IDIAP RESEARCH REPORT

EEG-based BCI Systems and IDIAP EEG Database

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Abstract. After giving an overview of the current BCI systems that use non-invasive techniques, we describe in details the database that has been acquired at IDIAP, under the Brain Machine Interface project.

1 Introduction

There is a growing research interest in developing new communication systems, called Brain Computer Interfaces (BCIs), which enable a person to operate computers or other devices by using only the electrical activity of the brain [9]. The main motivation for research in this direction is to provide physically-impaired people, who lack accurate muscular control but have intact brain capabilities, with an alternative way of communicating with the outside world. Current possible applications of BCI systems are: the use of a virtual keyboard to select letters on a computer screen [4, 10, 15]; the control of a motorized wheelchair [12] and the basic control of a hand neuroprosthesis [16].

Apart from a few systems which use electrodes implanted in the cortex that can measure the activity of single neurons, most BCIs use non-invasive electrodes placed over the scalp. Because of the low conductivity of the skull, the cerebrospinal fluid and the meninges, there is a reduction and dispersion of the activity originated in the cortex and recorded at the scalp. Thus the signal coming from each electrode is tiny (in the range of 5-100 microvolts) and encompasses the activity of many neurons. This poor spatial resolution is compensated by a high temporal resolution: the electroencephalographic (EEG) signal is sensitive to changes that occur in milliseconds and thus can provide important informations about fast changes in the activity of certain parts of the brain.

In this report, we give an overview of current BCI systems that use non-invasive techniques, that is, EEG-based BCIs, and we present the EEG database recorded at IDIAP, currently used for the experiments within the Brain Machine Interface (BMI) project.

The rest of the document is organized as follows. In Sec. 2 the present day EEG-based BCIs are described and an objective measure for comparing different BCIs is introduced. Sec. 3 describes in details the database recorded at IDIAP using two different protocols. Future works are discussed in Sec. 4.

2 Present Day EEG-based BCIs

Present day EEG-based BCIs can be classified into two main groups, according to the nature of the EEG signal that they use as input: those using evoked potentials, that is EEG waveforms generated in response to specific stimuli, and those using spontaneous EEG signals, that is EEG waveforms that occur during the course of the normal brain function.

The EEG is measured using small electrodes that are positioned over the surface of the scalp, in a number that can vary from one to 256. The electrodes are placed at certain predefined positions according to the 10/20 international system [7] or variants of that system.

2.1 Evoked Potentials

The most widely used evoked potentials are *visual evoked potentials* [8, 20, 21], that is EEG waveforms generated in response to visual stimuli that can be used to determine the direction of eye gaze, and *P300 evoked potentials* [5, 6], that is positive peaks at a latency of about 300 milliseconds generated by infrequent or particularly significant auditory or visual stimuli, when alternated with frequent or routine stimuli. These signals can be, in principle, easily detected and do not need an initial training of the user, but they have the disadvantage of requiring the synchronization of the subject with the stimulus and the involvement of sensory modalities.

2.2 Spontaneous EEG Signals

Birbaumer and his colleagues [4] analyze *slow cortical potentials* (SCPs) measured over the top of the scalp. SCPs are slow voltage changes lasting from 300 milliseconds to several seconds or minutes. Negative SCPs are related with movement and other functions involving cortical activation, while positive SCPs are related to reduced cortical activation. A drawback of SCPs is the long time they need to develop, which makes them unsuitable for a fast BCI.

Other groups concentrate on brain oscillations associated with sensory and cognitive processing and motor behavior. When a region of the brain is not actively involved in a processing task it tends to produce near sinusoidal oscillations in the EEG known as rhythms, such as the *Rolandic μ rhythm*, in the α band (7-13 Hz), and the *central β rhythm*, above 13 Hz, both originating over the sensory-motor cortex. Sensory and cognitive processing or movement of the limbs are usually associated to a decrease in μ and β rhythms (*event-related desynchronization* (ERD)). A similar blocking, which involves similar brain regions, is also present when a subject only imagines to make a movement but the movement does not take place.
Pfurtscheller and his colleagues [18] measure ERD at fixed time intervals after the subject is asked to imagine a specific movement. Wolpaw, McFarland and their colleagues [22] analyze continuous changes in the amplitude of μ or β rhythms associated to motor tasks. Anderson [2], Millán [11] and Roberts and Penny [19], in addition to motor-related tasks, analyze changes of EEG rhythms associated with cognitive tasks such as arithmetic operations, music composition, rotation of geometrical objects, language, etc.

