

Comparing the Effect of Different Electrode Subsets on P300 Speller Performance

1st Sandra-Carina Noble

*Department of Electronic Engineering
Maynooth University
Maynooth, Ireland
sandracarina.noble.2017@mumail.ie*

2nd Tomás Ward

*Insight SFI Research Centre
for Data Analytics
Dublin City University
Dublin, Ireland
tomas.ward@dcu.ie*

3rd John V. Ringwood

*Department of Electronic Engineering
Maynooth University
Maynooth, Ireland
john.ringwood@mu.ie*

Abstract—The P300 speller is a widely used application in brain-computer interface research. It has been demonstrated that the P300 speller can serve as a neurofeedback training tool for attention enhancement by gradually increasing the difficulty of the spelling task. This adaptive approach makes it harder for users to spell words correctly, encouraging them to improve their attention to counteract the increasing difficulty. Therefore, the adaptive P300 speller has the potential to serve as a treatment option for children with ADHD, elderly patients with dementia, and as a cognitive enhancement tool for healthy adults. However, the training length, including setup time, needs to be quick to ensure user acceptability. This study investigates the effect of different electrode subsets on P300 speller performance, with and without the use of the xDAWN spatial filter. Results indicate that the xDAWN spatial filter can improve performance with many electrodes but can decrease results with fewer than eight electrodes. For scenarios where near-perfect performance is crucial and many electrodes are available, a set of 16 electrodes with the xDAWN spatial filter is recommended. For situations where cost and setup time are a concern and lower performances are acceptable, using six electrodes without the spatial filter were found to be sufficient.

Index Terms—P300 speller, brain-computer interface, BCI, electroencephalography, EEG, xDAWN, OpenViBE

I. INTRODUCTION

The P300 speller is a well-known brain-computer interface (BCI) application that was developed in the 1980s by Farwell and Donchin [1]. The speller works by presenting the user with a grid of symbols, where each row and column is highlighted randomly, and the user can select a symbol by counting each time the target symbol is highlighted, producing a P300 wave. The P300 speller has traditionally been used as a communication tool for people with paralysis, but has also been widely used to control computers [2], [3], robots [4], or smart home appliances [5], [6]. The popularity of the speller lies in its ease of use, as users can generally control the speller successfully with little training. It is therefore often implemented in open-source BCI software

such as OpenViBE [7] or BCI2000 [8], making it easy for researchers to use.

Recently, it was demonstrated that the P300 speller can be used as an effective neurofeedback training tool for attention enhancement in healthy adults [9]. By reducing the number of flashes per row and column based on the user's performance, the P300 speller challenges the user to improve their attention and produce a stronger P300 signal. This works because decreasing the number of flashes reduces the signal-to-noise ratio (SNR), making it more difficult for the user to spell words correctly. This type of neurofeedback training has potential applications for individuals with ADHD, dementia, or for maintaining brain fitness in healthy individuals [9]. Neurofeedback training can be time-consuming, which can limit its acceptability, particularly among healthy individuals who may not be as motivated to use it as those using it for treatment. One way to accelerate the adaptive P300 speller for attention training is by reducing the number of flashes per row and column more quickly. However, the time required to set up the EEG cap is another factor that affects the duration of the training. Reducing the number of electrodes used can speed up the process and reduce the cost of experiments, but it often comes at the expense of performance in the BCI, which is why electrodes need to be chosen carefully.

There have been numerous studies investigating the effect of electrode selection on P300 speller performance. Some studies utilize spatial filters to determine the optimal electrode set for each subject, such as [10]–[12]. Other studies determine the electrode set empirically, as in [13]. Interestingly, Ludwig and Kong [13] found that the optimal number of electrodes varies across subjects, with some subjects requiring only 3 electrodes while others need up to 10 out of 14 electrodes to reach their best performance. All studies mention that the most commonly used electrodes are in parietal and occipital locations. Personalizing the electrode set generally results in better performance, but also means that larger electrode sets are required, and data with this larger set need to be collected for all subjects before experiments with the small electrode set can be conducted. This may not be practical or feasible in clinical or commercial

