

Evaluating the Impact of Electrode Type and Montage on Classification Performance in Assistive P300-based BCIs

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ABSTRACT: Severe motor disabilities from neurological conditions often prevent individuals from accessing modern Assistive Technologies (AT) for communication. Brain-Computer Interfaces (BCIs) bypass motor pathways, translating brain activity into device control. Among non-invasive BCIs, P300-based systems, exploiting the P300 Event-Related Potential, are widely investigated for communication: in the P300-speller users select letters by focusing on target stimuli, enabling communication for individuals with severe motor impairments. BCIs are therefore promising, but usability, setup complexity, and gel-based EEG caps limit integration. Traditional gel-based caps provide high-quality signals but are uncomfortable and slow to set up, while semi-dry headsets improve comfort and usability, but typically have suboptimal montages for P300-applications. This raises questions about the effects of electrode type and montage. This study compared a commercial semi-dry 7-channel headset for out-of-the-lab applications and a traditional wet EEG cap during P300-speller tasks. Classification performance was evaluated online and offline, providing insight into how electrode design and configuration influence the usability and effectiveness of BCIs.

INTRODUCTION

Severe motor disability is a common consequence of a wide range of neurological conditions, including traumatic brain injury, stroke, cerebral palsy, spinal cord injury, and neurodegenerative diseases. These conditions often result in deeply impaired communication and interaction, affecting quality of life and social participation [1]. Recent advances in Assistive Technologies (AT) have enabled people with disability to access mainstream digital communication through advanced input devices (i.e., eye-trackers, switches, joysticks, alternative keyboards [2]) and customizable software platforms to facilitate access to communication and interaction [3]. However, despite the maturity of commercial AT, for individuals with severe motor impairments these solutions often remain inaccessible due to the complexity of control, limited operability, or requirement for residual motor abilities [4]. Brain-Computer Interfaces (BCIs), particularly non-

invasive EEG-based systems, offer a promising alternative by establishing a direct channel for communication and control from the brain to external devices, bypassing muscular and peripheral nervous system pathways [5, 6]. Among non invasive BCIs, P300-based systems, exploiting the P300 Event-Related Potential (ERP) as control feature, are widely investigated for communication [1, 7]. The P300 ERP is a positive deflection in the EEG, occurring approximately 300 ms after a rare and task-relevant stimulus, reflecting the user's attentional orientation and cognitive processing [8]. The typical paradigm to elicit the P300 is the oddball, where frequent non-target and rare target stimuli are presented [8]. The oddball paradigm sets the basis for more sophisticated interfaces such as the P300-speller [9], which is one of the most extensively validated BCIs for communication. The user is presented with a matrix of letters flashing in rows and columns, and focuses on a specific character. Each flash containing the desired letter to be spelled represents a "rare target" eliciting the P300, while flashes of other letters act as "frequent non-targets". By evaluating the P300 following each flash, the system identifies the target letter as the intersection of the row and column with the largest P300 responses [9].

The acquisition of the EEG signal is a crucial step in BCI systems, as signal quality directly influences subsequent processing and overall performance. Traditional gel-based, or wet, electrodes are the gold-standard in hospitals and laboratories. Typically based on Ag/AgCl sensors with conductive gel, they ensure low and stable electrode-skin impedance and high-quality signals. However, their use requires skin preparation and conductive gel application, resulting in time-consuming setups performed by technicians, while users often experience discomfort and must wash their hair after recordings. These practical limitations have restricted gel-based EEG to laboratory settings [10, 11]. Dry electrodes represent an alternative, as they do not require gel or skin preparation, allowing faster and more user-friendly setups [11]. However, they often present higher impedances and lower signal quality, limiting their reliability [10]. Semi-dry electrodes have been proposed as a compromise between these approaches. They require only a small amount of

electrolyte fluid and combine the signal reliability of wet electrodes with the faster setup and improved comfort of dry systems. This enables stable recordings while reducing preparation and post-recording cleaning times [10]. Nonetheless, semi-dry caps often feature fixed montages, which may not be optimal for P300-based applications. Indeed, electrodes' placement plays a critical role in the classification performance of the system, and the optimal configuration depends on the specific use. P300-based BCIs benefit from including electrodes at positions with a prominent P300 response, namely the midline positions Fz, Cz and Pz [8, 12]. Also posterior and occipital electrodes provide supplementary discriminative information that improves target from non-target detection [13]. *Spencer et al.* (2001, [14]) reported that frontal, central, and posterior electrodes capture the majority of P300-related variance, identifying a component from Cz to Oz and P7 to P8 as accounting for the largest portion of variance, and a component from Cz to Fz accounting for the second largest portion [14].

