Mind Controlled Robot - project

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Overview

Title of the project: Mind Controlled Robot project: EEG-based mobile robot control project using a non-invasive brain-computer interface with neurofeedback.

The following report covers the basic knowledge behind the science of the brain and technological tools related to gathering and interpreting brain electrical activity. Further, the details of the project are demonstrated, among others we focus on the proposed Robot Control System, data exploration and development of a classification model.

The link to the GitHub repository with the project files:
https://github.com/miodine/mind_controled_robot

Introduction

The topic of mobile robot control using brainwave activity is not a new concept, as the earliest examples of said task can be dated to late 1980s [9], despite the technological limitations of that era. Naturally, as the technology progressed, more and more development in the are of BCI's were made. We have reached the era of signal extraction from nerves as small as a single micrometre, building sophisticated prosthetic limbs, and - in fact - being able to control mobile platforms with non-invasive BCI.

Despite the fact that it has already been achieved, as the years went by the approach in the latter area became stale, and one particular paradigm has emerged - the visual cue-based control, in which the user, more often than not, would have to look at a particular part of the computer screen - as to produce a characteristic brain activity in the occipital lobe (to be picked up by EEG electrodes mounted at the back of the head).

One of our objective, was to challenge that paradigm; rather than mapping visual activity, we wanted to map motor activity, and use it as basis for intention interpretation. The motivation is quite trivial - motor activity does not require one to delegate all their attention onto singular endeavour such as looking and focusing on the screen. Even in terms of merely thinking of doing given action with your limb is something, which does not require one to focus very heavily.

To illustrate this point, let us consider the following: the main motivation behind BCI based control of mobile platforms is for the human operator to be less cognitively occupied with the task of controlling the robot. If we require a visual translation layer for both neurofeedback and control commands, then this objective is not really achieved; constant focus on the screen is required.

Obviously, there is a motivation for this paradigm to exist; we have every reason to expect that brain activity in the visual cortex is influenced by what the eyes are seeing at every point in time, and if we simplify it - to for example 4 section screen, then we have a very easy job interpreting that activity. Other reason as to why we can find examples of visual-cue (with translation screen) based system it has to do with the fact, that it was the most thoroughly tested and one can be fairly certain that it is a method that will lead one to the expected results. Some of the projects done with this approach have extraordinarily great and real-world applicable results. It has been done on a cheap equipment, as in our case and with compact robotics systems. The remaining thing, is to decouple the control intention from the visual system, to have a truly user-friendly way of controlling robotised systems. To conclude it all - we would risk a statement, that it is more ergonomic and has more potential to be applied in real-world to *just imagine* a movement of a hand in given direction and effortlessly calque that onto a control command, than it is to achieve the same control command with staring at a screen in absolute focus.

The following report is meant to serve as an *outline*, of the work we did on the topic of mobile robot control commands synthesis based the EEG readouts; to be utilized in a non-invasive BCI system. Obtained results serve as a valuable proof of concept for the examined control paradigm and demonstration of the potential of such a system. It is a demonstration of possibility of achieving state-of-art BCI control system with fairly common and inexpensive components.

1. On Brain, Brain Activity, and BCI.

1.1. Brain - cerebrum

The brain is an organ that serves as the centre of the nervous system for most animals. It is involved in the control and coordination of mental and physical actions.

The human brain consists of the cerebrum, brainstem and cerebellum.

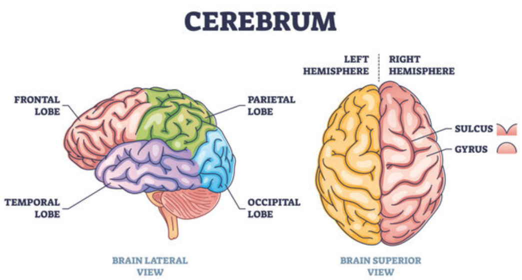

Figure 1: Brain anatomy.[source]

Definition: **Cerebrum** (fig.1) is the largest part of the brain divided into four sections called lobes: the frontal, temporal, parietal and occipital.

From the top view, the cerebrum is divided into two hemispheres: left and right.

The surface area is affected by gyrus (ridges) and sulcus (furrows). Increase of the surface area is profitable for brain's effective functioning (i.e. more neurons can be present with greater surface).

1.2. Structure of the cerebrum - lobes

The cerebrum is divided into four sections called lobes. Each handles a specific function of the cerebrum presented below:

- **Frontal lobe**: responsible for judgement, reasoning, creativity, planning and impulse control (damage lead to risk-taking behaviour, diminishment of ability to learn),
- **Temporal lobe**: primarily functions in auditory processing, also involved in learning, emotions,
- **Parietal lobe**: is responsible for understanding sensory information,
- **Occipital lobe**: plays a role in processing visual informations.

