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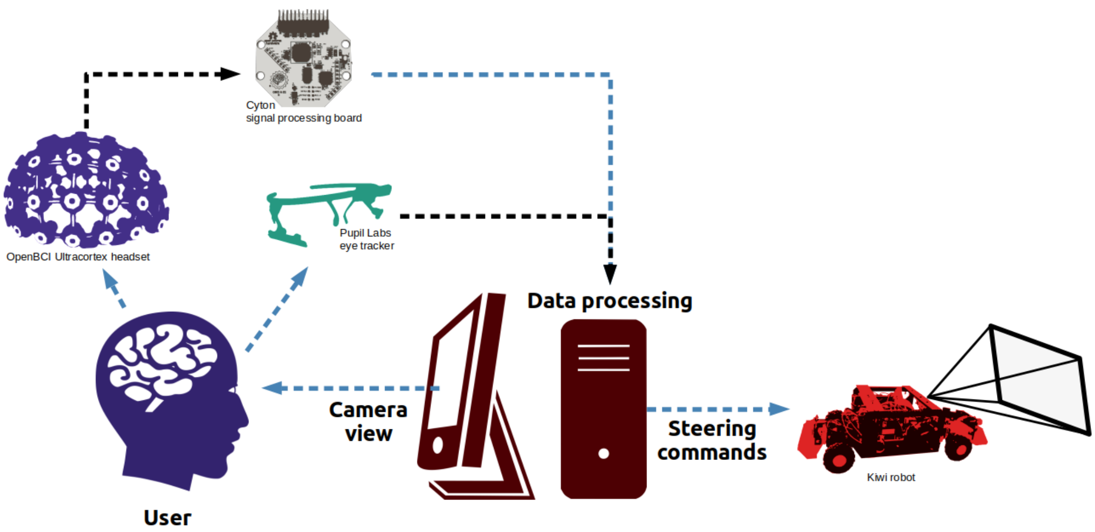


# Brain–computer interface for autonomous vehicles

## An investigation of a hands-free control system

Master's thesis in Complex Adaptive Systems


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Cover: a schematic illustration of the experimental brain–computer interface setup with its core elements and connections.

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# Abstract

Brain–computer interfaces have been a subject of growing interest in recent years and devices measuring brainwave activity are being used within vehicles for evaluating attentiveness and detecting steering intentions. Implementation of such an interface for vehicle control is the main focus of this thesis.
In this work, a novel EEG-based interface supported by eye tracking is investigated in a vehicle control application. The proposed solution merges algorithms utilized in autonomous driving systems with a brain–computer interface based on a P300 response. The control method introduces target following rather than directional steering as a principle of BCI driving, potentially simplifying control and reducing the influence of delay typical for electroencephalography classification.
The interface has been tested by five untrained participants in a simulated laboratory environment. The testing platform consisted of an OpenBCI EEG headset, Pupil Labs wearable eye tracker connected to a standard PC unit, and a miniature robot platform equipped to semi-autonomously maneuver, follow and avoid objects which served as a controlled vehicle. The participants were asked to perform simple driving tasks by observing the frontal camera feed on the computer monitor while their brain response was being recorded and a signal pattern acted as a trigger. Target marking was realized by tracking the gaze position in the character of a selector, and a brain response matching a theoretical P300 was interpreted as a will to interact with the object.
The subjects were interacting with the interface intuitively and were generally able to complete the tasks. The hardships arose in relation to the measuring equipment, which was revealed to be of unsatisfactory quality. While the results are very promising and point to the proposed target-based steering as preferable for BCI driving, further work is recommended to fully estimate the applicability in a real world scenario.

Keywords: brain, computer, interface, EEG, P300, autonomous, driving, BCI.

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Kamila Kowalska

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# 1

# Introduction

Developing a driving assistant system introducing an interface capable of reading a driver's brain signals has been a subject of interest in numerous recent studies. The investigated possibilities are diverse; the analysis of brain electrical activity can be used to estimate the driver's level of attention, aid in performing actions such as braking and lane changing, as well as present an alternative way of vehicle control. Most importantly for this study, the brain–computer interfaces can be seen as a tool enabling disabled individuals to regain autonomy and participate in everyday tasks. According to The World Health Organization, as many as 500 000 people suffer from a spinal cord injury every year [7, 8], 37% of which are considered quadriplegic (partial or total paralysis of the limbs from the shoulders down). Moreover, degenerative disorders such as amyotrophic lateral sclerosis affect approximately 5 in 100 000 people [9]. This fact calls for an invention of a system allowing users to control devices in an alternative way, without the need of limb movement nor oral commands.

Today, brain activity can be detected by wearable electronics and widely available gaze trackers read the eye position with an accuracy allowing to replace a computer mouse. Utilizing an EEG-based headset with an eye tracker raises hopes for creating a robust and responsive system of communication allowing to interact with the surroundings without muscle and oral commands. The solution could both answer the needs of people with severe neuromuscular disabilities as well as introduce new ways of interacting with autonomous cars.

## 1.1 Background

Brain computer interfaces (BCI) are a method of communication between the brain and a machine which relies on measuring the central nervous system activity without employing speech, muscles or peripheral nerves. Today, these systems are widely investigated as tools for enabling severely disabled people to communicate and perform everyday tasks, in neuro-rehabilitation as a way to help patients after a stroke [10], as well as for entertainment purposes. One of the most important applications of BCI systems is supporting body movement, achieved by controlling external prosthetics or driving a vehicle such as a wheelchair.

The main method of detecting changes in brain activity for this application is electroencephalography (EEG). The data can be acquired in real time at a relatively low cost with consumer-grade electronics, however such readings deal with very high amounts of noise and poor spatial resolution due to inevitable skull influence and

external factors interfering with a weak signal. Recent advancements in machine learning methods allow for detecting long-known changes in brain activity with a greater success [11] despite these obstacles. Some of the common solutions for realizing motion employ P300 event related potential and signals invoked by imagined limb movements.
Research involving brain–computer interfaces in direct control of a car, realized as movement limited to four directions, showed that such a solution is possible at a low velocity of around 5 kilometers per hour [12], however other mobile robots achieved much lower speeds closer to 0.65 kilometers per hour [13]. These results appear unsatisfactory and limiting the real life use. The development of self-driving cars and the abundance of systems capable of autonomous movement planning opens the question of whether interpreting driving intentions could be further simplified. Considering that an autonomous vehicle can perform many complicated tasks safely without continuous control, the input could be limited to seldom specification of a spatial goal. P300 response is one of the three most commonly utilized EEG signals for BCI steering, as it is easily detectable and does not require prior training by the user. However, two of its main disadvantages are high latency and the need of averaging the signal over several samples depending on required certainty, where issuing a single command can reach 20 seconds. While relying on this type of brain signal, changing the approach from direction-control commands to specifying a movement target can potentially improve these results. For this type of task, an eye tracker is sometimes used alongside EEG headset to select an object [14, 15].

### 1.1.1 Brain–computer interfaces for realizing motion

The interfaces supplying users with communication and control channels that do not depend on brain's normal output channels of peripheral nerves and muscles can be referred to as brain–computer interfaces [16]. Non-invasive (not requiring surgery) methods of achieving movement control of a robot, wheelchair or another vehicle are generally diverse and can be divided both in regards of brain signals used as the control setting and other factors.
Brain inputs used by the non-invasive BCIs can rely on electroencephalogram (EEG), magnetoencephalogram), blood-oxygen level signals and oxyhemoglobin concentrations [13]. The non-invasive BCIs usually rely of EEG readings and include a speller interface allowing patients to communicate or call for help. However, these interfaces are not useful for the disabled alone. Apart from games and virtual environments created for entertainment purposes, reading the brain state allows to detect the reaction to traffic lights and enact braking [17], and is tested regarding providing vital information about the driver's state in safety systems [18]. Additionally, possible areas of usage targeting healthy individuals include enabling additional communication channels for complicated tasks, such as when hands manipulation and oral communication are not possible [19]. However, today these interfaces have a limited use due to their slowness and low information throughput, usually restricted to a few types of recognized signals.

### 1.1.2 EEG activity and hands-free control

The use of EEG for reading the mind state and its utilization for communication and control has been discussed since it was first described. Today, it remains one of the most important parts of BCI systems, as it is non-invasive and comparatively inexpensive.
Different components of electrical brain signals can be analysed for this application. The P300 is a signal occurring in a short time in reaction to an external image representations of possible options, e.g. letters, symbols or directions to choose. Other methods investigate changes in the signal invoked by the imagination of self movements, where focusing on a limb on the left or right side of the body could specify the intended direction. However, detecting the exact intention—such as exact movement path—remains an unsolved challenge for in-vehicle BCI systems. The P300 response and characteristics of an EEG signal considered in this study are described further in sect. 2.

### 1.1.3 Autonomous driving systems and BCIs

The use of direct brain interfaces in vehicles can potentially enable new, hybrid methods of driving, as well as allow to obtain detailed information about the driver's state. However, introduction of a headset in a car comes with its own set of challenges. While enabling new ways to detect hazardous situations and recognize driver's awareness and intentions, the possibility of incorrect readings is high. This, in turn, can add psychological stress and potentially put the driver in danger, especially if the system were to suddenly act on a non-existent trigger. Shifting of the electrodes together with sudden car movements has been recognized as one of the biggest factors leading to false readings and incorrect responses.

## 1.2 Problem formulation

The aim of this thesis is two-fold: firstly, to present a novel method of an EEG-based vehicle control based on a natural target selection. Secondly, to introduce a safe testing platform to enable future work on BCI interfaces with eye-tracking for autonomous vehicles. The primary focus of this work is thus to estimate how well a passive brain-to-computer interface used without prior training can function in an autonomous driving application, performing the tests in simplified laboratory conditions.
Previous studies exhausted the possibilities of introducing an arrangement of commands where a user is presented with a number of options to choose from, such as steering directions, braking or reversing, which allow to successfully control an RC car [20], wheelchair [21] or a drone [22]. However, these methods rely on a rather lengthy process of option selection; the number of choices assigned to a pre-learned rhythm modulation pattern set is either very limited, or visual stimulation with a feedback loop is employed. The methods of the latter type commonly use the P300, where rows and columns of a choice grid are highlighted multiple times to create an EEG feedback.

In order to control a vehicle, a new command needs to be issued for every change in motion that is desired. This, combined with currently unavoidable slowness of P300 EEG reading, which expects a high latency of around 500 ms, causes the methods relying on it to be relatively slow and inaccurate. Another commonly investigated signal is that invoked by motion imagery, where a measured EEG reading is coming from imagined movement of a limb and can be used to steer a car. Such solutions based on motor imagery require prior training, but the signals can be identified much quicker. Generally, the control systems based on selecting a turning direction allow the user to finish a simple maneuver task in the time frame of several minutes. The principle of both of the EEG-reliant brain–computer interface systems is further discussed in sect. 2 of this report.

In the solution presented here, the user is observing the surroundings in a natural way, from the perspective of a driver, and no artificial interface elements are available to interact with. The need of providing steering or directional commands is redundant in an autonomous driving scenario; a modern car fully equipped with distance sensors and an intelligent vision system should be able to identify a safe path of movement towards a goal, ultimately surpassing the humans ability to do so. By utilizing an eye tracking system to detect the fixation point of the user's eyes at any time, the recognition of sudden changes in EEG signal should allow the selection of a candidate object to avoid or move towards. This approach allows to eliminate a P300-Speller lattice of commands and could potentially shorten and facilitate the communication process to a great extent. In particular, expecting the commands to be provided scarcely minimizes the concerns related to P300 reading delay.
The main difference compared with previous studies is thus the method of steering. In this experiment the need to provide commands such as turning the wheel or selecting the direction is lifted from the user, who only needs to specify a spatial target.

### 1.2.1 Key objectives

The objectives of this study can be broken down into four main research questions:
**RQ1** To what extent is it possible to control a car in real time with the use of a BCI and eye-tracking technology?
**RQ2** How well can an untrained person control a vehicle equipped with this technology?
**RQ3** Is it possible to safely test the system with the use of a miniature car and gather readings relevant to all kinds of vehicles?
**RQ4** How many EEG channels are needed to perform the task?

### 1.2.2 Experimental setup

In the experiment the user drives a remote controlled miniature car by observing a live stream from its frontal camera. The perspective from the frontal camera is akin to being seated onboard the vehicle and the participants are not able to see nor interact with the car directly. All subjects taking part in the study were tasked with navigating the robot car between simple plain coloured objects and sections in a small arena built for this purpose. After the initial setup and calibration done individually for each participant, the driving task is explained, after which the BCI system is turned on and camera view is unveiled. For the entire duration of the experiment, the participant seated in a desk chair is wearing an EEG headset and an eye tracker; the driving intention is expressed through locking gaze on a selected item or area and eliciting an electric potential. The setup of the experiment and the time of introducing the subject to the driving goals are designed to evoke a P300 response in the moment of locating the next goal object in a natural way. The participants start the experiment without any prior training and perform the task twice, in two steering modes. A detailed description of the experiment setup and all its elements can be found in sect. 4.

### 1.2.3 Evaluation

To analyze the performance of the system, the evaluation focused on the time and accuracy of the experimental tasks completed by the test subjects. Moreover, the subjects' individual responses were collected in order to assess the intuitiveness, comfort of use, and possible flaws of the interface seen both as a proposed control method and an experimental platform for future experiments.
The feasibility of all the system elements has also been assessed.

### 1.2.4 Contribution

This work proposes a novel, non-invasive brain–computer interface for vehicle control based on target selection. The difference of this approach lies in the steering method which combines solutions known from autonomous machines with direct driving, as well as the type of a brain signal used, since this study attempts to utilize a P300 response detected during spontaneous decision making.

## 1.3 Limitations

This study is limited to simplified and well controlled conditions. It focuses on the analysis of suitable control methods and does not attempt to name obstacles which may arise in a commercial or non-academic use of the proposed solutions. Specifically, this study does not investigate and does not find solutions for possible signal inferences in a moving vehicle. However, this has been already proven to be of little significance [23]. On the contrary, the studies have pointed out that sudden movements caused by the motion of the car can lead to incorrect readings of the EEG headset. The influence of motion is one of the main challenges limiting the use of the equipment utilized here outside of the experiment.

