Final Doctoral Plan

An EEG-based gaze-independent visual Brain-Computer Interface

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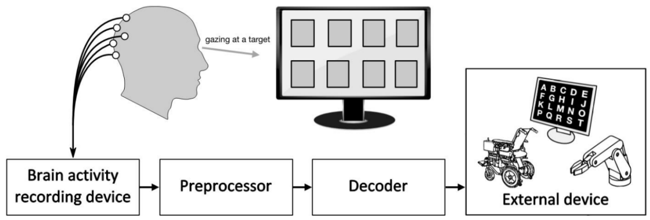

Figure 1: A visual Brain-Computer Interface illustrated. The brain activity is recorded in response to flashing targets on a screen. The signal is then preprocessed and the intent of the user is decoded by a classifier. The output can control a device.

1 Introduction

Brain-Computer Interfaces (BCIs) decode brain activity with the aim to establish a direct communication pathway bypassing speech and other forms of muscular activity. They have raised great hopes for patients devoid of these abilities, for whom BCIs can provide a means to communicate or to control devices. The quest for performant and affordable solutions is most evident in visual BCIs based on the electroencephalogram (EEG), where it has led to a gamut of increasingly sophisticated decoders and paradigms tailored to the needs of specific stimulation paradigms and use contexts. An effective and proven method is the visual event-related potential (ERP)-based oddball interface. Here, targets are shown in short pulses on a computer screen. Each time the user observes a target, an ERP is evoked, the presence of which can be detected in the EEG-signal. The ERP consists of multiple components, of which some are modulated by the attention of the user, specifically the N2 and the P3 component. Decoding this modulation allows for information transfer controlled by the user's brain activity, as sketched in Figure 1. However, visual BCIs cannot operate efficiently when the user does not direct their gaze onto the desired target [3].

This leads to an often not adressed paradox: the BCI target population consists of patients who suffer from pathologies like Amyotrophic Lateral Sclerosis (ALS), Multiple Sclerosis (MS), stroke (specifically brain-stem stroke) or traumatic brain injury, which can lead to several degrees of paralysis, or even to Locked-in Syndrome (LiS), the complete loss of muscle control with preserved consciousness. While BCIs are most attractive as a solution for these patients compared to other assistive technologies like eye-tracking, studies often report bad performance in patient populations precisely due to the lack of adequate eye motor control, or patients with gaze impairments are excluded. Table 1 reports the relatively high frequencies of eye motor problems, which can range from involuntary eye movements to control issues and even to partial or complete ophtalmoplegia. Different degrees of eye motor impairment can render visual BCIs uncomfortable or outright impossible to use. When operating a visual BCI, the usual rapid series of forced saccades followed by fixation is tiring over time, even for healthy control subjects. A suitable alternative would allow the

	ALS	MS	Stroke	DMD	SMA	LiS
Minor	50%	31%	40-70%	+	-	
Severe	33%	3%	+	-	-	98%
Complete	17%	-	+	-	-	2%

Table 1: Incidence of eye motor impairment in Brain-Computer Interface target populations: (ALS: Amyotrophic Lateral Sclerosis, MS: Multiple Sclerosis, DMD: Duchenne's Muscular Dystrophy, SMA: Spinal Muscular Atrophy, LiS: Locked-In-Syndrome).

user to keep their eyes in an at-rest position of their choice while operating the BCI. This points to the need for gaze-independent BCIs.

