Professionalisation internship report

3rd year of engineering school, cognitic speciality

École Nationale Supérieure de Cognitique

Gaze independent Brain Computer Interface with locked-in patients using eye tracking

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Centre de Recherche en Informatique, Signal et Automatique de Lille (CRIStAL)

BCI team (thematic group : interaction and collective intelligence)

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Company supervisor : François Cabestaing

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Abstract

Introduction : This internship is about a visual reactive Brain – Computer Interface (BCI) used for communication purposes by patients who experience ocular impairment and have trouble controlling their gaze.

Methods : To achieve this, experiments were carried out with patients. We also studied if using eye tracking data could enhance the performance of independent-gaze BCI thanks to data fusion.

Results : We constructed a patient dataset and found some methods to fuse the data. Some leads show that these methods could enhance performance.

Conclusion : Further study is needed to implement data fusion methods.

Keywords

Brain – Computer Interface - Patients - Ocular impairment - Eye Tracker

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Résumé

Introduction : Ce stage porte sur les interfaces cerveau-ordinateur (ICO) visuelles et réactives utilisées à des fins de communication par des patients présentant des problèmes oculaires et ayant des difficultés à contrôler leur regard.

Méthodes : Pour y parvenir, des expériences ont été menées avec des patients. Nous avons également étudié si l'utilisation de données de suivi oculaire pouvait améliorer la performance des ICO indépendantes du regard grâce à la fusion de données.

Résultats : Nous avons construit un ensemble de données de patients et trouvé certaines méthodes pour fusionner les données. Certaines pistes montrent que ces méthodes pourraient améliorer les performances.

Conclusion : Des études supplémentaires sont nécessaires pour finaliser la mise en œuvre de la méthode de fusion de données.

Mots clés

Interface Cerveau-Ordinateur - Patients - Problèmes oculaires - Suivi du regard

Contents

1. Acknowledgements

I would like to warmly thank my tutors, François Cabestaing and Arne Van Den Kerchove, for their enlightened and regular advice. The numerous exchanges not only efficiently guided me in my mission but also deepened my understanding of the research world. I would also like to thank all the BCI team for their numerous advices and guidance during the team meetings. Finally, I would like to extend my gratitude to my school tutor, Liliana Audin Garcia, for her guidance and support throughout my six-month internship.

2. Internship Summary Sheet

Training year : 3rd year

Professional contract : no

Company and/or place of internship : CRIStAL laboratory, University of Lille, Villeneuve d'Ascq, France

Company supervisor : François Cabestaing, Arne Van Den Kerchove

ENSC supervisor : Liliana Audin Garcia

Subject : Gaze independent Brain Computer Interface for locked-in patients using eye tracking

Start date : 12/02/2024

Duration (in week) : 24

3. Introduction

"A brain-computer interface (BCI) is a system that measures brain activity and converts it in (nearly) real-time into functionally useful outputs to replace, restore, enhance, supplement, and/or improve the natural outputs of the brain, thereby changing the ongoing interactions between the brain and its external or internal environments. It may additionally modify brain activity using targeted delivery of stimuli to create functionally useful inputs to the brain" [BCI society, 2024]. This is the definition of BCI voted by the BCI society, an organisation composed of around three hundred researchers in the BCI fields. As explained in this definition, BCI can be used for different purposes, the one of our interest is to use BCI to replace communication. Indeed, patients in a completely locked-in state cannot control their muscles any more and, therefore, cannot communicate via natural speech. This locked-in syndrom can be caused by a traumatic brain injury or a stroke in the brainstem.

There are several types of BCI depending on the modality (visual, auditory, etc...) and the presentation of stimuli (reactive or passive). In our case, our system involves a visual BCI in which visual stimuli are displayed on the screen. Our system is also reactive, it means that the BCI responds to specific stimuli that the user is engaged in.
This type of system is based on event-related potentials (ERP). An ERP is a brain response time locked to a particular sensory, cognitive, or motor event. The one we are interested in is the P300, this potential is positive and elicited between 250 and 500 ms, centering around 300 ms after the arrival of a stimulus that is rare relative to other stimuli, such as the stimulus that is the object of the user's attention ([Luck and Kappenman, 2013]). In our context, the user aimed to select a target on a screen, such as a specific letter in a keyboard. Letters on the keyboard are being flashed, and the user is asked to count how many times the letter he wants to select has been flashed. In fact, every time the user is counting, a P300 is elicited which allows knowing which letter he wants to select. In addition, there are Visual Evoked Potentials (VEPs) that elicit after a visual stimulus.

Nevertheless, for this task, users have to stare at a specific target. But comorbidities of their paralysis condition such as oculomotor problems are not always taken into account and have an impact on the use of this technology. The goal of this study is, therefore, to study how to enhance the performance of this type of system in this context for patients.

My internship contributed to this project by conducting experiments on patients and studying the interest of combining eye tracker data and brain signal. Thus, the final goal is to have my own contribution to this project on one side, and be able to conduct experiments with patients on another side.

The internship took place at the CRIStAL laboratory in Villeneuve d'Ascq, in the north of France. The laboratory tutor was Pr.François Cabestaing, the manager of the BCI team. I also worked closely with Arne Van den Kerchove, a PhD student.

4. Presentation of ENSC and cognitics

The Ecole Nationale Supérieure de Cognitique (ENSC) is an engineering school part of the Bordeaux INP group, specialised in cognitics.
"Cognitics is the scientific and technical discipline concerning the automatic processing of information and knowledge, for humans, machines, their interfaces, and their collaboration" ([Leblanc, 2024]).
This field combines on one side fundamental science such as computer science, signal processing or mathematic and on the other side, cognitive science such as psychology and human factors. It allows the cognitician to be aware of all stages of the creation of a product, from the user-centered design to the implementation.
My internship is directly correlated with this field since my topic of research combines computer science and signal processing on one side with the decoding of the brain signal, and on the other side, the part related to the brain and the patient care.

5. Presentation of the CRIStAL laboratory

The Centre de Recherche en Informatique, Signal et Automatique de Lille (CRIStAL) is a joint research unit of the University of Lille, the CNRS, Centrale Lille and is in collaboration with the INRIA Centre of University of Lille.
It is composed of 34 research teams divided in nine thematic groups (Figure 5.1). Teams of research cover a wide range of them from fundamental science to more applied ones such as artificial intelligence, cybersecurity, numeric health or robotics.
The team in which I worked was the BCI team, part of the thematic group named interaction

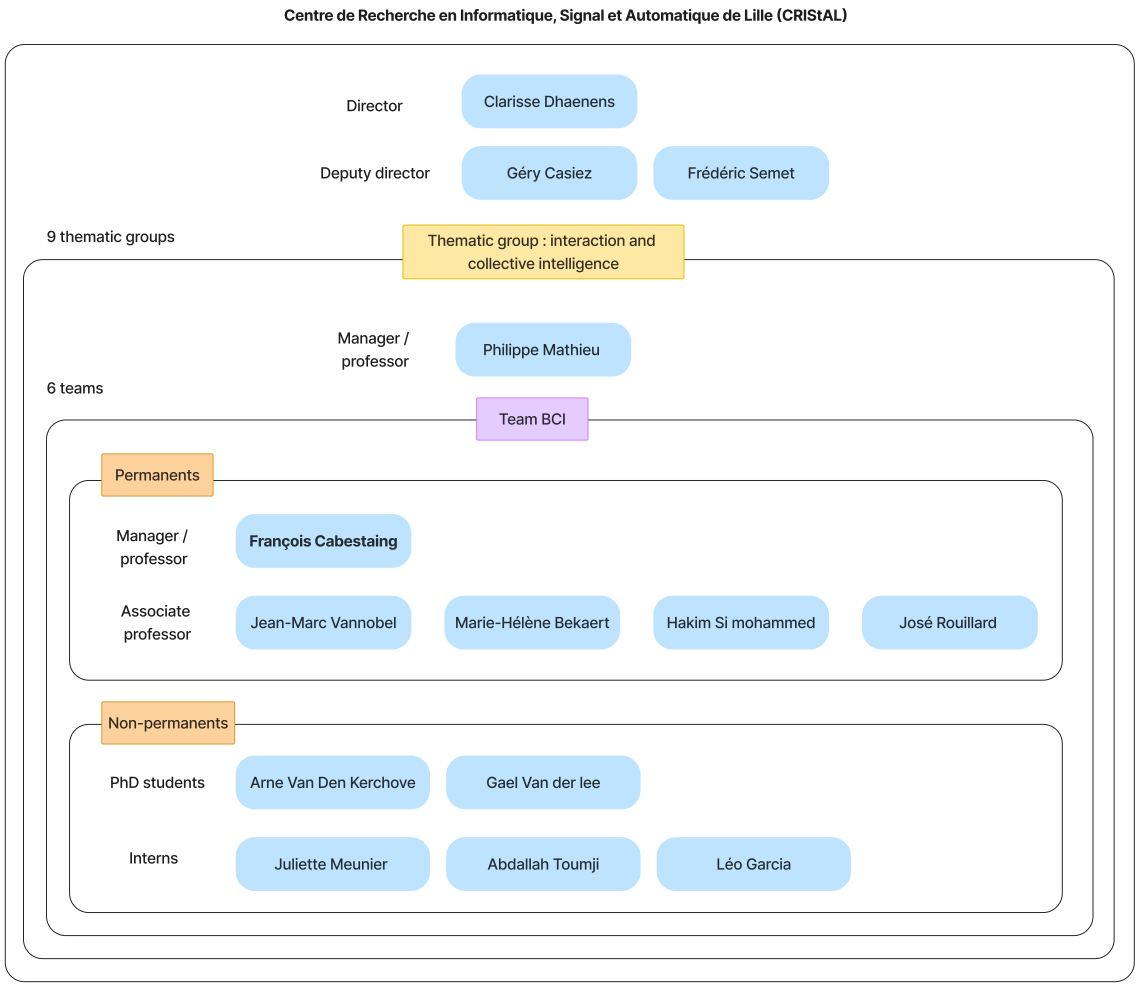


Figure 5.1: Organisation Chart of the CRIStAL

and collective intelligence. My internship tutor, François Cabestaing, is the manager of this team.

The team is divided between permanent members, who are all associate professors except for François Cabestaing who is a professor. And temporary members such as PhD students and interns. Arne Van Den Kerchove is the PhD student of François Cabestaing and has been my co-tutor during the internship.

The topic of research of this team focuses on Brain Computer Interface (BCI) with specification and implementation of it in multiple contexts such as communication for disabled people or finding markers for Virtual Reality sickness for example.

My internship was part of Arne Van Den Kerchove's PhD project which focused on expanding the topics treated in this work.

6. Problem analysis

6.1 First objectives

When I arrived in the CRIStAL laboratory, there were two first objectives for this internship :

1. Assist the PhD student, Arne Van Den Kerchove, with his experiment on patients.

2. Define a project that I will pursue on my own, in order to complement the PhD of Arne Van Den Kerchove. This project is in the continuity of the experiment and on the same subject, but this will be my own contribution to the project.

With these two objectives in mind, the first step was to dive into the literature in order to understand the experiment and the aim of the research project.

6.1.1 Understanding the patient's context

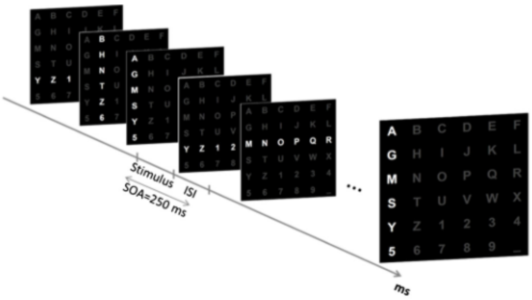
Paradigm

As explained in the chapter 3, users can communicate with a BCI thanks to keyboards and targets. There are different types of keyboards or matrices that can be used.

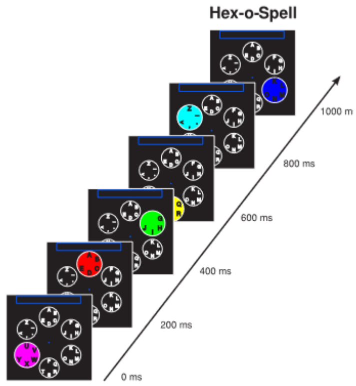
- **Traditional Matrix speller** (Figure 6.1a) : Matrix where there are all the letters of the alphabet or number displayed in lines and columns. Lines and columns are flashed alternatively.

- **Hex-o-Spell matrix** (Figure 6.1b) : Designed in [Blankertz et al., 2007], it allows for a two-level selection to keep the same vocabulary as the Matrix speller, even if the number of targets displayed in the matrix is smaller. The first selection of a group of letters, the second selection of a specific letter.