### 1.3.1 Equipment limitations

Both the eye tracking equipment and the EEG reading headset have a limited use outside of the experiment setting. Mainly, the Pupil Labs eye tracker is used with a two-dimensional estimation mode, which limits its ability to provide correct readings when the user's position changes. The participants are asked to stay perfectly still during all the tests. In order to address this problem, the eye tracker could be replaced with a more sophisticated device consisting of several cameras, which estimates the pose of the user in order to provide right values. The EEG headset used is a device suited for tests and research, while the comfort and time of setup is not being addressed.

### 1.3.2 Safety concerns

When discussing a wheelchair scenario, it is important to note that such system would require a very high safety standard to be allowed to transport a disabled person. At the same time, a BCI system installed in a car with the expectation of recognizing and handling sudden emergency situations may encounter incomparably bigger challenges. While the safety systems utilizing sensors of a vehicle would be able to detect a threat in some of the cases, the reaction-reliant systems such as emergency braking assistance would be of no use when the user is not attentive and does not expect to be in control of the vehicle. Thus, the introduction of the discussed control method to a car in a standard driving scenario should be considered as an aid only. In this application, the EEG signals can be used to recognize the driver's intention to brake up to 420 ms faster than in action-observant cases [17], leading to an increased safety.
As described previously, the safety of the passenger can be compromised by incorrect readings caused by external factors. In order to be used in such a setting, the EEG headset would need to be reliably prevented from shifting during sudden changes in the vehicle's motion to avoid a system failure.
Moreover, because of high latency, the P300 readings should never be preferred if other channels are available.

### 1.3.3 Ethical concerns

Introducing interfaces to be used by disabled individuals to enable movement and daily functions brings its own unique challenges. Since the paralyzed and quadriplegic patients of limited body functions are especially vulnerable, the autonomous elements of the steering algorithms have to be carefully studied in order to preserve personal autonomy [24].

# 2

# EEG in Brain-computer interfaces — an overview

The use of electroencephalography for reading and utilizing silent processes of the mind for communication and control has been discussed since it was first described. Today, it remains one of the most important parts of BCI systems, as a non-invasive and inexpensive method of monitoring brain activity.

As brain–machine interfaces are a new and dynamically changing area of research, many types of classification have been suggested. One of the proposed systems divides the interfaces regarding their dependency on other signal reading methods (i.e. muscle, eye and oral signals), invasiveness and the source of the stimuli [25]. It has already been proven that the control of a robot through brain signals is possible with the use of invasive techniques to a great extent, including the well known study by Carmena *et al.* on primates controlling a robotic arm [26]. However, the non-invasive methods such as EEG, which rely on wearable devices and do not require the implantation of electrodes, are preferred in general use for obvious reasons.
A very significant difference impacting the interface usage is tied to the source of the measured potential. The most common systems rely on reproducing certain patterns by the user and usually have to be learned through long training, which include inducing certain wave patterns or imagining a limb motion. Conversely, the signals can be invoked by external factors such as blinking light at specific frequencies (SSVEP) or occur as a response to a target stimuli when the user is engaged (P300).
This section will review the common signal sources in non-invasive brain-computer interfaces, while focusing on their usability within vehicle control.

## 2.1 Electroencephalography

Electroencephalography (EEG) measures the electrical activity of the brain. The voltage fluctuation is recorded from the scalp surface with the use of electrodes and conductive media, positions of which should follow the 10–20 international placement system. Although the number of electrodes can differ in BCI applications, it was observed that the performance generally diminishes below eight electrodes [27] when P300 response was measured. On the contrary, another study by McCann *et al.* [4] showed that the classification accuracy did not rise substantially above four electrodes.

An invasive equivalent of EEG is electrocorticography (ECoG) in which the the electrodes are placed on the brain surface, but still do not penetrate the blood–brain barrier. Recording the electrical activity directly from the cerebral cortex without the influence of the skull results in considerably better signal-to-noise ratio which makes it another possible candidate for BCI systems in certain cases [28].
Despite the noise levels, EEG can measure a variety of specific responses for the use in a machine interaction context. This can be done by averaging the signal over a time period when some stimulus is present—when analyzing evoked potentials (EPs), which signify a reaction to some visual, somatosensory or auditory stimulus—or detecting a more complex response pattern by filtering and classification of the signal. Event-related potentials (ERPs) and synchronization (ERS) are often challenging to detect and require the use of machine learning for best results [29].

## 2.2 Event related synchronization

Oscillations in the alpha and beta frequency bands (8–32 Hz) can be blocked or can show an increase in amplitude in response to an event—these responses are referred to as event-related desynchronization (ERD) and synchronization (ERS) respectively [30]. In brain-computer interfaces they can be invoked through actual or imaginary motion, and have been successfully utilized to control a wheelchair [31] where four steering commands were assigned to imagined motions of hands and feet. The main advantages of utilizing this potential are short calibration and setup time, since they require few electrodes [32]. While this type of signal is a good candidate for a state-switch BCI, the downsides include the need of prior training and limited possibility of producing the signal by some users. The research has shown that paralyzed people gradually lose the ability to invoke such potential and the respective EEG patterns are considerably less pronounced compared to healthy individuals [33].

## 2.3 Steady state evoked potentials

Steady state evoked potentials, especially visually evoked (SSVEP) are signal responses to stimulation at a specific frequency which can be detected in brain activity measurements. When exposed to a stimulus flickering within the 1 to 100 Hz range [34], a signal of the same frequency can be read from the primary visual cortex. A typical setting in which this potential is used requests the user to focus on a group of visual stimuli flickering at different frequencies, each corresponding to a different command; an example is selecting one of the four directions to move a cursor or selecting an icon to call for assistance. The use of this response in an interface thus requires the existence of an artificial visual interface, although such a solution is still potentially possible in a vehicle setting. However, a requirement to achieve high accuracy is both the user's attention and fixating the gaze on the selected object. In experiments where the subjects instead observed a point between flickering targets, the accuracy decreased from 90 to about 70 percent [35]. This suggests that despite a good signal-to-noise ratio and ability to invoke in nearly all people, similar results


**Figure 2.1:** A typical P300 speller grid with the middle row highlighted [1].

can be obtained with eye tracking alone. Moreover, in some of the cases prolonged exposure to certain frequencies can induce fatigue or seizures.

## 2.4 P300 response

A P300 response is a type of an event-related potential (ERP), which is an electrophysiological potential recorded following a stimulus. This response is typically seen in oddball paradigm experiments, when participants are focused on a series of similar stimuli sparingly interrupted by a different ('odd') one. The P300 response can be recorded around 300 ms after the odd stimulus is presented, but its strength is closely related to the level of attention of the subject [35]. What makes it particularly valuable, the response can indicate the specific target selected by the user from a visual or auditory sequence. One of the most common applications of this response is a BCI speller, a communication tool consisting of a 6x6 letter grid in which columns and rows are highlighted in succession. When a row containing the letter which the subject is focusing on, a P300 response can be detected as a positive deflection in voltage. An example of such a letter grid can be seen in Fig. 2.1.
A modified oddball paradigm introduces a distractor, in which an infrequent additional stimuli appears alongside the target and standard stimuli. This experiment led to the discovery of two subcomponents of P300: P3a and P3b [36]. The signals vary in intensity, location and duration, P3a being the short and involuntary response to the stimulus which hasn't been attended to. P3b has been determined to depend solely on the attention level and its latency can vary depending on the type of the task. Generally, it is expected to occur 300 ms after the target stimuli—or after a point of "resolution of uncertainty" [37] when the subject recognized the target.

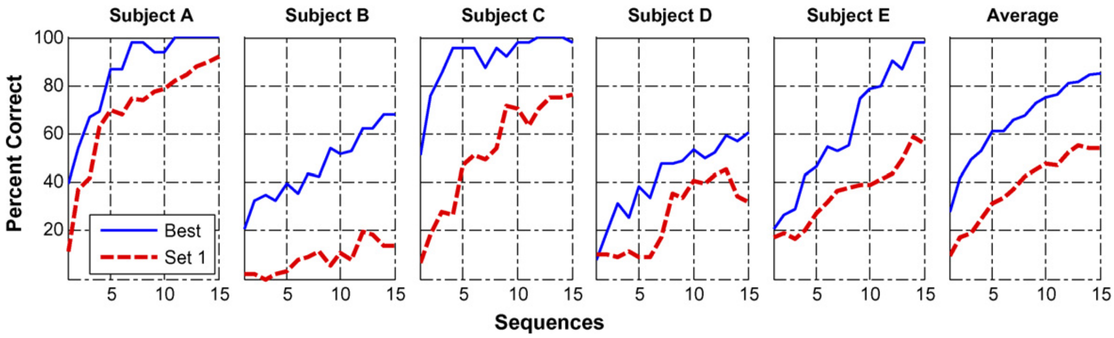



**Figure 2.2:** Performance comparison between two subsets of electrodes in a P300 speller with five participants. From a study made by Krusienski et al [2]

The P300 response has a wide application in brain–computer interfaces and various applications for people with disabilities, used for communication, vehicle control and games. Apart from grid-like interfaces, it has been used to select objects within the subject's surroundings [38].
The individual response strength and required number of highlight cycles in a typical grid-speller scenario varies between individuals. The results obtained by Krusienski *et al.* shown in Fig. 2.4 suggest that a good classification accuracy depends on both individual predispositions and measurement location.

## 2.5 Other possibilities

The description of various EEG communication methods does not exhaust all possibilities. It has been proven as early as in 1970 that humans are capable of taking control over certain brainwave bands after sufficient training with visual or auditory feedback [39]. Thus, suppression and increase of amplitude within certain brainwave range can be learned through practice and used in brain–computer interfaces. Lastly, the future application of intracranial reading methods in devices targeted for general public should not be ruled out. Potentially, the use of such high precision readings could be made possible through a less invasive implantation method. Such investigation is currently carried by Neuralink in the hopes of introducing a minimally invasive system of improved biocompatibility [40].

# 3

# Eye tracking methods — an overview

Currently, there are many systems available for eye tracking, suitable for user identification, augmented reality solutions, wearable devices and in car use. This chapter serves as an overview of solutions possible for implementation in a brain-computer interface, with a focus on pupil tracking.

## 3.1 Available systems overview

From the eye tracking solutions available today, two main types can be distinguished. Firstly, the tracking can be realized through systems of cameras suited to be permanently mounted in a vehicle or similar settings (offered by Smarteye, Tobii and others), which provide high accuracy at the cost of being less flexible. However, such multi-camera solutions where the view includes not only an eye, but an entire head or silhouette, allows for calculating pose estimation relative to interface or car appliances. This type of a solution could find application as a component integrated with a vehicle. Another type of trackers are wearable devices, which are equipped with one or two cameras pointed directly at the tracked eye and one front-facing camera. The frontal camera registers the surroundings and, while it corresponds to the user point of view, allows to map the gaze to actual observed points during calibration. Due to the fact that only two cameras are required for correct functioning of the device in the least complex configuration, and that the eye-facing camera can register the pupil position even at a relatively low resolution (Pupil Labs solution require an image of 200 x 200 pixels, sampled at up to 200 Hz [41]), wearable eye tracking can be seen as a low-cost and easy to implement solution. In a general case discussed here, both systems are considered for use in a potential future work.

## 3.2 Eye tracking in a car setting

Tracking the eye pupil has been used to analyze which elements of the scene the user pays attention to when driving or performing other activities [42]. Moreover, it can be utilized as a mean to detect drowsiness and general attention decrease, where parameters such as PERCLOS (percentage of eyelid closure) and head pose are measured [43]. Such methods of user awareness evaluation or reaction time loss detection are investigated for use in various systems issuing suitable notifications or limiting the velocity range of the controlled vehicle.

Eye trackers provide a non-intrusive way of monitoring the driver's state and thus can be seen as a valuable addition for BCI control systems of a wide span of usage. Various methods of vehicle control based on eye tracking alone have also been studied.

## 3.3 Eye-controlled steering

As of today, several methods of driving a vehicle through tracking eye positions have been introduced. Numerous studies investigate control methods for wheelchairs which involve direction of the gaze ([44],[45]) or divide a camera stream into sections corresponding to movement in selected directions [46]. The studies of these systems, while successfully allowing to control a wheelchair, report difficulties when users close their eyes and point to a general disadvantage, which is referred to as a conflict between looking passively at the environment and issuing commands. Thus, an off switch or a *free gaze* area is usually introduced for the purpose of allowing the user to observe the surroundings freely.

## 3.4 3D and 2D tracking

Typically, gaze tracking methods are based on recognizing pupil contour from infrared images of the eye [47]. One of the problems impacting the accuracy of pupil detection arises due to changing lighting conditions and particularly point shaped reflections obscuring the pupil. As wearable tracking and in-car vision systems are inevitably exposed to rapid changes in lighting in a real-use scenario, it is thus of crucial importance for gaze tracking systems to reduce the influence of such artifacts. This can be achieved through at least two approaches. Traditionally, a series of controlled glints has been used to analyze the eye refraction and improve accuracy, however such a solution is more difficult to achieve in a lightweight wearable device. More recently, several methods of three dimensional eyeball modeling were introduced to counter these unwanted effects [47]. In a more typical approach, the gaze position estimation has been realized as a mapping between a 2D position of the pupil within the camera view and the gaze point in the scene camera coordinates [48].
More recently, 3D tracking for both mapping the gaze within 3D space and modelling a 3D pupil pose has been implemented. Three dimensional tracking is based on creating and constantly updating a 3D model of the eyeball, which allows to counter slippage (movements of the headset). However, as reported by the developers of the Pupil Labs software used here, the final achieved accuracy can be lower by a factor of 2.5 compared to 2D tracking [49].

## 3.5 Experiment choices

When focusing on in-car use, mounted devices consisting of multiple cameras with own systems for compensating refraction could be reasonably selected, as they find

use in numerous studies and driver state estimation applications today. Wearable trackers, however, serve as a less expensive alternative and at the same time provide a direct front camera stream very similar to the field observed by the user. This characteristic highlights them as especially fitting for the driving experiment described here, in which a miniature car and its frontal view camera stream mimic the view of a car driver. In a small vehicle scenario, such as wheelchair control, utilizing the frontal view from the eye tracker would have been most appropriate.
When considering the limitations of eye tracking systems, as well as the high possibility of unwanted light reflections interfering with the results, a decision has been made to carry all the experiments in the same room and placement. This is despite the fact that the tracking unit can be easily moved and reconstructed elsewhere.
The problem of gradual loss of accuracy when head movements occur after calibration has been answered by choosing the subjects to remain entirely still after the calibration has finished, a requirement crucial for electroencephalograph readings as well. At the same time, asking the participants to remain completely still relates better to a possible application in a vehicle controlled by quadriplegic user.