This research is supported by the Irish Research Council under project ID GOIPG/2020/692 and Science Foundation Ireland under grant number SFI/12/RC/2289_P2.

settings. Krusienski et al. [14] report that a 6-electrode set (Fz, Cz, Pz, PO7, PO8, Oz) used across subjects leads to comparable or better performance than a 19-electrode set. Speier et al. [15] found that the set consisting of PO7, PO8, POz, and CPz is sufficient and leads to similar results as using a 32-electrode set. McCann et al. [16] compare performances achieved with sets of 1 to 16 electrodes and also found that the performance improvement of larger electrode sets compared to sets of 4 electrodes is limited.

In this paper, the authors analyse data from 47 healthy adults who used the adaptive P300 speller for attention training to investigate the effect of different electrode subsets and the use of a spatial filter on speller performance. The paper aims to provide a practical guide for researchers who want to use the P300 speller, and is structured as follows: Section II describes the data used in the study, Section III describes the electrode subsets investigated, Section IV presents the results of the investigation, Section V discusses the implications of the results and the limitations of the study, and Section VI concludes the paper.

II. THE DATASET

The dataset used for this study was obtained from a randomized controlled trial that aims to compare various adaptation methods for the adaptive P300 speller for attention enhancement. The study included 47 healthy adults, ranging in age from 18 to 62, who completed 9 runs of a P300 speller implemented in OpenViBE. Table I outlines the words that the participants had to copy-spell, the number of flashes per row and column used, and whether or not feedback was provided for each run. The first two runs were used to train the xDAWN spatial filter [17] and linear discriminant analysis (LDA) classifier, and did not provide feedback. The xDAWN spatial filter was chosen due to its effectiveness in P300 spellers [18] and its ease of use since it is standard functionality in OpenViBE. Runs 5 to 8 had varying numbers of flashes per row and column, which were either adapted based on the subject's previous performance using the algorithm developed by Arvaneh et al. [9] or an iterative learning controller (ILC) developed by the authors, or chosen randomly. Only runs 3 to 9 were considered in this study. Spelling accuracy, which is the percentage of correctly identified letters in a word, was determined for all numbers of flashes between 1 and the actual number used in all runs.

EEG data was collected using the ANT Neuro eego™ rt amplifier [19] with a 32-channel waveguard™ cap [20],

TABLE I
SUMMARY OF EXPERIMENTAL PROTOCOL.

	Run 1	Run 2	Run 3	Run 4	Runs 5-8	Run 9
Word	the	quick	dog	beautiful	beautiful	dance
Number of flashes	12	12	12	10	varying	12
Feedback	no	no	yes	yes	yes	yes

and electrodes were placed in standard 10-20 positions. AFz and CPz served as the ground and reference electrodes, respectively, and impedance was kept below 5 k Ω during recording. EEG signals were acquired in OpenViBE at a sampling rate of 500 Hz, band-pass filtered between 1 and 20 Hz, and downsampled by a factor of four before further processing.

III. ELECTRODE SETS

In this study, the performance of the P300 speller using different numbers of electrodes is investigated. Specifically, 32, 16, 8, 6, and 4 electrodes are tested.

The original dataset consists of EEG signals collected from 32 electrodes, as shown in Figure 1. The xDAWN spatial filter is applied to transform the signals from the 32 channels into 3 components, resulting in a matrix that assigns a weight to each electrode for each subject.

To select which electrodes to include in the subsets, the electrodes are ranked based on how often they are among the top 16 weighted electrodes across all subjects. The electrode subsets are then chosen based on this ranking. However, to ensure symmetry in the subsets, some adjustments are made. For example, if the 4 highest ranked electrodes are P3, P4, O1, and Oz, then P3, P4, O1, and O2 are chosen to keep the subset symmetrical.