2.3 Learning Process and Protocols

Birbaumer et al. [4] and Wolpaw et al. [22] have demonstrated that some subjects can learn to modify the amplitude of their SCP or μ rhythm and generate fixed EEG patterns after a period of training. Apart from the specific limitation of SCP that needs a long time to develop, a general drawback of these BCIs is that all effort is put on the user and thus a long period of training is necessary. Furthermore, EEG signals display considerably different characteristics from subject to subject. Thus, for example, in Wolpaw's experiments subjects were selected on the basis of having a strong μ rhythm and some of them still failed to achieve good control of the system. In other words, approaches based on fixed EEG features preclude the possibility to develop an interface that can be used by everybody.

Figure 1 shows a clear example of strong differences in distribution of power in the upper α band (10-11 Hz) for two subjects performing repetitive left and right hand movement imagination. These topographic maps result from the spectral analysis of the database acquired at IDIAP. The first subject presents a strong μ rhythm over the sensory-motor cortex, with differences between the left and right hemisphere, while in the second subject this rhythm is not visible.

From these considerations, it turns out that a more successful approach is to use, in addition to the user's training, classifiers that adapt to the EEG characteristics of each user, in order to develop individual interfaces. In the sequel, we will only discuss the approaches in this direction that appear more interesting.

2.3.1 Synchronous Protocol

The Graz-BCI, developed by Pfurtsheller's group [17, 18], uses motor-imagery-related EEG patterns and is based on a synchronous protocol where the subject must follow a fixed and repetitive scheme. Each trial lasts 8 seconds and consists of a warning signal followed by another indicating when the subject has to undertake the desired mental task for a fixed amount of time. Two consecutive trials are separated by a short resting period.
The system can use several combinations of features and classification algorithms: spectral features, adaptive autoregressive coefficients or common spatial patterns [17] classified by a Learning Vector Quantization network or Linear Discriminate Analysis; or Hjort parameters discriminated using Hidden Markov Models [14].

2.3.2 Asynchronous Protocol

The synchronous protocol has the advantage of generating synchronized trials that can be more easily analyzed, but results in a slow and non flexible BCI system. On the contrary, in the asynchronous protocol the user does not follow any fixed scheme, but operates the system in a free manner.