Despite the potential of P300-based BCIs [1], they still cannot seamlessly integrate with commercial AT software. Their real-world use remains limited by performance variability, low selection speed and practical constraints related to EEG acquisition systems. Users and AT experts have emphasized the need for setups that are fast, reliable, comfortable, and easy to mount, supporting everyday use outside laboratory environments [15]. In response, portable EEG headsets based on dry and semi-dry electrodes can represent an alternative to improve usability and reduce preparation time. However, these systems often rely on predefined montages, limiting flexibility in electrode placement according to the specific requirements of the intended use.

The trade-off between the reliability and quality levels of the gold-standard gel caps, and the portability, comfort and ease of use of recent commercial headsets raises an important question: how do electrode type and montage affect BCI performance? In this study, the question was addressed by comparing two EEG headsets. Healthy participants performed a P300-speller task twice: first using a semi-dry commercial headset with a fixed 7-channel montage, emphasizing comfort and ease of setup but with an electrode configuration not specifically designed for P300 applications; then using a traditional wet EEG cap with an 8-channel montage commonly used in P300-BCI communication research [16], representing the gold-standard. This comparison allowed to evaluate whether the practical advantages of portable semi-dry systems can be achieved without substantially compromising BCI performance. The results provide preliminary insights into how headset design and electrode configuration may influence BCI performance and usability, helping to inform future device development and customization.

MATERIALS AND METHODS

Participants: EEG data were collected from a popula-

tion of 10 healthy volunteers (7F-3M, 28.8 ± 4.3 years old) according to the following inclusion criteria: *i*) no history of neurological or psychiatric diseases; *ii*) age > 18 years old. All the research was conducted in accordance with the declaration of Helsinki. The study protocol was approved by the Independent Ethics Committee of Fondazione Santa Lucia in Rome.

Experimental procedure: Subjects were administered with a traditional P300-speller paradigm [9], repeated twice during two experimental sessions acquired within the same day, 30 minutes apart. The two sessions comprised the same P300-speller protocol, administered through the BCI2000 framework [17], but differed in terms of EEG headset employed to acquire the signal (see section below). The order of the sessions was counter-balanced across participants. The stimulation protocol consisted of a 5x6 matrix with 30 alphabetic characters (Fig.1) sequentially intensified in rows and columns in pseudo-random order. Each stimulation flash had a duration of 120 ms, with an inter-stimulus interval (ISI) of 120 ms, obtaining a stimulus onset asynchrony (SOA) of 240 ms. The stimulation was presented through a 24" screen located 60 cm away from the subject's eyes. Participants were required to spell 9 predefined words of common use (i.e., 9 runs), selected from the Italian dictionary so that the target characters covered the most of the spelling matrix. All words were 5-characters long. Subjects were instructed to focus their attention on the letter to write (i.e., the target stimulus) and mentally count how many times the row and the column in which it was contained were intensified. Each target was intensified 16 times (i.e., 8 rows and 8 columns), corresponding to 8 stimulation sequences. The number of stimuli presented was kept constant during the whole experiment for all subjects, to ensure the consistency of stimulus presentation and allow for direct online and offline comparisons between participants. At the beginning of each trial (i.e., set of flashes to write a letter), the target character was cued at the top of the screen.

Each session consisted in a calibration phase with no feedback provided, and a spelling phase in online copy-mode. Within the copy-mode, the subject was allowed a fixed number of selections and was asked to write predefined words, with no possibility to correct any error. The EEG data acquired during the calibration process, comprising 4 words (20 selections: "BACIO", "POSTO", "METRO", "ZEBRA"), was used to compute the BCI classifier parameters of each subject, by applying a Stepwise Linear Discriminant Analysis (SWLDA) [16]. The classifier parameters were used to provide the online feedback in the copy-mode, consisting of 5 words (25 selections: "DANZA", "GUSTO", "MENTE", "VIOLA", "FIORE"). The spelling of the five words was completed in its entirety, and no criterion was established to stop the task based on performance.