2 Objective

The general goal of this PhD is to tackle the gaze-dependency in visual BCIs. Traditionally, gaze-independency [5, 1] can be realized in three ways: Firstly, by avoiding visual stimulation entirely and opting for auditory or somatosensory stimulation instead. However, these alternatives often result in lower information transfer rates, increased mental effort and variable outcomes for different users. Secondly, gaze-independence can be achieved by adapting the interface to display stimuli such that they are always in the center of the field of view, by exploiting visual non-spatial attention (feature attention), or a combination thereof. These interfaces suffer equally from reduced information transfer rates. Moreover, they still rely to some extent on eye motor control, necessitating central gaze fixation. We make a distinction here between spatially organized interfaces, where multiple targets are displayed at the same time at different spatial locations, and temporally organized interfaces, like Rapid Serial Visual Presentation, where targets or small sets of targets are shown consecutively. Traditionally, spatially organized interfaces have a higher information transfer rate, but are also more gaze-dependent than temporally organized interfaces. Third, stimuli can be presented in a standard BCI paradigm, but *mental* attention can be decoded separately from *visual* attention.

This leads us to adopt a specific approach: improve the performance of a spatially organized visual oddball ERP-based brain computer interface by using a suited decoding strategy. Hence, our working hypothesis is as follows:

> *A spatially organized visual oddball ERP BCI with a suited decoder can achieve similar or higher information transfer rate in patient populations with eye motor deficits than other gaze-independent alternatives described in literature.*

To achieve our goal, we innovate on decoder development and interface design, and we collect data from healthy control subjects, which allow us to test our decoders. Finally, the findings of these experiments will be leveraged to de-

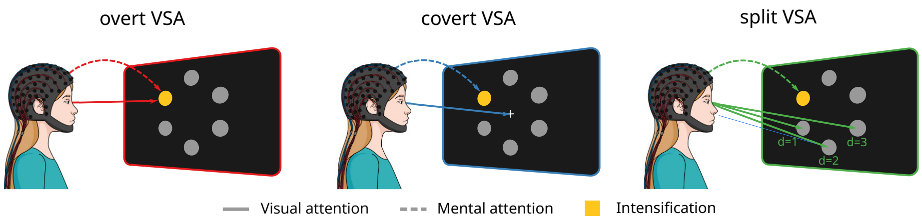

Figure 2: Visuospatial attention (VSA) conditions in our experiment. The user is asked to dissociate their visual and mental attention by gazing at a crosshair while attending a target, depending on the prompted condition.

velop a BCI for patient use, which will be tested in a case-based patient study in which both performance and user comfort will be evaluated.

3 Methods

3.1 Interface design

We designed a visual oddball interface that helps us study and adapt to the effects of eye motor impairment on the ERP, when using existing state-of-the-art decoders and on our own proposed decoders. In a first series of experiments, we recorded data with this interface from healthy participants. The goal of these experiments is to benchmark gaze-independent ERP decoding algorithms. We denote this dataset as the Covert Visuospatial Attention ERP dataset (CVSA-ERP) This study was approved by the Ethics Commission of University Hospital Leuven (S62547).

Using a hexagonal lay-out interface, similar to the visual Hex-o-Spell proposed by Treder & Blankertz [7], we present six flashing targets (without letters or symbols) to the participant while the EEG and electro-oculogram (EOG) are recorded, as well as eye gaze using eye tracking. To simulate the dissociation between the eye gaze (visual attention) and the intended target (mental attention) which could occur in patients with hampered eye motor control, healthy participants are cued to operate the BCI in specific visuospatial attention (VSA) conditions. Each subject performs 5 different VSA conditions as illustrated in Figure 2. In the overt case, subjects are instructed to gaze at the cued target they are also mentally attending; in the covert case, subjects are instructed to gaze at the center of the screen while mentally attending to the cued target. Finally, we introduce a VSA condition that is understudied in the context of gaze-independent BCI development: split VSA. In split VSA, the participant mentally focuses on one cued target while gazing at another (the distractor). Depending on the inter-target distance along the hull of the hexagon between the attended target and the distractor we discern three split VSA subconditions: the distractor is either clockwise or counterclockwise directly next to the attended target ($d = 1$), there is one other target between the attended target and the distractor ($d = 2$), or the distractor is opposite the intended target ($d = 3$).