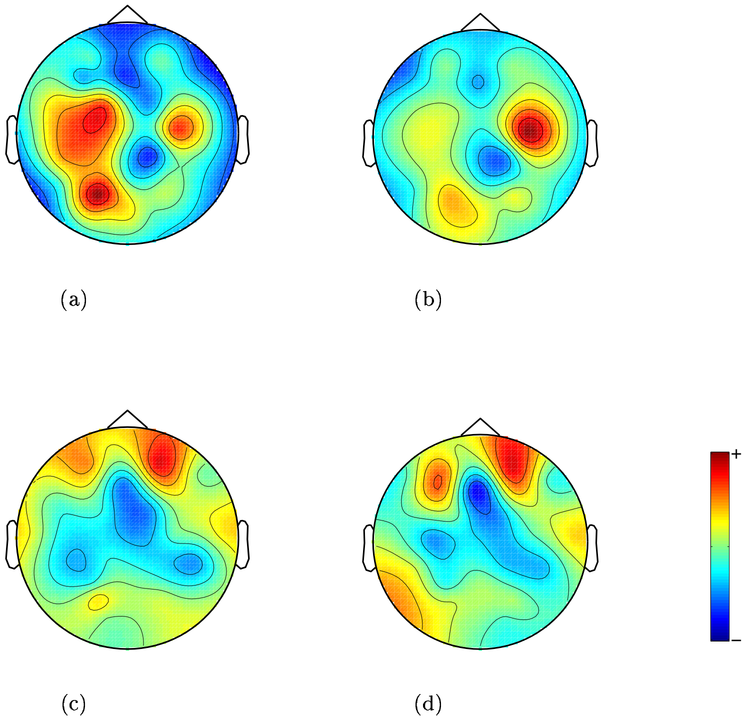


Figure 1: Topographic distribution of power in the upper α band for two subjects performing repetitive imagined movements of the left (a, c) and right (b, d) hand. Subject 1 (upper panel) presents a strong μ rhythm over the sensory-motor cortex, with differences between the left and right hemisphere. Subject 2 (lower panel) presents a strong activity in the frontal area due to ocular activity, but does not exhibit any clearly observable difference in activity between the left and right hemispheres over the sensory-motor cortex.

In Roberts and Penny's approach [19], the user concentrates on two different cognitive or motor-related tasks to drive one-dimensional cursor movement on a computer screen. The cursor moves in proportion of how well the subject performs the associated task. An autoregressive model is applied to sliding windows of data. The resulting features are classified using a logistic classifier. The classifier is trained under a Bayesian paradigm which results in the estimates of the weights and the uncertainty of the weights. The time of response of this BCI is 2 seconds.
Millán's approach [11] is based on an asynchronous protocol in which the subject is trained with the help of feedback to perform three different cognitive or motor-related tasks. EEG spectral features are computed over sliding windows and evaluated using a static local neural classifier. In this classifier every hidden unit represents a prototype of one of the mental task to be recognized. During training units are pulled toward the EEG samples of the mental task they represent and are pushed away from EEG samples of other tasks. During the mutual learning process between the user and the interface, the prototypes associated to different mental tasks tend to reach separate, increasingly circumscribed regions of the space [13]. A rejection criterion is introduced to avoid risky decisions. In this case the time of response is 0.5 seconds.

2.4 Performance Measure

In the previous sections we have seen that BCI systems differ greatly in their characteristics and thus they are difficult to compare. In the last few years the *channel capacity* has been introduced as an objective measure for evaluating and comparing the performance of different BCI systems. The channel capacity is a theoretical measure of the maximal rate of information given by a particular channel. An information channel is, in this context, an algorithm which relays information from the sender to the receiver, and which can be represented by a conditional distribution $P(X_2|X_1)$, where X_1 denotes a random symbol entering the channel, and X_2 the corresponding symbol exiting the channel. In a BCI, the channel is the classifier, the input corresponds to the command that the user wants the system to execute, encoded in the EEG signal, and the output is the command recognized by the classifier.
The channel capacity is based on the concept of *entropy* $H(X_1)$ of a random variable X_1, which measures the information content of the variable and is defined as:

$$H(X_1) = -\sum_{x_1} P(X_1 = x_1) \log_2 P(X_1 = x_1).$$

An unrealistic perfect BCI with N equally likely commands needs to communicate $H(X_1) = \log_2(N)$ bits of information to perform one of the N commands. In a real BCI, the probability that a wrong command is output affects the information flow by a quantity $H(X_1|X_2)$, the *conditional entropy*, defined as the a posteriori information content of X_1, given X_2. Thus the measure of transmitted information in a noisy channel is the *mutual information*:

$$I(X_1; X_2) = H(X_1) - H(X_1|X_2)\,.$$

If we assume that the classifier cannot be trained, i.e. $P(X_2|X_1)$ remains constant, by maximizing $I(X_1; X_2)$ with respect to $P(X_1)$ we can get the maximal rate of information that the channel can relay, that is, the channel capacity:

$$C = \max_{P(X_1)} I(X_1; X_2)\,. \tag{1}$$

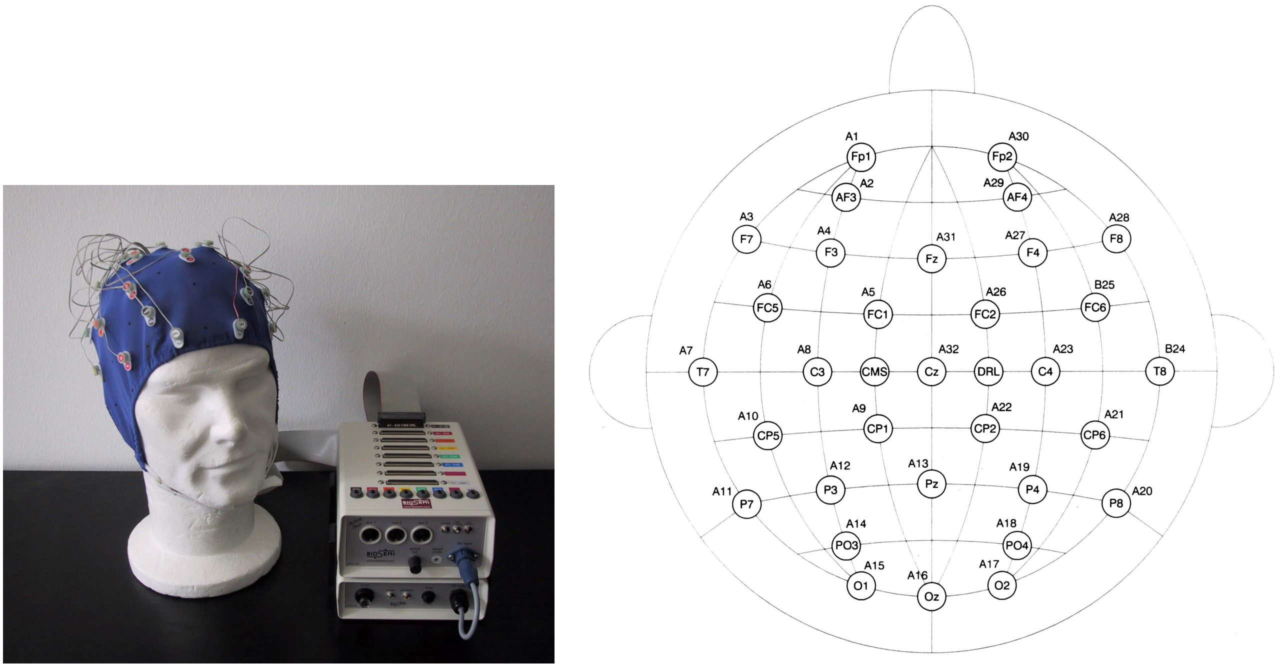
For a BCI, the channel capacity should be expressed in bits per time by dividing Eqn. (1) by the decision interval of the system.
In the particular case of a BCI with N commands with the same probability p to be correctly selected and in which the probability that an undesired command will be actually selected is the same $(1 - p)/(N - 1)$ for all commands, equation (1) has the following simple analytical solution:

$$C = \log_2 N + p \log_2 p + (1 - p) \log_2 \frac{1 - p}{N - 1}\,. \tag{2}$$

In the more general case, the Arimoto-Blahut algorithm [3] can be used to find a numerical solution. Apart from a few exceptions [1], researchers in the BCI field consider Eqn. (2), even if the underlying assumptions may not be fulfilled.
In general, it is worth to notice that the information channel capacity defined above is only a theoretical measure, because $P(X_1)$ depends on the particular application.
At the current state-of-the-art, the best BCI systems provide a channel capacity ranging from 0.2 to 2 bits per second.

3 IDIAP EEG Database

The EEG database currently available at IDIAP has been recorded using the BioSemi acquisition system (`http://www.biosemi.com`), which is a portable system with 32 electrodes covering the whole scalp. The electrodes are integrated in a head-cap that greatly facilitates the operation of the system, as shown in Fig. 2. The data has been acquired from five healthy subjects without any experience with BCI systems, using two different protocols.



(a) (b)

Figure 2: (a): Portable 32-channel system used at IDIAP. (b): Placement of the 32 electrodes over the scalp.