Otherwise, ERP-based BCI systems are intended for use by real users, such as stroke patients who experience locked-in syndrom. However, one of the symptoms of stroke is the deterioration of gaze movement. Since, in order to select a target, users have to look and focus on a specific target, we can wonder if ERP-based BCI is reliant on gaze movement. Visuospatial attention is the cognitive process that allows individuals to selectively focus their attention on visual and spatial information. Hence, gaze and visuospatial attention can each



(a) Traditional Matrix speller



(b) Hex-o-Spell matrix

Figure 6.1: Different types of keyboard, (a) taken from [Aricò et al., 2014], traditional Matrix speller, (b) taken from [Treder et al., 2011], Hex-o-Spell matrix

be focused on different locations. As a result, there are different conditions, that can be used in ERP-based BCI (Figure 6.2), involving the types of attention listed below ([Van Den Kerchove et al.,]) :

- **Overt attention** : The subject's gaze and visuospatial attention are both directed at the same target.
- **Covert attention** : The subject's gaze is fixed in the middle of the screen (where there is no target) while their visuospatial attention is focused on the target they wish to select.
- **Split attention** : The subject directs their gaze at one target while focusing their visuospatial attention on another target, which is the one they intend to select. There are three conditions involving the split, where the two targets are positioned at different distances.
- **Free attention** : The subject is instructed to perform in whatever manner is most comfortable for them.

Covert attention is more difficult for users to perform ([Treder and Blankertz, 2010]), since in human vision, there is the fovea, the centre of the vision in which your vision has the best acuity. But in peripheral vision, there is a decrease of acuity and a difficulty to identify objects due to the crowding effect (if objects are similar, it is hard to distinguish them, [Bouma, 1970]). Therefore, the traditional Matrix speller is inevitably influenced by these unique characteristics, and there is a need to adapt the keyboard design in order to avoid this

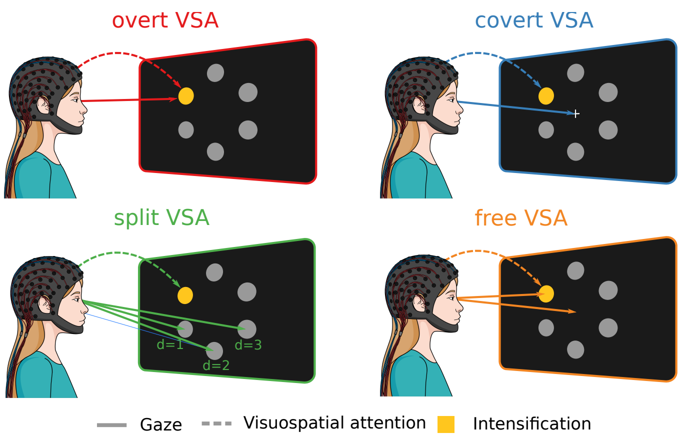


Figure 6.2: Different types of visuospatial attention adapted from [Van Den Kerchove et al.,] : overt, covert, split and free attention.

drawback ([Treder and Blankertz, 2010]). One approach to achieve this would involve enlarging the letter size while simultaneously reducing the available letters, thereby limiting the user's freedom to communicate. But the Hex-o-Spell matrix allows to use covert attention without reducing vocabulary. Some studies such as [Treder et al., 2011] or [Aloise et al., 2012] have focus on the design of the matrix by redesigning it into a not "line x column" matrix any more in order to facilitate the use of covert attention.

Performance and processing

[Treder et al., 2011] explored the potential use of covert attention in an ERP-based BCI. They discovered that, although covert attention falls below the usability threshold and overt attention yields better performance, it is still feasible to use covert attention.

One hypothesis regarding the decrease in performance when using covert attention is the absence of VEP and its contribution to the classifier. Indeed, [Frenzel et al., 2011] have suggested that the VEP component N200 corresponds to the gaze and that the P300 component to attention. As a result, in the covert attention, the N200 component does not elicit.

Another potential explanation for the lower performance could be a lower stability in the P300's potential.

[Aricò et al., 2014] found that the decrease in performance was not solely attributable to the absence of VEP, but also to the variability of P300 latency or latency jitter. Latency jitter, corresponds to the variation in timing of brain responses, denotes the variability observed among one subject during a session in their brain's reaction times and is typically measured by the standard deviation of these responses.

[Thompson et al., 2012] have already studied and attempted to find a solution to this issue by developing a Classifier-Based Latency Estimation (CBLE). This solution involves applying a classifier to various time shifts to maximise the classifier's accuracy. It has been demonstrated that this method can predict BCI performance using two types of classifiers. [Mowla et al., 2017] conducted offline analysis to assess whether their adaptation of the CBLE (applying a wavelet transform to the CBLE transformation output) could enhance performance rather than solely predict it. Their findings revealed performance improvements, particularly in marginal cases. However, their adaptation of the CBLE is not directly applicable in a classification decoding setting (when the user has direct feedback on their use), and it can only compensate for latency jitter without completely eliminating it. [Van Den Kerchove et al.,] have applied a CBLE and adapted it to an iterative method similar to Woody iterations ([Woody, 1967]) in order to enhance gaze-independent BCI performance, which they named WCBLE. They found that the WCBLE can improve performance at the decoding stage in gaze-independent settings. Comparing to the classical CBLE, the WCBLE is better in covert attention, even if in overt attention it is not.

6.1.2 Experiments

The primary objective of these experimental studies is to evaluate the accuracy of the WCBLE classifier, as presented earlier, irrespective of the attentional mode. To achieve this, the study was conducted on four attentional modes: overt, covert, split, and free (Figure 6.2).
For both studies, an Electroencephalogram (EEG) has been used to record brain signals. And an eye tracker and Electro-oculogram (EOG) have been used to control where the gaze is on the screen.

Healthy subjects

Firstly, in order to have a proof of concept, a study has been carried out on 15 participants, mean age 26.34 $\pm$3 years. Indeed, healthy subjects were able to control their gaze and compare the different types of attention. This study has already been carried out, with an article that has been accepted ([Van Den Kerchove et al.,]).

Patients

After testing the study on healthy subjects, it was important to include patients with a very limited ability to control or maintain a constant gaze direction in order to have a more ecological condition. This was the goal of the second study.

6.2 Data fusion project

In the continuity of the patient's experiment and with the will to enhance the performance of independent-gaze BCI, the question of whether to use eye tracking data in addition to the brain signal arises. Especially, that there was an eye tracker in the set-up of the experiment.

Eye tracking is a technology that allows for the detection of movements and positions of the eyes. There are three types of it : eye-attached tracking, optical tracking, and measurement of eye muscles with electrodes. In our study, we used the optical tracking and EOG.
Thus, we were wondering if eye tracking could improve the performance of this ERP-based BCI , particularly with patients who experience ocular impairment. In this context, the interplay of gaze and visuospatial attention is more important than with healthy subjects, hence, an approach that combines both could contribute well here.

6.2.1 Literature and first definition of the project

One approach to integrating an eye tracker into a BCI is through a hybrid BCI, which combines EEG and eye tracking modalities. Hybrid BCI follows three primary objectives : increase BCI classification accuracy, enhance the number of BCI controls and reduce the time required to detect brain commands ([Hong and Khan, 2017]). This combination of BCI and eye tracker could be useful for artifact removal and remote control, as highlighted in the literature review of hybrid BCI by [Hong and Khan, 2017]. For remote control, for example, Steady-state Visual Evoked Potential (SSVEP) based BCI could be combined with eye tracker ([Stawicki et al., 2017]) which allows for better control and user-friendliness. For artifact removal, the performance of BCI could be improved by removing eye blink on data using EOG [Zhang et al., 2010]. These are examples of the scope of usability of a hybrid BCI .

On the other side, according to the study of [Lim et al., 2022], eye tracker could be used in classification and machine learning for decoding the focus of attention. The data from the eye tracker provide several features that can be used for classification such as pupil size, saccade , blink, pupil position, fixation or velocity. Each of the features allows, depending on the study, to get different information on cognitive states. As the population of this study consists of patients in a locked-in state, gaze movement and gaze control could be difficult. In order to use and get all the features, an eye tracker should be calibrated at the beginning of the use. But as not everyone controls their gaze movement, calibration is not always an option. [Abul Hassan et al., 2023] have studied the question of the use of an eye tracker without calibration in order to know which features could be collected without the calibration. They also studied an eye test that allows for the quantification of eye movements. Finally, they have shown that you can get ocular movements and symmetry of the eyes with or without calibration with a commercially available eye tracker.

In addition, [Ge et al., 2022] have studied the question of the fusion of input data from eye tracker and BCI in order to enhance the performance of intention detection. They compared the performance of few classifiers with EEG alone and fusion. They used the fixation duration in order to extract epochs (which correspond to data in a specific time window) and using these epochs as input to the classifier. Thus, they were able to use this type of input with EEG epochs in order to enhance performance. However, this study used a free visual search paradigm, which is not the same as our paradigm. The same idea could be used in our case, where the eye tracker could allow discriminating between overt attention and covert attention . Even if, distinguishing overt attention and split attention could not be done with an eye tracker.

Finally, there was another idea that did not come from data fusion literature. In the study of [Van Den Kerchove et al.,], they compared the CBLE, WCBLE and Toeplitz-LDA (t-LDA), a specific classifier. We presented the CBLE and WCBLE in the subsection 6.1.1. The t-LDA was proposed by [Sosulski and Tangermann, 2022] and offers robust regularisation, as highlighted by [Van Den Kerchove et al.,], resulting in improved decoding performance. They finally found that WCBLE outperformed t-LDA and CBLE for covert and split condition. And that with the t-LDA, overt condition outperformed both other conditions. Hence, we could use eye tracking data in order to determine with which attention the trial is performed and use the best classifier.

6.2.2 Study question and hypothesis

From this, we could imagine how we could use the eye tracker further. There is a scope of possibility regardless of where the data is fused : at the input of the classifier, at the output or by selecting the better classifier for EEG data depending on eye tracking data. Hence, we will try to answer the question :

- are the selections made by a hybrid BCI more reliable if eye-tracking data is taken into account in addition to EEG data, especially for patients with ocular impairment ?

Our hypothesis is :

- taking eye tracker into account allows a more reliable BCI and a better classification performance.

It is interesting to note, that we could expect eye tracking to not work that well in patients with oculomotor impairment because of the eye movement issues but that we could maybe nevertheless harness their residual eye motor control to improve a hybrid system.

6.3 Previsional planning

The Gantt chart (Figure 6.3) is divided into several work packages (WP) :

- WP1 : Discovering study context with the literature review and the discovery of data.
- WP2 : Patient's experiment.
- WP3 : Definition of the project with another literature analysis and a zoom on the data fusion theory.
- WP4 : Implementation of the data fusion project.
- WP5 : Preparation of the report and presentation.

Combining with these work packages, there were milestones corresponding to the deadlines of the laboratory and the school.
The team presentation corresponds to the end of my first part of the literature review on the patient's experiment, as well as the literature analysis for defining the subject. This meeting allows for feedbacks from several members of the team.

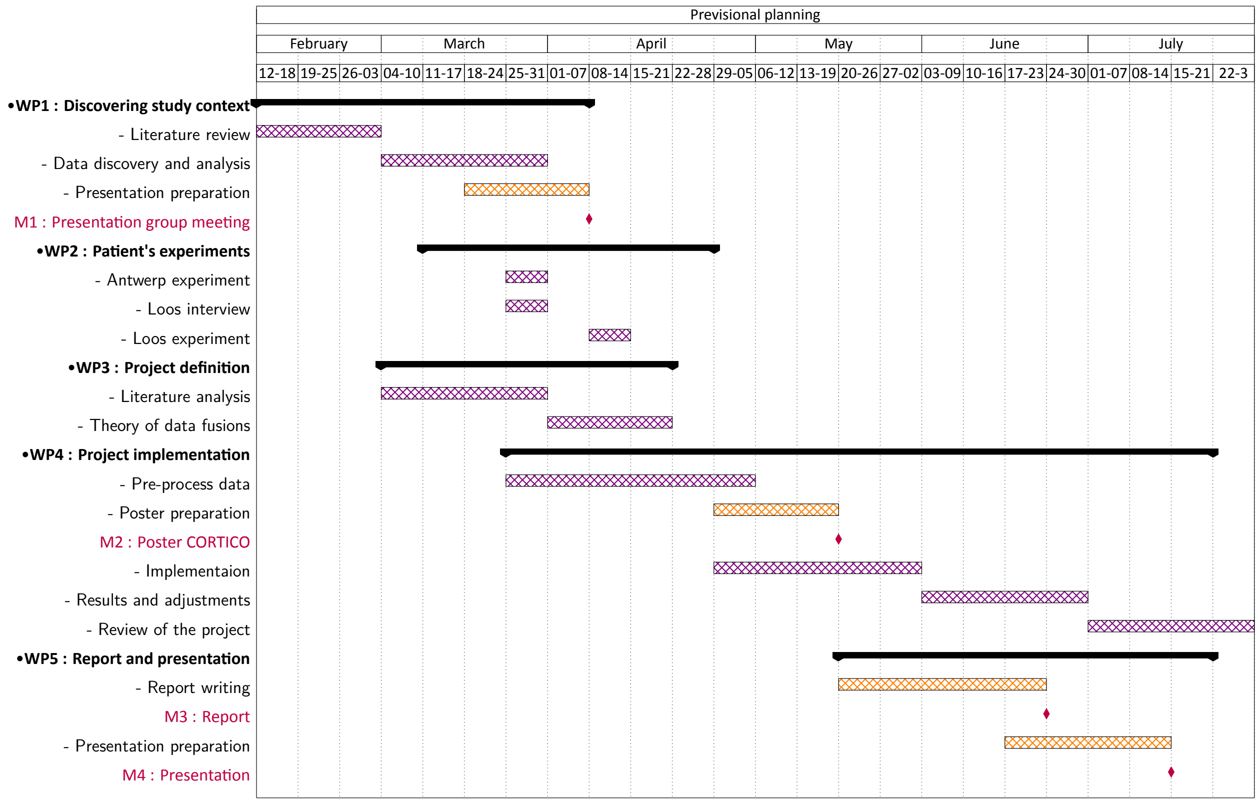


Figure 6.3: Previsional Gantt chart ; in red : milestones (M), in violet : task grouped in work package (WP), in orange : preparation of milestones.