A previous study [15] shows that using a subset of electrodes consisting of PO7, POz, PO8, and CPz leads to comparable or better performance than using larger sets of electrodes. Since not all of these electrodes are available with the EEG recording hardware used in this study, an additional subset with electrodes close to those reported by Speier et al. [15] (P7, P8, POz, and Pz) is investigated. This means that two 4-electrode sets are investigated in this study: the one similar to the proposed electrode set by Speier et al. [15] (P7, P8, POz, and Pz), and the one determined by ranking the electrodes as described above (P3, P4, O1, O2).

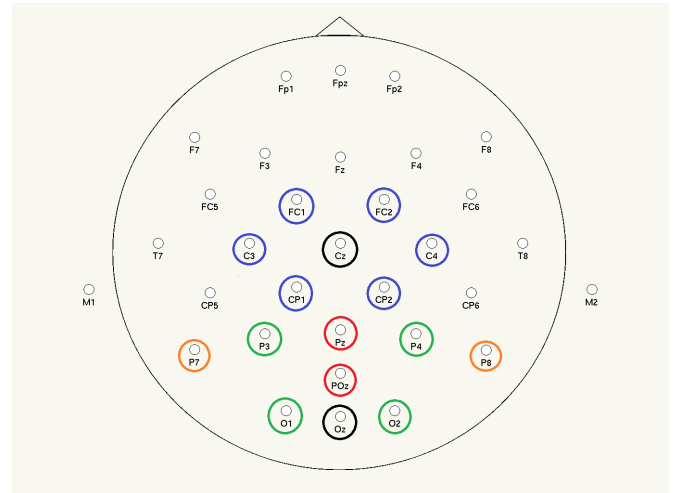


Fig. 1. Electrode sets used in this analysis. Set 1: all 32 electrodes shown; set 2: all 16 coloured electrodes; set 3: 8 electrodes coloured in black, green and red; set 4: 6 electrodes coloured in green and red; set 5: 4 electrodes coloured in green; set 6: 4 electrodes coloured in red and orange.

Figure 1 shows all the electrode subsets used in the study. P300 speller performance is evaluated for each subset with and without the xDAWN spatial filter. To ensure adequate electrode coverage, it is recommended to use at least 4 times more electrodes than xDAWN components. Thus, for subsets of 32 and 16 electrodes, 3 components are used; for 8 electrodes, 2 components are used; and for 6 and 4 electrodes, only 1 component is used.

IV. P300 SPELLER PERFORMANCE

In total, the performances achieved with 12 different configurations (6 electrode sets with and without the spatial filter) are investigated. Only the performances obtained by using 32 electrodes with the spatial filter are from the original dataset. The performances of the remaining 11 configurations are obtained using the functionality in OpenViBE to replay experiments using the recorded signals. This means that the performance for the 11 configurations that were replayed should be viewed as approximations.

For each configuration, the average spelling accuracy is calculated for each number of flashes per row and column between 1 and 12 for each subject across the 7 runs with feedback (see Section II). It should be noted that there are different numbers of samples for each number of flashes, and each subject, due to the variation in the training.

The performance is then averaged across subjects. A comparison of average performance achieved with or without the xDAWN spatial filter, for each electrode set, is displayed in Fig. 2.

It can be seen that, for large electrode sets, i.e. 32 and 16 electrodes, using the xDAWN spatial filter leads to better performance. With 8 electrodes, and 2 xDAWN components, the performance with or without the spatial filter are very similar. For small electrode sets, i.e. 6 and 4 electrodes, using the spatial filter leads to poorer performances than omitting