# 4
# System and experiment design

In order to test the viability and various performance aspects of the control principle proposed in this work, several participants were invited to take part in a series of tests.
The experimental platform built in order to evaluate the interface in vehicle control tasks consists of multiple hardware and software components. The design choices regarding both aspects, as well as experiment tasks performed by the participants, are described in this chapter in detail. A special focus is given to brain potential interpretation and software communication.

## 4.1 System overview

The test unit consists of the following elements:

- An OpenBCI EEG headset with the Cyton measuring board and USB bluetooth receiver;
- A Pupil Labs head-mounted eye tracker with a single eye camera;
- A Kiwi car, miniature autonomous robot running OpenDLV software;
- A single PC running Pupil Labs software and microservices handling input and output from all components;
- A chair with a headrest.

The user of this experimental system observes the stream from the front-facing camera of the miniature car while seated in front of a computer. This setting intends to recreate a driving scenario where the subject is a passenger in a self-controlled car without the risks which driving a full sized vehicle or wheelchair would involve. Thus, the electroencephalography data, gaze positions, camera stream as well as all the data from sensors mounted onboard the robot are processed on the computer. The robot car remains out of direct sight of the participant during the entire experiment and receives steering commands wirelessly through a local network. A symbolic visualization of the experimental setting with its core components and communication routes can be seen visualized in Fig. 4.1.

### 4.1.1 OpenDLV

The software for this project was created with OpenDLV, an open software framework designed for autonomous vehicles, developed by the research laboratory Chalmers Revere. Suited to work independently of platform, the framework is not limited by

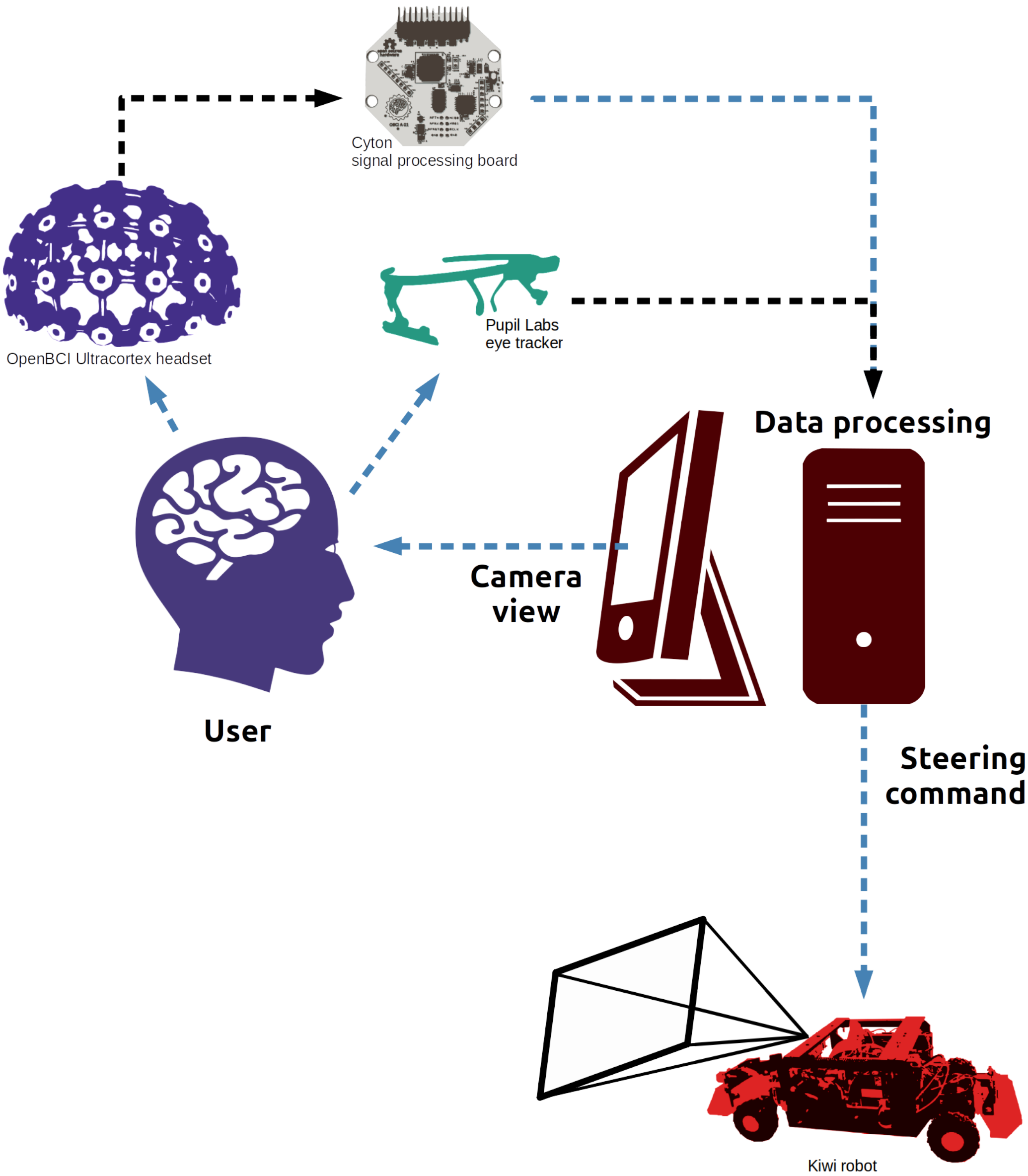



**Figure 4.1:** A graph visualizing the experimental setting with a simplified representation of the information flow between core components of the proposed brain–computer interface. Blue arrows indicate wireless connections. The user is pictured observing the camera stream from a Kiwi robot located in a separate area.

the type of vehicle and is suitable for different hardware architectures and handles communication between sensors and hardware. Multiple repositories for interfacing with several types of sensors are readily available, although it is possible to introduce other interfaces, including those from EEG and eye tracking devices. Moreover, the software can be easily tested on a simple 3D-printed car equipped with a set of sensors and deployed on a real-sized vehicle without code changes. This quality allows for easy future expansion as well as a potential deployment in a real product or service. Thus, all four parts of the brain-computer interface described here (eye tracking, EEG interpretation, steering, computer vision) are written as OpenDLV interfaces able to be deployed independently of other systems or adapted for work on any vehicle.

## 4.2 Brain activity measurements

Reading brain activity through electroencephalography is a core element of the investigated system. Considering the availability of commercially sold equipment and eligibility for use by several participants, an OpenBCI headset has been selected as suitable for this experiment.
A clinical grade recording equipment could provide a significantly higher accuracy of signal measurements, although the use of such devices in the scenario discussed here requires portability and easy setup, especially in regards to the time the application of electrodes can take. One of the main disadvantages of typical medical recording devices is the use of wet electrodes. These systems require application of a conductive liquid between the scalp surface and electrodes, in order to reduce impedance and ensure optimal contact with the skin. Both the time needed to apply the liquid and the necessity of cleaning the skin afterwards appear unsuitable for a scenario of daily use and self-application of the measuring system. Dry EEG electrodes serve as a good alternative allowing to quickly evaluate the plausibility of the proposed system due to the less time-consuming preparation. Their accuracy and performance in event-related potentials classification tasks has been measured [50] and proven to be of marginal difference. Thus, an adjustable headset with dry electrodes was selected for this experiment for easier testing.
OpenBCI is a well known provider of open biosensing systems which has been successfully applied in numerous studies and academic projects [51]. This device consists of a set of dry comb electrodes, a 3D-printed head-mounted frame with 35 node locations, a Cyton processing board taking voltage readings from up to eight channels and a rechargeable battery. An assembled headset can be seen in Fig. 4.2.

The set is additionally equipped with two reference nodes in the form of ear clips. They serve as an additional input normalizing the values from electrodes and were used in all the tests. Ideally, securing the headset and adjusting the electrodes in their sockets should not take more than a few minutes before measurements can be performed.

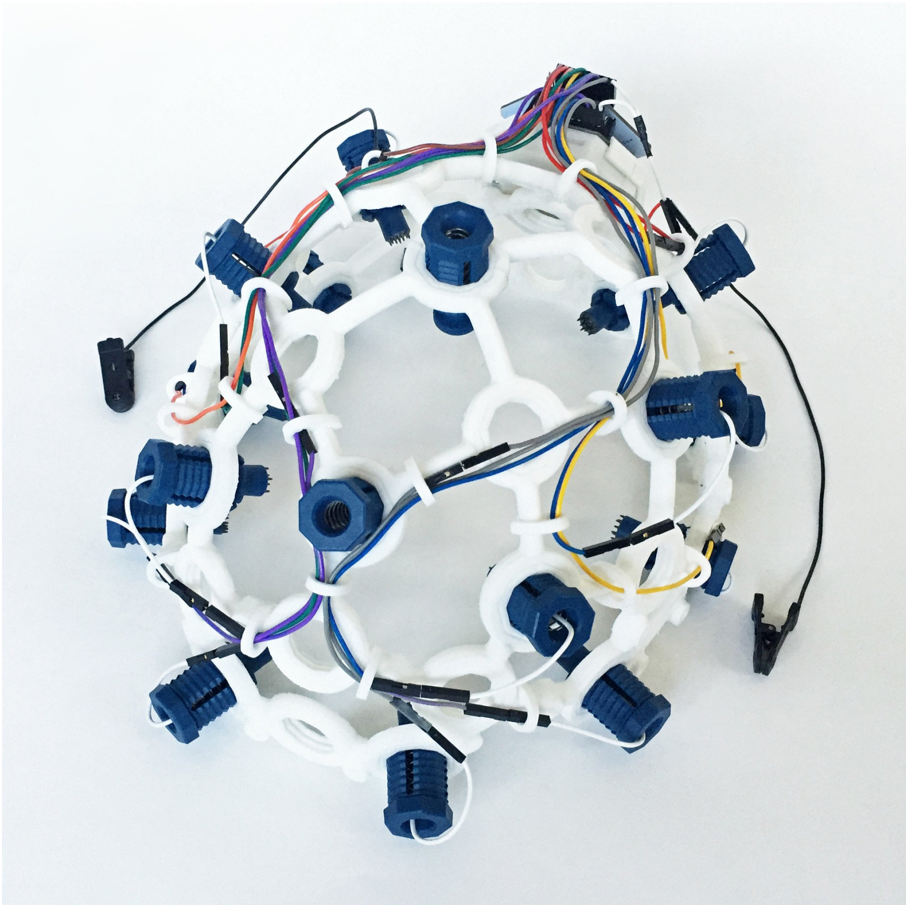
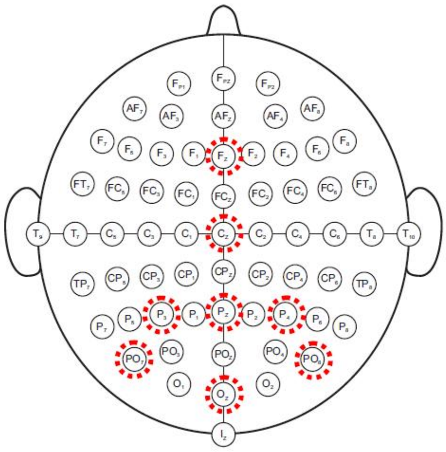


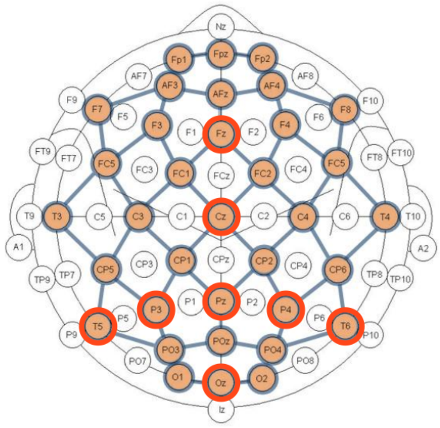
**Figure 4.2:** An assembled Ultracortex Mark IV EEG headset from OpenBCI. Shown in the image: a set of electrodes positioned within sockets of the headset, inactive comfort nodes used purely for positioning the headset, and a Cyton electronic board mounted in the back. Two reference nodes in the form of ear clips are visible on both sides of the headset. From the OpenBCI store [3].

### 4.2.1 Electrode placements

Considering the choice to focus on P300 response, an appropriate set of electrode positions for relevant measurements had to be selected. Based on several studies involving P300, typically used placements were compared with available electrode sockets in the OpenBCI Ultracortex headset. These accessible placements of Ultracortex, as in the 10–20 system, are presented in Fig. 4.3 in comparison with a diagram of typical locations in relevant use; the placements selected for the experiment are marked red. It is worth noting that some positions in the back of the head as seen in the picture are inaccessible due to the sensing board and battery, which are mounted in a socket in the back of the headset.



**(a)** Typical electrode positions for P300 potential detection. The placements were found optimal [52].




**(b)** Ultracortex Mark IV headset possible electrode placements in 10-20 convention. Selected placements are marked with red circles.

**Figure 4.3:** A comparison between optimal electrode placements and positions selected for the experiment.

It has been proven that an increased number of electrodes improves the classification accuracy of EEG potentials. In a P300 classification task investigated by McCann, the larger sets of electrodes were proven to always perform better, however with a change less significant in subsets of four or more electrodes [4], which generally performed on a similar level. It is worth noting that both the widely used configuration proposed by [52], visible in Fig. 4.3 b) on the left side, and the optimal configurations shown in Fig. 4.2.1 rely on similar electrode positions. It is notable especially in the smaller subsets of up to four placements, which are located in the back side of the head, consisting entirely of readings from the occipital (O-) and parietal (P-) lobe. Thus, while a maximum of 8 available electrodes was selected for the driving experiment, as seen in the figure 4.3 on the right side, a smaller set of three electrodes mounted on a headband over occipital lobe has been used during initial system tests and in order to evaluate P300 classification viability alone. The description of this additional P300 detection evaluation can be read in Sect. 4.5.3.