For the poster presentation, I was able to present all my literature review and methodology I have found. I also had my first results to present.

Finally, it was important to keep time to write this report and prepare the final presentation.

7. Realisation

7.1 Experiment with patients

The experiment on patients has been conducted in parallel in Belgium and France.

When I arrived in the team, experiments in Belgium had already started with Arne Van Den Kerchove. And he needed help to carry out the experiment in France.

7.1.1 Eye test

In order to measure ocular impairment before each session, an eye-test was conducted. A first version of it was already implemented, but as in the original article whose test was described, the description was not precise, it was difficult to reproduce the same.

That is why my first task was to search and precise this test to ensure reproducibility.

[Abul Hassan et al., 2023] have studied an approach to quantifying eye movements with a non-calibrated eye-tracker. In fact, most studies exclude people who cannot complete the calibration task, that is why it would be interesting to know what you can operate with no calibration. In order to do that, they analysed the correlation between fixations, smooth pursuits, saccades and the effect of calibration. They finally found that eye tracking with no calibration can be used to measure eye movements symmetry. As the study population of the experiment includes some patients who have ocular disorders, in order to ask them to focus on visual cues, it is important to measure what they can do with their eyes.
That is why we implemented an eye test, which is inspired by the NeuroEye test of [Abul Hassan et al., 2023].
The NeuroEye test is inspired by standard bedside ocular tests that are described in [Ng et al., 2021] and used directly with stroke patients [Kattah et al., 2009]. To have more precision about the technical parameters of the tasks, we combined the NeuroEye test with similar tests that are used in [Kapoula et al., 2010].
Each test was displayed on a computer situated 50 cm from the participant and preceded by written instructions. As the patients have different levels of ocular impairment, we used three different speeds.

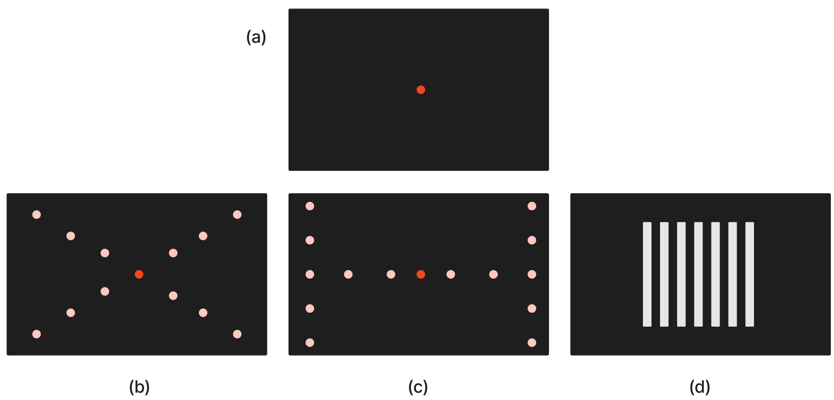


Figure 7.1: Different screens of the eye-test : (a) rest screen (b) dot-test, allows measuring fixation and eye coordination (c) H-test, allows measuring smooth pursuit (d) Optokinetic nystagmus task N-test, allows measuring the shift from smooth pursuit to change the direction of the gaze.

The first test is the dot-test (Figure 7.1 (b)), which allows measuring fixation and the quality of eye coordination when you have to switch your gaze from dot to dot when they appear on the screen. Stimuli were a red dot ([Abul Hassan et al., 2023]) with an angular size of 0.2° [Kapoula et al., 2010]) situated one by one at different locations on the screen. In fact, in each diagonal, there were five dots displaying in line starting in the right or left, top or bottom corner. They were displayed with a saccade interval of 1, 2 or 3 seconds.

The second test is the H-test (Figure 7.1 (c)), which permits measuring smooth pursuit ([Abul Hassan et al., 2023]). Following the shape of an H, the patient needs to track the dot with their gaze. Stimulus was a red dot of 0.2°, as in the previous test.

The final test we are using is the Optokinetic nystagmus task (OKN-test, Figure 7.1 (d)). Here, we are evaluating the ability to shift from smooth pursuit by following a clue to a saccade , when your clue disappears and you take another. The given instructions were to focus on the moving bar. A sinusoidal grating pattern with a spatial frequency of 1.875° was displayed. The phases were 0.0125, 0.025 and 0.05 which permitted the change of speed. Each trial lasted 10 s for each direction : left, right, up and down.

Between each test, there was an only red dot in the middle of the screen in order to fix the gaze before the beginning of the test (Figure 7.1 (a)).
I implemented these three tests in Python making use of the PsychoPy library (Psychopy 2, [Peirce et al., 2019]), in the existing code of the experiment.

7.1.2 Methodology of the study

Material

For every experiment, we used the same setup in order to collect data (see Figure 7.2). First, there is the EEG cap with 16 active electrodes (EASYCAP GmbH, germany) which permits recording brain waves, connected with an amplifier (Compumedics NeuroScan, Australia) which allows capturing, amplifying, and converting the collected data into a digital format. There is also the eye tracker which captures the gaze position for each eye and period of blink, fixation or saccade . The eye tracker used was a Tobii pro eye tracker (Tobii, Sweden), an optical tracking.
The EOG which was made of two bipolar leads (horizontal EOG and vertical EOG) using passive electrodes, allows recording eye movement from the vertical and horizontal axis. Finally, stimulation tracker (Cedrus, CA, USA) permits to synchronise all the data by adding events depending on what happened on the screen.

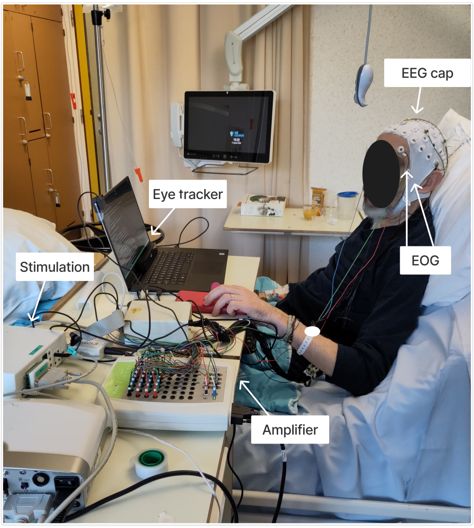


Figure 7.2: Photo of a patient from previous experience in Belgium with annotations of the setup.

Protocol

The protocol was already established and validated by the ethics committee of the University Hospital, Leuven (S62547) when I arrived. In an experiment, it is very important to have a strict protocol to follow in order to have the same condition for every subject.

During the task, there is a Hex-o-Spell interface (explained in subsection 6.1.1) displayed on the screen that is flashing. In this study, there is no letter inside the target, in order to have a proof of concept and a minimal number of variables. Patients are asked to count how many times the target they want to select is flashed.

As explained before (Figure 6.2), there were 4 types of visuospatial attention used in the study corresponding to 6 conditions : overt, covert, split 1, split 2, split 3, free. The split condition is divided into three conditions :

- Split 1 = The distractor (= target where the gaze is) is either directly next to the attended target in a clockwise or counterclockwise direction (d = 1).
- Split 2 = There is one target between the attended target and the distractor (d = 2).
- Split 3 = The distractor is directly opposite the attended target (d = 3)

For every patient, the study was divided into three steps.

- **Inclusion visit** : This visit aimed to meet a first time patient, and check the inclusion and exclusion criteria. It also permitted to be sure that patients understand everything and obtain their informed consent. Before this visit, an information letter was sent to them.
- **Offline session** : During this session, patients were prepared for the recording and performed the experiment. There was no direct feedback provided : when they were asked to select a target, they received no information on whether the algorithm recognised the target they wanted to select or not.
- **Online session** (optional) : If the first session went well and the patient was able to have a good performance, an online session with direct feedback can be conducted. The task is the same as during the offline session, but with feedback and performance that were directly given.

Each session lasted about 1 hour and 15 minutes including about 30 minutes to put the cap on with gel, 30 minutes of signal recording and tasks, and 15 minutes at the end.

7.1.3 Experiment in Antwerp (Belgium)

We conducted four experiments in the Belgian-based neuro rehabilitation centre TRAINM in Antwerp. Their mission is to assist children and adults with neurological deficits in achieving measurable recoveries.

Patient's condition

There were three patients who had Friedreich's Ataxia, one with a traumatic brain injury and one with multiple sclerosis (MS) that could not be included due to vision.
According to [NINDS, 2024], Friedreich's Ataxia is a rare-inherited disorder that leads to progressive damage to the nervous system, causing movement and sensory symptoms, as well as difficulties with walking and gait. It can lead to motor weakness such as loss of sensory functions in arms and legs and dysarthria (slowness and slurring of speech).
These four patients were all in a locked-in state, which means that all or most of their bodies are paralysed. Not all patients had the same degree of loss of movement, and we used the [Wolpaw et al., 2006] categorisation of locked-in syndrom to describe them :

- First class : Patients who are in a total locked-in state with no residual movement.

- Second class : Patients with an extremely limited ability to control neuromuscular functions.
- Third class : Patients who still possess significant neuromuscular control, particularly in speech and/or hand movements.

These 4 patients were still able to talk, but with difficulty, except one who was communicating with a keyboard (third class).
Due to the motor dysfunction of this disorder, they had trouble to fix their gaze.

Experiment

As experiences were conducted in the Flemish part of Belgium, patients were not talking French. Therefore, I could only talk in English or let Arne Van Den Kerchove explain most of the parts.
I mostly helped by installing the helmet and filling gel into electrodes at the beginning, and monitored the signal during sessions.

7.1.4 Experiment in Loos (France)

We were in contact with a French Medicine professor, doctor, at Lille CHU, Etienne Allard, who enabled us to find patients and make the first connection with the Maison d'Accueil Spécialisée in Loos.

Pre-experiment

Before beginning experiments, it was important to have one or two meetings with the patients in order to have a chance to discuss it with us and ask some questions that were relevant for the study.

First meeting with everyone

Firstly, we met the four patients at the same time during a meeting with the MAS's staff and some members of the family that were interested. It allowed us to discuss with them the study and the expectations that everyone had. During this meeting, we realised quickly that most of the patients were really hopeful about these technologies and hoped to be able to use it after the experiment. The first step was, so, to explain that this was a study that would permit improving this type of BCI , but that at the end, they would not be able to use it in their daily lives.

Interview one by one

After the previous meeting, we emailed them to re-explain all of that and to plan another meeting one by one with them in order to get their final consent and ask demographic questions. The demographic questions were divided into different parts :

- General information : age, gender, laterality.
- General information about the diagnosis : neuromuscular diagnosis and time of diagnosis.
- Information about ocular impairment : oculomotor diagnosis and time of diagnosis, vision.

All this was very important because of informed consent.

Patient's condition

There were four patients who had strokes : three of them of the brain stem and the last of the left cerebellum.
According to [NIH, 2024], stroke is a medical condition that happens when a part of the brain is cut off of blood supply. Depending on the part of the brain the stroke is, impacts and impairments are different. After a stroke, people often need rehabilitation in order to recover their lost functions or permanent care.
Three of them were able to communicate with a paper keyboard by pointing with a finger letter by letter (second class of [Wolpaw et al., 2006] classification). The last one could only communicate by blinking, with special techniques for announcing the letter, it is also possible to communicate letter by letter (first or second class, depending on the day).

Experiment

This time, all patients were only speaking French. Therefore, it was me who was in charge of communication with patients in order to explain instructions and go through the experiment step by step while ensuring that the patient was fine. As they were not able to talk, being

aware of any change in the patient's behaviour was essential. Indeed, even if the patient had given informed consent, they were allowed to stop at any time.
Moreover, due to their paralysis, putting the helmet on was not always easy, especially with one who could not hold his head on his own or when the patient had undergone a tracheostomy.
Finally, we had to postpone one experiment due to pain in the neck of one of the patients.