1.3. Brainwaves

Neurons are an important type of cells within the brain that act as information messengers as they send electrochemical signals between various areas of the brain and the rest of the nervous system. As a result of this activity, one can observe so called *brainwaves.*

Definition: **Brainwaves** are oscillating electrical voltages in the brain measuring just a few millionths of a volt [1]. The amplitude and frequency of the brainwaves are changing according to what the examined object is doing, feeling and thinking.

1.4. Brainwaves - meaning behind them

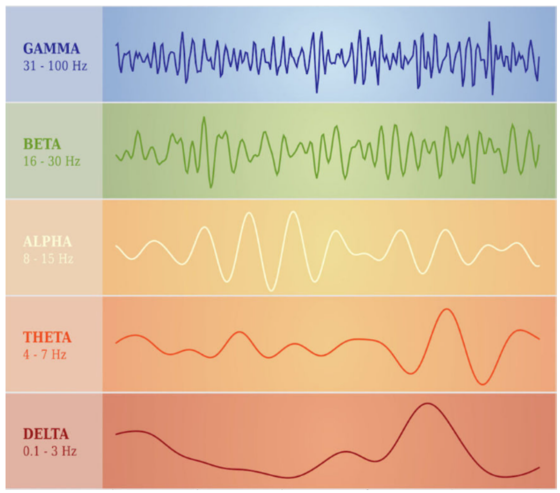

Figure 2: Brainwaves - frequencies and amplitudes [3].

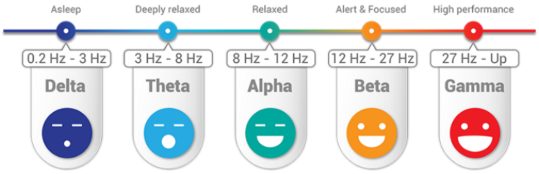

Figure 3: Five types of brainwaves and their meanings [3].

Each brainwave is a composition of signals of various frequencies and amplitudes. Among them, we can discern certain values of frequencies and amplitudes that are typical of different conditions of the human brain (fig.2, fig.3).

- **Delta** (0.2 to 3 Hz): deep, dreamless sleep, deep meditation, coma. In this state of brain activity, external awareness is suspended and healing and regeneration are stimulated.
- **Theta** (3 - 8 Hz): meditation, daydreaming and repetitive tasks that do not require conscious input. Theta brainwaves are important for learning, memory and intuition.
- **Alpha** (8 - 12 Hz): quietly flowing thoughts, and relaxation. It is the resting state of the brain that aids mental condition, calmness and the mind-body connection.
- **Beta** (12 - 27 Hz): normal state of consciousness while the attention is directed towards some tasks and the external world. In this state, humans are alert, attentive and engaged.
- **Gamma** (> 27 Hz): related to the simultaneous processing of information from different parts of the brain. It is crucial for learning, long-term memory, information processing and cognitive functioning.

1.5. Neurofeedback - Basics

Definition: **Neurofeeback** (NFB) is a type of biofeedback in which brainwaves are measured and a feedback signal is provided that can further help assess and improve one's brain activity.

Typically, information about the electrical activity of the brain is collected via **EEG**.

Neurofeedback therapy is often used to help with ADHD, epilepsy, anxiety, depression, insomnia, etc.

2. EEG

2.1. EEG - Basics

Definition: An **EEG - electroencephalography**, is a method of registering brain activity using electrodes placed externally on the scalp. It is thus used as a signal gathering part of the non-invasive brain-computer interfaces. The EEG methods allow one to obtain the readouts in form of collection of time-series of change in electrical activity in different parts of the brain.

2.2. EEG - Brief history

1. The history of EEG begins in XIX century → discovery of brain's spontaneous electrical activity and its examination on animal brains [wiki].
2. In 1924 the first human EEG is recorded, using the device called electroencephalogram; the name which persisted till this day.
3. Over the following 30-40 years, numerous modifications to the EEG were made, leading to many important discoveries in neuroscience, such as discovery of the REM sleep phase.
4. The first trials in engineering - EEG readouts of NASA flight crew members (1965-1966), and the first usage of EEG activity to control a robot (1988).
5. One of the most recent breakthroughs - 2018 first proposition of brain-to-brain interface using EEG, with successful application (81% success rate).

2.3. EEG - the Principle of Working

EEG uses the principle of differential amplification or recording voltage differences on the electrodes located on the scalp. Electrodes are attached to wires that sense nerve signals, which are electrical impulses. These impulses are the representation of the above-mentioned brainwaves.