After data collection from healthy participants and decoder development, we will carry out a patient study using a similar interface. The goal of the patient study is to evaluate the influence of eye motor deficits in patient populations on existing state-of-the-art decoders and on our proposed decoding methods.

3.2 Decoders

During this PhD, we explored different lines in decoding strategies, trying to tackle several problems that arise from gaze-independence, such as the lack or decrease in amplitude of specific ERP components, and the increased non-stationarity of the signal. As mentioned, state-of-the-art decoders have poor performance in covert attention settings. The general goal is thus to design a machine learning classifier that represents the ERP signal in a specific way, such that it becomes more robust to the problems occurring in covert attention conditions.

3.2.1 Regularized spatiotemporal beamforming

Due to the lack of the N2 component and decrease of amplitude of the P3 component in covert attention settings [7], the signal-to-noise ratio (SNR) of the ERP is lower than in overt attention settings. Therefore, a straightforward way to reach satisfactory gaze-independent decoding performance, might be by increasing overall ERP decoding performance. A more accurate classifier could yield relative improvements in those settings where performance is not yet near the achievable maximum.

Therefore, we have improved upon an in-house developed, state-of-the art ERP decoder, the spatiotemporal beamformer [10], by reformulating this classifier as a linear discrimination problem and imposing regularizing constraints by structuring the noise covariance matrix (STBF-struct). Furthermore, these regularizing constraints impose temporal stationarity on the background noise, which is of use in our next efforts to cope with the non-stationarity of the P3 signal component.

3.2.2 Classifier-based Latency Estimation with Woody iterations

Literature shows that better covert attention performance can be achieved by counteracting the non-stationarity of the P3 ERP component in covert attention settings [2]. This can be done by estimating the latency of each single-trial ERP and aligning the P3 peaks to all fall at the same moment. The resulting aligned data and the set of latencies can then be used to train a classifier that is more robust to jitter.

Existing latency estimation methods are either not applicable to the classification problem of labeling unseen data, or are not robust enough to deal with the

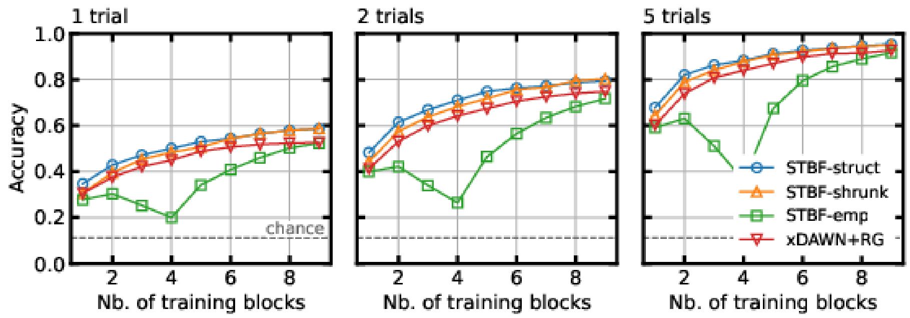

Figure 3: Target selection accuracy in the presence of limited training and evaluation data (nr. of training blocks and trials respectively). Our proposed method (STBF-struct) outperforms other state-of-the-art methods in low data availability settings and performs on par when more training data is available.

low SNR of the ERP. Classifier-based Latency Estimation (CBLE) [4] is a technique that can leverage ERP latency estimation in a decoding setting, but our results show that it yields no improvement in gaze-independent settings. We improved upon this technique and extended it to a probabilistic, iterative method named Classifier-based Latency Estimation with Woody iterations (wCBLE).