7.1.5 Data preprocessing

When I arrived in the internship, there was already a pipeline of preprocessing for the healthy subjects. The first step was therefore to understand it and adapt it for the patient's experiment.
In this pipeline, EEG data, eye tracker data and EOG were processed together.
The analysis was made in Python and the library used was "MNE-Python" ([Gramfort et al., 2013], a library specialising in EEG analysis. Recently new functionality related to eye tracking has been added.

- **Read data**

- Select electrode and set montage : In order to analyse data with "MNE-Python", it is important to specify the montage of the EEG cap. Indeed, thanks to this library, the location of electrodes is taken care of.

- Rename events and stimulation : In order to deal with the different condition, during the experiment, there are events in the data corresponding to each condition. A first step is therefore to assure that events have the right label. There was a need for adaptation here since, events between healthy subjects and patients were not the same.

- Merge EEG and eye tracking data : Thanks to the marker, synchronising EEG and eye tracking is easier. Indeed, the stimulation box allows adding markers and having the exact time for each event. At the end, it is possible to merge data into a unique raw with different channels with the same markers.

- **Clean data**

- Annotate breaks : One useful tool in the "MNE-Python" library is the annotation. Annotation allows adding information to a part of the data. Here, annotations allow locating breaks between conditions. Indeed, between conditions and between blocks of trial, data was still recorded, but not relevant. There was also a need here, to redefine the time of a break, since between both experiments, it was not the same. The risk is to mark as a break, data that is not.

- Filter : In order to process EEG data, a mandatory step is to filter the signal. Actually, the EEG signal is very noisy due to several factors such as the power line interference at 50 Hz and other electromagnetic interference originating from the brain, the body, the environment and nearby machinery. As the P300 has been found in a frequency range of 1 to 12 Hz ([Luck and Kappenman, 2013]), we band-pass filter the data from 0.5 to 16 Hz in order to remove noise and focus on ERPs that interest us.

- Mark bad channels : It can happen that electrodes are bad due to a wrong impedance (electrical resistance of the scalp) or a default in the material. This step allows verifying via different methods if electrodes are bad to remove them from the data.

- Rereference : During the experiment, there are two electrodes that are the common reference electrodes. These electrodes are placed behind the ears on mastoid bones. These electrodes allow the removal of noise that is not relative to the brain signal. Indeed, these reference points help to standardise the EEG recordings by providing a stable comparison for the measured brain activity.

- **Independent Component Analysis (ICA)**

It is a computational technique used to decompose a multivariate signal into its additive subcomponents. As we can see, on the Figure 1, what is interesting about applying an ICA on EEG data is that it has a spatial decomposition and finds components that correspond to eye blinking. In fact, handling muscles artifact is also a very important step. EOG is also used with this ICA, in order to identify more precisely, eye blink.

- **Epoch data**

Data is being epoched depending on the events. In the ”MNE-Python” library, there is a special object named epoch that permits the creation and processing of this.

- **Reject epoch**

Epochs that are rejected correspond first to the ones present in the eye blink ICA components. On the Figure 1 (Appendix), we can see that the ICA002 and ICA007 correspond to the eye blink components. Secondly, for healthy subjects, in order to control if they were looking at the right target and respecting the instructions, an eye tracker was used. Epochs where they were not looking at the right location were dropped. Here, as we want to study ecological conditions and as patients may not control their gaze, we do not want to remove these epochs.

7.2 Data fusion project

7.2.1 Theoretical basis of data fusion

In the continuity of the experiment with patients for a gaze-independent BCI, I was working on the possibility of using eye tracking data in addition to EEG data alone. More precisely, I was studying data fusion for hybrid eye-tracking ERP BCI. Indeed, as explained in section 6.2, hybrid BCI could offer better performance by adding different information with the eye tracker and allowing adapting data processing in a gaze-independent system for patients with oculomotor problems. The goal here was to find a methodology in order to test the hypotheses that taking eye tracking data into account allows for a more reliable BCI and better classification performance.

What is data fusion ?

The goal of data fusion is to combine multiple sources. However, data are often imperfect. Imperfection of data can come from different issues such as inaccuracy, uncertainty/reliability or incompleteness ([Lefevre, 2012]).

- **Inaccuracy** : It is referring to difficulties when stating knowledge such as an exact measure by an instrument that is not possible, or the way is formulated a stating. For example, between a child, an adult and an old man, there is no precise frontier.
  - **Incompleteness** : The notion of inaccuracy also refers to incompleteness, when there is no information.
- **Uncertainty** : This notion is about the quality of the information and not the presence or not of an information.

Another aspect that must be taken into account is the conflict between the data.
The problem of data fusion is therefore to deal with the imperfection of the data on the one hand, and to handle conflicts between sources on the other hand [Frikha and Moalla, 2015].

Different levels

In order to fuse data, there are different levels of fusion which allow for the fusion of different types of information. As we can see, on the Figure 7.3, there are three layers of fusion.

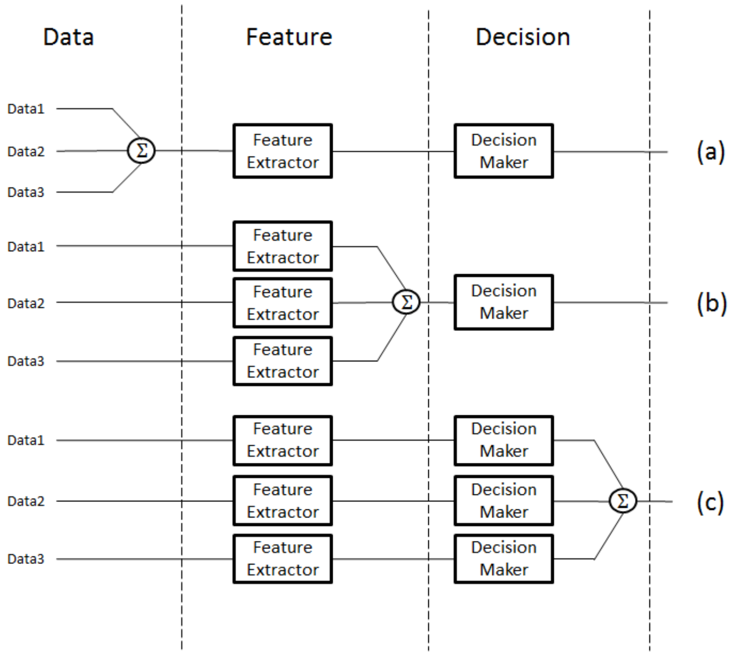


Figure 7.3: Different fusion levels : a) Data level fusion : data merged on a raw level, (b) feature-level fusion : data fused in a unique feature vector, (c) decision-level fusion : fusion between final decision for each sensor ; Figure taken from [Liu, 2015].

- **Sensor/Data layer** : Data are being merged at a raw level, all data are concatenated into a same matrix before extracting feature of this single element.
- **Feature layer** : After signal processing and extracting features from each sensor, features are being fused in an only feature vector representation before going to the classifier.
- **Decision layer** : Each sensor with their own data are being process, features extracted and finally pass by classifiers which give a decision. The fusion is between final decisions of each sensor.

Depending on the use of fusion and the context, some layers can be more convenient than others.

7.2.2 Methodology : possibility of fusion

After studying data fusion from a theoretical aspect, I have searched for a more practical implementation of data fusion in a context that was closer to our data : fusion between EEG and eye tracker.

Feature-level fusion

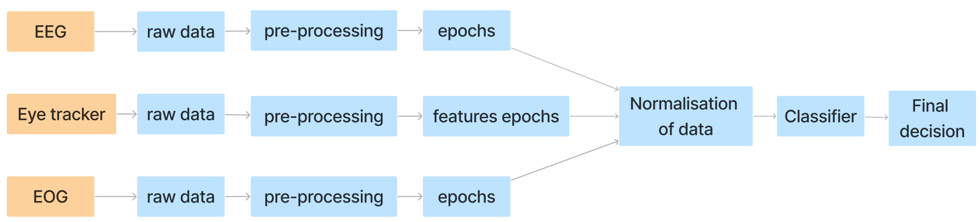


Figure 7.4: Diagram of the implementation of one feature-level pipeline, adapted from [Cheng et al., 2020] ; fusion is made on a feature-level by combining eigenvectors from EEG, eye tracking and EOG data.

In the study of [Cheng et al., 2020], authors are fusing EEG and eye movement in a BCI based on motor imagery (MI). They are fusing their data on the feature level by combining eigenvectors from the different sources.

Before combining them, they normalised the features with a min-max method

The Figure 7.4 showed an adapted version of this process for our data, with the addition of the EOG with eye tracker.

Decision-level fusion

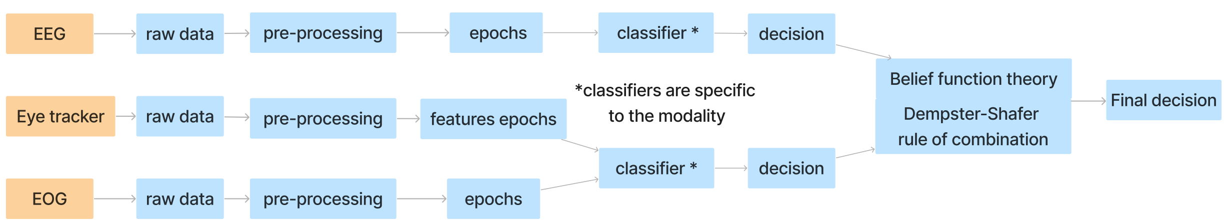


Figure 7.5: Diagram of the implementation of one decision-level pipeline, adapted from [Cheng et al., 2020] ; use of Belief Function Theory and Dempster-Shafer rule for combining decision from EEG and eye tracker-EOG decision.

[Cheng et al., 2020] in addition to study the fusion at the feature level, compare a fusion on another level : the decision level. Feature extraction was conducted on the collected EEG and eye movement data to obtain the corresponding eigenvectors. Then, classifiers were used to classify these eigenvectors to produce preliminary results of each classifier . They used the Belief Function theory (BFT), and especially, some combination rules such as Dempster's Shafer evidence theory (explained in subsection 7.2.3).

The Figure 7.5 showed an adaptation of this fusion for our data, with the addition of the EOG with eye tracker .

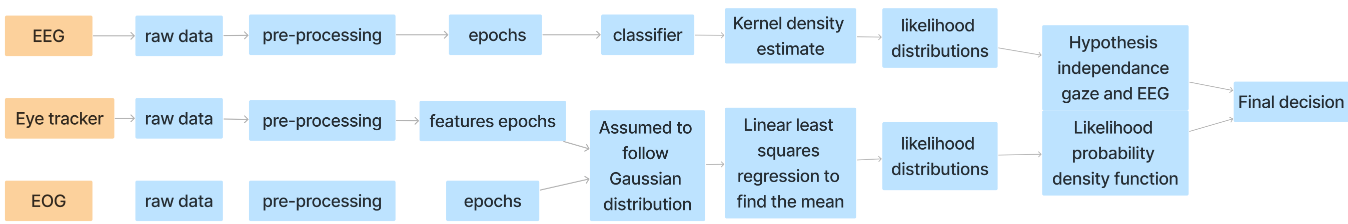


Figure 7.6: Diagram of the implementation of one decision-level pipeline, adapted from [Kalika et al., 2017] ; likehood distribution of each modality (EEG and eye tracker-EOG) are being combined with the hypothesis of independence between gaze and EEG.

Another example of a decision-level fusion could be the one described in [Kalika et al., 2017]. This study is particularly interesting since it is also on EEG and eye tracker in a context of a spelling task with a P300 . The principle of this fusion is to estimate the probability of each character being the target character after a flash, given the available EEG and eye gaze data (i.e., sequentially update the character posterior probabilities by using the previous posterior probabilities as the prior).

That is why, after epoching (to epoch something), depending on the modality, likehood distribution of if this is a target or not is calculated. For the EEG, a kernel density (i.e. histogram smoothing) is estimated with the value of the classifier used. For the eye tracker , it is more complicated since, it is not binary. A linear Least Squares (LS) method is used to find the mean and find the Gaussian distribution of the gaze position. At the end, the probability and the likehood distribution of all sources are combined.

They hypothesised that the gaze and the EEG were independent in order to simplify probability calculation. This hypothesis is interesting for our case since, in overt attention and covert attention , gaze and EEG are really independent. The Figure 7.12 shows an adaptation of this fusion for our data, with the addition of the EOG with eye tracker .

Mixed approach

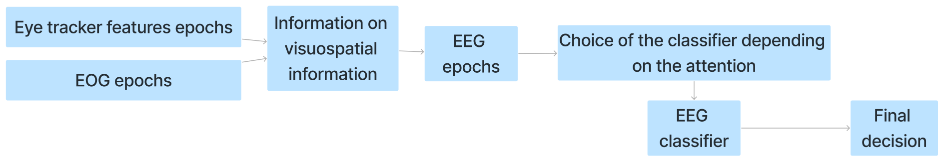


Figure 7.7: Diagram of the implementation of a mixed approach ; depending on where the gaze is and the amplitude of EEG, conditions are being assumed in order to apply the best classifier.