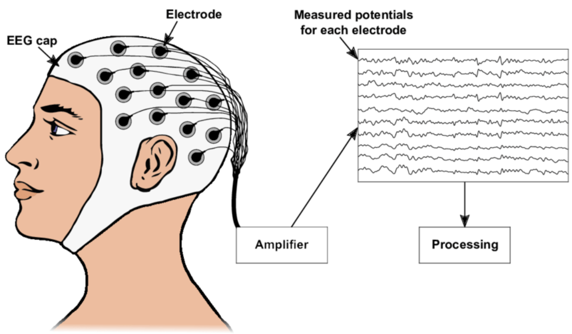

Figure 4: EEG - principle of operation.[source]

2.4. *EEG - the Methods of Collecting Brainwaves*

The registered electrical brain activity is collected using *electrodes* which differ depending on their build. **Types of EEG - by electrodes** There are three types of such electrodes:

1. Passive electrodes - signals amplified far from the electrode cap
2. Active electrodes - signals amplified close to the electrode cap; voltage sources might be closer to the electrodes.
3. Sponge/R-NET - the electrode cap is made of sponge.

2.5. *The 10-20 system*

Despite their types, the principles of EEG stay the same. Thus the location of the electrodes on the scalp remains the same, and it is defined by the so-called **10-20 system**

The naming convention The "10" and "20" refer to the fact that the distances between electrodes are either 10% or 20% of the front↔ back distance or right↔ left distance along the surface of the scalp.

Every EEG device follows this system (or at least a similar one, like the so-called 10-10 system). This includes the MUSE equipment that is meant to be used in our project (although in its case the number of electrodes is vastly limited as compared with e.g. the medical EEG caps).

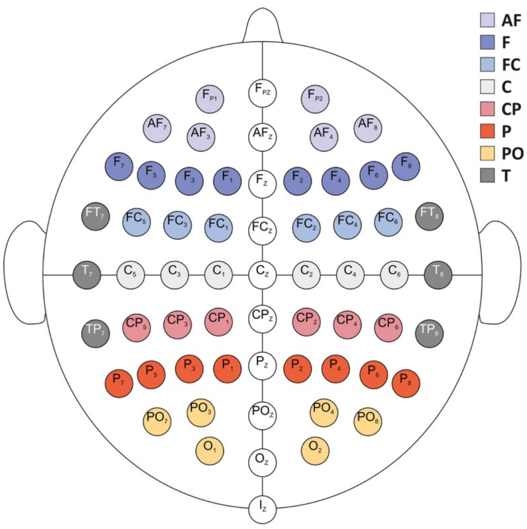

Figure 5: The 10-20 system

2.6. *EEG - Applications*

The EEG was developed to be used for studying the human brain. Its applications are vast, especially in the medical field. One can extract meaningful data from the EEG readouts, for example, to diagnose brain defects, or use them as an aid to study and treat psychosomatic diseases. There are other applications, outside of medicine which lay purely in the engineering domain. However to successfully utilise these data in other fields, one would need to have special electronic equipment - a system which would parse and translate the EEG readouts for further use - this is a **brain-computer interface**.

3. Brain-Computer Interface (BCI)

3.1. *BCI - Basics*

Definition: A **brain-computer interface** (or brain-machine interface) is a physical electronic system [1] used for communication between a brain and a computational unit. It allows for translating registered brain activity onto particular commands and receive feedback from the command execution [5].

To be fully compliant with the definition [5] [8], the system has to allow for bi-directional communication with a machine, despite of how limited one of the communication ways would have been.

What can be considered a BCI? A simple EEG scan (more about it later) is not considered as a BCI by itself, unless it is a part of a system which does provide **a feedback** to the BCI user.

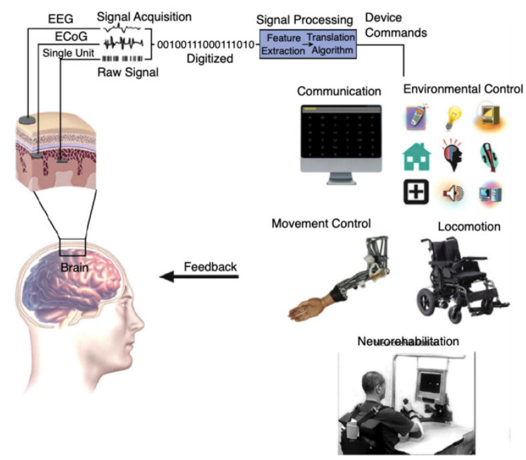

Figure 6: Exemplary BCI system.