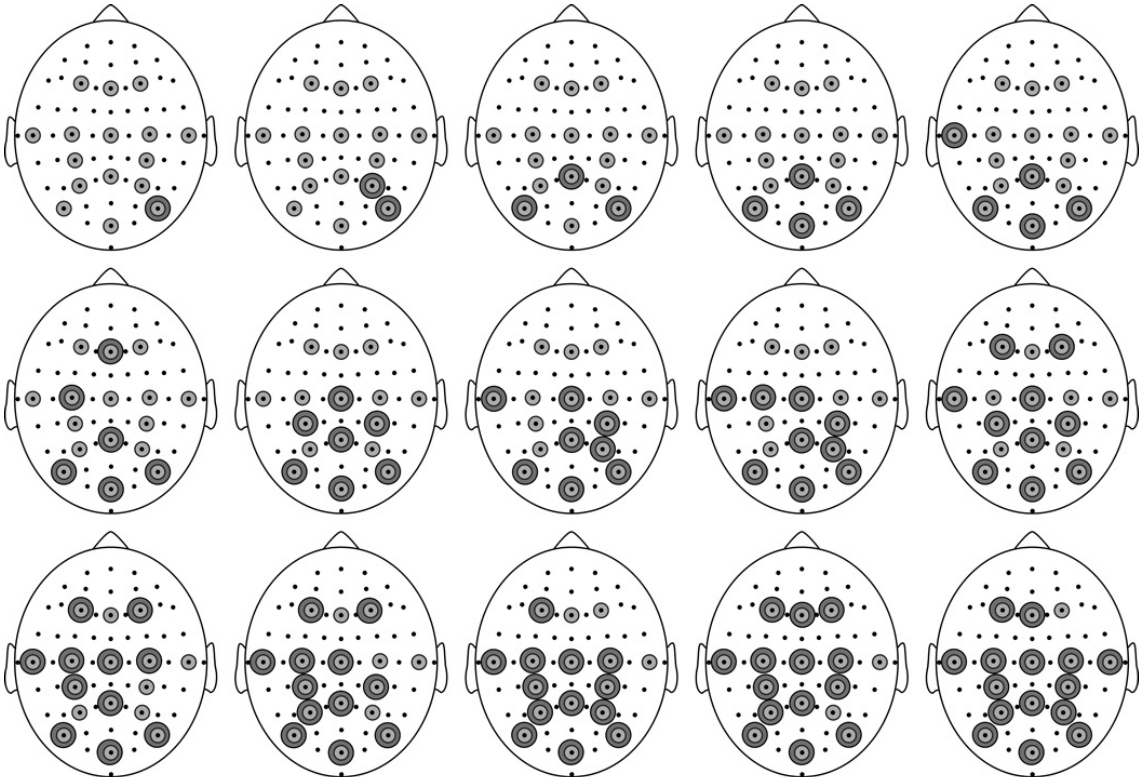


**Figure 4.4:** Electrode placements for P300 detection found to be optimal by McCann et al [4] for subsets of one to fifteen electrodes. The optimal subsets are marked with big grey circles while small circles are the positions analysed in the study.

### 4.2.2 Data acquisition and processing

The Cyton board has been configured to take readings at a recommended rate of 250 Hz with a variable number of channels–however, most of the tests included all eight possible readings. Although OpenBCI offers specialized software for this equipment, it is mainly suited for filtering and recording data for later analysis rather than real time applications. Thus, a separate interface was prepared for this experiment to handle communication with the board, receiving and parsing of the desired data. The process of obtaining the relevant brain information is explained in detail in Sect. 4.5.2, describing the software architecture.
The electronic board is powered by a rechargeable battery, does not connect to the power line and thus does not introduce a risk of electric shock through electrodes touching the scalp.

## 4.3 Eye tracker

A wearable Pupil Labs eye tracker with a single eye camera has been used in the experiments. It consists of two cameras in total: a front-facing 2 MP camera registering an image in full RGB range, and a second eye-facing camera registering an infrared image at 30 Hz in a resolution of 400x400 pixels. The eye tracker used in this experiment can be seen in Fig. 4.5.

**Figure 4.5:** A rendering of the Pupil Labs eye tracker with one eye camera tracking the right pupil. The front-facing world view camera is visible at the top. From the Pupil Labs store [5].

The tracker requires to be connected to a computer by a USB cable, one per camera used, and does not allow a wireless connection.

### 4.3.1 Software

The eye tracking is realized by Pupil Capture—an eye tracking application from Pupil Labs created to work with Pupil Labs trackers. This software realizes the gaze calibration and provides several plug-ins, three of which are used in this work: Pupil Remote, Surface Tracker and Fixation Detector. Fixation allows to distinguish free eye movement, such as when evaluating the surroundings, from locking the gaze on one object (when the position remains relatively still for a specified amount of time). Surface tracking is a feature enabling the mapping of the eye position within a user-defined frame. Remote allows for accessing the current measurements and

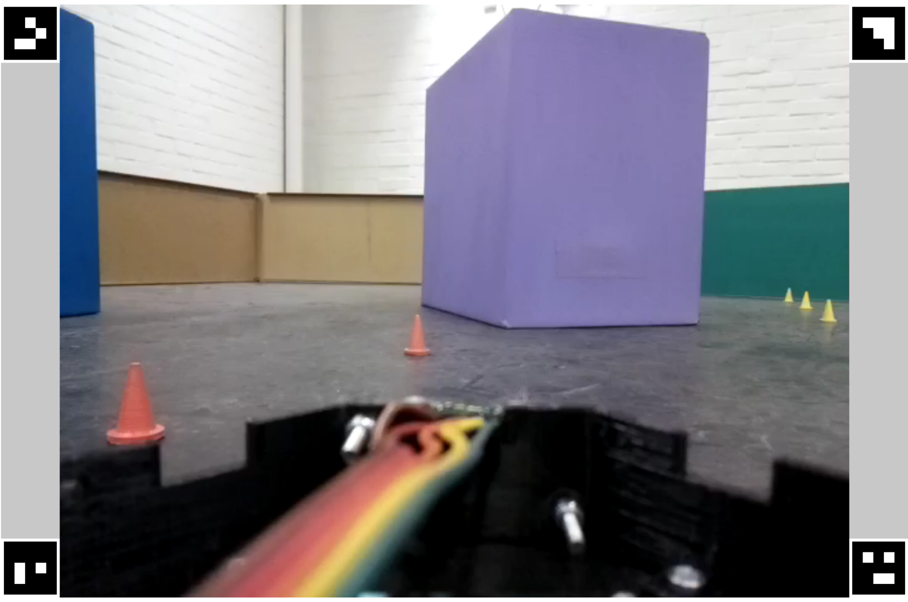


**Figure 4.6:** View displayed by the vision microservice with `--markers` parameter provided, containing the current camera frame and a set of four Pupil markers displayed around the border.

communicating with the Capture application through the network. The microservice written as part of this work connects as a subscriber to Pupil Remote and forwards processed information to other parts of the software. The project uses Pupil Capture version 1.9.7.

### 4.3.2 Screen mapping

Pupil Labs provides a set of markers available to be printed or displayed on-screen, which then can be used to define a named surface. An area enclosed by at least four markers can be selected and stored by the application. Since in this experiment it is crucial to map the gaze to positions within the car view, which itself is displayed on the computer screen, a set of four markers was chosen to mark the boundaries of the Kiwi camera stream. The markers are displayed around the stream in the same window rather than physically attached to the PC monitor. This solution, while most convenient, is prone to unwanted negative effects arising from differing refresh rate of the camera and the screen, as well as problems related to screen color balance and contrast. To mitigate these factors, the digital markers were placed over a contrasting border and increased in size until the tracking was fully stable in all conditions. Moreover, the camera frames are of 4:3 ratio, which otherwise leaves an unused boundary on a typical 16:9 monitor. Lastly, displaying the markers allows to save time and start tracking immediately on any platform.
The camera frame with the markers is presented in Fig. 4.6. As shown, the image is expanded only in the horizontal axis. This design decision was made in order to display a stream of maximum size while not obstructing the view with markers. Due to this choice, an additional offset is introduced in the eye tracker microservice to counter this effect and map the pixel positions correctly.

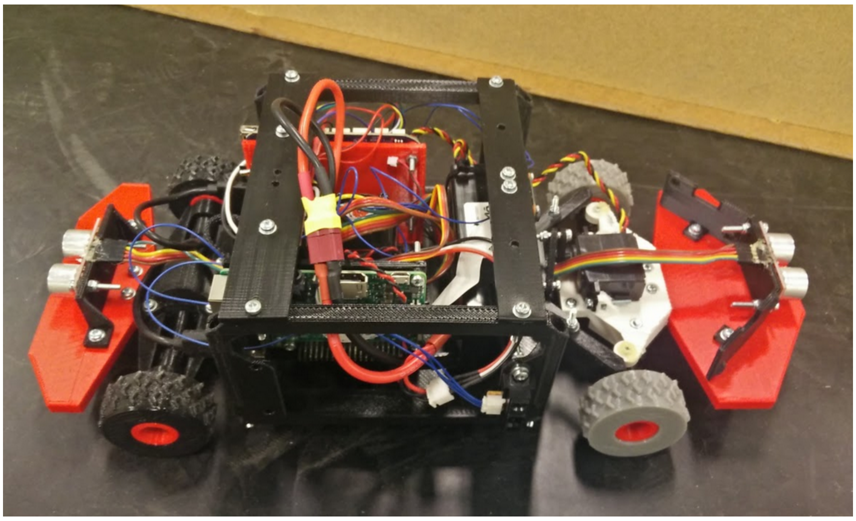


**Figure 4.7:** An assembled Kiwi car.

## 4.4 The Kiwi robot

The Kiwi platform is a miniature mobile robot for testing autonomous vehicle systems designed by Chalmers Revere. The robot serves as a testing platform for various software applications and its main advantages include the ability to run and connect the same microservices as the ones utilized in full scale vehicles. The platform consists of a BeagleBone Blue board connected to a set of ultrasonic (front, back) distance sensors and two (left, right) IR distance sensors, and a Raspberry Pi 3 B board connected to a front-facing camera. Additionally, the robot is equipped with a steering servomotor, a single driving motor and a rechargeable battery [53]. All other parts are 3D-printed and their models are available online.
In this experiment none of the signal processing has been run on the robot itself. As equipment utilized for data gathering uses USB interfaces and image processing required for object detection is rather complex, the software runs on the computer instead.

This platform was selected due to availability, testing safety and possibility of both remote control and streaming the real time camera view from the perspective of a passenger.

## 4.5 Microservices

The code was divided into four independent parts handling different components of this BCI system: (1) decoding and processing EEG stream for detecting brain responses, (2) connecting to the Pupil Remote server to retrieve current eye position respective to the screen in front of the user, (3) interpreting camera view, and (4) controlling the car. The microservices are run as one libcluon[1] session and communicate by broadcasting messages through UDP multicast. The electroencephalography

[1] https://github.com/chrberger/libcluon

and eye tracker modules connect to data sources and broadcast processed information, while the main vision microservice processes both these inputs in regards to the current camera frame. Based on the BCI input and the image, where basic object detection and other simple image processing is realized, the service interprets the user's intentions and sends a suitable action request. Lastly, this interpretation is transformed into steering signals by the steering microservice, which decides the final velocity and direction after comparing data from distance sensors mounted on the vehicle. This last step allows for safe and situation appropriate driving. A diagram visualizing the services and the data flow can be seen in Fig. 4.8.

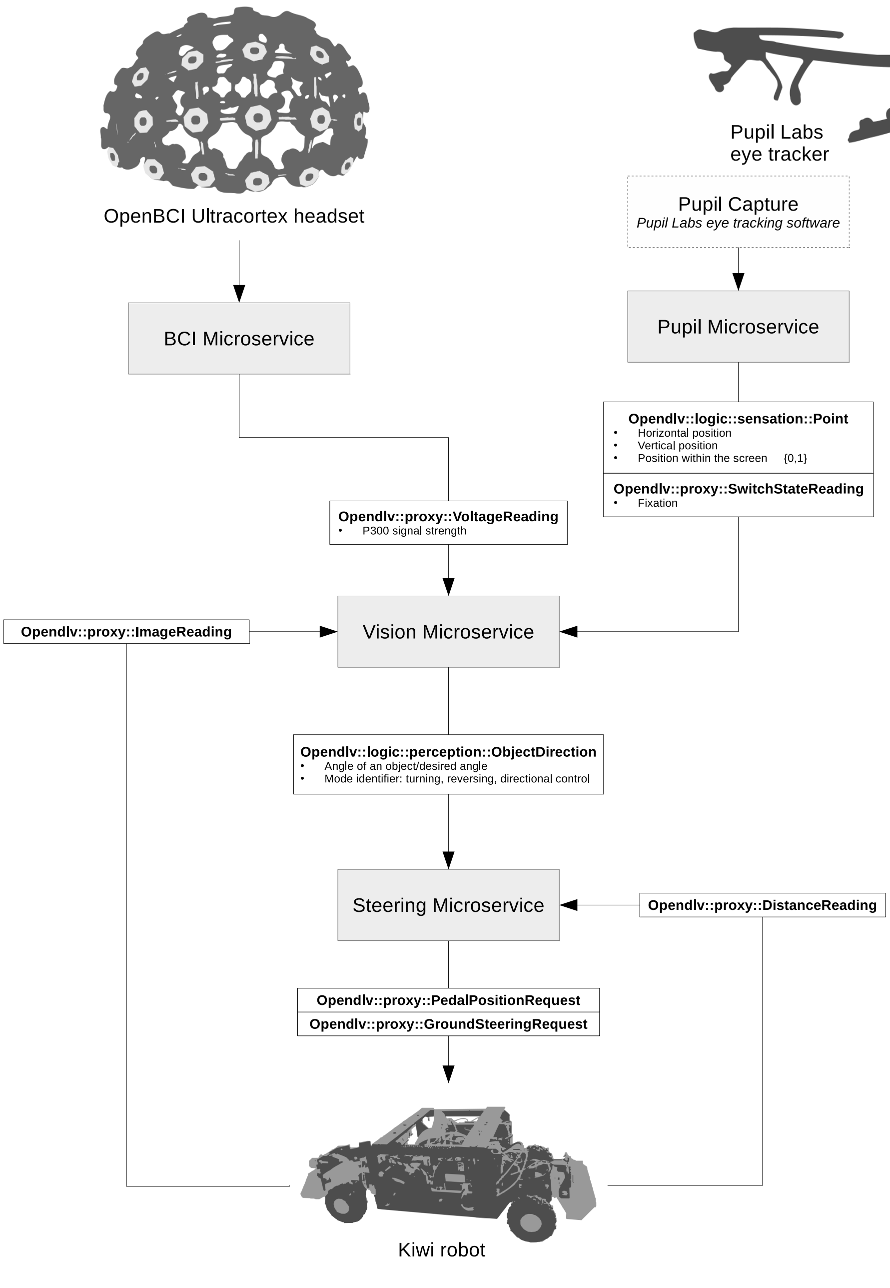



**Figure 4.8:** A diagram showing the configuration of the system with the specification of all the UDP messages exchanged by the microservices.