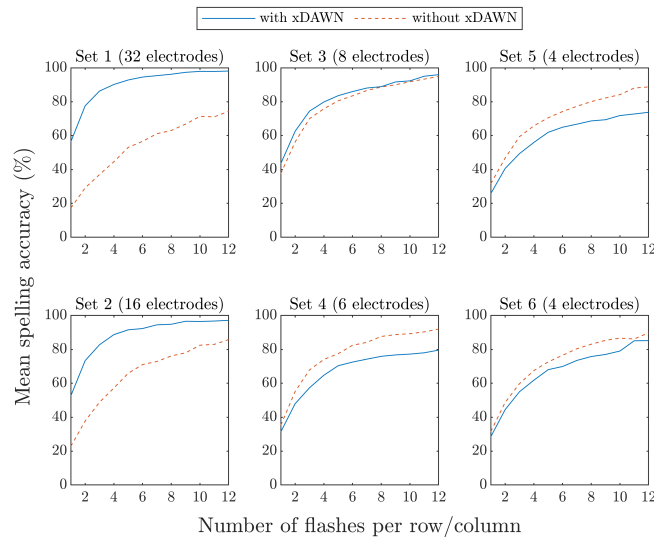


Fig. 2. Average P300 spelling accuracy achieved with the different configurations described in Section III.

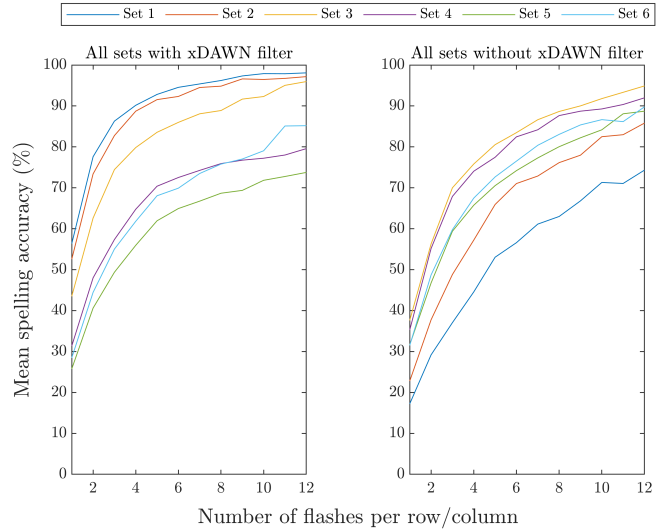


Fig. 3. Average P300 spelling accuracy for different configurations with and without the xDAWN spatial filter.

the filter. This phenomenon is further illustrated in Fig. 3, which shows the improved performance with larger electrode sets when xDAWN is used, and the opposite effect when xDAWN is not used.

Fig. 4 shows the average performance with the different configurations for 5 randomly sampled participants. It can be seen that, while more noisy, all subjects follow the trend seen with the average performance.

Table II summarizes the difference in mean spelling accuracy across subjects between all configurations. The “X” after the set number indicates the use of the xDAWN spatial filter. The highlighted cells represent configurations that result in very similar performance (less than 3% mean difference). It can be seen that set 1, without the spatial filter, has the lowest performance compared to all other configurations. Similarly, set 2 without the spatial filter outperforms only set 5 with the xDAWN filter, while showing comparable performance to sets 4 and 6 with the xDAWN filter. However, sets 4, 5, and 6 all perform better without the spatial filter. When the spatial filter is used with sets 1 and 2, they outperform all other configurations but are very similar to each other. Sets 5 and 6, both with 4 electrodes, result in similar performances, as do sets 3 and 4, with 8 and 6 electrodes, respectively.

V. DISCUSSION

The results presented in Section IV suggest that the use of the xDAWN spatial filter in OpenViBE leads to improved spelling accuracy for large electrode sets only when three resulting xDAWN components are used. The performance difference between the presence or absence of the spatial filter is small when two components are used, as in the case of set 3 (mean difference=2.73%). On the other hand, the performance without the spatial filter is better when only one component is used, as in sets 4 to 6. These results are consistent with the findings of Rivet et al. [17], where