3.1 PROTOCOL I

The first data set has been collected using an asynchronous protocol in which the subject had to concentrate repetitively on a mental task for a given amount of time and to switch directly from a task to another, without passing through a resting state.
The data was recorded during three consecutive days. Each day, the subjects performed 5 recording sessions lasting 4 minutes, with an interval of around 5 minutes in-between. During each recording session the subjects had to concentrate on three different mental tasks: imagination of repetitive self-paced left and right hand movements and mental generation of words starting with a given letter. The subjects had to change every around 20 seconds between one mental task and another under the instruction of an operator. The only difference between this protocol and the real operation of the system, is that in the latter case the changing of mental task is performed as soon as the task has been recognized by the system.
After the five sessions common to all the subjects, some extra data has been acquired. Some of the subjects performed a sixth session with actual movements instead of imagined movements, a relax session or sessions containing some of the artifacts commonly present in the EEG: eye movement and swallowing. A detailed description of the database in presented in Table 1.

TASKS CATEGORIES:

- **Imagination of left/right hand movement (IL/IR):** The subject imagines to move repetitively the left/right hand without performing the actual movement.

- **Actual left/right hand movement (AL/AR):** The subject performs repetitive real movements of the left/right hand.
- **Word association (W):** The subject thinks to a letter and generates words starting with that letter in his/her native language.
- **Relax (R):** The subject relaxes keeping the eyes open.

ARTIFACT CATEGORIES:

- **Blinking (B):** The subject performs repetitive blinking.
- **Swallowing (S):** The subject performs repetitive swallowing.
- **Horizontal/Vertical eye movement (HE/VE):** The subject performs repetitive horizontal/vertical eye movements.

SUBJECT	FIRST DAY	SECOND DAY	THIRD DAY
2	s02001-5.bdf: IL-IR-W s02006.bdf: AL-AR-W	s02007-11.bdf: IL-IR-W	s02012-16.bdf: IL-IR-W s02017.bdf: R
3	s03001-5.bdf: L-R-W s03006.bdf: AL-AR-W	s03007-11.bdf: L-R-W s03012.bdf: R	s02013-17.bdf: L-R-W s02018.bdf: R
5	s05001-5.bdf: IL-IR-W s05006.bdf: B-S-VE-HE	s05007-11.bdf: IL-IR-W s05012.bdf: B-S-VE-HE	s05013-17.bdf: IL-IR-W s05018.bdf: B-S-VE-HE
7	s07001-5.bdf: IL-IR-W s07006.bdf: B-S-VE-HE	s07007-11.bdf: IL-IR-W s07012.bdf: B-S-VE-HE	s07013-17.bdf: IL-IR-W s07018.bdf: B-S-VE-HE
8	s08001-5.bdf: IL-IR-W s08006.bdf: B-S-VE-HE	s08007-11.bdf: IL-IR-W s08012.bdf: B-S-VE-HE	s08013-17.bdf: IL-IR-W s08018.bdf: B-S-VE-HE

Table 1: Database recorded at IDIAP with Protocol I, and some extra sessions with actual movements, relax and artifacts. Each session is saved in the biosemi data format (BDF) and is indicated with sxxyyy.bdf (xx is the subject's code and yyy is the session's number). The data from the missing subjects has been removed from the database for various reasons.

3.2 PROTOCOL II

In this protocol, the subject performed finger movements instead of hand movements. Another difference with the previous protocol is in the real movements which have been performed pressing a mouse button. This way, we can have precise time information about the beginning of a task, as in the synchronous protocol. A detailed description of the database in presented in Table 2.

TASKS CATEGORIES:

- **Imagination of left/right finger movement (IL/IR):** The subject imagines to move repetitively the left/right index finger without performing the actual movement.
- **Actual left/right finger movement (AL/AR):** The subject press repetitively the mouse button with the left/right index finger.
- **Word Association (W):** The subject thinks to a letter and generates words starting with that letter in his/her native language.

SUBJECT	FOURTH DAY	FIFTH FIVE
2	s02018/20/22/24.bdf: AR s02019/21/23/25.bdf: AL s02026-28.bdf: IL-IR-W	s02029/31/33/35.bdf: AR s02030/32/34/36.bdf: AL

Table 2: Database recorded at IDIAP with Protocol II.

4 Future Work

In the near future we intend to acquire new data with an on-line feedback that informs the user on whether a mental task has been correctly or incorrectly recognized. This way the subject will be more motivated during the recording session.

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