### 4.5.1 Eye tracker listener

The eye tracker application has a simple function of retrieving and parsing the data coming from the Pupil Capture server. Provided an address and port, it subscribes as a listener and awaits selected messages. As the Pupil application allows to track surfaces while storing the information of the selected set of markers, it is able to measure the gaze position in units expressing distance to its boundaries. A floating point variable equals to 0 at the origin of each of the surface axes and 1 at length or width respectively. The listener service does not process these relative values other than normalizing them to the correct axes and sends them as `opendlv::logic::sensation::Point`, where the last value is a boolean denoting whether the gaze is positioned within or outside of the surface. A second listener thread awaits for fixation information and sends current fixation status as a single boolean value `opendlv::proxy::SwitchStateReading`. The parameters of fixation detection can be chosen within the software provided by Pupil and are limited to the duration of the gaze, maximum angle dispersion and confidence threshold. In this experiment the dispersion threshold was set to 2.5 degrees and minimum duration to 500 ms. The messages parsed by this microservice are unpacked by msgpack and JSoN. It should be possible to perform the encoding using the msgpack only, thus simplifying the code, given multi-dimensional arrays support. The Pupil listener microservice does not process the data further and its output is interpreted in the main vision service.

### 4.5.2 EEG listener

The principle of signal retrieval was introduced in Sect. 4.2. The EEG microservice connects to the serial port adapter issued by OpenBCI and handles activating the stream and decoding voltage values of all active channels from messages sent by Cyton board. The processed values are stored in a circular buffer of a fixed length, on a first-in first-out basis; the number of readings is specified by the user when launching the service and set to 150 by default.

After the buffer is filled for the first time, the potential difference is ready to be measured and sent, which occurs with a selected frequency. At the time of the measurement, the buffer is treated as consisting of two parts, assuming a suspected P300 trigger to occur at the very first sampled value in the buffer. Thus, at a default frequency, the detected potential from a buffer of length 125 corresponds to a stimulus which occurred 500 ms earlier. Under this assumption, the information contained in the buffer at any time expresses a classic P300 response; if no such activation took place in reality, the measured potential should be close to zero. Before each calculation, the values from all channels are copied to a separate two-dimensional array.

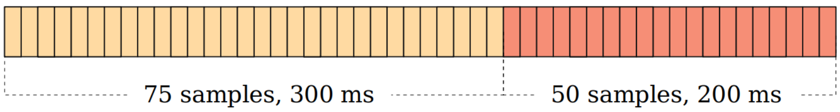



**Figure 4.9:** A data buffer of length 125 for frequency 250 Hz

In order to isolate low frequencies and compute the strength of P300 response, the following steps are taken:

- The values are normalized across the buffer: the mean value is subtracted;
- The buffer is divided into two arrays corresponding to the section *before* and *after* the expected P300 response: the first 300 ms and the remaining part of the buffer;
- A fast Fourier transform (using the FFTW package[2]) of both sections is computed;
- The output magnitude spectrum values are transformed into real values;
- Brackets in the output spectrum corresponding to frequencies 1–20 Hz are summed for both parts respectively.

This process is repeated for all active channels. The amplitudes of the relevant frequencies are added and the ratio between the total "before" and "after" part of the buffer is returned as the output value. Since it is assumed that 300 ms after the related trigger a spike in low frequency bands should occur, a resulting high value signifies a potential P300 response. Due to the fact that very small amplitudes of low frequency components in the first section of the buffer might elevate the returned ratio to undesirably high values, the following condition was introduced:

$$p(\mathbf{x_a}, \mathbf{x_b}) = \begin{cases} \frac{\overline{x}_b}{\overline{x}_a}, & \text{if } \overline{x}_a \geq 1 \\ \overline{x}_b - \overline{x}_a, & \text{otherwise} \end{cases}$$

where x denotes the amplitude vector of the relevant frequencies for the a, b parts of the buffer respectively.

A graphical representation of the data contained in both sections of the buffer can be found in Fig. 4.10. There, a color-coded buffer has been visualized over a plot of two data sequences from a single EEG channel, one of which contains a typical P300 response which starts around 350 ms after a target stimulus.

An example of a raw recording from a single EEG channel has been pictured in Fig. 4.11. The top chart pictures voltage fluctuations recorded over a period of above two seconds (520 samples, 2.08 s). Strong high frequency vibrations are immediately apparent when reading the plot, which is confirmed by the FFT magnitude output pictured in the bottom chart. The highest spike is positioned around 50 Hz, which corresponds to power line oscillations. Next notable elements of the signal are low frequency components of up to around 15 Hz (delta, theta and alpha waves) and some fluctuations around 15–30 Hz (beta waves). A spike in a frequency of above

[2]http://www.fftw.org/

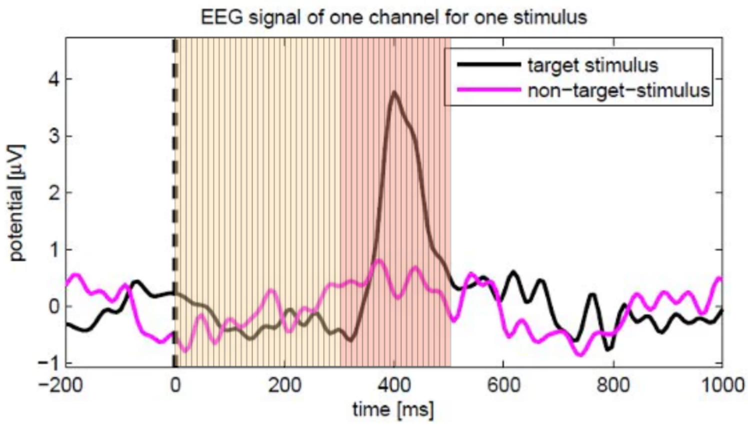



**Figure 4.10:** An example of a potential response from one channel with a buffer visualization overlay. The amplitude signal visualisation from Martinovic *et al* [6].

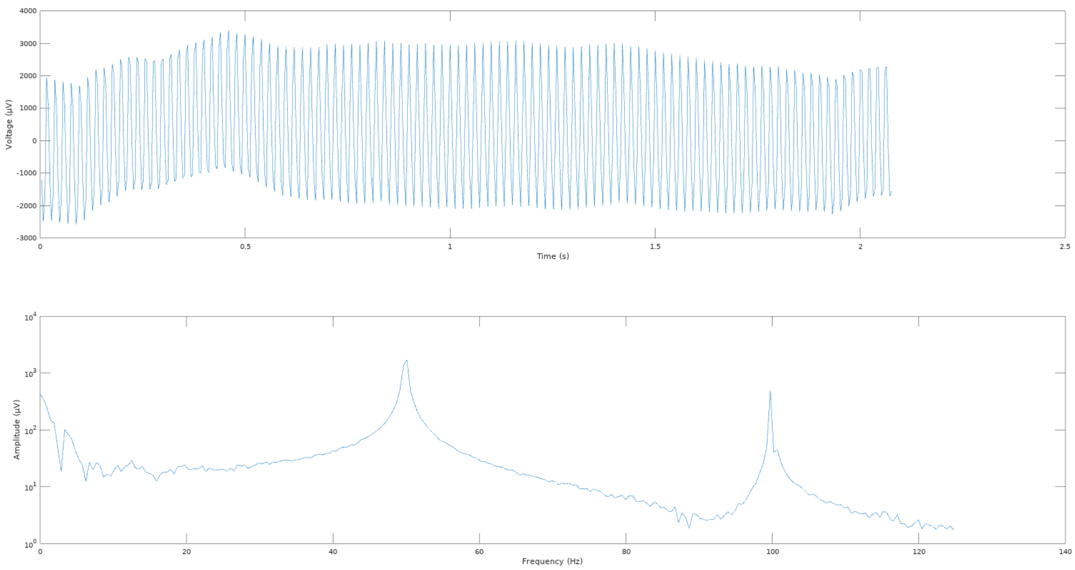



**Figure 4.11:** A chart displaying a raw EEG recording of around two seconds length from one channel placed over the occipital lobe, normalized to zero mean (top). A fast Fourier transform of the signal showing magnitude spectrum of frequencies found in the recording (bottom) with the amplitude plotted with logarithmic scale.

100 Hz most likely appears along the 50 Hz spike due to the interference of nearby electrical appliances, although it cannot be reliably detected under a sampling frequency of 250 Hz. Moreover, the highest notable neural oscillation detectable in humans, gamma, averages around 40 Hz and spans from 25 to 100 Hz [54].
When launching the service, the following commands can be specified: `--channels`, which tells the decoder how many electrodes are currently connected, `--bins` which decides the length of the buffer and `--freq`, which specifies an interval between sent measurements. The EEG microservice multicasts the measured P300 relative strength in a `opendlv::proxy::VoltageReading` message as its only output.

### 4.5.3 P300 detection evaluation

In order to evaluate the validity of the signal analysis function described above, an additional microservice has been created to measure these potentials in a setting similar to a P300 speller. This test aims to detect the response when invoked in a well known oddball paradigm scenario. The application is intended to be used separately from the BCI system, as it serves only as an evaluation process; the test assesses the response strength of individual participants and at the same time allows choosing the best performing parameters. The ability to record strong responses during this test was assumed to impact later performance of the participants in the completion of experiment tasks.
In this application, a 2x3 grid of circles is displayed to the user who is tasked with counting the number of flashes of the circle of their choice. The response 300 ms after every flash is then analyzed and the two strongest responses are visualized and printed in the console as the application's guess to which circle has been chosen by the participant. In order to minimize the influence of the first flash, all of the circles blink simultaneously at the beginning of the experiment and perform a short series of quick flashes before the actual measurement begins.
Since the application returns two guesses, the accuracy is measured without (*) and including (**) its second guess. For simplicity, in the second case the guess is then counted as correct regardless of whether the correct figure appeared as the first or the second value.
The results of the short study have been summarized in Table 4.1.

**Table 4.1:** A table comparing the P300 test application performance among different participants

| Subject | Repetitions | Accuracy* | Accuracy** | Notes |
|---|---|---|---|---|
| 1 | 10 | 0.3 | 0.5 | Long hair |
| 2 | 10 | 0.4 | 0.6 | - |
| 3 | 20 | 0.30 | 0.55 | - |
| 4 | 8 | 0.375 | 0.5 | Long hair |
| 5 | 4 | 0.5 | 0.75 | - |

A typical setting for this test can be seen in Fig. 4.5.3, showing a participant whose P300 response is measured while observing a grid of flashing figures.

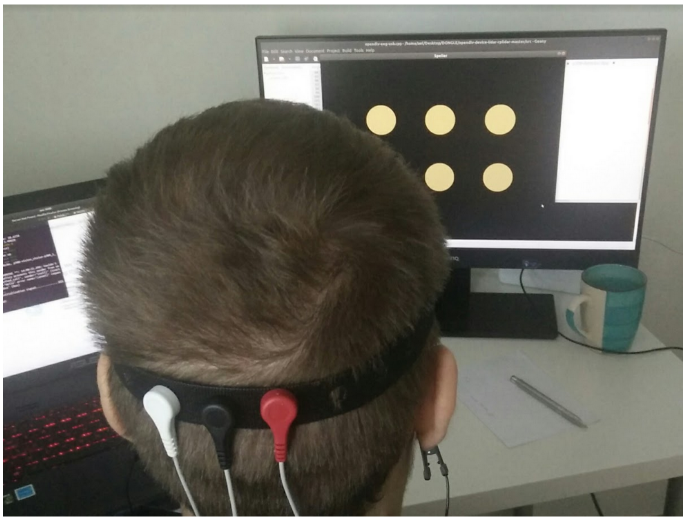


**Figure 4.12:** A participant observing a simplified P300 speller grid wearing a headband with the smallest subset of three electrodes covering the occipital lobe placements.

As seen from the table, correct selection accuracy varies between participants, ranging from a minimum of 0.3 to the best achieved value of 0.5. While the detector falls behind commercially used and, in a wide sense, P300 spellers present in recent research, its accuracy is arguably better than a random selection (0.17). A performance comparison can be made by investigating the results of the 2008 study by Krusienski *et al* included in Fig. 2.4. In the study, the percentage of correctly typed letters is measured in regards to both different set of electrodes (a set of 3 and 16) and number of flashing sequences. It can be seen from the rightmost chart of averaged values that in case of only three highlights, the accuracy is generally achieved between 20 and 50%. Moreover, typical spellers in which objects can be highlighted several times in a long sequence—such as letters in the mentioned study—rely on statistical methods and outlier detection, which is substantially easier, rather than maximal response as it is done here. This different approach is however crucial for usability of the detection system in a natural driving scenario where the same stimulus cannot be repeated. During driving, the functionality of the EEG detector is assumed to be supported by gaze tracking data, and as such its applicability should not be evaluated only by comparison to a speller. Lastly, the final evaluation of this approach has been performed in connection with the experiment results and individual participants performance in driving tasks in Sect. 5.
While this solution deals with significant difficulties and influence of interfering elements, assessing its accuracy including the second guess rises the average of correct guesses to 0.6. The result is then likely influenced by interference or unpredictable factors, such as head movements, wrong measurements and user's distractions, rather than a flawed approach. The results moreover appear to be negatively impacted by the hair length, as the electrodes do not touch the participants' skin directly in such case.

### 4.5.4 Vision application

The vision application serves as the core of the integrated system and therefore receives input from two listener microservices (eye tracker, EEG) in order to process the user's intentions. An additional input exists in the form of a current frame from the car front-facing camera, which is decoded and normalized before further processing. This element is crucial for testing, where navigation is realized through observing the car surroundings as if from a passenger's point of view, which could be replaced with front-facing camera of the eye tracker in a real scenario. Here, as a mean to simplify the proposed target-based steering, objects within the camera view are detected and selected based on their color and uniform surface.