EEG recordings: For each participant, two different EEG systems were used: *i*) the 7-channel commercial semi-dry X.on headset (Brain Products, Germany: F3,



Figure 1: P300-speller 5x6 matrix used for the stimulation protocol. A row or column intensifies for 120 ms every 120 ms. The word at the top of the window is the text to be spelled.

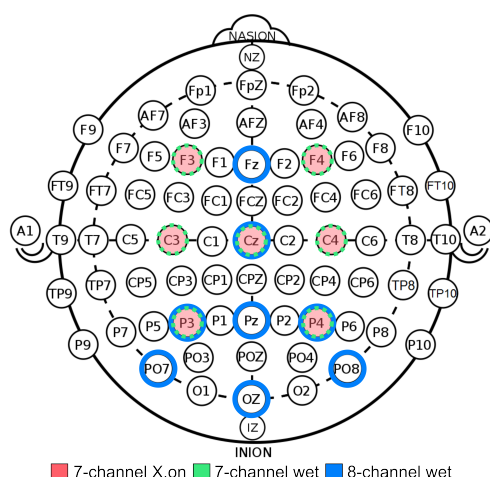


Figure 2: Electrode configurations stored and analyzed. The 12-channel wet cap was the union of the 8-channel wet and 7-channel wet subsets. The online analysis involved the 7-channel X.on and the 8-channel wet montages, while for the offline analysis also the 7-channel wet montage was considered.

F4, C3, Cz, C4, P3, P4, reference and ground on the right ear lobe; sampling rate 250 Hz); *ii*) a 12-channel wet EEG cap (EasyCap-LiveAmp, Brain Products, Germany: F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, PO7, PO8, Oz, reference and ground on the right ear lobe; sampling rate 250 Hz) based on the International 10–20 system. The 12 channels used in case (*ii*) represent the union of the X.on montage with the 8-channel configuration commonly adopted in the literature for P300-spellers [16]. Despite 12 channels being acquired and stored, only the 8 channels' subset from *Krusienski et al.* (2006, [16]) was considered during the online protocol and transmitted to the BCI2000 framework in the calibration and the copy-mode phases. The wet 7-channel's configuration was then only evaluated through an offline analysis by considering the proper subset of channels from those acquired. In Fig.2, the three configurations are highlighted. To obtain a wet montage fully comparable with the fixed X.on configuration for the offline analysis, the ground electrode was moved from the right mastoid to the right ear lobe.

Data Analysis: The performance of the two BCI systems was evaluated in terms of *online accuracy* and *of-*

line information transfer rate (ITR) [18]. The online accuracy was defined as the percentage of correct selections in the copy-mode, expressed as the ratio between the total number of correct selections across the five copy-mode runs. The EEG data acquired and managed online by the BCI2000 framework was band-pass filtered [0.1, 70] Hz, with a notch filter at 50 Hz, decimated by a factor 10 and segmented into 800 ms epochs from stimulus onset. In the copy-mode runs, the processed and segmented signal was then averaged for each stimulus type prior to the SWLDA classification. The same procedure was adopted for data acquired with both the 7-channel semi-dry X.on montage and the 8-channel wet montage [16], extracted as a subset of the 12-channel configuration. Two distributions of the online accuracy index were therefore obtained: *a*) the 7-channel semi-dry X.on, *b*) the 8-channel wet from the EasyCap-LiveAmp system.

The ITR metric was evaluated via an offline analysis of the four calibration runs, carried out in MATLAB environment (MATLAB R2023b). The ITR (bits/min) is an offline metric defined as the amount of information transferred per unit of time, incorporating information on both speed and accuracy. In fact, maintaining a constant number of stimulation sequences in the calibration and copy-mode phases improves the standardization of the experimental task between participants, but does not account for individual differences in their ability to process the stimuli, not fully reflecting realistic conditions of use in terms of speed and accuracy. The ITR combines the accuracy level, time and optimal number of sequences to reach it [7]. Three configurations (i.e., datasets) were obtained from the recordings through the two systems: *a*) the 7-channel semi-dry X.on; *b*) the 7-channel wet subset reproducing the X.on electrode's placement; *c*) the 8-channel wet subset reported in the literature [16]. To avoid feedback-related effects influencing the evaluation of the ITR, the offline analysis was performed on data from the calibration phase. In fact, during the online copy-mode, feedback was computed using the 8-channel wet montage transmitted to the BCI2000 framework. Therefore, using the same data to evaluate the performance of the 7-channel wet subset offline would have introduced a bias in the comparison. For each dataset and stimulus sequence (i.e., $n=1, 2, \dots, 8$), an offline accuracy value was computed using a leave-one-run-out cross-validation technique applied to the four calibration runs: at each iteration of the cross-validation process, three runs were used as the training set, and one run was used as the test set. Within the training phases, data segments from the three runs were concatenated by channel for each intensification, generating a single feature vector for training the classifiers and extract the SWLDA weights [16]. The mean offline accuracy for each subject and stimulation sequence was obtained by averaging the values resulting from the four iterations. Starting from the offline accuracy values, the ITR was computed by applying the bit-rate definition [18] and multiplying the bit-rate by the selection speed (selection/minute). Fi-