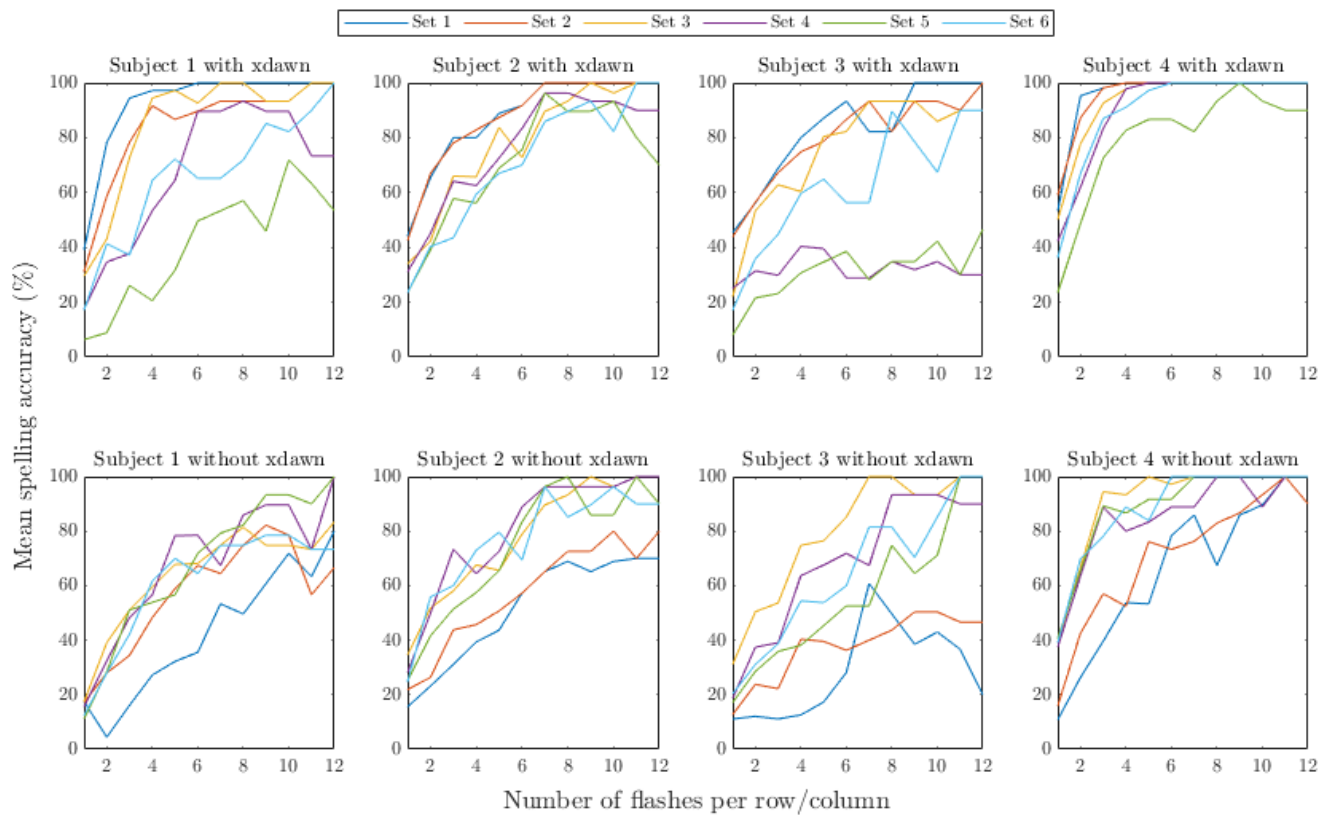


Fig. 4. Average P300 spelling accuracy for sample subjects achieved with all configurations.

using one xDAWN component leads to significantly poorer performance, while using two components leads to slightly worse performance compared to no spatial filtering, and using four components results in better performance.

It is important to note that the results of this study are limited by the specific conditions in which the data was collected. The data was gathered in an electronically shielded room, which likely resulted in a higher SNR than would be found in typical laboratory, or real-world EEG recordings. This means that the reported spelling accuracies may be higher than what could be achieved in other recording environments. Additionally, it should be noted that only the performances with set 1 and the xDAWN filter are based on experimental data, while the performances for set 1, without the spatial filter, and sets 2 to 6 are only investigated in offline analysis. Therefore, the reported performance for these sets should be considered as approximations. The classification algorithm used in this study is a simple LDA classifier. While it is effective for this study, other classification algorithms may perform differently and could potentially yield better results. Other classifiers are not investigated in this study.