As explained in subsection 6.2.1, depending on the type of attention, there are some classifiers that are better in some condition than another. That is why, we can imagine using eye tracker in order to select the right classifier .

Thus, if the gaze is not on a target, we know that we are in a covert attention and used the right classifier in consequence.

7.2.3 Zoom on the Belief Function Theory

In the previous explained method, some of them are using the Belief Function Theory (BFT). It was therefore relevant to study the theory behind it.

Origin of the theory

The BFT has been initially introduced by [Dempster, 1967] and justified by [Smets and Kennes, 1994]. According to [Frikha and Moalla, 2015], it is a general framework for modelling uncertainty and imprecision where the available data is imperfect.

This theory follows the formalism of the probability theory, which is historically the most used ([Lefevre, 2012]). But the formalism of probability theory has limitations. First, the probability between an equivalent situation and someone who does not have knowledge is represented in the same way, with a probability of 0.5. Secondly, the additivity axiom requires the fact that for any event, the probability is equal to one minus the probability of the opposite event. Therefore, there is an impact on opposite events even if they are not correlated. The BFT allows going beyond these limitations.

Basic principle of BFT

The BFT is based on function that permits to model conflict and imprecision. Here are the basic principle of the BFT.

- Θ is called a frame of discernment, which is a finite and exhaustive set of the problem under consideration.
- A is a subset of Θ.
- $\mathrm{m(A)}$ is the mass which is the degree of belief attributed exacted to A.

There is the belief function (Bel), it is the total belief committed to $\mathrm{A} \subseteq \Theta$:

$$\mathrm{Bel}(A) = \sum_{BA} \mathrm{m}(B), \forall A \subseteq \Theta$$

.

And the total of uncertainty : $\mathrm{m}(\Theta) = 1$ and $\mathrm{m}(A) = 0, \forall A \neq \Theta$

There are multiple methods used in this theory, here are some examples :

- **Combination rules**
  - Dempster's rule of combination ([Shafer, 1976]):

$$\mathrm{m}(A) = \frac{1}{1-K} \mathrm{m_i}(B) * \mathrm{m_j}(C), \forall A \subseteq \Theta$$

with K the global conflict of combination (between $\mathrm{m_i}$ and $\mathrm{m_j}$) :

$$\mathrm{K} = \mathrm{m}_{\oplus}(\Theta) = \sum_{B \cap C = \Theta} \mathrm{m_{i(B)}} * \mathrm{m_j}(\mathrm{C})$$

This rule of combination verifies mathematical rules such as commutativity and associativity.

Limitations : When they are high conflicts, it can not be used since counterintuitive behaviours will be generating.

- **Assessment criteria**

  To estimate reliability of sensors, a single criterion could be used such as quality of data, non-specific, uncertainty or conflict between sensors. However, to reflect reality, mono criteria is not enough. That is why, there is also multiple criteria.

– First class : imperfection of information provided by each sensor.

There are function to minimise contradiction, imprecision and uncertainty.

For example, contradiction (St) (introduced by [Klir and Parviz, 1992]) is the fact that an element of interest cannot belong to only one or several disjoint subsets of Θ :

$$\mathrm{St}(m) = -\sum_{A\in F} \mathrm{m}(A) Log_2[\sum_{B\in F} \mathrm{m}(B)(|AB|/|A|)]$$

.

– Second class : conflict between sensors.

A conflict is when one sensor strongly supports one target and the other strongly supports another target, and both targets are different ([Liu, 2006]).

There are several measures : conflict, dissimilarity or disparity.

For example, the Shafer's weight of conflict (Conf([Klir, 1993]) :

$$\mathrm{Conf}(\mathrm{m_i}, \mathrm{m_j}) = -Log_2(1 - \mathrm{K})$$

.

[Frikha and Moalla, 2015]

7.2.4 Data preprocessing

Even if the final goal of this study is to be applied to the patient's data. To begin with, and to have a proof of concept, I used data from healthy subjects. Indeed, in terms of reliability, data from patients can be questioned due to the calibration that cannot always be done.

EEG

Uncertainty of data

When we look back at the subsection 7.2.1, in EEG, we can wonder about the uncertainty of data. Indeed, as explained before, EEG data have noise due to the external environment or muscle artefacts.

As explained in subsection 7.1.5, there are multiple ways to deal with this kind of drawback :

- Filter to remove electro magnetic noise of the environment.

- ICA and EOG to remove eye blink noise.

- Common reference electrode to remove muscle artefacts from the whole body or external noise.

Features

Features used for EEG data were epochs of the preprocessed signal.

For the EEG data, there was no need to alter the preprocessing that was set up in subsection 7.1.5.

On the Figure 7.8, we can see ERPs related to the covert attention condition. A peak is observed around 400 ms which corresponds to the P300 component.

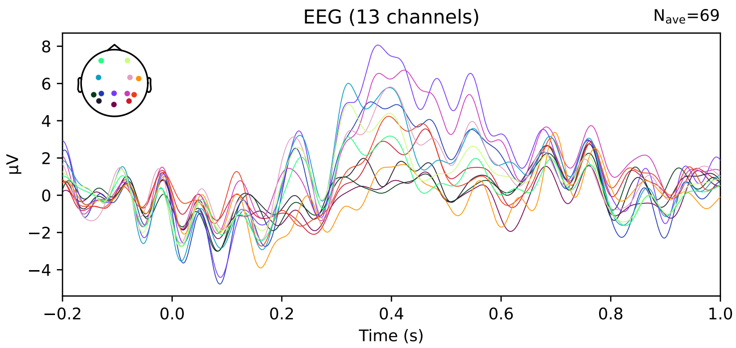


Figure 7.8: Plot of average ERP for the subject A02 in the covert/target conditions.

Eye tracker

Uncertainty

In the beginning of an experiment, a calibration is done in order to be more precise. For this calibration, the average error and the maximum error are calculated which can indicate if the data collected can be trusted.

This method works for healthy subjects that are able to do the calibration. For patients, as explained in Figure 7.1, there is the eye test that can be used to indicate oculomotor issues.

Incompleteness

A problem of optical eye tracker is the fact that when one eye is closed, there is no value (a NaN). Therefore, there are missing values that can cause problems. One way to deal with that is to interpolate these missing values.

Interpolation refers to the process of estimating or predicting values that lie between existing data points within a defined range in numerical analysis. In our context, using linear interpolation means that when there is a missing value, this method will average the previous and next values in order to replace the NaN.

Features

In the eye tracking data, I had different features and information that could be used :

- Eye position on the screen for each eye and each axis (X or Y) (Figure 7.9)
- Pupil sizes

In the first pipeline of preprocessing, these were the only data that we have access to.
In a second analysis, I realised that in the raw files, there were some annotations that can be used : fixation, saccade and blink.
I have therefore had to adapt a preprocess pipeline again in order to include this type of information.

In order to facilitate further classification, I added two other features :

- **Cartesian distance between screen center and the gaze** :

  $$\text{distance} = \sqrt{(\text{xpos\_avg} - \text{screen\_center\_x})^2 + (\text{ypos\_avg} - \text{screen\_center\_y})^2}$$

  with :
  - xpos_avg and ypos_avg, the average of the position of the gaze on the screen between the right and left eyes
  - screen_center_x and screen_center_y, the coordinate of the center of the screen

  This distance is, in fact, the Cartesian measure with an x and y component.

- **Angular distance**:

  $$\text{polarDistance} = \arctan 2(\text{ypos\_avg} - \text{screen\_center\_y}, \text{xpos\_avg} - \text{screen\_center\_x})$$

  The advantage of adding this feature is to use instead of Cartesian coordinate with x and y, the polar coordinate, the radius and the angle.

EOG

The EOG data was mostly preprocess with EEG and eye tracker data.

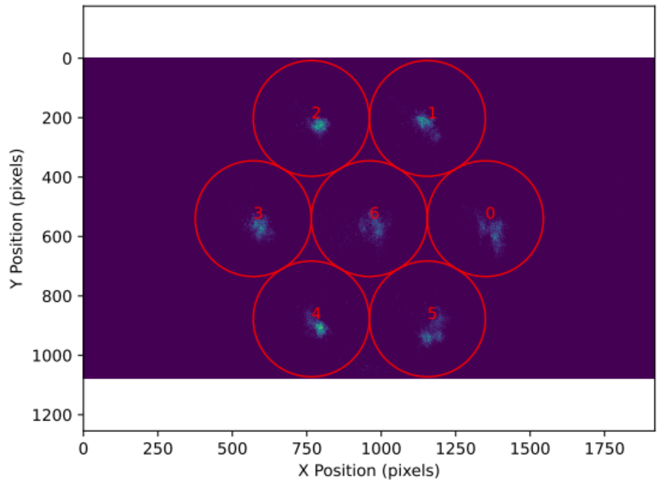


Figure 7.9: Plot of the gaze data with the 6 targets corresponding to the Hex-o-Spell matrix and the center of the screen

7.2.5 Implementation of data fusion

Position of the gaze on the screen

In order to be able to define where the subject is looking on the screen and use this information in one of the possibilities of fusion, we can think of a classifier with seven classes corresponding to the six targets on the screen and the centre.
To explore, this possibility, I chose to begin with a decision tree, which is a supervised learning method used in machine learning. This technique uses a classification tree as a predictive model to derive inferences from a set of observations. This type of model is very practical due to the visual and explicit representation of the decision.

In this decision tree, the entropy ($\mathrm{H(X)}$) is used as an indicator of splitting. Entropy, in a decision tree, is a measure of disorder or uncertainty in a node ([Dash, 2024]). The greater the disorder measured in a node, the higher its entropy will be. In a binary classification, the entropy is between 0 and 1, but as we are in a multiple class decision, the entropy can be higher.

$$\mathrm{H(X)} = -\sum_{i=1}^{n} p_i \log_b(p_i)$$

The Cartesian distance and angular distance, presented in subsubsection 7.2.4, has been used here. Cartesian distance is interesting here since targets are at different distances from the centre, allowing to discriminate targets more easily. And the addition of the angular distance allows better classification since targets regarding the centre of the screen are located around it circularly and at different angles.

We can see in the Figure 7.10, that nodes are made based on the angle first and depending on the distance at a deeper level. The entropy gets lower through the different layers. At the end, we have, on the fourth layer, the seven classes that we want.

I tested this model with a train-test split method. It means that the data was split into 70% for training the model and 30% left to test the model. The accuracy of this model on the test set is 0.998 which is very high. It could be because of an overfitting of the model on the given training data or simply because the targets are at different places on the screen and therefore, easy to classify. In further study, it will be interesting to use another indicator of performance, such as the ROC curve. It will also be interesting to use other methods, such as random forest, which builds multiple decision trees and merges their results to improve accuracy and control.

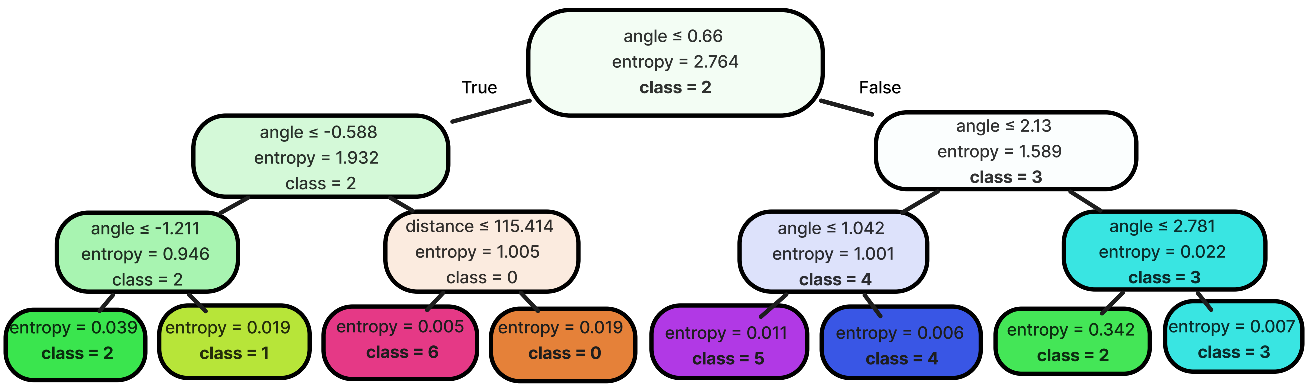


Figure 7.10: Visualisation of the decision tree to classify the 7 classes of the gaze on the screen.

Use of amplitude

As explained before, we can choose the best classifier to use, depending on the condition. However, if the gaze is on a target, with the eye tracker it is difficult to know if we are in an overt attention or split attention . To do so, the amplitude of the signal could be used.