4 Obtained results

4.1 Regularized spatiotemporal beamforming

We introduced a covariance estimator using adaptive shrinkage (STBF-shrunk) and an estimator exploiting prior knowledge about the spatiotemporal nature of the EEG signal (STBF-struct). We compared these estimators with the original formulation of the spatiotemporal (STBF-emp) beamformer and a state-of-the-art Riemannian Geometry method (xDAWN+RG) in an off-line P3 detection task on an existing dataset. Our results, presented in Figure 3, show that the structured estimator results in higher accuracy in general, and specifically when training data are sparsely available. Results can be computed faster and with substantially less memory usage. Since these algorithms are not paradigm-specific, the conclusions can be generalized to other ERP-based BCI settings. These results have been published in [8].

We have tested our proposed methods and similar methods in gaze-independent and covert VSA settings, but we did not observe a relative increase in performance in these settings.

4.2 Healthy control study

The CVSA-ERP dataset consists of recordings of 15 healthy participants, mean age 26.38 ± 3.15 years. This dataset gives us insight in the ERP dynamics in overt, covert and the novel split VSA condition, and confirms our hypothesis that P3 jitter has a significant impact on performance in covert and split VSA, as well as that the amplitude effect observed for covert VSA also holds for split VSA.

We have evaluated our proposed wCBLE algorithm, the baseline CBLE algorithm and a state-of-the-art algorithm (tLDA) [6] that uses similar techniques as our proposed STBF-struct method on this dataset as well as a publicly available dataset [1] that also contains the overt and covert VSA conditions. We evaluated the BCI decoding performance in a single-trial classification experiment, as well as in a target selection experiment reflecting BCI operation. Performance was significantly different between decoders, but this result was significantly dependent on the VSA condition and the dataset. While CBLE performed overall on par with the state-of-the art method for both datasets, wCBLE was outperformed by tLDA in overt VSA decoding but outperformed tLDA for covert VSA. For the split attention conditions in the CVSA-ERP dataset, wCBLE yielded a significant improvement over CBLE and the state-of-the-art method only for d = 1 and d = 3. These results were corroborated by analyzing selection accuracy and information transfer rate, which showed similar behavior for both datasets, except in overt VSA, where accuracy and information transfer rate were not harmed by the lower single-trial selection performance of wCBLE.

To further study the gaze-independent performance of these algorithms, transfer learning between VSA conditions is studied to simulate conditions where a patient can end up in different VSA settings within a BCI operation session due to their lack of eye motor control. When trained and evaluated on overt VSA data, our proposed wCBLE algorithm results in a significant decrease in performance over the state-of-the art tLDA decoder, consistent with the within VSA condition results. For all other pairs of training and evaluation VSA condition, however, wCBLE never yields a significant decrease in performance and often significantly outperforms the other methods. Results of the within condition and transfer evaluations are show in Figure 4.

These results show that there is an interest in developing a new class of ERP-BCI interfaces for patients that prefer to rest their eyes on a chosen point on the screen, so as to avoid the effort of redirecting their eye gaze at different spatial locations on the stimulation screen. Furthermore, the performance gain in the split VSA conditions and in the between-VSA condition transfer settings are promising for patients with even less eye motor control, such as patients experiencing involuntary saccades or fatigue. An accurate decoder would allow them to comfortably operate a BCI while resting their eyes on whichever portion of the screen they prefer, even when there is another target present at that location or this location varies during the course of the experiment. Our results show that whenever the eye gaze is directed at a different spatial location other than that of the mentally attended target, the wCBLE decoder can more accurately discern the locus of mental attention, promoting in this way accurate gaze-independent decoding. This comes, however, at the cost of a decreased performance compared to overt VSA operation. We will publish these results this year as [9].