As the number of electrodes used decreases, the choice of which electrodes to include becomes increasingly important, as can be seen when comparing the performances of sets 5 and 6. It is possible that alternative electrode subsets could result in better performances for the smaller electrode sets investigated in this study. Finally, it should be noted that

the use of a single-sized EEG cap for data collection means that electrode locations may not have been optimal for all subjects, potentially explaining why some subjects performed better with set 5, while others performed better with set 6.

VI. CONCLUSIONS AND FUTURE WORK

Overall, this study provides valuable insight into the selection of electrode subsets and the use of spatial filters for P300 speller experiments in OpenViBE. The findings suggest that the choice of electrode subset and spatial filter can significantly impact spelling accuracy, and that researchers should carefully consider their priorities and constraints when making these choices.

Based on the findings, a 16-electrode set with the use of the xDAWN spatial filter is recommended for experiments where near-perfect spelling accuracy is important. If low spelling accuracy is tolerable and cost-effectiveness is important, the authors suggest a 6-electrode set without the use of the xDAWN spatial filter. In this study, a 6-electrode set, without the spatial filter, results in the highest performance of all the configurations that only require an 8-channel chip (6 signal electrodes with 1 reference and 1 ground electrode). Since performance is sensitive to electrode choice with small sets, researchers might want to explore different electrode positions in sets of 8 electrodes or less.

However, when the P300 speller is used as a neurofeedback training tool, it is desirable to have a lower spelling accuracy

TABLE II
DIFFERENCE BETWEEN SETS IN TERMS OF MEAN SPELLING ACCURACY ACROSS SUBJECTS AND NUMBER OF FLASHES.

	Set 1 X	Set 1	Set 2 X	Set 2	Set 3 X	Set 3	Set 4 X	Set 4	Set 5 X	Set 5	Set 6 X
Set 6	17.71	-18.56	15.8	-7.19	9.48	6.75	-5.16	4.7	-12.19	-1.61	-5.39
Set 6 X	23.1	-13.17	21.19	-1.8	14.87	12.14	0.23	10.09	-6.8	3.78	
Set 5	19.32	-16.96	17.41	-5.58	11.09	8.36	-3.55	6.31	-10.59		
Set 5 X	29.91	-6.37	27.99	5.01	21.68	18.94	7.03	16.9			
Set 4	13.01	-23.26	11.1	-11.89	4.78	2.05	-9.86				
Set 4 X	22.87	-13.4	20.96	-2.03	14.65	11.91					
Set 3	10.96	-25.31	9.05	-13.94	2.73						
Set 3 X	8.23	-28.05	6.31	-16.67							
Set 2	24.9	-11.38	22.99								
Set 2 X	1.91	-34.36									
Set 1	36.27										

Each cell shows the result of the mean spelling accuracy of the column set minus the mean spelling accuracy of the row set.

to challenge the user. Thus, in future experiments with the adaptive P300 speller for attention training, it is beneficial to use a smaller electrode subset, not only to save time during setup but also to provide a greater challenge to the user. The authors plan to test sets 3, 4, and 6 in their experiments to determine the best electrode set, which leads to fast setup times and a good balance between challenging but not frustrating the user.

To analyze how close the approximations presented in this study are to reality, the experimental results will be compared to the results obtained in this offline analysis.

