Real-time robot arm control using motor imaginary movements decoded from EEG signals

RESEARCH PRACTICE

submitted by
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Abstract

A short (1–3 paragraphs) summary of the work. Should state the problem, major assumptions, basic idea of solution, results. Avoid non–standard terms and acronyms. The abstract must be able to be read completely on its own, detached from any other work (e.g., in collections of paper abstracts). Don't use references in an abstract.

Contents

Chapter 1

Introduction

People with severe neuromuscular disorders, such as late-stage amyotrophic sclerosis (ALS) and those paralyzed from higher level spinal cord injury are unable to actuate any of their muscles. Communication with the outside world is therefore problematic for the suffering people. Cognitive and sensory body functions, however, are often only minimally affected. Therefore, an electroencephalogram (EEG)-based communication which does not require any neuromuscular control is considered to be particularly helpful to enhance the disabled's quality of life by increasing their independence [1].

Besides EEG, there are other techniques for monitoring brain activity, such as functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), positron emission tomography (PET) or single photon emission computer computer tomography (SPECT). The advantages of those methods are a better accuracy and better spatial resolution compared to EEG. However, due to their large size, heavy weight and high price, they are not as suitable for BCI applications as EEG. Furthermore, EEG offers a better temporal resolution, portability and relatively low cost. Recently, low-cost consumer devices came on the market (e.g. EMOTIV EPOC+), which will further push the advancements in the area of EEG-based BCI [2].

In general, the information flow in a BCI follows the following path: signal acquisition, signal (pre)-processing, feature selection and extraction, classification (detection of distinct signal pattern), application interface (e.g. to a robot arm), and feedback (see figure 1.1).
For the project of this research practice, the main objective is to implement algorithms similar to those described by Meng and Yong [3, 4] to discriminate and decode four motor imagery movements (left hand, right hand, both hand imaginary movement and rest) from EEG signals. Afterwards, the classification has to be used to control a robot arm in a real-time scenario. Motor imagery (MI) is defined as the mental rehearsal or imagination of a physical movement without actually performing it physically [5]. On a neurophysiological level, similar brain regions are

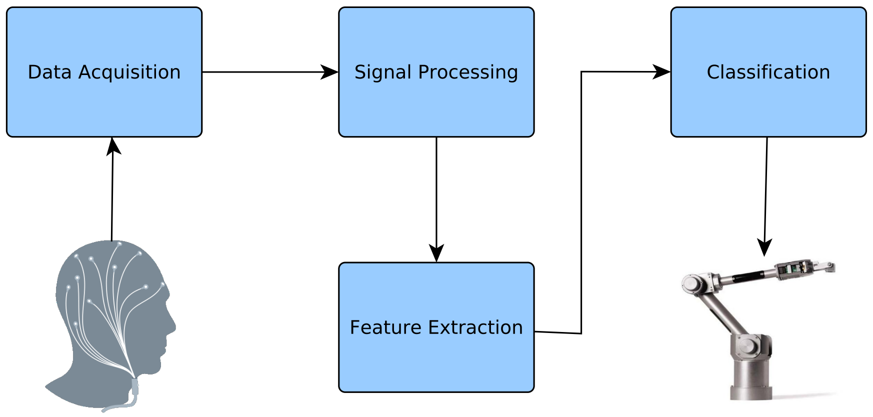

Figure 1.1: Information flow for a BCI system controlling a robotic arm.

activated during motor execution and motor imagery, however, the performance is blocked at a corticospinal level. Studies based on fMRI showed similar activation patterns during motor imagery and actual movement execution [6]. For operating a BCI, motor imagery has proven its capability as an efficient mental strategy.

Concerning the positioning of the EEG electrodes on the scalp, an internationally recognized method called the 10-20 EEG system is used (see fig. 1.2 for illustration). It was developed to ensure reproducibility by standardizing the electrode positions so that one subject's studies could be compared to each other. The system is based on the relationship between the location of an electrode and the underlying area of cerebral cortex. The "10" and "20" refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total front-back or right-left distance of the skull [7]. Previous studies show that electrode positions C3, Cz and C4 are suitable for recording characteristic motor imagery signals, as they are directly covering part of the sensorimotor area.

In the following, first the design and implementation of the BCI project will be discussed. Following that, the accuracies that have been reached will be presented and drawbacks of the approach and possible improvements will be discussed.