The service can work with different settings. The simplest and most important difference is a choice between relying on EEG potential or eye fixation alone as an action trigger. When such trigger is activated, the desired action is interpreted and sent to the steering application. In the simple mode, pictured in a Fig. 4.13, the main steering method relies on capturing the angle relative to the vertical center of the image. Under this setting, the car assumes a default velocity and the steering direction is taken from the gaze angle. In both directional and target-oriented steering, the borders of the camera view act as special regions for activating pre-defined sequences. Selecting the top or bottom edge of the screen starts a reversing sequence, while side borders of the screen cause the car to turn sharply. This solution is similar to those proposed before in gaze-only steering systems. The system described here is however expanded by several additional functionalities. Most importantly, regardless of the steering mode it does not send steering signals when the user has not fixated the gaze nor shown a relevant brain activity, which aims to solve typical problems of gaze-reliant systems and to make free observation of the environment possible.

Before the vehicle can move in the selected direction, the vision algorithm has first to receive the triggering signal, determine whether the gaze position is located within the frame and check for the border cases. If none of them were activated, the microservice sends a `DIRECTIONAL` signal, retrieves the gaze angle relative to the center of the view and selects it as a desired steering angle. The exact wheel turn is later interpreted by the steering application, including possible offset axis. Initially, the desired speed was defined as the gaze height relative to the horizon of the image, although it introduced additional hardships. In this scenario, the user has to keep in mind the height associated with the right speed, which appeared to be non-intuitive. Instead, the constant velocity was chosen as slightly above the slowest possible for the robot platform, in a way to allow enough time for reaction.

The target-oriented algorithm used in the first part of the driving tasks can be seen visualized in the Fig. 4.14. This system is based on the idea that driving should be possible by selecting objects in the driver's view as anchors to approach or move away from. When eliciting a P300-similar response when looking at an object, it is isolated from the background through a separate image processing algorithm and

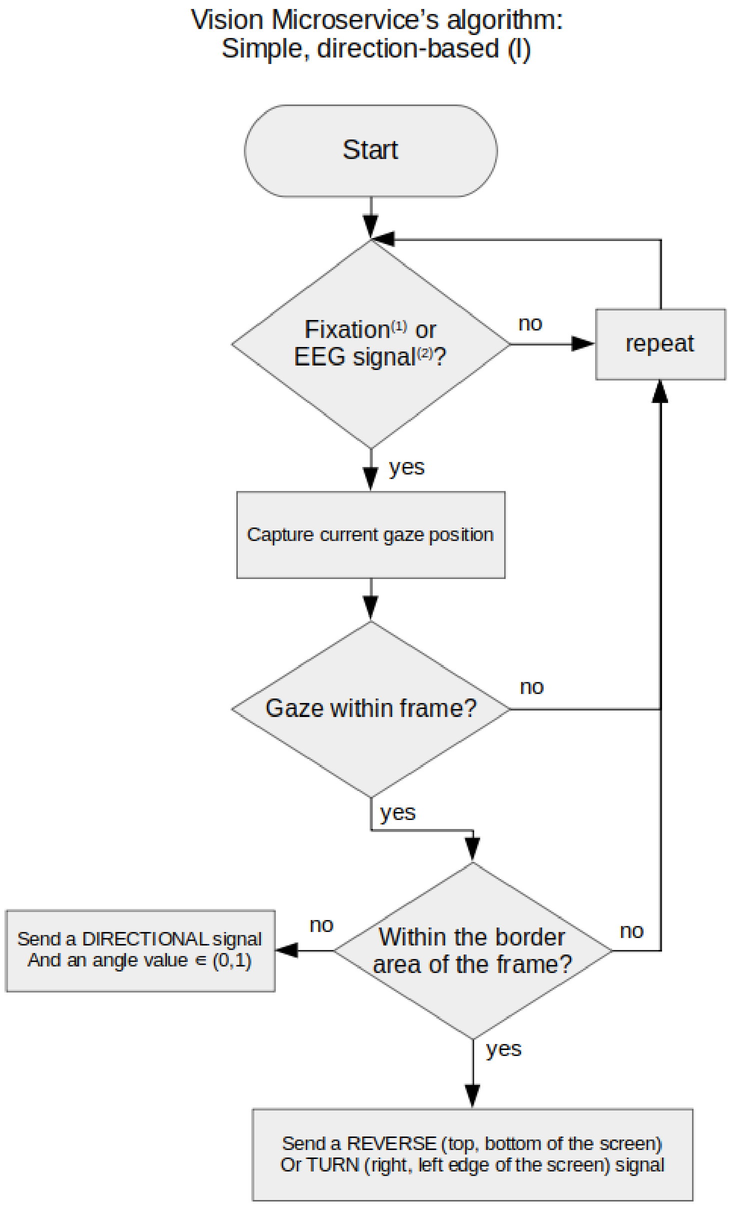



**Figure 4.13:** A simplified flowchart of the vision microservice algorithm in the simple variant limited to directional (angular) steering.

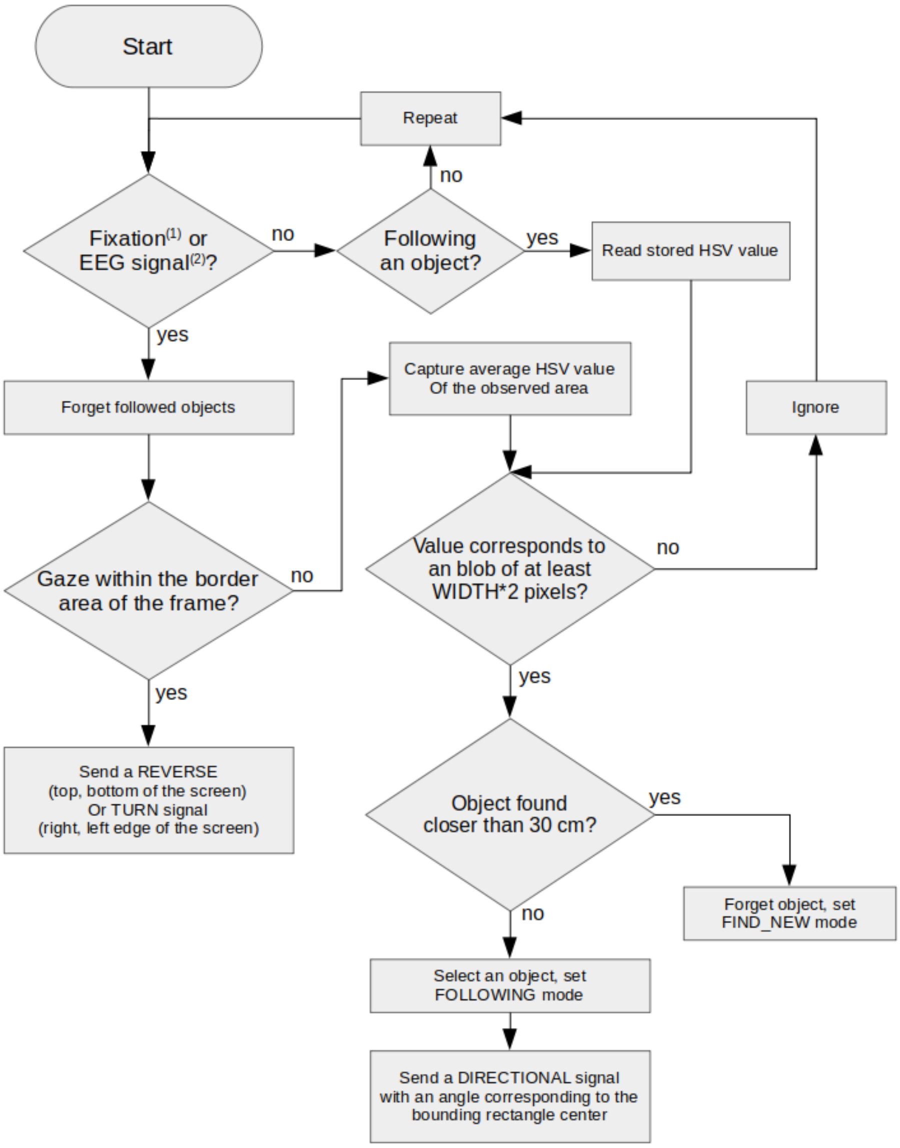



**Figure 4.14:** A simplified flowchart of the vision microservice algorithm in the object-tracking variant.

marked as the target. Initially, such selection of a target object was assumed to be interpreted as a desire to approach exclusively, but after a consultation with participants another exception was made: if the object is located very close and directly in front of the vehicle (detectable through frontal distance sensors), the interpreted action is to move away from the object. This decision was made while investigating a case of an obstacle partially covering a target region; the participants confirmed that in such case, they would primarily lock their eyes on the obstacle.

The object-oriented steering mode first performs the same steps the simple mode offers: the border cases are still available for the user. If the gaze is not locked on any of the pre-defined areas, the service attempts to isolate the selected object from the background. If failed to do so, the action is simply ignored. The image processing method used here is a general algorithm suitable for uniform objects of distinct colors; no machine learning solutions were used in this scenario, as design-

ing a scene-understanding computer vision system does not lie within the scope of this work. Instead, the average HSV values of the observed region are taken and the contour of the entire object, if located, is identified through thresholding and multiple filtering stages.
After an object (i.e. target), which is interpreted as center of attention, is detected, the algorithm changes into `FOLLOWING` mode. The mode ensures that after a single selection, the object will be followed over several cycles until approached or a new command is issued. The color of the object in HSV format is stored and the contour is located in every camera frame. The desired angle, akin to the simple mode method, is decided as the point in the center of the bounding box around the contour.
If the height of the bounding box is found to be above the threshold associated with a very short distance—at least 62% of the frame height—the following sequence ends. Conversely, if the user selects an object within this distance, the intended action is interpreted as reversing. A simplified chart of the algorithm is pictured in Fig. 4.14. All steering signals are sent as to the steering microservice in `opendlv::logic::sensation::ObjectDirection` messages. The message contains the code of the selected action and, if applicable, the desired steering angle.

Additionally, the vision microservice performs the following steps in every cycle, in the pre-processing stage:

- Obtaining the current camera frame;
- (Optional) Normalizing the frame;
- Re-scaling the image to the required size;
- (Optional) Placing the frame on a background with generated Pupil markers;
- Displaying the frame.

An example of a frame with added Pupil markers can be seen in Fig. 4.6. The normalizing algorithm has been added to minimize the influence of variable lighting and camera error in resulting average frame brightness and hue. Normalizing the frames is performed by adjusting each RGB channel curve by a calculated difference factor. The frame discoloration is measured by computing average values of the bottom part of the frame (which always contains the front of the car) and comparing them with the goal values. The effect of applying the normalizing filter can be seen in Fig. 4.15, where it has been applied to four different cases. The first two images display hue correction. The fourth example, the picture taken in an inappropriately dim lighting, shows unnatural colors after correction. However, the hue values are nevertheless correct and the resulting image is easier to interpret by a human user.

As a whole, the vision application can work in three modes:

- `--mode=0`: Simple, directional mode;
- `--mode=1`: Target mode;
- `--eeg=0`: Specifies the minimum potential needed to record the user input. If set to zero, allows to ignore the readings and act on eye fixation only.

If `--mouse` has been chosen, the eye tracker input is replaced by mouse pointer. This parameter serves as a debugging measure.

For all image processing purposes in this microservice, the OpenCV[3] library was used.

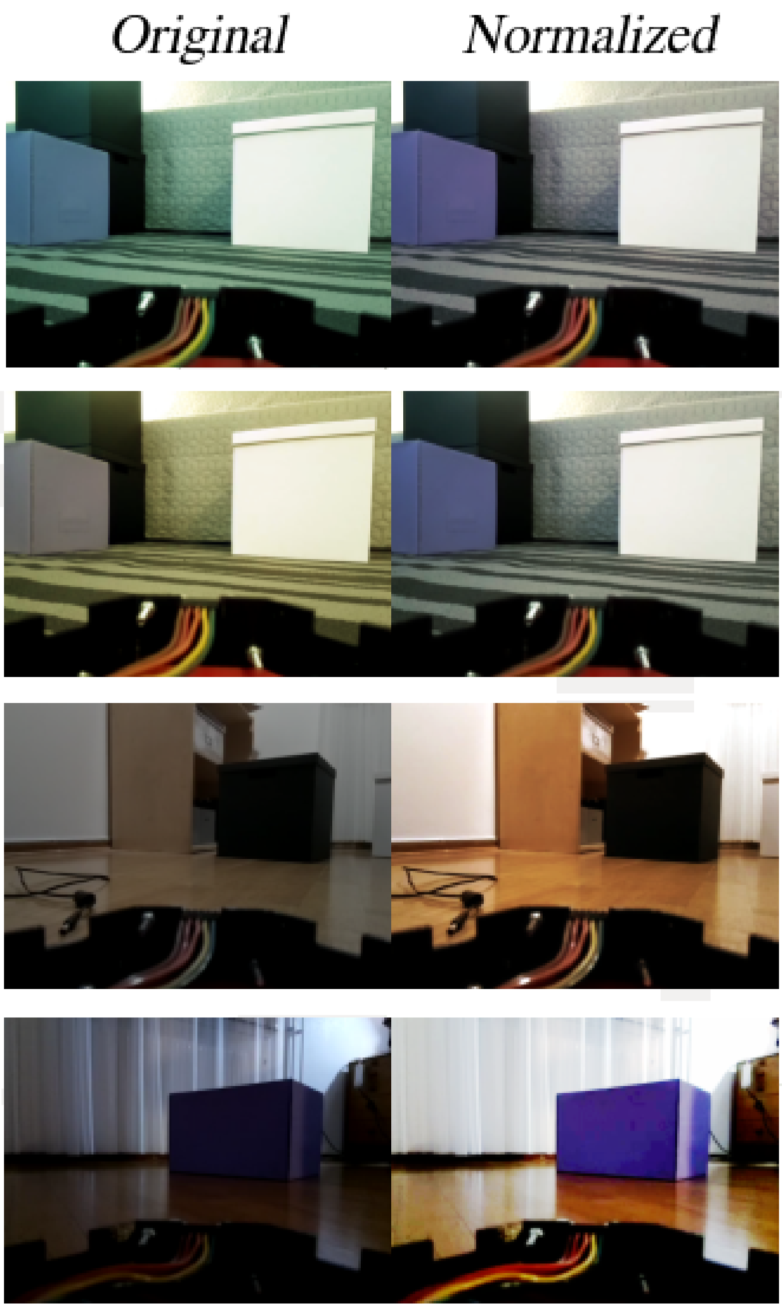



**Figure 4.15:** A comparison of camera frames exposed to different lighting conditions and artificially discolored (left) and the same frames processed by the normalizing function (right).