3.2. *BCI and MMI (HMI) Comparison*

This type of peripheral is fundamentally different from any other man-machine interface (MMI): such a connection in fact does not require any prior transformation of the electrical signal emitted by cerebral activity into muscular (psychomotor) activity.

[1]constituing of sensors, computational devices and algorithms running on them

In which way are BCIs better than other man-machine interfaces? By breaking free from the "brain, nerves, muscles, conventional human-machine interface" reaction chain, response times can be shortened by several tenths of a second in the case of urgent interaction. In addition, they leave the motor and semotor and sensory organs (hands, feet, eyes, etc.) free and available for other types of simultaneous commands.

Despite its advantages in terms of theoretical responsiveness and ease in usage, this technology is still too young to fully replace typical man-machine interfaces. In some cases replacement of MMI with BCI would not even be feasible, as for the current state-of-the-art - the cost would outweigh the benefits.

Thus the ideas such as people wearing EEG headbands to control all their domestic devices, streaming text from words directly to one's messaging application, or manifesting complex art-form and visualising it on the computer screen, despite their appeal, will be still a domain of science-fiction, at least for the upcoming decade.

3.3. BCI - Invasive and Non-invasive

Main difference: The **invasive** and **non-invasive** BCI classifications are derived from the *placement* of the signal-registering elements (electrodes) with respect to the brain.

1. The non-invasive BCIs are gathering the brain signals through electrodes located ON the head, but not inside of it.
2. The invasive BCIs on the other hand - do gather the signals from the brain using the electrodes located inside of the head, be it either on the brain (partially invasive) or inside of the brain (fully invasive).

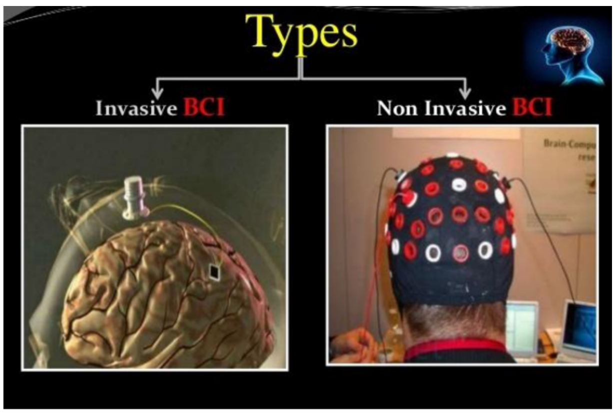

Figure 7: Types of BCIs - illustrated [source]

3.4. BCI - Applications

Figure 8: BCI applications domains.

- **Medicine** - the oldest of applications. Medical applications involve providing alternative communication channels for disabled users.
- **IoT systems** - creating smart environments such as smart houses, transportations, or workplaces.
- **Marketing** - BMIs are used to measure the attention generated post watching of a commercial on TV or any other marketing channel
- **Education** - BMIs can help to determine the degree of clarity in the information studied. Cognitive biometrics in the field of security and authentication is an application of the BMI technology to overcome the vulnerabilities encountered in this field.
- ... robotics!

BMIs can be and have been successfully used in a variety of fields spanning the discipline of robotics, from the control of autonomous vehicles [2], to biorobotics and cybernetics [12].

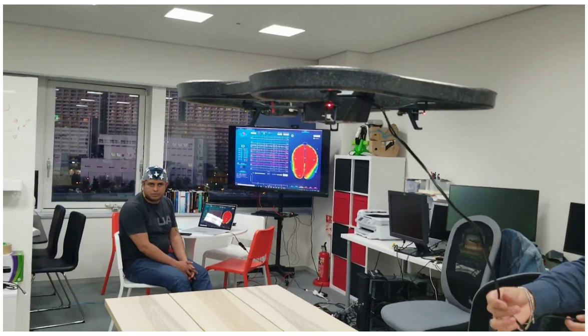

Figure 9: BCI for UAV control [source]

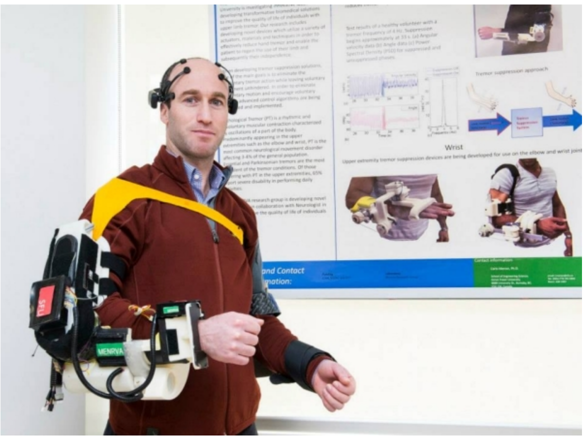

Figure 10: BCI for exoskeleton control [source]