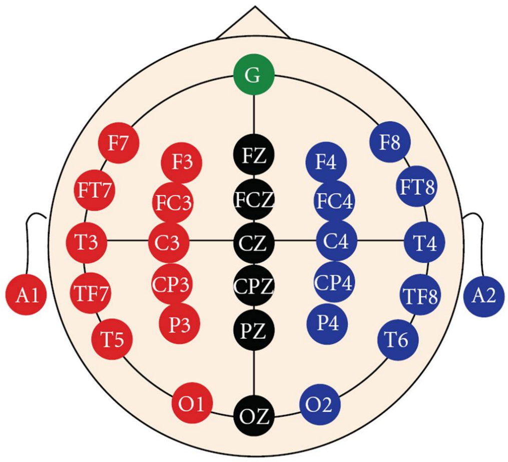

Figure 1.2: International standard 10-20 electrode placement system.

Chapter 2

Experimental Design and Implementation

The basic principle on which this BCI project for controlling a robot arm is based on the following idea: First, a training dataset is recorded for subject that wants to execute control commands. Second, that data is used for training a classifier. Subsequently, the trained classifier model is saved and reused for on-line processing the subject's EEG data, enabling real-time robot control. In order to accelerate that procedure and minimize time constraints, there exist several frameworks for BCI applications. To name some of the most commonly used:

- BCILAB
  ◦ "Open-source MATLAB-based toolbox built to address the need for BCI methods development and testing by providing an organized collection of over 100 pre-implemented methods and method variants, an easily extensible framework for the rapid prototyping of new methods, and a highly automated framework for systematic testing and evaluation of new implementations" [8].

- OpenVibe
  ◦ "OpenViBE is a software for real-time neurosciences (that is, for real-time processing of brain signals). It can be used to acquire, filter, process, classify and visualize brain signals in real time. OpenViBE is free and open source software. It works on Windows and Linux operating systems" [9].

- BCI2000
  ◦ "BCI2000 is a software suite for brain-computer interface research. It is commonly used for data acquisition, stimulus presentation, and brain monitoring applications. BCI2000 supports a variety of data acquisition systems, brain signals, and study/feedback paradigms. [...] BCI2000 is available free of charge for research and education purposes" [10].

2.1 First approach: OpenVibe and Emotiv EPOC+

As previously mentioned, using an existing software framework accelerates development enormously. Therefore, the first approach was to use OpenVibe to implement the BCI system. This was possible because the EEG system for signal acquisition that was available in the beginning of the project was the Emotiv EPOC+. The EPOC+ is a wireless, 14 channel-device with a sampling rate of 128 Hz (see fig. 2.1 on the right-hand side). Its electrodes cover many of the electrode positions as proposed by the 10-20 system (see above), thus also the area near the sensorimotor cortex at C3 / C4 locations. Furthermore, Emotiv offers driver support for its use with OpenVibe.
OpenVibe's programming paradigm is based on building blocks representing individual signal processing algorithms which can be easily connected to each other. Using Python and/or C++, it is also possible to build new blocks with user specific algorithms (see fig. 2.1 on the left-hand side for an illustration). The interface

