelligent Data Analysis (IDA) group using this approach quite exhaustively in their Berlin BCI. They extended CSP with temporal filtering [18], made it more robust for nonstationarities [19] and reduced calibration time by transferring knowledge learned during previous sessions [20]. After almost a decade this method still proves it superiority based on the results of the fourth BCI competition[1]. Still, this BCI setup is less accurate than the P300-based BCI and initially

[1]On `http://ida.first.fraunhofer.de/projects/bci/competition_iv` you can find the data sets and results of the 4th BCI Competition. By using CSP and combining two classifiers (support vector machine and ordinal regression) we were able to claim second place.

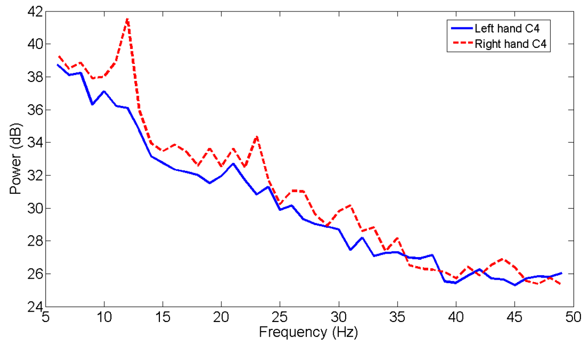


Fig. 4: The solid (blue) line represents the spectrum on channel C4 averaged across all left hand trials. The dashed (red) line corresponds to the right hand trials. The trials display the biggest correlation with the labels around 12 Hz. It's also clear that the power is strongly attenuated in this frequency range for the left hand trials.

needs a longer training time. Some people are even unable to achieve proper control. There are two possible explanations for the reduced accuracy compared to the P300 systems. Firstly, the P300 potential is a fairly robust feature, meaning that the parameters controlling its shape do not change as drastically as SMR features. And secondly, P300 systems are able to use averaging techniques to increase the signal-to-noise ratio.

2.4 Slow Cortical Potential

Slow cortical potentials are slow positive or negative DC shifts that can last up to several seconds. SCP's are global signals and represent the mobilization of neural resources for cognitive tasks if the shift is negative. Positive SCP's are measured during task execution and hence represent consumption of resources. People are able to modulate the amplitude of this slow wave through extensive feedback training and thus able to control a spelling device [21]. It's also an important feature for neurofeedback applications in treatment of several disorders. Patients with epileptic seizures are able to decrease seizure frequency by self-regulation of the SCP [22]. Also people suffering from attention deficit hyperactivity (ADHD) disorder show improvements in symptoms after SCP feedback sessions [23].

3 Feature translation and adaptivity

In the first BCI systems subjects had to learn to alter their brain signals in order to reach a desired level of control indicated by feedback of the signal features. However, due to the rapidly growing interest of the machine learning community in BCI another way of thinking was introduced. Now, instead of the brain adapting and learning to reach that level of control, machine learning techniques are used for translating the features extracted from the ongoing EEG. These models are trained offline after the first training session and together with the feature extractor try to capture the subject specific variations in the features. This way the machine takes over the learning role which reduces the initial training time. Up till now, a lot of different algorithms have been tested, but most of them remain static after initial training sessions. This is a major shortcoming in current setups, because not only subject specific features need to be captured, but also variations occurring during BCI use. Indeed, factors like fatigue and illness can influence the features. In [24] the authors observe this as a change in distribution of the data between the training session and test session. They simply solve this problem by recomputing the bias of the model instead of retraining it completely. Also (and more importantly) neurofeedback can cause changes in the data distribution while using the BCI. Through feedback, the BCI user tries to modulate his features to achieve better control, which is facilitated by brain plasticity. In other words, the brain adapts and attempts to incorporate the controlled external device into its body representation (see [6] for a study in primates). Thus, the feature translation device has to be able to grasp these ongoing changes.

Some attempts have been made to include adaptivity or online learning mechanisms into BCI [25, 26, 27], but most of them require class labels which are not available in real-life applications. Only a handful of researchers propose different approaches to tackle this problem [28, 29, 30]. In [31] the authors present the possibility of giving feedback to the model by detecting so called error potentials. These potentials are typically elicited if the brain detects a deviation from its original prediction and can be detected fairly accurate in single-trial EEG. Here, the error potential is generated as a consequence of a misinterpretation of the user command by the BCI and could be used to reconfigure the parameters of the classifier.

Hence, we are evolving in a direction where the brain adapts to the machine through feedback while at the same time the machine tries to learn these ongoing changes, resulting in a fairly complex interaction.