Condition	Overt	Split 1	Split 2	Split 3
p-value	4.065e-08	2.203e-17	4.149e-16	1.198e-18

Table 7.1: Table of the p-value of amplitude of EEG data for overt and splits conditions for the shapiro-wilk test

Condition	Overt/Split 1	Overt/Split 2	Overt/Split 3
p-value	3.998e-187	9.443e-252	9.105e-161

Table 7.2: Table of the p-value of amplitude of EEG data for overt and splits conditions for the student t-test

Thus, we studied if there were differences between amplitudes for the overt attention and split attention.

- The first step was to calculate evoked (average of signal in an epoch) and to average this evoked between all subjects (N=10).
- The second step was to crop the signal between 0.25 and 0.45 in order to focus on the time windows of the P300. At this point, we have the amplitude of the signal between 0.25 and 0.45 ms for each of the electrodes averaged between all subjects.
- Finally, the average between all sensor was made in order to have for one value of amplitude for each time point for each condition.

After preprocessing the data in a format that we wanted, the next step was to calculate if there was a significant difference between these amplitudes.

To do so, we can use a Student t-test. However, to apply a t-test, it is better that the data follow a Gaussian distribution. To test, this hypothesis, we can use a Shapiro–Wilk test which tests the null hypothesis that a sample came from a normally distributed population.

Therefore, we conclude that our data does not follow a normal distribution (Table 7.1). Indeed, p-values are all inferior to 0.05, which means that the H0 hypothesis is rejected. Otherwise, under weak assumptions, the central limit theorem ensures that for large sample sizes, the sample means will approximate a normal distribution, even if the data in each group is not normally distributed. Hence, we can do a Student t-test in order to test if there is a significant difference in amplitude between conditions.

P-values show in Table 7.2 means that between overt and each split condition there is a significative difference which can be visualised on the Figure 7.11.

The Figure 7.11 is a box plot. A box plot is a method of visualisation that sums up five information : the minimum, which is the lowest point of the dataset, the first quartile, which is the median of the lower half of the dataset (25%), the median, which is the middle value of the dataset, the third quartile, which is the median of the upper half of the dataset (75%) and the maximum, which is the highest value of the dataset.
We can clearly see that there is a significant difference between conditions, and that the closer the visuospatial attention is to the gaze, the higher is the amplitude.
Thus, depending on the signal, we can determine in what condition we are.

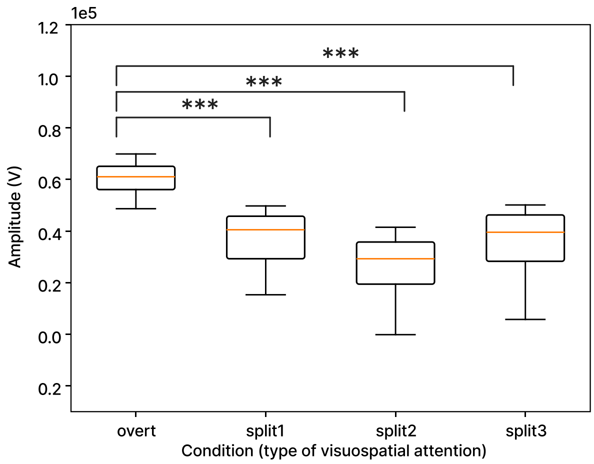


Figure 7.11: Box plot of the amplitude of the signal depending on the type of visuospatial attention; *** = p-value<0.001 for the Students-t-test.

Finally, thanks to eye tracker data and EEG data, we will select the right classifier to apply.

7.2.6 Planned and future work

In the previous section, I showed first leads to implement methods for data fusion.
Nevertheless, there are some limitations that can be pointed out and will be corrected at the end of the internship.
P300 amplitude decreases with tiredness and the length of the experiment. It can also be influenced by factors such as mental workload and distractions, which are not directly related to the mode of visuospatial attention ([Luck and Kappenman, 2013]).
Furthermore, finding a significant difference between the amplitude conditions can hint towards the condition, but nothing can be deduced for sure. A classifier for attention

conditions should be developed with amplitude as a feature. The presence or not of VEP will also be informative of the mode of visual attention and be used in this classifier.

After determining the condition with this classifier, the last step will be to apply the right classifier depending on this result in order to see if it can enhance the performance.

7.3 Other activities

7.3.1 CORTICO conference

In May, I had the chance to attend a conference in Nancy : CORTICO (COllectif pour la Recherche Transdisciplinaire sur les Interfaces Cerveau-Ordinateur).
CORTICO is an association that aims to promote research and innovation in the BCI field. Every year, they organise a conference with all the members of the French BCI community in one town in France. It lasted two days during which they had one day dedicated to young researchers when they could present their work during a presentation or poster. There were also some guests from the Netherlands who presented some talks around BCI in different fields, such as statistics (professor. Robert Oosterhuys) or design (professor. Maryam Alimardani)
I presented a poster this year (Appendix 3) on the data fusion subject (section 6.2). I was involved in the entire process, including submitting an abstract, the review and acceptance process, preparing a poster and a speech to present it and at last, presenting my poster during a session. I also had to prepare a flash presentation of 50 seconds in order to promote my work.
It was very interesting to be able to talk about my work with other researchers in the field, which allowed me to get some feedback and ideas for the rest of my internship.

7.3.2 Discussion with school girls

In order to promote science, especially the academic side of it, a group of 30 school girls of 11 years old came to the CRIStAL laboratory. The goal was to present what research is and also to inspire young girls to continue in the scientific path.
For that, some discussions were planned with women researchers and students, including me. I was able to present my educational path and, therefore, the ENSC and what is cognitic. But also, to present what a BCI is.

Explaining science to young people was a good exercise, since explaining a difficult principle as a BCI with easy understanding was kind of a challenge. Science outreach is an important part of a scientist's research job.

7.3.3 Demonstration for high school students

Since last year, during several hackathons, I have had the chance to be part of the BrainKart project. BrainKart project is a project that aims to promote and popularise what a BCI is. To do so, people can try to wear an EEG cap and controll the speed of a robot.
Actually, there are several characterised brain signals in the brain that correspond to different frequency ranges. The one that interests us is the alpha waves, which corresponds to 8 to 12 Hz and characterise a state of relaxation. The more relaxed a person is, the higher the amplitude of the alpha wave is. By focusing and performing cognitively demanding tasks, it is possible to get a lower amplitude for these types of waves. Thus, the speed of the robot will be inversely correlated with the amplitude of these waves, the more focused the user is, the faster the robot will go.
In the first year of high school, all students have an internship to complete, hence, there were three groups of students that were in the CRIStAL laboratory for two weeks. I proposed this activity for one of these groups in order to make them discover what a BCI is. During two hours, we presented what a BCI is and made them perform this demonstration.

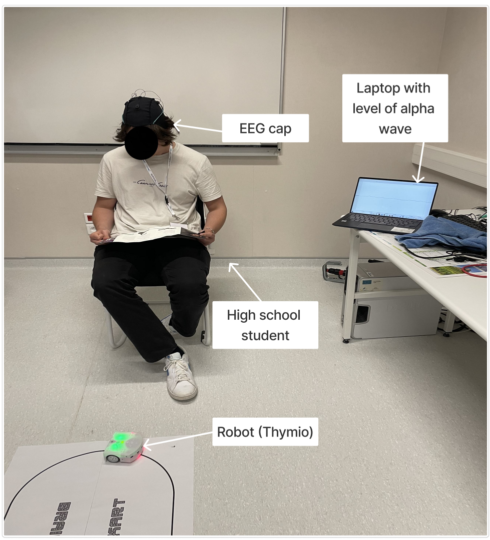


Figure 7.12: Photo of a high school student using BrainKart during the activity

7.4 Effective planning

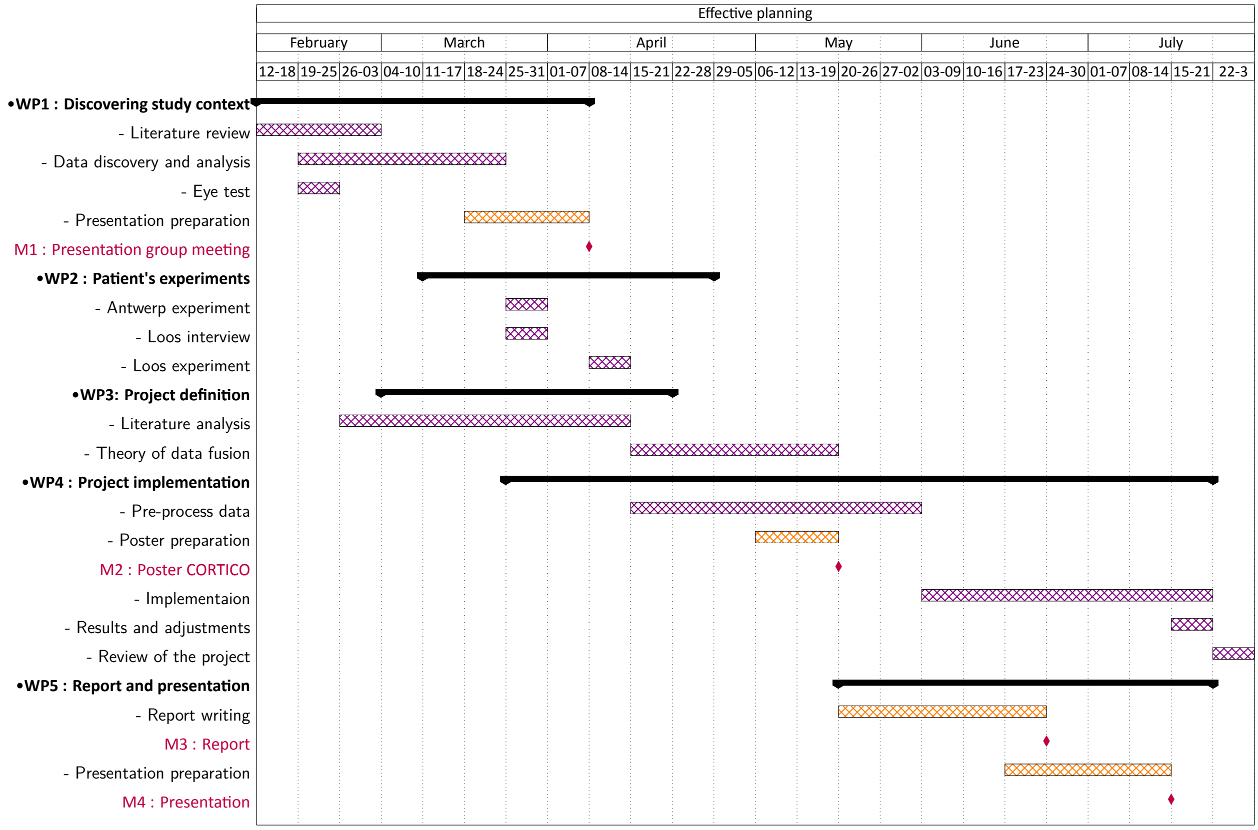


Figure 7.13: Effective Gantt planning ; in red : milestones (M), in violet : task grouped in work packages (WP), in orange : preparation of milestones.

Here is the effective planning, where we can find the previous section and subsection. When we compare effective and previsional planning, on the side of the experiment with patients, there were some tasks that changed with regard to the previsional planning. At first, there was the eye test (subsection 7.1.1) which was not planned but appeared necessary in the protocol after reading the literature. Secondly, as there was already data from the previous experiment, I started to discover data earlier than expected, it allows switching between reading articles and analyse data.

Regarding the data fusion project, the proposal was too short to define the subject. All the literature and reading took longer than expected. Indeed, data fusion was a totally new subject for me, so it was necessary to gain some knowledge on it.

8. Market study

As this is a research project for a very specific application (independent-gaze BCI), there is no direct competition for what I have done since this is at an early stage of conception, there is no intention to commercialise it in a close future. However, the paradigm with ERP-based BCI and Hex-o-Spell matrix is not the only that exists. Hence, I will present in this part, some other BCI types used for communication with their advantages and limitations.

8.1 VEP BCIs

VEP BCIs are BCI based on VEP and are used to communicate. There are multiple types of VEPs BCI, but the most widely used are the Steady-State VEPs (SSVEPs) and the code-modulated VEPs (c-VEPs).

8.1.1 SSVEP BCI

The Steady State Visually Evoked Potential (SSVEP) is the visual cortex's oscillatory response that shares the same fundamental frequency as the stimulus that initiated it, such as a screen flashing, for example. Indeed, when the retina is excited by a specific frequency, there is ERP that elicits at the same frequency.

The **advantage of the SSVEP** are that it tolerates artifacts such as blinking, that it is robust to variations between user performances. The **disadvantages of the SSVEP** is that it can cause visual fatigue due to the light twinkling and the change of contrast [Wang et al., 2021]. It means that even if performance is good, it can be unadapted to the person using it ([Müller and Hillyard, 2000]).

In order to deal with these limitations, a similar paradigm as SSVEP has been created, such as the SSMVEP (Steady-State Motion VEP) which combines a SSVEP BCI and a motion-VEP BCI (instead of a flickering light, the visual stimulus involves motion). This system combines the steady-state aspect with motion, meaning the brain's response is to a steady, repetitive motion.
This type of BCI allows the removal of the drawbacks of SSVEP and [Stawicki et al., 2021] showed that with the SSMVEP you can reach 70% of accuracy for most users without training

sessions.

