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

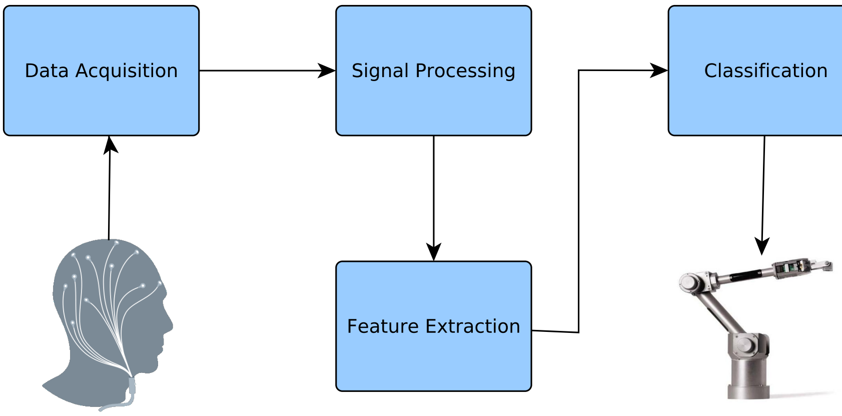

Figure 1.1: Information flow for a BCI system controlling a robotic arm.

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.

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.

Chapter 2

Solution Design and Implementation

Figure below depicts the essential information flow for a BCI system.

2.1 Experimental Design

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

- OpenVibe
- BCILAB
- ...
- my Design

  time-constraint is present, because experimental design is a cue-based approach

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

2.2 Experimental Results

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

2.3 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

Bibliography

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