[3]https://opencv.org/

### 4.5.5 Steering

The steering service works as an intermediate connection between the vision microservice and the Kiwi robot. The input is taken both in the form of a user-selected action and a series of readings from the distance sensors mounted on the vehicle. Therefore, the robot can react accordingly if an obstacle is detected in dangerous proximity or in the path to the object. The algorithm stores the information of the action and can temporarily interrupt the main sequence to perform a secondary obstacle-avoiding action. The steering sequences are: turning, left- and right-swerve, reversing and sharp turns. if no sequence is being performed, the algorithm simply moves the car in a selected `DIRECTIONAL` angle. Due to a very limited turning angle, a turning movement triggered by looking at the border of the screen consists of a reverse-then-forward sequence to facilitate navigation around sharper turns. The standard reversing sequence is a simple backward movement in a straight line.
While the algorithm omits sophisticated obstacle detection and path-planning functions, the simple reactions based on distance sensors' measurements proved enough to avoid collisions in the experiment example.
A flowchart of the algorithm outlining the basic functionality can be seen in Fig. 4.16.

### 4.5.6 Summary

The system consists of four microservices running on the PC side. The main parts handle reception and processing of the input from the OpenBCI and Pupil Labs equipment as well as receive sensor and image data from the Kiwi robot. The four services can be launched simultaneously through a single Docker Compose file.
The connection between the robot and PC is realized through a separate `proxy` microservice running on both platforms, which provides a TCP bridge for communication of multiple devices within the same network. Moreover, Kiwi itself runs microservices for decoding sensor data, encoding camera frames and processing steering requests.
The main constraint of the system impacting the shortest achievable completion time of the driving task is the velocity and steering angle range. The car velocity was constrained to a value of around 0.8 m/s and the steering radius is limited by the mechanical construction. The latter drawback is partially countered by introducing turning in reverse.

## 4.6 Experiment design

In this study, the controlled vehicle is a real device, however the driver is separated from the platform and observes the camera feed. A virtual driving setting such as a three dimensional simulation was avoided. One reason for this decision was that creating an artificial environment could introduce an unintentional bias when designing the driving algorithm and experiment task. Thus, a real setting was chosen in the hopes of reflecting real driving situations and helping participants to immerse in the driving scenario. Secondly, the robot platform was readily available and both

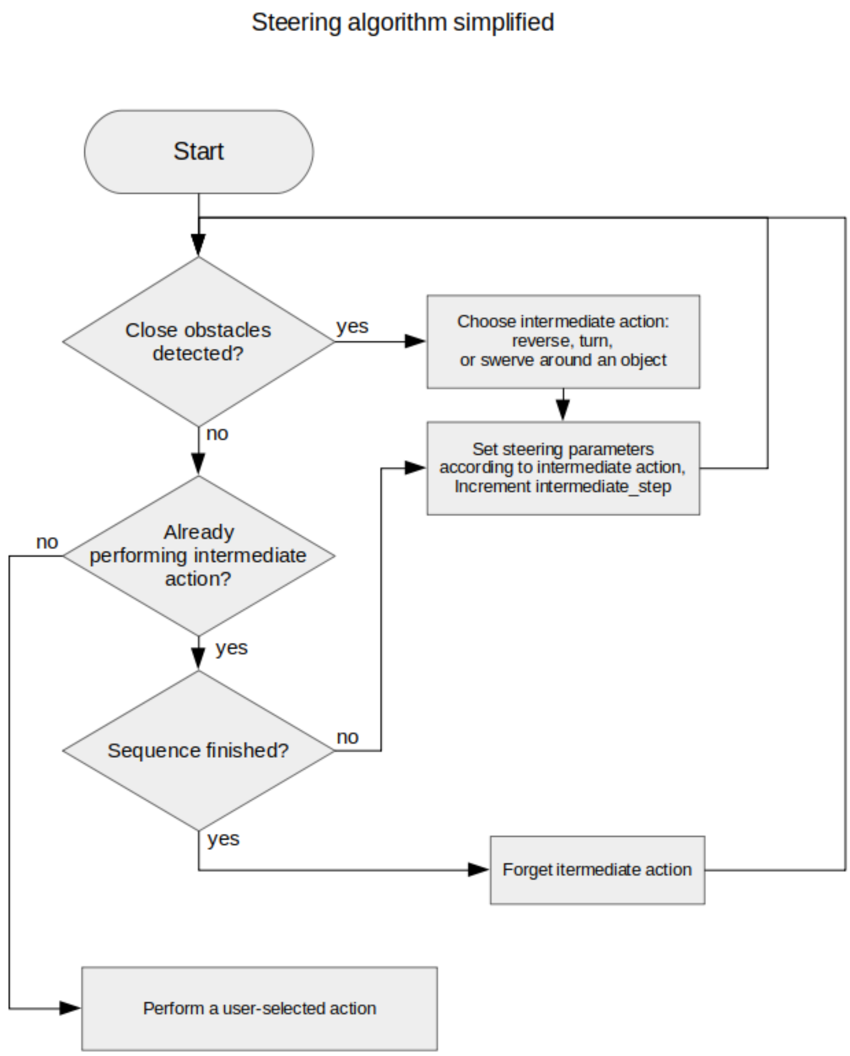



**Figure 4.16:** A simplified flowchart of the steering microservice algorithm

the framework and the steering signals are compatible with real vehicles.
At the beginning of the experiment, each subject takes a seat in front of a monitor. The eye tracker and EEG headset are secured on the participant's head and a short test reading is performed to ensure all electrodes touch the scalp and receive the signal correctly. In the next step, the P300 test is performed to evaluate the individual applicability of the potential detection system designed in this study. The results are gathered for later analysis.
The eye tracker is calibrated individually for each subject. After a sufficient tracking accuracy is achieved, the participant is asked to remain still and the driving task is explained. At this point, the system is ready to be launched and the user starts driving the vehicle.

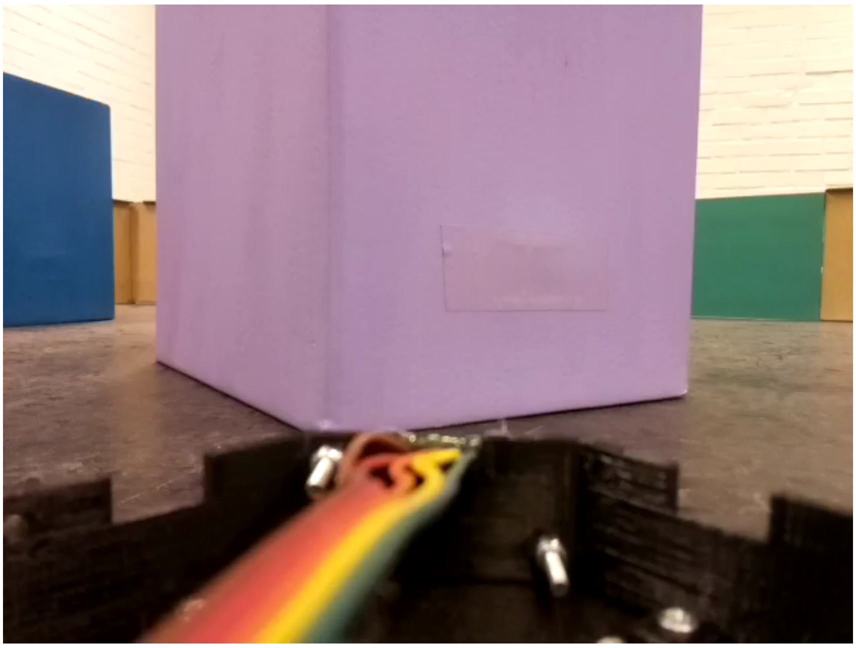


**Figure 4.17:** A view from the Kiwi car at the start of the experiment

### 4.6.1 Arena design

The testing arena consists of a small enclosed space with simple uniformly colored objects, which the user can use as targets. The three task-relevant elements are a green wall section, purple box and a blue box. Other wall sections and flooring have non-distracting, toned colors which simplifies the color-based object detection.

An example of a view at the beginning of a driving tasks, which includes the aforementioned objects, is included in Fig. 4.17.

### 4.6.2 Driving tasks

In order to analyse the potential of the proposed brain–computer interface, all participants are tasked with performing a simple driving task, which is explained before launching the BCI system. The users have to perform the following steps:
- Approaching the green wall section;
- Turning;
- Moving towards the blue box.

Due to the steering constraints, command delay and the chosen velocity, the task can be potentially finished in time not shorter than 10 seconds.

### 4.6.3 Subjects

Five subjects were invited to participate in this study. All participants were healthy and did not report any health conditions that could possibly interfere with the experiment, such as color blindness, nor specify any restrictions in the use of the equipment. The participants gave informed consent and were able to interrupt the experiment or leave at any time. All measurements were noninvasive, including the electroencephalography readings which are sent wirelessly. The subjects who were familiar with the system as well as those who have not undergone any prior training were participating in the study and their performance is compared.

# 5 Results

This section presents and analyses the results of the experiment as described in the previous part of this thesis. Gathered data in the form of individual completion times of the driving tasks, as well as general responses of the participants are included. Overall performance of the created testing platform in regards to all its elements, identified problems as well as additional design choices made during the tests, are presented and explained. The last part of the section presents an experiment in a car setting.

## 5.1 Testing platform and its components

A functional BCI system operating on the principles described in this thesis has been successfully built and tested by volunteers. Several parts have been combined in order to create a testing environment for evaluation of the proposed approach. The testing environment consisted of the elements outlined in Sect. 4 where the general structure and software communication channels were visualised in Fig. 4.1 and 4.8. All the relevant parameters were exactly described in this section with the exception of different electrode placements in selected tests and alternative eye tracker calibration used where applicable.
During the tests, each subject took a seat in front of a laptop screen, elevated to eye level for easier visual stimulation. The BCI equipment consisting of the Ultracortex headset with a Cyton electronic board and Pupil Labs eye tracker was precisely positioned for appropriate readings. The arena for the mobile robot was located in the same space, although not directly visible to the users, who had to depend solely on the camera view streamed on the laptop in front of them. Below, all parts of the system and relevant decisions are evaluated.

### 5.1.1 Electroencephalography

During the initial tests, all eight electrodes—the maximum number which can be simultaneously connected and tracked by the Cyton board—have been applied on the participants' scalp and calibrated for testing. The positions of electrodes and motivation for the chosen arrangement can be read in Sect. 4.5.2 and Fig. 4.3. Due to the Ultracortex Mark IV headset design and dry comb electrodes shape, the participants have unfortunately reported skin irritation and additional sources of discomfort such as leaving skin marks have been observed. The combination of electrodes used in the tests, selected to cover mainly the occipital and parietal lobe,

caused the weight distribution of the headset to become off-centered. The comfort nodes included with the headset proved difficult to place in a way to counter the weight of the headset and prevent slippage. The weight of the Cyton board and battery mounted in the back of the head contributed to the problem.
The dry comb electrodes in screw-in sockets introduced additional trouble for participants with longer hair, which were often caught in the comb nodes. All subjects wearing the Ultracortex headset expressed complaints about minor to average discomfort present during the experiment.
Before the final experiment phase, a group of volunteers have participated in a shorter test evaluating the proposed method of P300 signal detection utilized for vehicle control as described in section 4.5.3. During these tests, only three comb electrodes mounted on a headband in placements corresponding to occipital lobe were used. The tests proved that detection accuracy acceptable for this task can be obtained with the use of such a limited number of electrodes. Thus, due to discomfort caused by the Ultracortex headset and the much shorter calibration phase of the headband experiment variant, it has been chosen in later experiments to replace Ultracortex. The change did not have any immediately visible impact on the overall system performance.
During the calibration phase, the stream from all connected electrodes was visualized with OpenBCI GUI in order to determine the quality of the signal from all electrodes and whether it is recorded correctly. With the rigid Ultracortex headset, the time of calibration extended to several minutes due to the need of adjusting all electrode sockets and comfort nodes. The headband did not introduce such inconvenience.

### 5.1.2 Eye tracking

The Pupil Capture software was tracking the robot camera stream encapsulated in a border with Pupil markers displayed on the laptop screen. Capturing the eye position relative to the markers allowed for tracking the user gaze in real time. Before the individual experiments began, the eye tracker was calibrated with different positions and adjusted lighting until a satisfactory (subjective and measured by the system) accuracy has been achieved. Under perfect conditions, this solution allowed for intuitive navigation and selection of active regions with sub-centimeter precision. The eye tracker however appeared prone to gradual calibration loss and the overall performance varied between participants even during calibration stage, which in more than half (four out of six) cases required tracking in less applicable 3D mode. All subjects noted that the eye tracking lacked accuracy and precision, reporting that the perceived offset grew as the experiment progressed. Multiple recalibrations of the system were necessary to continue testing.
Despite the outlined shortcomings, all participants were able to use the tracker intuitively and the low accuracy did not render the system unusable, but rather slowed down the process of selection of the desired action. Selecting the biggest active area of the screen, used for triggering movement in reverse, did not pose a challenge at any stage.

### 5.1.3 Robotic platform

The experiment was based on the idea of safe control of a miniature mobile robot by untrained participants by replicating the view of a vehicle passenger on the computer screen. The participants found the setting natural and were able to successfully steer the robot in the experiment arena. The reported issues regarded delay and insufficient responsiveness of the system, as the participants at some points could not change the direction in time. While collisions were usually avoided by the safety system in the steering microservice, the users often found themselves backing out of walls after unsuccessful actions. Moreover, the design of the robot caused occurrences in which one of the protruding side elements collided with arena objects to be rather common, where a direct interaction with the car was necessary.
The participants reported the camera stream to sporadically freeze for a duration of around half a second at a time, which further impacted their ability to control the car.