8.1.2 c-VEP BCI

The c-VEPS (code-VEP) were originally described in [Sutter, 1984] but since other studies have reproduced the results. In this type of BCI, each target is periodically modulated or flashed within one stimulus period.

The **advantage of the c-VEP** is that it is the best (comparing to SSVEP and SSMVEP) in terms of performance and user-evaluation ([Volosyak et al., 2020]). However, the **disadvantage of the c-VEP** is that it is a training-free data method, that does not require training data and allows new users to use it without calibration, is not feasible.

Finally, we have seen that both c-VEPs and SSVEPs have their advantages and limitations. On one hand, SSVEP allows great performance but is not very user-friendly. But with a similar system such as SSMVEP which allows a calibration free system. And on the other side, c-VEP which has great performance and user-friendliness, but needs a time of calibration. Indeed, when you think of someone using a BCI in their daily life, the goal is to minimize the time taken before using the BCI and thus, the training part.

8.1.3 Comparison with our system

These VEPs-system are, as we demonstrated, quite practical due to their possibility of no calibration, their good performance and their user-friendliness. There is therefore a good option for communication purposes. Nevertheless, these systems involve the control of the gaze, which is the limitation that we want to remove from our system.
In our study, for now, we do not offer an online session, but if we did, we would need a training session. In this aspect, these types of BCI are better.

8.2 Motor imagery speller

Motor imagery (MI) speller is another type of communication with a BCI. It involves another task for the user : motor imagery, which refers to the mental simulation of movement without any actual physical movement. In this context, users imagine performing specific motor actions, such as moving a hand or foot, which generate distinct brain activity patterns. [Blankertz et al., 2006], introduced the Hex-o-Spell matrix with a motor imagery pattern,

where the user can select a target by imagining a movement of the hand or the foot. In fact, the imagination of a movement changes the direction of an arrow that points to a specific target.
Actually, compared to previous keyboards, this speller does not require external stimuli such as a flash.

The **advantage of MI speller** is that it does not require external stimulation, but its **disadvantage** is that it allows a lower performance than visual BCIs.

8.2.1 Comparison with our system

This speller allows, as well as the one we used, not using VEP. A person with an oculomotor problem is able to imagine a movement of the hand or foot. However, this type of speller is less studied than others due to its lack of performance.

8.3 Invasive BCI for communication

Invasive BCI involves the implantation of electrodes in the brain, compared to using an EEG. This method allows for a less noisy signal and better performance.
Indeed, thanks to invasive BCI, they are studying the real-time synthesis of imagined and whispered speech ([Angrick et al., 2021]).

On this side of BCI, we can cite Elon Musk's Neuralink which is a system of invasive BCI that recently gained some traction.

9. Analysis of Sustainable Development and Social Responsibility

9.0.1 Sustainable Development

About the question of sustainable development, the laboratory is quite aware of this question. Here are some examples of the action of CRIStAL on this question.
The lights are automatic, which permits not having open light when a room is unoccupied. In the social room, we can see many ways to recycle the waste you want to throw in a bin. They are also reusing the rainwater for toilet flushing and using some solar panels for electricity. In addition, during the month of May, there was the ”Mai à vélo” in which the challenge was to go to work only with a bike. There were ads everywhere in the laboratory to promote these

events, and even some helped to achieve this goal. For example, they provide a map of itinerary that were possible for Lille Center to the laboratory. Finally, as the laboratory is in collaboration with the engineering school Polytech, it was possible to test some electrical cars and bikes that they were lending.

9.0.2 Social Responsability

As the applications of BCI are, for some part, allowing highly disabled people to be able to communicate. We can say that in terms of improving health and taking into account the handicap, in the BCI team it is a success. Indeed, in the process, as I explained before, we met some locked-in syndrome patients and therefore took into account what they needed to communicate and be sure that they are comfortable.
Moreover, when I met the eleven-years-old school girls, it was to promote women in science, which is very important. Indeed, women are still underrepresented in the science field, that is why, organising meetings like this could be very beneficial.

10. Conclusion

The goal of this internship was to study an independent-gaze BCI for patients in locked-in states who have oculomotor problems. Our hypothesis was that having an independent-gaze hybrid BCI with EEG and eye tracking data would enhance performance and allow for a more reliable BCI.

Experiments have been carried out on patients with different conditions. A summary of the literature regarding data fusion methods and their link with BCI has also been conducted. We explored different possibilities for data fusion and methods. Our first leads show that the mixed approach could be the next step and allow for enhanced performance. However, it is important to acknowledge that there was a significant workload for this study since I had no knowledge on this subject. Due to time constraints, choices were made to prioritise testing at least one method : the mixed approach. But there are some other methodologies that could be very interesting to look at, such as the decision-level approach of [Kalika et al., 2017] presented in the methodology.

Regarding the planning, most of the planned tasks were carried out, though some experienced delays. In fact, organisation and planning in a laboratory differ significantly from those in a company. In a research laboratory, the planing is based on your own progress and sometimes on strict deadlines for a submission, for example. Contrary to a company, where tasks are planned precisely related to other coworkers or clients.

Finally, this internship confirms my intention to pursue the research field with a PhD in order to have an academic career.

References

[Abul Hassan et al., 2023] Abul Hassan, M., Aldridge, C. M., Zhuang, Y., Yin, X., McMurry, T., Rohde, G. K., and Southerland, A. M. (2023). Approach to Quantify Eye Movements to Augment Stroke Diagnosis With a Non-Calibrated Eye-Tracker. IEEE Trans. Biomed. Eng., 70(6):1750–1757.

[Aloise et al., 2012] Aloise, F., Aricò, P., Schettini, F., Riccio, A., Salinari, S., Mattia, D., Babiloni, F., and Cincotti, F. (2012). A covert attention P300-based brain–computer interface: Geospell. Ergonomics, 55(5):538–551.

[Angrick et al., 2021] Angrick, M., Ottenhoff, M. C., Diener, L., Ivucic, D., Ivucic, G., Goulis, S., Saal, J., Colon, A. J., Wagner, L., Krusienski, D. J., et al. (2021). Real-time synthesis of imagined speech processes from minimally invasive recordings of neural activity. Communications biology, 4(1):1055.

[Aricò et al., 2014] Aricò, P., Aloise, F., Schettini, F., Salinari, S., Mattia, D., and Cincotti, F. (2014). Influence of P300 latency jitter on event related potential-based brain–computer interface performance. J. Neural Eng., 11(3):035008.

[BCI society, 2024] BCI society (May, 23 2024). BCI Definition | bcisociety.org — bcisociety.org. https://bcisociety.org/bci-definition/. [Accessed 17-06-2024].

[Blankertz et al., 2006] Blankertz, B., Dornhege, G., Krauledat, M., Schröder, M., Williamson, J., Murray-Smith, R., and Müller, K.-R. (2006). The berlin brain-computer interface presents the novel mental typewriter hex-o-spell.

[Blankertz et al., 2007] Blankertz, B., Krauledat, M., Dornhege, G., Williamson, J., Murray-Smith, R., and Müller, K.-R. (2007). A note on brain actuated spelling with the berlin brain-computer interface. In Universal Access in Human-Computer Interaction. Ambient Interaction: 4th International Conference on Universal Access in Human-Computer Interaction, UAHCI 2007 Held as Part of HCI International 2007 Beijing, China, July 22-27, 2007 Proceedings, Part II 4, pages 759–768. Springer.

[Bouma, 1970] Bouma, H. (1970). Interaction effects in parafoveal letter recognition. Nature, 226(5241):177–178.

[Cheng et al., 2020] Cheng, S., Wang, J., Zhang, L., and Wei, Q. (2020). Motion imagery-bci based on eeg and eye movement data fusion. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 28(12):2783–2793.

[Dash, 2024] Dash, S. (Last reviewed on November, 2022 ; accessed on June 18, 2024). Decision trees explained-entropy, information gain, gini index, ccp pruning..

[Dempster, 1967] Dempster, A. P. (1967). Upper and lower probability inferences based on a sample from a finite univariate population. Biometrika, 54(3-4):515–528.

[Frenzel et al., 2011] Frenzel, S., Neubert, E., and Bandt, C. (2011). Two communication lines in a 3 × 3 matrix speller. J. Neural Eng., 8(3):036021.

[Frikha and Moalla, 2015] Frikha, A. and Moalla, H. (2015). Analytic hierarchy process for multi-sensor data fusion based on belief function theory. European Journal of Operational Research, 241(1):133–147.

[Ge et al., 2022] Ge, X., Pan, Y., Wang, S., Qian, L., Yuan, J., Xu, J., Thakor, N., and Sun, Y. (2022). Improving intention detection in single-trial classification through fusion of eeg and eye-tracker data. IEEE Transactions on Human-Machine Systems, 53(1):132–141.

[Graimann et al., 2010] Graimann, B., Allison, B., and Pfurtscheller, G. (2010). Brain–computer interfaces: A gentle introduction. Brain-computer interfaces: Revolutionizing human-computer interaction, pages 1–27.

[Gramfort et al., 2013] Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., and Hämäläinen, M. (2013). Meg and eeg data analysis with mne-python. Frontiers in Neuroscience, 7.

[Hong and Khan, 2017] Hong, K.-S. and Khan, M. J. (2017). Hybrid Brain–Computer Interface Techniques for Improved Classification Accuracy and Increased Number of Commands: A Review. Front. Neurorobot., 11:35.

[Kalika et al., 2017] Kalika, D., Collins, L., Caves, K., and Throckmorton, C. (2017). Fusion of p300 and eye-tracker data for spelling using bci2000. Journal of Neural Engineering, 14(5):056010.

[Kapoula et al., 2010] Kapoula, Z., Yang, Q., Vernet, M., Bonfils, P., and Londero, A. (2010). Eye movement abnormalities in somatic tinnitus: Fixation, smooth pursuit and optokinetic nystagmus. Auris Nasus Larynx, 37(3):314–321.

[Kattah et al., 2009] Kattah, J. C., Talkad, A. V., Wang, D. Z., Hsieh, Y.-H., and Newman-Toker, D. E. (2009). HINTS to Diagnose Stroke in the Acute Vestibular Syndrome: Three-Step Bedside Oculomotor Examination More Sensitive Than Early MRI Diffusion-Weighted Imaging. Stroke, 40(11):3504–3510.

[Klir, 1993] Klir, G. J. (1993). Developments in uncertainty-based information. In Advances in computers, volume 36, pages 255–332. Elsevier.

[Klir and Parviz, 1992] Klir, G. J. and Parviz, B. (1992). A note on the measure of discord. In Uncertainty in Artificial Intelligence, pages 138–141. Elsevier.

[Leblanc, 2024] Leblanc, B. (Acessed on June 10, 2024). Présentation de l’ensc - ensc-bordeaux inp. https://ensc.bordeaux-inp.fr/fr/presentation-de-l-ensc: :text=La

[Lefevre, 2012] Lefevre, E. (2012). Fonctions de Croyance: de la théorie à la pratique. PhD thesis, Université d’Artois.

[Lim et al., 2022] Lim, J. Z., Mountstephens, J., and Teo, J. (2022). Eye-Tracking Feature Extraction for Biometric Machine Learning. Front. Neurorobot., 15:796895.

[Liu, 2015] Liu, K. (2015). Dual-Sensor approaches for real-time robust hand gesture recognition. PhD thesis.

[Liu, 2006] Liu, W. (2006). Analyzing the degree of conflict among belief functions. Artificial intelligence, 170(11):909–924.

[Luck and Kappenman, 2013] Luck, S. J. and Kappenman, E. S. (2013). The Oxford handbook of event-related potential components. Oxford university press.

[Mowla et al., 2017] Mowla, M. R., Huggins, J. E., and Thompson, D. E. (2017). Enhancing P300-BCI performance using latency estimation. Brain-Computer Interfaces, 4(3):137–145.

[Müller and Hillyard, 2000] Müller, M. M. and Hillyard, S. (2000). Concurrent recording of steady-state and transient event-related potentials as indices of visual-spatial selective attention. Clinical Neurophysiology, 111(9):1544–1552.

[Ng et al., 2021] Ng, P. M., Abdullah, J. M., Idris, Z., Ghani, A. R. I., and Abdul Halim, S. (2021). What are Your Eyes Revealing? The Contemporary Bedside Neuro-Ophthalmological Examination. MJMS, 28(5):142–148.

[NIH, 2024] NIH (Last reviewed on September 22, 2022 ; accessed on June 10, 2024). Stroke. https://www.nhs.uk/conditions/stroke/. National Health Service (NHS)).

[NINDS, 2024] NINDS (Last reviewed on March 06, 2024 ; accessed on June 10, 2024). What is friedreich ataxia ? https://www.ninds.nih.gov/health-information/disorders/friedreich-ataxia. National Institute of Neurological Disorders and Stroke (NINDS).