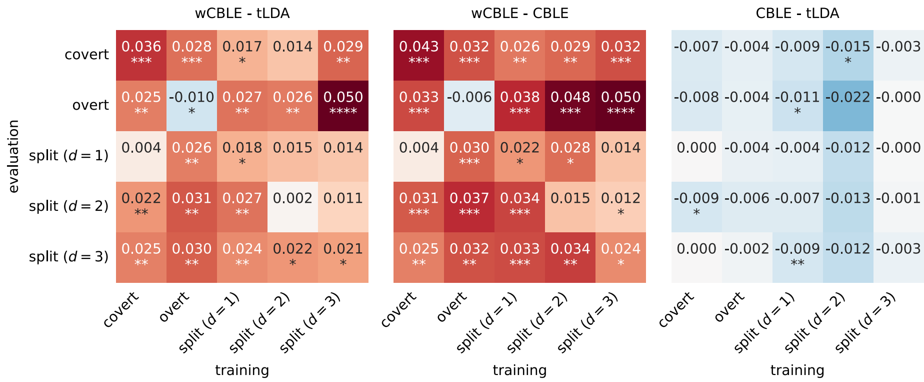

Figure 4: Relative increase or decrease in area under the reciever-operator characteristic curve (ROC-AUC) comparing our proposed decoder (wCBLE) against the original formulation of CBLE and a state-of-the-art method (tLDA) training and evaluating on different VSA conditions, simulating gaze-independent BCI operation. The diagonal represents within condition results, while-off diagonal elements show generalization to other VSA conditions. While the ROC-AUC of wCBLE is significantly lower than that of tLDA when training and evaluating in only overt VSA, for all other combinations there is no significant decrease in performance and often a significant increase.

4.3 Patient study

We gathered pilot data with the same experiment in 6 patients suffering from Duchenne's Muscular Dystrophy (DMD), allowing us to prototype and test the experiment and system used for patients. Preliminary results obtained from analyzing ERPs gathered in these experiments show similar ERP dynamics in this patient group as observed in healthy participants. It is worth noting that, due to the nature of their condition, these patients do not suffer from eye motor impairment. They will be included in the patient study as a control group representing patients with a neurological condition yet with preserved eye movement.

5 Planned experiments

In the following year, we will continue to gather patient data. In this multicenter study, we are actively recruiting patients at UZ Leuven, CHU Liège and the TRAINM neurorehabilitation clinic in Antwerp. We have also submitted a proposal for ethical approval to the ethical commission at CHU Lille, where we will recruit patients when our protocol is approved. We aim to carry out a case-based study with a small number of eye-motor control deficient patients ($N = 5$), since the format of the experiment and the possibilities of conducting it depend heavily on the severity of the paralysis of the patient, their degree of eye motor control and other confounding factors due to their disease.

The experiment for these patients and for control patients will consist of two sessions. In the off-line session, we will gather benchmarking data in a similar manner to the healthy control study. As in the healthy subject study, the gaze position will be cued to match the overt, covert and split VSA conditions for part of the experiment, to the extent where the user is able to follow the instructions given their pathology. Additionally, this session will include runs where the gaze is uncued, and the patient is allowed to direct their gaze as they deem most comfortable. Performance of several decoders will be evaluated in these conditions. The eye movement pattern will also extensively be evaluated, allowing us to use it as a covariate in the analysis of decoder performance. Depending on evaluation of the ERP signal, decoder performance and the eye movements, a patient can be included in a second session of this study. Data from the first sessions from all participants will be used to develop the most suited decoder for the second session.

In the second, on-line session, we will apply a decoder in real time to the recorded EEG signal, allowing us to prompt the patient with the target that was decoded from their selection, as would happen when actually using a BCI for communication or control. This feedback loop and the changes in the EEG signal over time will have effects on decoding performance and signal characteristics, which necessitates studying BCI operation in real-time to be able to draw conclusions about real-world BCI operation. In this on-line session, we will study the accuracy and information transfer rate of our proposed system, allowing us to compare it to state-of-the art alternatives. Additionally, we will study the comfort or discomfort the patient experienced while operating this system, with the help of the NASA Task Load Index questionnaire.

6 Remarks

This research suffered delays due to the COVID-19 pandemic. Because of sanitary guidelines, it was not possible to start experiments until the second year of this PhD. We adjusted our research plan to this situation, prioritizing decoder development early in the PhD.

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