



Translation of Brain Activity Patterns of a user into Commands using Electroencephalography (EEG)

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Brain-Computer Interfaces (BCI) are systems that can translate the brain activity patterns of a user into messages or commands for an interactive application. The brain activity which is processed by the BCI systems is usually measured using Electroencephalography (EEG). The BCI system uses oscillatory Electroencephalography (EEG) signals, recorded using specific mental activity, as input and provides a control option by its output. A brain-computer interface uses electrophysiological signals to control the remote devices. They consist of electrodes applied to the scalp of an individual or worn in an electrode cap. The computer processes the EEG signals and uses it in order to accomplish tasks such as communication and environmental control.

Keywords: BCI; EEG; oscillatory signals; electrodes.

1. INTRODUCTION

People with severe neurological impairments face many challenges in sensorimotor functions and communication with the environment; therefore they have increased demand for advanced, adaptive and personalized

rehabilitation. During the last several decades, numerous studies have developed brain-computer interfaces (BCIs) with the goals ranging from providing means of communication to functional rehabilitation. Here we review the research on non-invasive, electroencephalography (EEG)-based BCI

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systems for communication and rehabilitation. We focus on the approaches intended to help severely paralyzed and locked-in patients regain communication using three different BCI modalities [1].

The brain-computer interface (BCI) is the computational platform or device, which considers the input signal from the brain and decodes the information to control the soft-ware or physical interface, cognitive augmentation or restoration. BCIs are utilized for communicating and controlling brain activity, and for the treatment of neurological disorders [2-5]. BCI converts the brain signal into control signals for commanding external devices, like wheelchairs or prosthetic limbs [6,7].The primitive goal of BCI is to neither restore nor bypass neuromuscular activity to experience neurological deficits that cause Parkinson’s disease, stroke and amyotrophic lateral sclerosis. Hence, introducing BCIs is more effective for communicating with the surrounding environment with the use of brain signals [1].

Several brain-imaging modalities are employed for implementing BCI applications to communicate with patients in LIS [8-11]. From these, electroencephalogram (EEG) has been the most broadly utilized modality due to its portability, non-invasiveness, resolution and cost, when compared with other neuroimaging tools, like magneto-encephalography (MEG), near-infrared spectroscopy (NIRS) and .The EEG signal is non-invasive with low cost, portability and good temporal resolution. EEG signal is measured by the electrodes placed on the human scalp. EEG signals reveal the electrical activity originating from the neurons when the

task is performed [12-15]. This activity is measured by the electrodes located on the surface of the head [16,17].

2. SYSTEM DESIGN AND METHODOLOGY

Designing a BCI is a complex and difficult task which requires multidisciplinary knowledge in computer science, engineering, signal processing, neuroscience and psychology. In order to use a BCI.

2.1 Two Phases Are Generally Required

1. An offline training phase during which the system is calibrated and
2. The operational online phase in which the system recognises brain activity patterns and translates them into commands for a computer.

2.1.1 An online bci system is a closed-loop, generally composed of six main steps

2.1.1.1 Brain activity measurement

Brain activity measurement allows to acquire the raw signals reflecting the user’s brain activity. Various types of sensors can be employed, there are some EEG measurement techniques.

2.1.1.2 Pre-processing:

Pre-processing consists in cleaning and denoising input data in order to enhance the relevant information contained in the raw signals. [18-20].