Figure 11: BCI for driving a wheelchair [source]

4. Summary

In the theoretical part of the report, we have covered:

- What exactly is the brain, how it is built, we spoke about its electrical activity and its frequential properties.
- About EEG - the most common and the least invasive method of examining the brain.
- About BCI - how data extracted by technologies like EEG can be used for control and communication purposes

5. Overview of the Produced Solution

5.1. Broader Perspective

Due to time constraints imposed on the mode,- and limitations on the form of realised project, we have established an end-goal which was a golden mean between what is possible to do, and what has the greatest impact in terms of pushing the state-of-art further. The goal was to create a proof of concept, a working simulation for control of the BB8 mobile robot platform based on EEG signals from the provided dataset.

5.2. Realisation of the Project

Achieving the goal was a complex task, which required extensive research in the domains of systems engineering, signal processing, and machine learning. In order to realise the project smoothly, a selection of an appropriate technological stack was needed. We decided to utilize the following technologies:

1. Robot Operating System (ROS) - middleware abstraction layer for robotics systems. It is suitable for coordinating all the processes going within the system, it is mature and has a large supporting community (ergo - all encountered problems were already solved by someone else). It also comes with a lot of utilities that proved to be useful in the development. Our main criterion for selection was modulairty - we wanted the developed system to be used directly on the robot after simulation phase, and ROS allowes us to do just that - simply replace the simulation node with real robot, and BCI simulator with actual BCI and everything should be working as intended.
2. TensorFlow library for Python3 - one of the two top frameworks (alongside PyTorch) in the field of applied machine learning. It combines efficiency, scalability and ease of usage in development of ML models and pipelines. We knew, that in finding the right classifier we will be dealing with lots of different models, and that we would eventually need to write our own - that's where the high level of abstraction comes in handy, and TF allowed us to write simple and elegant solutions that were easily integrable into ROS ecosystem.

3. Gazebo simulation engine - despite being not as physically accurate as for example MuJoCo, or not as lightweight as WeBots, Gazebo has two major advantages over any other simulator that we considered. The first one being running natively in symbiosis with ROS, and... the fact that the best version of the BB8 robot has been modelled for Gazebo.

The other important factor was to determine how to map EEG readouts onto the control commands. As stated in the introduction, there exist ready-made methods to do that, but what we wanted to do, was to challenge the current paradigm. Over the process of testing multiple architectures, we finally arrived at a satisfactory solution, which is surprisingly simple. We introduced our own architecture, called *FourierFeaturesNet*, which (as the name suggests) introduces FFT processing layer, and feeds the resulting spectrum into the classifier being the classification head (SLP). Computation of frequency spectrum in case of EEG readouts is not anything new to the field, but our network has mutliple advangates over the existing solution, for example - the automatic feature extraction, allowing it to classify the chunked EEG signals directly. It is also extremely light-weight and robust. More on that in the further sections of this report.

5.3. Results

Overall we can consider the selected stack a good choice as the objective has been realised. More on the obtained results and the exact methodology used along the way, is presented in the following sections of this report.

6. Data Exploration and Development of a Classification Method

6.1. The Dataset

BCI systems can be divided based on paradigms of how the information is received. Some of the most discernible are motor imagery (MI), event-related potential (ERP) and steady-state visually evoked potential (SSVEP).

In this project, a dataset is an instance of MI-based data [10] obtained through BCI2000 [11], which is a general-purpose software BCI system capable to synchronize EEG signals and other biosignals/input devices. The dataset consists of samples acquired from 109 recruits. The data acquisition was performed in the following arrangement: a subject has a target shown on a certain side of the screen and accordingly performs a subscribed movement (close/open fists/feet), then the same sequence with imagining of the movement. Such sequence of tasks 12 has been repeated three times for each participant.

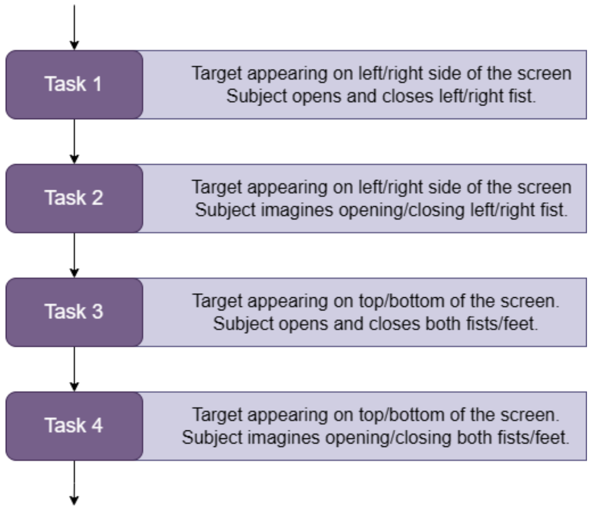

Figure 12: The arrangement of experimental tasks during data acquisition for the employed dataset [10].