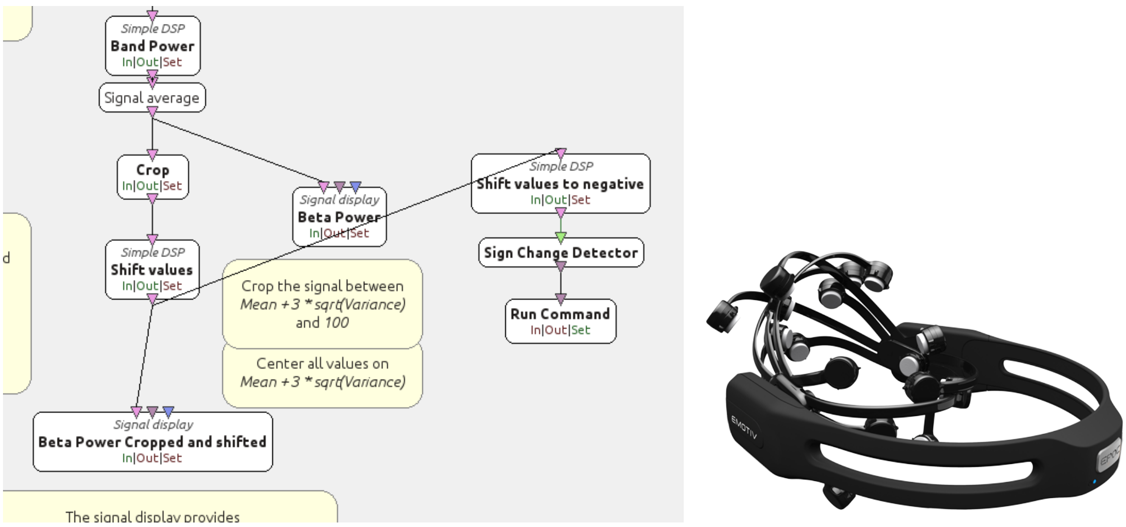

Figure 2.1: Left: Example for the work flow in OpenVibe using algorithmic building block. Right: The Emotiv EPOC+ headset for signal acquisition.

to the OpenVibe is the so-called *OpenVibe Acquisition Server*. For accessing the raw signals of the EPOC+, a premium software development kit (SDK) is needed. However, there are issues trying to connect the EPOC+ with the OpenVibe aquisition server. In fact, the connection succeeds but stops working when starting the acquisition (see fig. 2.2).
Two similar headsets with the official premium SDK were tested without success. Emokit reverse-engineering drivers written in Python (found on the Internet) were able to access some of the data. However, the electrode and quality indicators were disturbed by a strong jitter in the data. An EMOTIV EPOC+ headset with an older version number was working without any problems, but was unfortunately

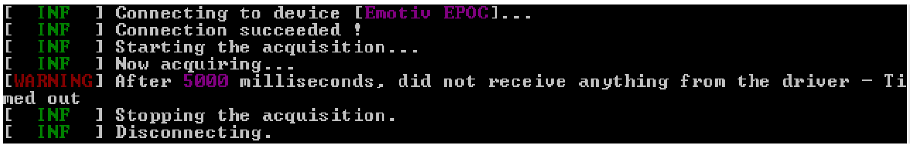

Figure 2.2: Error encountered when trying to connect the Emotiv EPOC+ with OpenVibe Acquisition Server.

available only briefly for testing purposes and not for the BCI project. Therefore, it is assumed that there were some changes done on firmware level by the company. In the end, the approach using an Emotiv EPOC+ in connection with OpenVibe was abandoned due to the previously described problems. The alternative to that will be explained in the following section.

2.2 Experimental Design

In this section the design of the proposed solution will be described, i.e. the overall architecture on an abstract level.
Experiment design:

- cue-based experiment
- acquiring samples

In this section, the implementation will be explained in greater detail.

- Chain of information processing
- Implementation in Matlab
- e

2.3 Experimental Results

- reached accuracies of SVM
- how to ensure that recording is successful
- ...

2.4 Discussion

- how to improve classification accuracy

  improve feature extraction, e.g. use ERD / ERS on α- / β-bands

- use different classifier

  ANN or SNN would be interesting to see. See paper xy for examples

  Convolutional NN or recurrent deep NN could significantly improve classification accuracy and therefore enable the system for a multiclass (more than two for instance) classification

Discuss and explain your results. Show how they support your thesis (or, if they don't, give a convincing explanation). It is important to separate objective facts clearly from their discussion (which is bound to contain subjective opinion). If the reader doesn't understand your results, reconsider if you have managed to extract the core information and explain it in a straightforward way.

Chapter 3

Conclusion

Don't leave it at the discussion: discuss what you/the reader can learn from the results. Draw some real conclusions. Separate discussion/interpretation of the results clearly from the conclusions you draw from them. (So-called "conclusion creep" tends to upset reviewers. It means surrendering your scientific objectivity.) Identify all shortcomings/limitations of your work, and discuss how they could be fixed ("future work"). It is not a sign of weakness of your work, if you clearly analyse and state the limitations. Informed readers will notice them anyway and draw their own conclusions, if not addressed properly.

Recap: don't stick to this structure at all cost. Also, remember that the thesis must be:

- honest, stating clearly all limitations;
- self–contained, don't write just for the locals, don't assume that the reader has read the same literature as you, don't let the reader work out the details for themselves.

This chapter is followed by the list of figures and the bibliography. If you are using acronyms, listing them (with the expanded full name) before the bibliography is also a good idea. The acronyms package helps with consistency and an automatic listing.

List of Figures

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