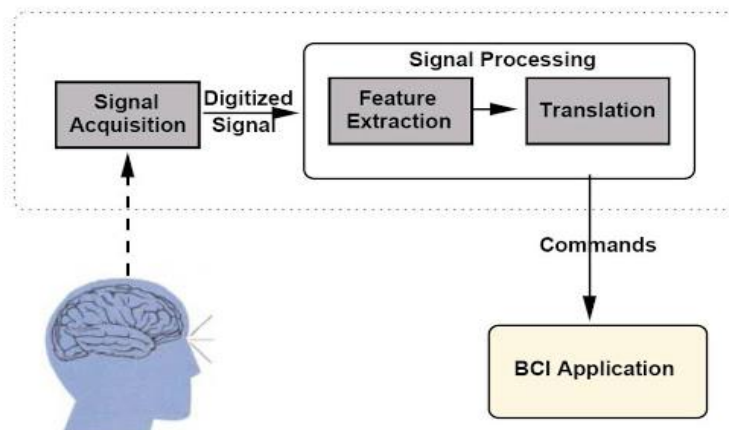


Fig. 1. General block diagram of a BCI

2.1.1.3 Feature extraction

Feature extraction aims to describe the signals by a few relevant values called “features”. These features can be, for instance, the power of the EEG over selected channels, and in specific frequency bands.

2.1.1.4 Classification

Classification assigns a class to a set of features extracted from the signals within a certain time range. This class corresponds to the kind of brain activity pattern identified (e.g., imagined left hand movement or imagined right hand movement). Classification algorithms are known as “classifiers”.

2.1.1.5 Translation into a command

Translation into a command associates a command to the brain activity pattern identified in the user’s brain signals, e.g., a recognised left hand movement could be translated into the command “move the cursor left”. This command is then used to control a given application such as a speller or a robot.

2.1.1.6 Feedback

Feedback is provided to the user to inform him/her about the recognised brain activity pattern. This aims to help the user modulate his/her brain activity and as such improve his/her control over the BCI. Indeed, BCI is a skill that needs to be learned and refined.

2.2.2 Other technology used

2.2.2.1 Electrode connection

EEG devices require a consistent electrical connection between the individual electrodes and the scalp of the individual wearing the device. This can be achieved in a variety of ways, some of which are listed below.

2.2.2.2 Wet EEG devices

There are different types of wet EEG devices.

2.2.2.3 Soft gel-based

Using this connection, electrodes connect with the scalp by applying conductive gel into the pocket of each electrode. After completion of an experiment, it is necessary to clean the headset

by removing the gel and cleaning the electrodes. This is often done with alcohol because of its evaporative properties.

2.2.2.4 Saline solution

Some of the EEG headsets require a conductive gel to help make low-impedance electrical contact between the skin and the sensor electrode. EEG headsets that have this technology connect electrodes by applying saline to each electrode.

2.2.2.5 Dry

Dry EEG devices do not use any gel or saline to connect the electrodes with the scalp, which makes it easier to record EEG data without the help of a trained technician.

2.2.2.6 Others

Some EEG sensor connections types do not fit cleanly into either of these two categories. Conductive solid gel materials, such as those produced by Enobio, have also been used successfully in EEG devices.

2.2.3 Data preprocessing

In general pre-processing is the procedure of transforming raw data into a format that is more suitable for the further analysis and interpretable for the user. In the case of EEG pre-processing usually refers to removing noise from the data to get closer to the true neural signals. The pre-processing aims at translating raw EEG signals, into the estimated mental state of the user. This translation is usually achieved by a pattern recognition approach, whose main steps are as follow [21].

2.2.3.1 Feature extraction

The first signal processing step is known as “feature extraction” and aims at describing the EEG signals by a few relevant values called “features”. Such features should be captured information embedded in EEG signals that is relevant to describe the mental states to identify, while rejecting the noise and the other non-relevant information. With BCI, there are 3 main sources of information that can be used to extract features from EEG signals [22].