Given the nature of the data, it was possible to realise the desired task, of linking motor activity to the control intention.

6.2. Signal Classification Approach and Classifier

As the recorded brain activity is in the form of EEG readouts, we needed to utilise classification method to work with time-series. The popular methods involve utilisation of 1D Convolutional Neural Networks. We have explored a number of solutions like these but none proved to be robust enough. We introduced an alternative method of extracting features from the signal - Real-valued Fourier Transform layer. By computing frequency spectrum the network can more easily determine the characteristics of the provided signals.

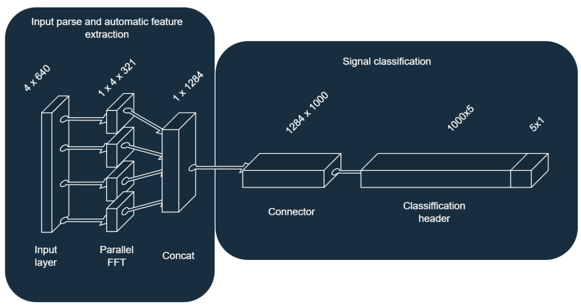

Figure 13: Outline of the proposed architecture.

This approached yielded good results, however there is a need of a couple of adjustments. In real-world application, there will be a need for a calibration - network re-training to make the controls adjusted to the user.

In the examined approach, we compared the performance in terms of accuracy with some of the current state-of-art methods. The ones with best performance found were the EEGNet [6] and ShallowConvNet [4].

Network	Accuracy
FFNet (fine-tuned)	0.807304
EEGNet	0.560261
ShallowConvNet	0.500783

Table 1: Best performing architectures.

As can be seen in the table above, our network performs the best. This does not mean that we managed to beat state-of-art. The primary reason for better performance is the nature of the task. Other networks (such as the ones listed above) in their respective papers were used on datasets containing more often then not signals from the full EEG headsets (meaning >72 electrodes). These proved to be incapable to handle data coming from only 4 electrode readouts for motor activity classification tasks.

There exist other excellent approaches such as MI-1D-CNN [7], which actually has been utilised for the same data-set, for the same type of classification, also with limited number of electrodes. As presented in the paper [7], the results of accuracy (as well as other classification metrics) were way up in the 95-th percentile. Given all this - one might wonder, why not even consider this architecture? As it turns out, there are more than one good reason as to stray away from it.

1. The results of the classification were obtained based on faulty data-set. As can be seen in the official GitHub repository README here, the training data leaked to the test data. The authors stated themselves that this flaw heavily influences the performance of the network.
2. The authors said that the journal had been 'promped' of said flaw, yet no offical erratum is to be seen. This makes a case for reasonable doubt of its utility.
3. As mentioned, the considered data in the paper concern usage of limited number of electrodes, just like ours. But unlike in our cases, the electrodes they considered were located on the scalp in the position corresponding to the border of frontal-to-parietal bones. This means, that what they did, is they took only the electrodes responsible for gathering signals from the *motor cortex*, as to maximise the accuracy of classification. In all fairness, it had every reason to work well, even despite the contamination of the data-set.

The last reason is the main one, as to why we excluded this architecture. We do not have signals from electrodes which are even remotely close to the motor cortex. MUSE2016 electrodes which gather signals from frontal and temporal/parietal (depending on how we're wearing the headset) lobes. Their placement is exactly such that it dodges the most relevant signals - the ones from the motor cortices. We were thus only interested in residual motor activity registered by our electrodes, which further implies that **our features to be extracted were burried deep down in the noise**. This is also the reason as to why we did not apply any filtration.

We had no reasons to assume that feature extraction by means of solemnly stacked timeseries-tailored CNN feature extrapolation will work. The filter parameters rarely ever converge to optimal values which allow us to extract features from seemingly unimportant signals. This is also why in our cases other CNN-based architectures failed.

7. Proposition and Creation of a Robot Control System

As stated in the introduction, the main goal of the proposed architecture was to leverage the modularity of the developed systems, such that we would be able to easily interface the core modules (i.e. those not related to the simulation part) with the real systems. We managed to achieve that with the following ROS-based architecture (fig.14):

In the considered simulation case, we have the following nodes:

7.1. Intention Controller and BCI Emulator

Intention Controller and **BCI Emulator** nodes belong to the same package, and both serve as the entry-point of the signal processing pathway for our control routine. It is sort of simulation of the human brain with BCI routines responsible for gathering and chunking the control signal.