[Peirce et al., 2019] Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo, H., Kastman, E., and Lindeløv, J. K. (2019). Psychopy2: Experiments in behavior made easy. Behavior research methods, 51:195–203.

[Shafer, 1976] Shafer, G. (1976). A mathematical theory of evidence, volume 42. Princeton university press.

[Smets and Kennes, 1994] Smets, P. and Kennes, R. (1994). The transferable belief model. Artificial intelligence, 66(2):191–234.

[Sosulski and Tangermann, 2022] Sosulski, J. and Tangermann, M. (2022). Introducing block-toeplitz covariance matrices to remaster linear discriminant analysis for event-related potential brain–computer interfaces. Journal of neural engineering, 19(6):066001.

[Stawicki et al., 2017] Stawicki, P., Gembler, F., Rezeika, A., and Volosyak, I. (2017). A novel hybrid mental spelling application based on eye tracking and ssvep-based bci. Brain sciences, 7(4):35.

[Stawicki et al., 2021] Stawicki, P., Rezeika, A., and Volosyak, I. (2021). Effects of training on bci accuracy in ssmvep-based bci. In Advances in Computational Intelligence: 16th International Work-Conference on Artificial Neural Networks, IWANN 2021, Virtual Event, June 16–18, 2021, Proceedings, Part II 16, pages 69–80. Springer.

[Sutter, 1984] Sutter, E. E. (1984). The visual evoked response as a communication channel. In Proceedings of the IEEE Symposium on Biosensors, pages 95–100.

[Thompson et al., 2012] Thompson, D. E., Warschausky, S., and Huggins, J. E. (2012). Classifier-based latency estimation: a novel way to estimate and predict bci accuracy. Journal of neural engineering, 10(1):016006.

[Treder and Blankertz, 2010] Treder, M. S. and Blankertz, B. (2010). R(Cese)aorchvert attention and visual speller design in an ERP-based brain-computer interface.

[Treder et al., 2011] Treder, M. S., Schmidt, N. M., and Blankertz, B. (2011). Gaze-independent brain–computer interfaces based on covert attention and feature attention. J. Neural Eng., 8(6):066003.

[Van Den Kerchove et al.,] Van Den Kerchove, A., Si-Mohammed, H., Van Hulle, M. M., and Cabestaing, F. Correcting for ERP latency jitter improves gaze-independent BCI decoding. (forthcoming).

[Volosyak et al., 2020] Volosyak, I., Rezeika, A., Benda, M., Gembler, F., and Stawicki, P. (2020). Towards solving of the Illiteracy phenomenon for VEP-based brain-computer interfaces. Biomed. Phys. Eng. Express, 6(3):035034.

[Wang et al., 2021] Wang, P., Song, Z., Chen, H., Fang, T., Zhang, Y., Zhang, X., Wang, S., Li, H., Lin, Y., Jia, J., Zhang, L., and Kang, X. (2021). Application of Combined Brain Computer Interface and Eye Tracking. In 2021 9th International Winter Conference on Brain-Computer Interface (BCI), pages 1–5, Gangwon, Korea (South). IEEE.

[Wolpaw et al., 2006] Wolpaw, J. R., Loeb, G. E., Allison, B. Z., Donchin, E., do Nascimento, O. F., Heetderks, W. J., Nijboer, F., Shain, W. G., and Turner, J. N. (2006). Bci meeting 2005-workshop on signals and recording methods. IEEE Transactions on neural systems and rehabilitation engineering, 14(2):138–141.

[Woody, 1967] Woody, C. D. (1967). Characterization of an adaptive filter for the analysis of variable latency neuroelectric signals. Medical and biological engineering, 5:539–554.

[Zhang et al., 2010] Zhang, L., He, W., He, C., and Wang, P. (2010). Improving mental task classification by adding high frequency band information. Journal of medical systems, 34:51–60.

Appendix

Contents of the appendix

- Figure 1
- Glossary
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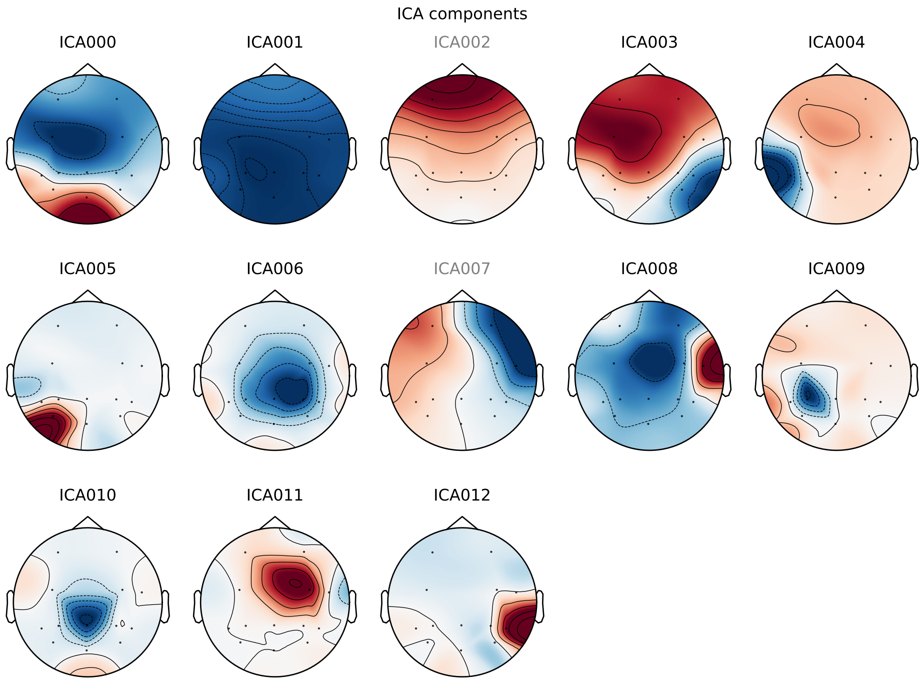


Figure 1: Independent Component Analysis of a subject ; ICA002 and ICA007 : eye blink component.

Glossary

artifact

Artifacts are unwanted noise in EEG signals. For example, muscular activity generates higher amplitude signals than brain waves, so when a subject moves, these muscular signals are referred to as artifacts . 12, 23, 40

BCI

A Brain Computer Interface (BCI) detects the brain activity linked to the user's intentions and converts it into control signals used for BCI applications [Graimann et al., 2010]. 1, 5, 7, 8, 11–14, 21, 24

CBLE

Introduced by [Thompson et al., 2012], the Classifier-Based Latency Estimation (CBLE) is an estimation algorithm that allow to del with the latency jitter ERPs . 11, 13

classifier

An algorithm that automatically sorts or categorizes data into one or more classes. 10, 11, 13, 14, 25, 27, 28, 36

covert attention

The subject's gaze is fixed in the middle of the screen (where there is no target) while their visuosptial is focused on the target they wish to select. 9–11, 13, 27, 28, 31

EEG

Electroencephalography (EEG) is a method to record electrical acivity from the brain. 11, 14, 26, 42

eigenvector

An eigenvector is a vector that does not change direction when a linear transformation is applied to it. [https://en.wikipedia.org/wiki/Eigenvalues_and_eigenvectors]. 26, 27

EOG

Electrooculography (EOG) is a technique used to measure the corneo-retinal standing potential, which exists between the front and back of the human eye. [https://en.wikipedia.org/wiki/Electrooculography]. 11, 12, 17, 23, 26, 27

epoch

An epoch refers to a specific time window of a type of data (here EEG data, eye tracker data or EOG data). 13, 23, 27, 31, 35

ERP

An event-related potential (ERP) is a brain response time locked to a particular sensory, cognitive, or motor event. 5, 31

ERP-based BCI

BCI that relies on ERP . 8–10, 12, 40

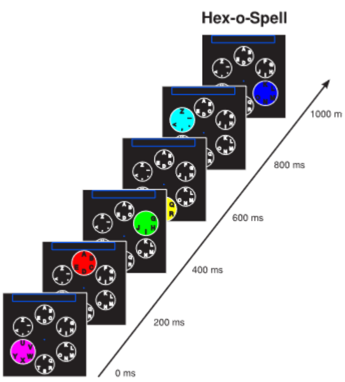
eye tracker

Technology that allows to detect the movement and positions of the eyes. 6, 11–14, 17, 24, 26–28, 31, 34, 36

fixation

Maintening gaze on the same location. 13, 16, 17, 32

Hex-o-Spell matrix



, from [Treder et al., 2011] . 8–10, 33, 40, 41, 58

hybrid BCI

An hybrid BCI is a BCI that combines one or multiple modality with EEG. 12

ICA

In signal processing, independent component analysis (ICA) is a computational technique used to decompose a multivariate signal into its additive subcomponents. [https://en.wikipedia.org/wiki/Independent_component_analysis]. 23

impedance

Impedance is the opposition to the flow of alternating current, similar to the bioelectrical neural activity generated by the brain. It consists of two components: resistance and reactance. In the context of electrode impedance, the primary interface between the equipment (i.e., electrode) and the human body is the skin's surface. [https://www.interacoustics.com/academy/evoked-potentials/abr-training/electrode-impedance:~:text=Description,human%20is%20the%20skins%20surface.]. 23

kernel density

Kernel density is a way to estimate the probability distribution of a dataset by smoothing out the data points.[https://en.wikipedia.org/wiki/Kernel_density_estimation]. 27

latency jitter

Variation in timing of brain responses. 10, 11

likehood distribution

Likelihood distribution shows how likely different outcomes are, given a set of observed data.[https://en.wikipedia.org/wiki/Likelihood_function]. 27

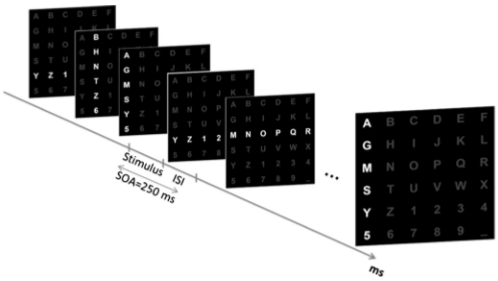
locked-in syndrom

Syndrom where patients are paralised in most of all the body, including a loss of the language . 5, 8, 19

LS

The method of Least Squares (LS) is a parameter estimation technique in regression analysis that aims to minimise the sum of the squares of the residuals, where a residual is the difference between an observed value and the value predicted by the model for each individual data point.[https://en.wikipedia.org/wiki/Least_squares] . 27

Matrix speller



, from [Aricò et al., 2014] . 8, 9

MI

Motor imagery (MI) speller is another type of communication with a BCI. It involves another task for the user : motor imagery, which refers to the mental simulation of movement without any actual physical movement.

. 26

min-max method

Min-Max method is a method used to normalise data in the simplest way by rescaling the range of features to the range in [0, 1] .[https://en.wikipedia.org/wiki/Feature$_{s}caling)].26$

N200

VEP that is negative and elicits 200 ms after the stimulus. 10

overt attention

The subject's gaze and visuosptial are both directed at the same target . 9–11, 13, 27, 34, 35

P300

ERP that is positive and elicits after 300 ms after the arrival of stimuli when this one is surprising. 5, 10, 23, 27, 31

ROC

A Receiver Operating Characteristic (ROC) curve is a graphical plot that illustrates the performance of a binary classifier model at varying threshold values. It is a plot of the true positive rate (TPR) against the false positive rate (FPR) at each threshold setting. [https://en.wikipedia.org/wiki/Receiver_operating_characteristic]. 34

saccade

A saccade is a rapid, coordinated movement where both eyes shift quickly between different fixation points in the same direction . 13, 16, 17, 32

smooth pursuit

Type of eye movement where eyes are fixed on a mooving movement. 16, 17

split attention

The subject directs their gaze at one target while focusing their visuosptial on another target, which is the one they intend to select. There are three conditions involving the split, where the two targets are positioned at different distances . 9, 13, 34, 35

SSVEP

Steady State Visually Evoked Potential (SSVEP) a paradigm used in BCI where there are visual stimuli at specific frequency. Indeed, when he retina is excited by a specific frequency, there is ERP that elicits at the same frequency . 3, 12, 40

t-LDA

Toeplitz-LDA (t-LDA) is a classifier introduced by [Sosulski and Tangermann, 2022], in which LDA is combine with toepliz matrixes that are particular parameters. 13

VEP

Visual Evoked Potential (VEP) is the potential that elicitis in response to a visual stimulation. 3, 5, 10, 37, 40, 42

visuospatial attention

Form of attention that involves directing attention to a location in space with a specific localisation of the gaze. 8–10, 12, 18, 36, 57, 58

WCBLE

Introduced by [Van Den Kerchove et al.,], WCBLE is an algorithm that combines elements of CBLE and the Woody iteration scheme. Instead of using CBLE directly to estimate features for a second-stage classifier, CBLE latency estimation is integrated into the Woody iteration process. 11, 13

Woody iterations

Woody's algorithm ([Woody, 1967]) is a straightforward and effective method for latency estimation. 11

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