2.2.3.2 Spatial information

Such features would describe where (spatially) the relevant signal comes from. In practice, this would mean selecting specific EEG channels, or

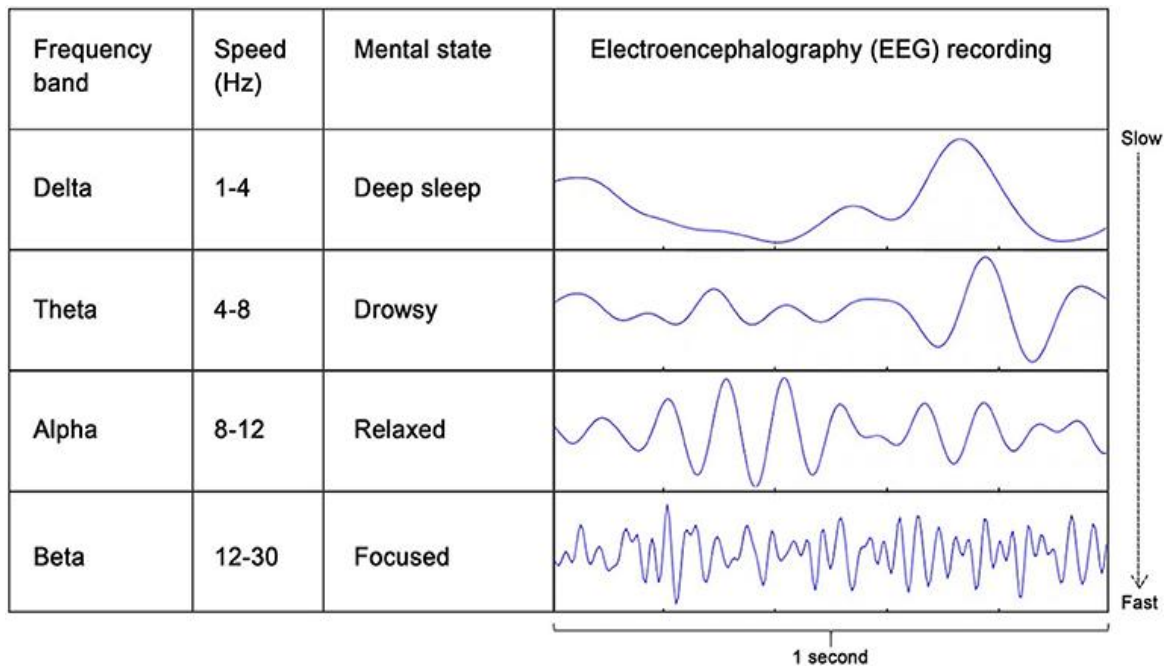


Fig. 2. Brain waves frequency and ranges

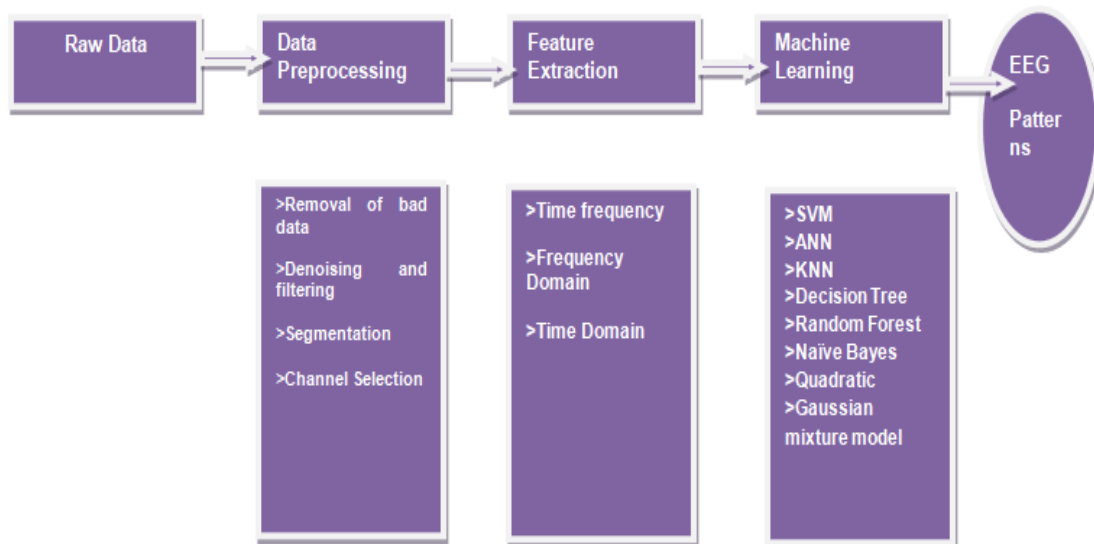


Fig. 3. Process of pre-processing

focusing more on specific channels than on some other. This amounts to focusing on the signal originating from specific areas of the brain [22].