## 5.2 Driving tasks

Four of the participants have successfully finished the driving tasks. The results of the experiment comparing the individual completion times are presented in table 5.1. The second column includes information on whether the subjects were familiar with the steering methods used, which is expected to be true if they participated in the project or have tried the system earlier. The users were presented with both modes – firstly, the target oriented one, secondly, the directional mode – and asked about the preference. After trying both of the possibilities, the best achieved time has been taken as the final task completion time. Overall, all subjects were capable of controlling the car through the BCI system, although technical difficulties arose during one of the experiments and interrupted following sessions.

**Table 5.1:** A comparison of the experiment results between participants

| Subject | Familiarity | Time (s) | Preferred mode | Notes |
|---|---|---|---|---|
| 1 | yes | 14 | Target | Long hair |
| 2 | yes | 12 | Target | - |
| 3 | no | 16 | Target | - |
| 4 | no | 37 | Directional | Long hair |
| 5 | no | - | Directional | technical problems |

It is apparent from the comparison that participants preferring the target oriented steering were able to finish the task in the shortest time. It is not surprising, as the system was made to move towards selected targets in an optimal way. However, the selection of target objects has not been intuitive for all subjects and closely depended on the correct EEG readings. Moreover, one additional participant tested the system in eye tracking mode without the use of EEG readings. The system was able to perform in a similar way based on eye tracking alone in directional mode. However, the user reported the constant necessity to focus on driving action uncomfortable.
None of the users interacted with the top active part of the screen, which has been

mapped to reverse movement. This action should be thus removed from the system, as it was interpreted as non-intuitive and possibly confusing.

## 5.3 Individual responses

The overall reaction of the participants after using the system was very positive, however the task completion times were longer than expected and the users encountered many hardships. In order to select potential reasons of these issues and and highlight improvement areas, the participants were asked questions specifically focusing on their negative impressions.
At the end of each experiment, the subjects were asked about their overall impression of the system, to describe their experience and especially point out the one element they would wish to change.
The following *negative* responses from the participants have been collected:

- The eye tracking accuracy was unsatisfactory;
- The delay made it impossible to turn in time;
- The car did the opposite of what the user attempted to do;
- The speed was too high;
- Some of the participants felt the arena was too small for convenient steering;
- Vision difficulties due to the lack of a possibility to use the eye tracker together with corrective lenses.

Most of the complaints regarding the control have been impacted either by the eye tracking inadequate accuracy or robotic system limitations, such as communication delay or limited steering angle. The fixed velocity of the car, however, was chosen as the lowest speed at which the car still operated as intended, i.e. could not be stopped by floor height irregularities.
The remarks about the control system performing unpredictable movements that the user did not intend are a very interesting case which is further analysed in Sect. 6 Overall, all participants expressed a positive impression about the system and found the experience entertaining.

## 5.4 Car driving

After the main experiment stage was finished, an additional test has been performed with the use of a real passenger car of a standard size. This experiment was performed to evaluate the possible use of the BCI system for car driving and test the created services for possibility of being adapted for use with different vehicles.
In this short test the services were modified to send the steering messages in a suitable format for a Volvo XC90 running OpenDLV software. The system was run in a directional mode without the use of a camera stream. Instead, the Pupil microservice has been connected to receive the gaze positions in front world tracking camera coordinates. As such, the relative gaze angle, which did not consider head movements, has been taken as steering input for rotating the wheel. The acceleration has been set to a variable corresponding to the distance upwards from the point corresponding to looking right above the car's hood, with lower angles stopping and

reversing the car. The EEG component has been disabled, and the steering commands were triggered by eye fixation alone.
The test proved the system to work correctly. However, the eye tracker did not achieve a satisfactory response in any of the outdoor settings. Desirable turn of the steering wheel was achieved only when the lighting was constant and dim, and seemed to suffer an additional accuracy loss compared to the main experiment.

# 6

# Discussion

This section serves as a summary of the previously described results. The analysis of experiment outcomes as well as a discussion of the topics brought up by participants aim to present an evaluation of the described brain–computer interface and suggest possible improvements.

## 6.1 Vehicle control in an experimental setting

The participants were able to successfully control a vehicle, in many cases completing the driving task within the first 15 seconds. This is an optimal time frame corresponding to the selection the first goal object, turning action and consequently the last target when the vehicle is driven in target mode. Due to velocity constraints and the design of the robot car it is impossible to achieve times significantly lower regardless of the chosen steering mode. The longer completion times were caused by incorrect turns and accidental movements made by participants unfamiliar with the system, which complicated the task further, requiring more turns to reach the destination. Apart from reported hardware errors, all participants were able to complete the task in less than 40 seconds.
Previous training does not appear to have a substantial effect on driving capability. While a more detailed study on a bigger group of subjects would be able to answer this question decisively, all participants taking part in this experiment were able to use the system without practicing. One of the major problems brain–computer interfaces face is the need of prior, time-consuming exercises needed to learn methods of eliciting specific brain signal required for control. The proposed solution does not rely on a selection of specific brain signals which might be hard to reproduce, but depends on a single potential naturally elicited during the process of decision making. Moreover, the control method relies heavily on eye tracking, allowing for a limited scope steering even while lacking an EEG source. Thus, no training in the common meaning of the word is required to use the system. While keeping its basic functionality, it would be still possible to expand the system to accept a bigger selection of EEG potentials. This could potentially allow the users to safely learn more complex commands while already using its basic steering functions.
In the current setting, which employs P300 detection for selecting targets or desired actions, the system works correctly even with a very small set of electrodes. This is due to the fact that it does not rely on exact potential recognition from noisy, unlabeled data. The electric potential detection works as a second confirmation step after the initial identification of eye fixation, which means that the risk of accidental

target selection is low. After analyzing a performance comparison of different sets of electrodes in P300 detection [4] and the results of this study, four electrodes over occipital lobe is a suggested number for further tests. A larger number of electrodes could, however, allow for future expansion into different types of brain signals used to express more complex commands.
The testing environment created for this study could be used in further work to investigate the control signals and improve components of the system. One of the main advantages of the testing method used here, which removes the participants from a vehicle and lets them control it while observing a camera stream, is increased safety. At the same time, the users found it natural and easy to control the miniature vehicle in this setting. Thus, experimental work on the platform could be continued in the future after revising the problems and applying the needed changes.
It has been brought up that the experiment arena felt too small to be adequate for free exploration with the robot car. Several interruptions occurred due to minor collisions of the vehicle with the elements of the arena, which could be resolved by either addressing the shortcomings of the platform, if possible, or expanding the testing area to accommodate the robot of limited movements. The users also felt limited by the perceived delay and freezing camera stream, which should be investigated. It could possibly be resolved by connecting to a different network or analyzing workload on the car processor.
The participants were generally able to use the system intuitively and completed the experiment task in a short time. Thus, the main limitations of the system are related to the equipment quality, network communication issues and constraints of the robotic platform.

## 6.2 Components of the investigated system

All the components of the brain–computer interface and control system have been successfully integrated and met the basic requirements for use in the BCI system as described here. However, several aspects negatively impacting the performance have been brought up by subjects participating in the experiment.

### 6.2.1 Eye tracking

As outlined in the previous section, the participants uniformly reported issues with eye tracking accuracy and troubles caused by calibration loss over time. The eye tracking reliability was pointed as the primary perceived flaw of the system.
The eye tracking control and using the gaze to select objects of interest was however seen as intuitive and overall functioned as expected. Thus, while the eye control aspect was easy to understand, declining accuracy caused problems of varying degree and in some cases caused sending unintended requests to the system. This difficulty likely stems from the inadequate eye tracking system selected for this experiment. While it allowed to present the idea and enabled the users to complete simple driving tasks, a more complex eye tracking system of a well documented accuracy should be used in further work.

### 6.2.2 EEG

The performance of the EEG system, as measured during the P300 tests, differed between participants. This was expected, as it has been proven that individual characteristics of this signal vary not only between individuals, but are affected by time of day, mental state and even ingested food [55]. Overall, the initial tests show that the potential detection algorithm leaves space for improvement. However, the users did not report specific complaints about the EEG system in particular; the problems arose due to discomfort associated with wearing a big and heavy headset with hard to fit electrodes. The device also appeared to be less suitable for people with longer hair.

While focusing on avoiding accidental interpretation of an unrelated signal fluctuation as a driving intention, the proposed system is however prone to falsely classify a momentary excitement or signal change during gaze fixation as such. It is not yet clear how many of the identified EEG signals were a correctly classified P300 response, as they might come from minor body movements and the design of the system might have allowed to select desired actions even under the absence of correct potential readings. Due to this fact, it is unclear whether a quadriplegic user could use the system with the same results.

For future analysis, two solutions are proposed. Firstly, a deeper investigation of suitable EEG signals and detecting algorithm improvement could help to refine the system. Secondly, a system based on P300 detection as described here could be limited to a simple wearable unit of four electrodes.

### 6.2.3 Steering

The control method described here introduced two alternative steering methods. The novel way of control, based on target selection, allowed for faster navigation and completion of the driving tasks. The directional control, which can be seen as an equivalent of steering systems previously investigated for similar tasks, has been successfully implemented as well. However, the directional control was seen as immediately intuitive by all participants, while only three were confident in the use of the target mode and selected it as preferable. This might be due to the disappointing quality of eye tracking and some imperfections in the vision system which made selecting target objects a difficult and slow task. Thus, removing these difficulties could possibly make directional control redundant for all participants. Conversely, a preference for directional steering might stem from familiarity with commonly used control systems in games and simulators. Additionally, both steering systems introduced active regions for triggering pre-defined actions. The participants intuitively used the bottom part of the screen for reversing and borders of the screen have been used for quicker navigation. The top of the screen has never been used and thus the experiment did not point to any potential of this solution.

Individual complaints of the steering system alone, which did not concern lacking components of the system or technical problems, lead to interesting conclusions. The participants pointed that the system sometimes performed an action opposite to their intentions, or the movement was unpredictable. Seemingly, this was a reaction to observing object-following sequences and multi-step turns. Some of these actions were introduced to enable time-efficient movements, such as sharper turns, in a car of limited range of motion. These reactions can possibly stem from the need to control the car movement directly, as well as human driving behaviors. When analyzing steering models applied for data sets from near-collision situations, it has been found that human driving behavior can be described by the simplest, yaw rate nulling model [56]. That might point to a possibility that an autonomous driving system performing an optimal action to avoid collision or a loss of traction can paradoxically induce a feeling of losing control over the vehicle in the user.

## 6.3 Future improvement

Overall, the findings of this study are promising. The participants were able to use the system without training and in selected cases the performance of the proposed method greatly exceeds existing solutions. However, technical problems impacted the ability to control the vehicle for some of the participants. Based on the collected responses, a few key aspects have been found requiring improvement. Further investigation of the target oriented control and the use of P300 signal in spontaneous target selection should thus be made under revised conditions. Moreover, the findings from this study can be also used to investigate different application of brain–computer interfaces.

### 6.3.1 Autonomous cars

This study focused on various components of the brain–computer interface in a simulated scenario with the use of a small robot car. This setting allowed for simplifying some of the aspects, including the choice of reducing movement and lighting changes. However, moving the BCI to the real car scenario introduces greater challenges.
The in-car test demonstrated that the software built for the purpose of this study can be adapted for use in real vehicles. However, a suitable eye tracking system would be unquestionably required, as the simple wearable eye tracker from Pupil Labs proved unsuitable for the rapidly changing light setting. Eye tracking felt less precise compared to the controlled environment and continuously degraded with the time after last calibration. A similar challenge would concern the EEG tracking, as it has already been shown that the movements of the headset during driving have a significant impact on readings. However, a limited functionality of the system was preserved—as a simplified solution aided by eye tracking alone, but not requiring any further changes to function apart from changing the control signals to those supported in the used vehicle. This fact raises hopes that the signal analysis can be performed in a moving car and that the conclusions from controlled test scenarios can be carried over to a real car setting with success.

### 6.3.2 Wheelchairs

Another crucial case investigated here concerns disabled, especially quadriplegic users. The use of brain signals which are not as prone to be lost in immobilized patients and testing the system in an environment not very far from a wheelchair case allows to hypothesize a similar system can find application in such a setting. Considering the special needs of these people, an exceptional attention has to be paid to safety and the feeling of autonomy. While the proposed target mode steering could improve the mobility of the disabled in the future, the unintentional effect of losing control of the autonomous vehicle could have incomparably larger, negative effects. Thus, a psychological aspect of this type of vehicle control should be investigated further.

# 7

# Conclusion

This study investigated a brain–computer interface for driving and introduced a novel steering method based on target following. The analysis has been made in regards to research questions, including a discussion of the topics brought up by participants and suggestions of possible improvements. Thus, the findings of this study can be summarized in four main points.

Primarily, a proof-of-concept interface for brain control of a robot car has been built and met the expectations. The participants invited to join the study were able to control the vehicle with ease and the overall response was positive. Driver behaviors under directional and a novel, target-oriented steering have been analyzed. While it requires further investigation, controlling the vehicle by selecting goals within the driver's surroundings has been shown to potentially improve navigation times.

The experiments have also successfully proven that the system can be operated by untrained users. This is an important quality, as many brain–computer interfaces in use today rely on specific signals which have to be learned and trained for weeks before satisfactory results are achieved. Moreover, this work avoided the use of brain signal types which were proven to lose strength in paralyzed patients, in hopes of finding a solution for quadriplegic individuals.

A testing unit for realizing the described tasks and potential future work on such interfaces has been created. The system introduces a safe environment for testing real vehicle driving where the user is removed from the car. Despite the technical problems which occurred during some of the experiments, most of the participants have been able to finish the driving tasks. Finally, parts of the presented solution could be tested in a real car setting. The simplified version of the system retained a limited function despite significant difficulties brought by changing environment and light levels. The flaws of the system have been identified and possible modifications for future work were proposed.

The analysis of electroencephalography signals and two measuring units proved that a small set of 3–4 EEG electrodes is sufficient for this task. While including more complex devices with more reading points for precise measurements has its clear advantages, testing the control system with a smaller subset enables the use of lightweight, comfortable and easy to apply reading devices. The proposed intention detection method which relies on gaze fixation reduces the risk of accidental identification. This makes the system less dependent on momentary shifts and signal interference which have been identified as main obstacles. The system also potentially allows users to start utilizing the interface with simple commands while learning the more complex, intentionally invoked brain potentials to perform precise actions.

The presented study hopes to help introduce novel ways of interaction between a human and an autonomous machine, open new communication channels and help to construct better performing brain controlled vehicles for the disabled.

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