The former node is tool for dictating what is the desired intention of the brain; which type of brainwaves should it produce, based on the desired intention. This intention is dictated by the *neurofeedback* aspect and the task realisation. In the testing stage, we have decided to involve human in the decision-making loop, instead of writing a telemetry parsing and assessment routines. Our choice was dictated by two factors (1) explanability of what is happening, for presentation and control quality assessment, especially in the context of (2) the ease of selecting arbitrary control goals, rather than test-specific ones.

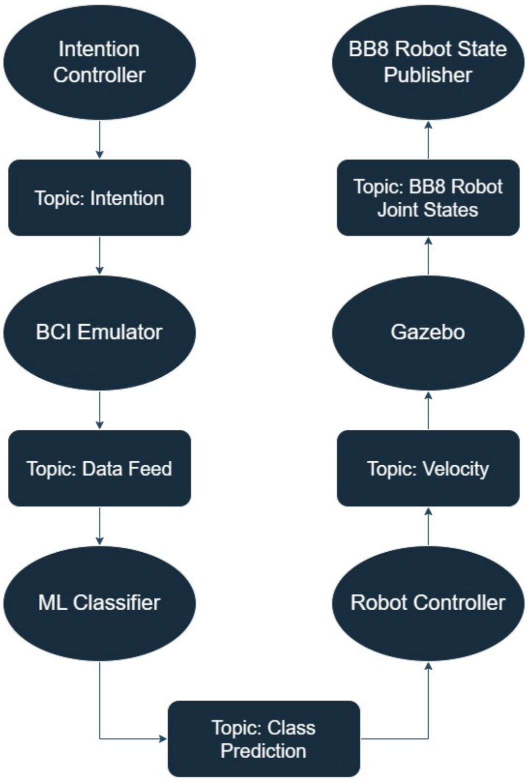

Figure 14: ROS-based architecture: Nodes and Topics Distinction.

The latter node emulates the brain activity and signal chunking routine. We are considering signal channels, corresponding to electrodes located closely to the ones present in MUSE2016 headset. Depending on the intention dictated by the Intention Controller Node, the BCI Emulator takes prepared data from the dataset, corresponding to given label, and feeds them into the appropriate topic. There is number of parameters to be influenced, such as the purity of the signals (fraction of data to be provided with false label), or height of the data stack (how many signal blocks to be drawn from the dataset; resets if height is 0).

7.2. Signal Classification Node

Signal Classification Node is running synchronously in the background and produces best predictions on the basis of the EEG data. It is running a machine learning model, the proposed *FourierFeaturesNet* and outputs the vector of probabilities to be used by the next node in the pipeline to interpret and define the appropriate control action.

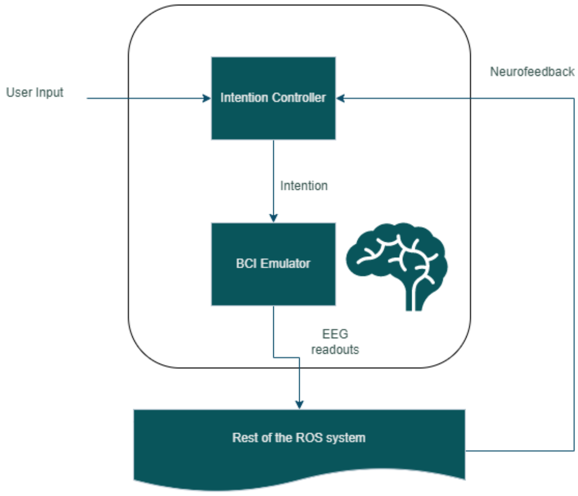

Figure 15: Intetion Controller and BCI emulator nodes.

7.3. Robot Controller Node

Robot Controller Node The final node in the control chain is the **Robot Controller Node** which is responsible for generating the velocity commands for the robot on the basis of movement intention probabilities.

7.4. GUI

The graphic user interface (**GUI**) serves us primarily as a tool for visualisation of what is happening in the system.

7.5. Message Package Format

For the purposes of clear communication in-between the nodes, we have introduced a number of message types, under the *mcr_messages* standard. The messages are based on ROS primitives, and defined as a separate page. The message types are:

1. Control Monit (*mcr_control_monit*) - messages carrying data about current states of the system.
2. Datastream packet (*mcr_datastream*) - carrying the chunked BCI signals from four electrodes.
3. Intention flag (*mcr_intention*) - conveying the generated intention to the BCI emulator.
4. Prediction vector (*mcr_predictions*) - message with generated predictions and extra data related to them.