nally, the highest individual ITR value for each subject, with an offline accuracy equal or above the 70% level, was considered as a representation of the subject's overall performance. As outlined in the literature, the 70% accuracy has been identified as the threshold sufficient for effective communication with a BCI [19].

Three ITR distributions were obtained: one for each of the aforementioned configurations (i.e., *7-channel semi-dry X.on*, *7-channel wet*, *8-channel wet*). The data used for the offline analysis underwent the same processing steps performed online by the BCI2000 framework.

Statistical Analysis: Online accuracy distributions from the two copy-mode phases (i.e., *7-channel semi-dry X.on*, *8-channel wet*) were statistically compared to evaluate differences between the two recording systems. A non-parametric Wilcoxon-matched pair test was performed (factor: RECORDING SYSTEM, 2 levels). To investigate the effects of the electrode type (factor: ELECTRODE TYPE, 2 levels) and positioning (factor: MONTAGE, 2 levels) separately, the offline ITR distributions underwent statistical analysis. The ELECTRODE TYPE factor was evaluated through a Wilcoxon-matched pair test between the *7-channel semi-dry X.on* and the *7-channel wet* distributions. This controlled for the montage effect, since both configurations consisted of the same channels, thus the electrode type could be evaluated independently. Conversely, the MONTAGE factor was investigated applying the Wilcoxon-matched pair test to the *7-channel wet* and the *8-channel wet* distributions. This controlled for the electrode type, since both configurations were acquired from the same electrodes at the same time, enabling the evaluation of the montage without confounds. All statistical analyses were performed in the MATLAB environment (MATLAB R2023b), and the level of significance was set to $\alpha = 0.05$.

RESULTS

Results of the online task are displayed in Fig.3a, presenting the online accuracy boxplots from the copy-mode phase. The distribution obtained for the *7-channel semi-dry X.on* exhibited a greater dispersion, with a median value around 85%, while the accuracy levels from the *8-channel wet* system showed a narrower distribution centered close to 98%. The statistical test revealed a significant difference between the two distributions ($p = 0.0039$), with the 7-channel semi-dry system exhibiting lower performance than the 8-channel wet system.

Concerning the offline analysis conducted on the four calibration runs to separately assess the effect of the electrode type and the montage, the results are summarized in Fig.3b, which shows the distributions of the maximum ITR in cross-validation. The ITR values were computed using EEG data from the *7-channel semi-dry X.on*, the *7-channel wet*, and the *8-channel wet* configurations. The 8-channel wet condition exhibited a wide distribution, with the median value centered at 55 bit/min. The distribution obtained from the 7-channel wet configuration