4 Applications

Most applications are designed to help people with severe disabilities to execute common every day tasks. One of these we already described when we talked about the P300 potential and the spelling device. Off course other applications exist. Since the 1970s researchers try to reconstruct movement from invasive recordings of motor cortex neurons [32, 33, 34]. Here, the ultimate goal is to employ these methods for controlling prosthetic devices. In [35] the authors are even able to use non-invasive techniques to restore grasp functionality in a tetraplegic patient through functional electrical stimulation (FES). Other research groups use EEG to record sensorimotor rhythms for two dimensional cursor control [25] and control of a wheelchair [36]. All the aforementioned approaches are control oriented and in contrast with goal oriented BCI systems where the subjects only specify their goal. The details for the execution of the task are then left to the software. According to Wolpaw [37] this is the direction to take, because cortical neurons might be unable to adapt to act as spinal motoneurons. P300-based BCI systems lend themselves perfectly for such goal oriented implementation. This is clearly demonstrated in a smart home application by Guger *et al.* [38].

BCI has for a long time been considered as a system for pure transduction of brain signals to some effector output. Presently, there's a growing interest in BCI for rehabilitation and treatment of disorders and thus the time has come to reflect on what BCI training can do for the brain itself. As mentioned in Section 2.4 slow cortical potentials (and SMR) have been used for treatment of epilepsy, ADHD and other disorders. Some believe it could also be used for restoring motor function in patients with motor disabilities caused by brain injuries or disease. Especially a lot of interest is directed towards the use of BCI for rehabilitation of stroke patients. One of the strategies (as reviewed in [39]) is to use a BCI system to drive a device that assists the patient in his movements. The observation and sensation of the movement together with the generation of normal motor-related EEG features through neurofeedback may possibly enhance neural plasticity mechanisms in the injured brain and hence promote compensation of dysfunctions. Therefore it may also serve as an adjunct to classical neuro-rehabilitation strategies and other neurophysiological treatments such as repetitive transcranial magnetic stimulation.

Neuroplasticity, a term coined by the Polish scientist Jerzy Konorski, is undoubtedly one of the most revolutionary concepts (and insights) in 20th century neuroscience. Indeed, the idea that the brain, after its developmental phase in childhood, is definitively shaped and remains unchanged, was long lectured as a central dogma in clinical neurology and neuroscience. In the second half of the previous century, evidence was found for ongoing neurogenesis in different central nervous system structures. However, this neurogenesis is slow and incomplete.

Neurophysiological investigations elucidated the mechanisms of synaptic plasticity underlying the formation of memory traces and learning. The integration of neurophysiological concepts with neuropsychological paradigms highlighted the importance of experience and reward for successful learning. Learning is the basic phenomenon underlying rehabilitation in patients with central nervous system lesions and diseases. This recovery depends on compensatory mechanisms and plastic phenomena in regions of the brain within the lesion, surrounding the lesion or even contralateral to the lesion. Pure sensory stimulation or passive limb movements or muscle massages are largely inadequate to restore functional integrity. As can be expected from basic neurophysiology, adequate rehabilitation is based on intensive and frequent training, feedback and learning experiences in an environment that offers reward reinforcement. The linking of BCI and virtual

reality (VR) is a logical step in this line of thinking. VR scenes are very interactive, rich and complex environments that are effective in demonstrating reward. As such, BCI have evolved from initial "mechanistic" tools towards plasticity enhancers which hopefully will continue to find their way to the clinical practice of rehabilitation in neurological and psychiatric disorders. BCI-VR paradigms realize a shift of focus from distal effector perspective to a more proximal point of interest: train your brain and change it.
Moreover, aside from regaining functionality due to brain lesions, these approaches could also prove to be useful in normal brains. Measuring or detection of mental workload in human operators is an essential element of complex control and surveyor tasks where attention and vigilance comes into play (*cf.* aviation pilots, driver fatigue, complex and dangerous construction work, road traffic control, medical profession). Assisting an operator by fine tuning information flow and workload to his or her momentary levels of attentional span and mental capacity will optimize effectiveness of operations and enhance security and quality.

5 Discussion

The future of BCI will strongly depend on two things. Firstly, from the effector point of view improvements need to be made in accuracy, speed, reliability, convenience and functionality. Functionality like a high number of controllable degrees of freedom for use in a prosthetic device might lead to a breakthrough. Secondly, successful implementation of BCI systems in the field of rehabilitation and treatment of disorders could also be beneficial for the future of BCI. More insight in the operation of the brain could help to accomplish this. Gaining further knowledge of brain function through experiments in vivo is slow, but can be circumvented by using simulations. In [40] the authors use simulations of the neocortex to study aspects of brain operation. Hopefully this will enable us in the future to rapidly get more insight in its internal workings which could in turn lead to better rehabilitation protocols or BCI features.

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