8. Summary and Potential Further Applications

Overall the results are very promising. We managed to obtain an architecture and classification system which can potentially enable the users to control the mobile robots with little to no effort. The system has a potential to be scaled up, and will serve as a valuable basis for people wanting to build 'mind controlled robot' solutions.

Despite all that, we notice that there are a few key areas that have some room for improvement, such as:

- The classifier propagation time - as it is running from an interpreted script, the solution is not optimized in terms of time. Possible solution is to utilise the model compilation toolkits provided by TensorFlow (TF Lite) and call the compiled model, to both minimize, and optimize the model in terms of call times and signal propagation. Other possible solution is to re-implement the classifier model in C/C++.

- By extension, all the nodes in ROS system could've been re-written to C++ and leverage the speed of compiled routines.

- The signal chunks of fixed length could've been replaced by a sliding window type of input. However, after testing similar solution on given dataset we arrived at a conclusion that this idea would be infeasible to be implemented at this time, but on the test-specific data - this could actually be a better solution. The key problem is that the classifier has to wait for the BCI to chunk a new portion of brain signals, rather than constantly evaluating a new stream of data, which causes deadzones to occur, and results in slower response time of the control system. In this case it might also be necessary to augment the classifier with a recurrent neural network layer. If signal continuity was an issue, then RNN could easily extract time dependencies from the parsed signals.

- The system might later need a very sophisticated state estimation with respect to the typed control actions. Since at the end of the day, we are dealing with predicted probabilities of given control instruction to give, one should consider implementing a Kalman Filter (predictions-to-control-commands) or something similar, preferably solution specific.

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References

[1] P. A. Abhang, B. W. Gawali, and S. C. Mehrotra, «Chapter 1 - introduction to emotion, electroencephalography, and speech processing», in *Introduction to eeg- and speech-based emotion recognition*, edited by P. A. Abhang, B. W. Gawali, and S. C. Mehrotra (Academic Press, 2016), pp. 1–17, ISBN: 978-0-12-804490-2.

[2] X. Duan, S. Xie, X. Xie, Y. Meng, and Z. Xu, «Quadcopter flight control using a non-invasive multi-modal brain computer interface. frontiers in neurorobotics», in (ISSN: 1662-5218, 2019).

[3] «Interpreting the meaning of brainwaves», in (2020).

[4] M. R. Islam, D. Massicotte, F. Nougarou, P. Massicotte, and W.-P. Zhu, «S-convnet: a shallow convolutional neural network architecture for neuromuscular activity recognition using instantaneous high-density surface emg images», in 2020 42nd annual international conference of the ieee engineering in medicine & biology society (embc) (IEEE, 2020), pp. 744–749.

[5] «Kawala-sterniuk, browarska, al-bakri,pelc et al. summary of over fifty years with brain-computer interfaces — a review.», in (ISSN:2076-3425, 2021).

[6] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, «Eegnet: a compact convolutional neural network for eeg-based brain–computer interfaces», Journal of neural engineering **15**, 056013 (2018).

[7] F. Mattioli, C. Porcaro, and G. Baldassarre, «A 1d cnn for high accuracy classification and transfer learning in motor imagery eeg-based brain-computer interface», Journal of Neural Engineering (2021).

[8] K. J. Miller, D. Hermes, and N. P. Staff, «The current state of electrocorticography-based brain–computer interfaces. neurosurgical focus. american association of neurological surgeons vol. 49.», in (2020).

[9] L. B. S. Bozinovski M. Sestakov, «Using eeg alpha rhythm to control a mobile robot», in (In G. Harris, C. Walker (eds.) Proc. IEEE Annual Conference of Medical and Biological Society, p. 1515-1516, New Orleans, 1988).

[10]G. Schalk, D. McFarland, T. Hinterberger, N. Birbaumer, and J. Wolpaw, «Bci2000: a general-purpose brain-computer interface (bci) system», IEEE Transactions on Biomedical Engineering **51**, 1034–1043 (2004) 10.1109/tbme.2004.827072.

[11]G. Schalk, D. Mcfarland, T. Hinterberger, N. Birbaumer, and J. Wolpaw, «Bci2000: a general-purpose brain-computer interface (bci) system», IEEE Trans. Biomed. Eng. **51**, 1034– (2004) 10.1109/TBME.2004.827072.

[12]M. Tariq, P. M. Trivailo, and M. Simic, «Eeg-based bci control schemes for lower-limb assistive-robots. frontiers in human neuroscience», in (2018).