REFERENCES

- [1] L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials," *Electroencephalogr. Clin. Neurophysiol.*, vol. 70, pp. 510–523, 1988.
- [2] S. Halder, A. Pinegger, I. Käthner, *et al.*, "Brain-controlled applications using dynamic P300 speller matrices," *Artif. Intell. Med.*, vol. 63, no. 1, pp. 7–17, 2015.
- [3] L. Citi, R. Poli, C. Cinel, and F. Sepulveda, "P300-based BCI mouse with genetically-optimized analogue control," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 1, pp. 51–61, 2008.
- [4] C. J. Bell, P. Shenoy, R. Chalodhorn, and R. P. N. Rao, "Control of a humanoid robot by a noninvasive brain-computer interface in humans," *J. Neural Eng.*, vol. 5, no. 2, pp. 214–220, 2008.
- [5] P. K. Shukla, R. K. Chaurasiya, and S. Verma, "Performance improvement of P300-based home appliances control classification using convolution neural network," *Biomed. Signal Process. Control*, vol. 63, no. 102220, 2021.
- [6] U. Masud, M. I. Baig, F. Akram, and T. S. Kim, "A P300 brain computer interface based intelligent home control system using a random forest classifier," in *2017 IEEE Symp. Ser. Comput. Intell. (SSCI)*, 2017, pp. 1–5.
- [7] Y. Renard, F. Lotte, G. Gibert, *et al.*, "OpenViBE: An Open-Source Software Platform to Design, Test and Use Brain-Computer Interfaces in Real and Virtual Environments," *Presence teleoperators virtual Environ.*, vol. 19, no. 1, 2010.
- [8] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, "BCI2000: A General-Purpose Brain-Computer Interface (BCI) System," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, 2004.
- [9] M. Arvaneh, I. H. Robertson, and T. E. Ward, "A P300-Based Brain-Computer Interface for Improving Attention," *Front. Hum. Neurosci.*, vol. 12, no. 524, 2019.
- [10] B. Rivet, H. Cecotti, E. Maby, and J. Mattout, "Impact of Spatial Filters During Sensor Selection in a Visual P300 Brain-Computer Interface," *Brain Topogr.*, vol. 25, pp. 55–63, 2012.
- [11] H. Cecotti, B. Rivet, M. Congedo, *et al.*, "A robust sensor-selection method for P300 brain-computer interfaces," *J. Neural Eng.*, vol. 8, no. 1, pp. 16 001–16 013, 2011.
- [12] T. Yu, Z. Yu, Z. Gu, and Y. Li, "Grouped Automatic Relevance Determination and Its Application in Channel Selection for P300 BCIs," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 6, pp. 1068–1077, 2015.
- [13] S. A. Ludwig and J. Kong, "Investigation of different classifiers and channel configurations of a mobile P300-based brain-computer interface," *Med Biol Eng Comput.*, vol. 55, pp. 2143–2154, 2017.
- [14] D. J. Krusienski, E. W. Sellers, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, "Toward enhanced P300 speller performance," *J. Neurosci. Methods*, vol. 167, no. 1, pp. 15–21, 2008.
- [15] W. Speier, A. Deshpande, and N. Pouratian, "A method for optimizing EEG electrode number and configuration for signal acquisition in P300 speller sys-

- tems,” *Clin. Neurophysiol.*, vol. 126, no. 6, pp. 1171–1177, 2015.
- [16] M. T. McCann, D. E. Thompson, Z. H. Syed, and J. E. Huggins, “Electrode subset selection methods for an EEG-based P300 brain-computer interface,” *Disabil. Rehabil. Assist. Technol.*, vol. 10, no. 3, pp. 216–220, 2015.
 - [17] B. Rivet, A. Souloumiac, V. Attina, and G. Gibert, “xDAWN Algorithm to Enhance Evoked Potentials: Application to Brain-Computer Interface,” *IEEE Trans. Biomed. Eng.*, vol. 56, no. 8, pp. 2035–2043, 2009.
 - [18] E. Chiou and S. Puthusserypady, “Spatial filter feature extraction methods for P300 BCI speller: A comparison,” in *2016 IEEE Int. Conf. Syst. Man, Cybern. (SMC)*, 2016, pp. 3859–3863.
 - [19] ANT Neuro, *eego (TM) rt*. [Online]. Available: https://www.ant-neuro.com/products/eego_rt (visited on 04/17/2023).
 - [20] ANT Neuro, *waveguard (TM) original*. [Online]. Available: https://www.ant-neuro.com/products/waveguard_original (visited on 04/17/2023).