VRIJE
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Graduation thesis submitted in partial fulfilment of the requirements for the degree of Master of Science in de Ingenieurswetenschappen: Computerwetenschappen

BRAIN CONTROLLED WHEELCHAIR

Using EEG data to gain basic control over remote controlled hardware

Lennert Bontinck

2021 - 2022

Promotors: prof. dr. Geraint Wiggins prof. dr. Arnau Dillen

sciences and bioengineering sciences

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Abstract

Todo

Acknowledgements

Todo

Contents

Chapter 1

Introduction

Brain-computer interfaces (BCIs) and brain-machine interfaces (BMIs) are starting to gather more interest from the general public. These systems, consisting of hardware and software, aim to read and stimulate a user's biomedical signals for a wide range of purposes. Neuralink, an Elon Musk company, helped to popularize them outside of the research field. Neuralink's initial white paper discusses its aim to create a scalable high-bandwidth BMI system, focusing on its mechanical achievements (Musk & Neuralink, 2019). Only a mere year later, the company held a conference with a live demo of their BMI implanted into the skulls of pigs.

Whilst such novel interaction application have yet to see wide spread market adoption, BCIs have been studied for decennia by researchers such as Vidal (1973). An in-depth history from BCIs can be found from Andrea Kübler (2020). Nicolas-Alonso and Gomez-Gil (2012) gives an overview of the different kinds of BCIs and corresponding techniques to be used. These sources give a great high-level insight into the technology and terminology used in this field. A good introductory book on BCIs from this same period is one from the well-known Professor in this field: Jonathan Wolpaw (Wolpaw & Wolpaw, 2012).

Whilst techniques used today remain relatively similar to those discussed in these older sources, the hardware complexity has been evolving drastically. An important issue researchers keep getting confronted with is the fact that there's still a lot of mysteries about the brain's inner working, leaving many of the finer intercepted brain signals unexplained. Hodson (2019) states that the progress of mapping the brain and it's billions of sensors and connections is accelerating yet still far from finished. This mapping would be a huge step in understanding the brain.

Luckily, novel machine learning (ML) techniques can help with processing and reasoning on the data these systems collect. Especially due to recent developments in deep learning (DL) and neural networks (NN), BCIs are being used more in treating neurological diseases (McFarland et al., 2017) but also more commercial applications, like a brain-controlled "virtual keyboard" as discussed by Renton et al. (2019).

A challenge with DL applications in general, and certainly with BCIs, is the fact that training a deep learner in an unsupervised manner can take a lot of data and time and be unpredictable due to it's black box principle. These things are unwished-for in BCI systems, especially when not only reading but also stimulating brain signals. In general, full supervised learning isn't possible either due to the lack of understanding the brain signals. Therefore, low-confidence labeled data is often used in a semi-supervised fashion as explained by Deiss et al. (2018).

1.1 Gaining popularity

As was already discussed, Neuralink, a company by Elon Musk aiming to provide an invasive BCI to be used by the masses as a mean for fast communication between human and machine, has put the research field in new daylight. However, the reason BCIs applications are gaining more and more interest follows from a wide variety of reasons. The following section will discuss the most important ones.

1.1.1 Commercialisation by big tech

TODO

1.1.2 Improved machine learning

TODO

1.1.3 More affordable hardware

TODO

1.1.4 Boost in efficiency

TODO

1.2 Helping people with disabilities

Whilst the commercial interest of BCIs is apparent, it is not the only reason these systems are gaining popularity. As technology evolves, it has often been the case that people with certain disabilities benefit from the evolution as well. Recently, image and speech to text technology has found its way directly into smartphone operating systems. Whilst it is handy for most to have the capability of generating subtitles for an audio track playing on your phone, people with limited hearing now have a direct way to enjoy more content too. Those people who have difficulties with vision can benefit greatly from a camera app with scene detection and text detection. But even simple application such as a color picker on the camera can aid people who have color blindness in determining whether if a banana is ripe and more. This section will highlight some of the benefits BCIs can offer to people with disabilities.

1.2.1 Parkinson's disease

TODO

1.2.2 Audiovisual aid

TODO

1.2.3 Wheelchair users

TODO

1.3 Small projects with big impact

TODO

1.3.1 TODO: example small project

TODO

1.3.2 TODO: example small project

TODO

1.3.3 Using a 3 signal system for basic controls

TODO

1.4 Ethical questions

TODO

1.4.1 Risk of data mining for advertising

TODO

1.4.2 Making the rich even richer

TODO

1.4.3 Confronting users with their brain

TODO

Chapter 2

Biomedical signals

Biomedical signals (biosignals) are any measurement over time of a living being

2.1 Origin of signals

TODO

2.1.1 Bioelectricity

TODO

2.1.2 Brain activity

TODO

2.2 Measuring signals

TODO

2.2.1 Modalities

TODO

2.2.2 Standardized systems

TODO

2.2.3 Common artefacts

TODO

Chapter 3

Processing signals

TODO

3.1 Making useful data

TODO

3.1.1 Pre-processing

TODO

3.1.2 Feature extraction

TODO

3.2 Interpreting signals

TODO

3.2.1 Computer aided interpretations

TODO

3.2.2 Automated interpretation

TODO

3.2.3 Offline and online systems

TODO

3.3 The role of machine learning

TODO

3.3.1 Artificial neural networks

TODO

3.3.2 Deep learning

TODO

Chapter 4

A general BCI pipeline

TODO

4.1 Training the system

TODO

4.1.1 Data gathering and windowing

TODO

4.1.2 Pre-processing

TODO

4.1.3 Feature extraction and generation

TODO

4.1.4 Training a ML classification model

TODO

4.2 Using the system

TODO

4.2.1 Applying the trained classifier

TODO

4.2.2 Moving towards an online system

TODO

Chapter 5

Three signal system for live control

TODO

5.1 Overview of the system

TODO

5.1.1 TODO

TODO

Chapter 6

Using the system and verifying the results

TODO

6.1 Performed experiments

TODO

6.1.1 TODO

TODO

Chapter 7

Self reflection and conclusion

TODO

7.1 Usefulness of the result

TODO

7.1.1 TODO

TODO

List of abbreviations and acronyms

B

BCI brain-computer interface.

biosignal biomedical signal.

BMI brain-machine interface.

D

DL deep learning.

L

latex Is a markup language specially suited for scientific documents.

M

ML machine learning.

N

NN neural networks.

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