2.2.3.3 Spectral (frequentlial) information

Such features would describe how the power in some relevant frequency bands varies. In practice, this means that the features will use the power in some specific frequency bands [22].

2.2.3.4 Temporal information

Such features would describe how the relevant signal varies with time. In practice this means using the EEG signals values at different time points or in different time windows [16].

2.2.3.5 Classification

The second step denoted as “classification” assigns a class to a set of features extracted from the signals. This class corresponds to the

kind of mental state identified. The step can also be denoted as “feature translation”. Using Machine learning techniques we can train a classifier to recognize from among our features which ones belong to one class or to another. The classification step in a BCI aims at translating the features into commands. To do so, one can use either regression algorithm or classification algorithms. This is very powerful technique and it’s extensively used in EEG data analysis.

Among studies analyzing EEG-based BCI applications most commonly used EEG devices are Emotiv EPOC from Emotiv, Quik-Cap from Compumedics Neuroscan and MindWave from NeuroSky [1].

2.2.3.6 Object control applications

One of the most common applications in BCI is game control. By implementing BCI, keyboard or game console can be replaced by EEG headset. Wheelchair is one of the applications that have been proposed in researches. BCI can also be used for robot arm control application, which often require users to have imaginary movements [16].

2.2.3.7 Object recognition

BCI can be used to recognize imaginary objects, taste, image familiarity and movement intention.

The research proposed a multichannel even related potential (ERP) lie detector. The detector is able to recognize whether the user is telling a lie, which can be differentiated by a trained classifier [21].

2.2.3.8 Rehabilitation and human assistance

BCI is often used in providing aid and ease one’s life. To aid patients with movement difficulties, research proposed a hand movement trajectory reconstruction approach. The study proposed a method to reconstruct various parameters of hands movement trajectory from multichannel EEG [16].

2.2.3.9 Neuromarketing

In the field of neuromarketing, economists use EEG research to detect brain processes that drive consumer decisions, brain areas that are active when we purchase a product/service, and mental states that the respective person is in

when exploring physical or virtual stores. Nowadays, studies can be conducted in mobile setups to gain insights into shopping habits and decision-making in real-world scenarios.

2.2.3.10 Medical use of EEG

EEG is one of the main diagnostic tests for epilepsy. A routine clinical EEG recording typically lasts 20–30 minutes. It is a test that detects electrical activity in the brain using small, metal discs (electrodes) attached to the scalp. Routinely, EEG is used in clinical circumstances to determine changes in brain activity that might be useful in diagnosing brain disorders, especially epilepsy or another seizure disorder [21]

An EEG might also be helpful for diagnosing or treating the following disorders:

- Brain tumour
- Brain damage from head injury
- Brain dysfunction that can have a variety of causes (encephalopathy)
- Inflammation of the brain (encephalitis)
- Stroke
- Sleep disorders

3. CONCLUSION

Overall, EEG-based BCI is currently a very active and dynamic research topic, with hundreds of labs involved, and with many promising potential outcomes in the future. Nonetheless, EEG-based BCI are still far from being free of limitations. With BCI becoming more mature, and increasingly more brain activity patterns being detectable in EEG signals, many new BCI-based applications could and should be explored. With BCI becoming more mature, and increasingly more brain activity patterns being detectable in EEG signals, many new BCI-based applications could and should be explored. Overall, EEG-based BCI research has very exciting research and development perspectives in the years to come and in this study wish to introduce brain activity of a coma patients.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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