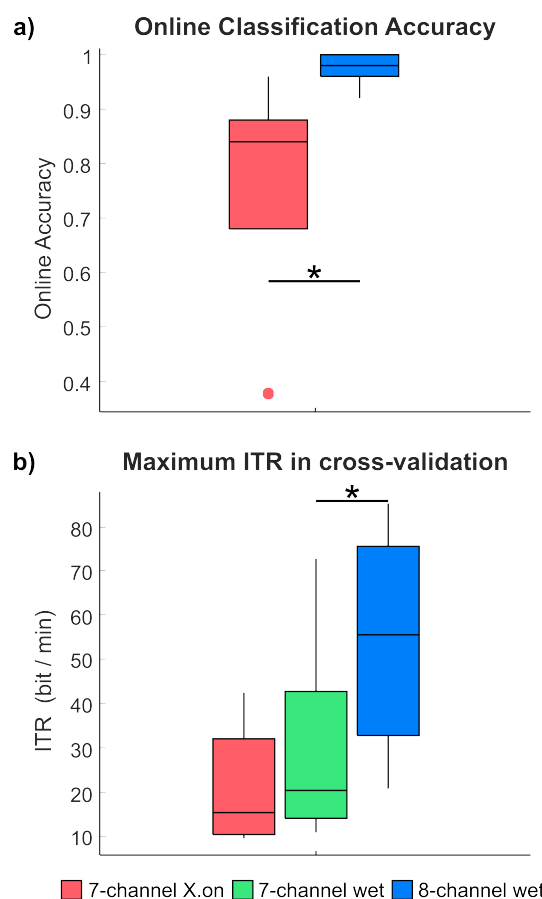


Figure 3: P300-speller classification performance: a) Online accuracy distributions computed for the five copy-mode runs for the *7-channel semi-dry X.on* and the *8-channel wet* configurations; b) Maximum offline ITR distributions, computed in cross-validation considering the four calibration runs for the *7-channel semi-dry X.on*, the *7-channel wet* and the *8-channel wet* configurations. For each subject, the highest ITR value, with an offline accuracy equal or above 70%, was taken into account. The symbol * highlights significant differences between two levels ($\alpha = 0.05$).

was narrower and shifted toward lower ITR values, with the median value around 20 bit/min. Finally, the values obtained from the data acquired through the 7-channel semi-dry system, exhibited a distribution that was similar to the previous condition with respect to dispersion and range. However, the median value was shifted slightly downward, centered around 15 bit/min. With regard to the ELECTRODE TYPE factor (2 levels: *7-channel semi-dry X.on*, *7-channel wet*), no significant differences were identified ($p = 0.46$). Conversely, a significant effect was highlighted for the MONTAGE factor (2 levels: *8-channel wet*, *7-channel wet*), with the 8-channel configuration exhibiting higher ITR values compared to the 7-channel condition ($p = 0.0039$).

DISCUSSION

The present study examined the impact of different EEG recording systems on the performance of a P300-based BCI in healthy subjects. A P300-speller task was pre-

sented twice. First, the X.on semi-dry commercial headset was used, featuring a fixed 7-channel montage that prioritizes comfort and ease of setup, but not specifically designed for P300 applications. Subsequently, a traditional 12-channel wet EEG cap was employed, transmitting the 8-channel montage widely regarded as the gold-standard to the BCI framework [16]. The influence on performance was evaluated through a dual approach: an online and an offline analysis to investigate multiple effects. From the online accuracy general information regarding the recording system was obtained. This hindered the independent evaluation of the electrode type and the montage effects, which were separately investigated within the offline analysis, where EEG datasets acquired from the semi-dry headset and subsets of channels from the wet headset were considered. This approach enabled the comparison of two types of electrode (i.e., semi-dry vs wet) while maintaining the same montage, and between two montages (i.e., 7-channel vs 8-channel) under the same electrode type condition.

The findings indicated that both recording systems allowed the attainment of an average across-subjects 70% online accuracy level, deemed sufficient for effective communication with a BCI [19]. However, recording the EEG signal through the 8-channel montage from *Krusienski et al.* [16], representing the gold-standard for P300-oriented protocols in the literature, yielded higher performance levels in both online and offline analyses. When assessing whether the performance drop in the 7-channel semi-dry X.on cap was due to the electrode type and/or positioning, no significant effect was found for the electrode type factor (i.e., *7-channel semi-dry X.on* vs *7-channel wet*). The result is consistent with previous literature comparing wet and semi-dry electrodes: semi-dry electrodes achieve impedances similar to wet electrodes [10, 20], and deliver comparable signal quality [11], thereby bridging the gap between high-fidelity laboratory setups and portable, user-friendly commercial devices [10, 20]. Semi-dry electrodes avoid hair contamination and require no post-recording hair washing, highlighting their applicability for frequent or prolonged use in home and clinical environments [10]. This supports the reliability of semi-dry systems and their potential for real-world BCI applications, where comfort, rapid setup, and ease of use are essential. In particular, their usability advantages may facilitate the adoption of BCIs in AT contexts, supporting practical communication solutions for individuals with severe motor disabilities.

In contrast, a significant effect emerged for the montage factor (i.e., *7-channel wet* vs *8-channel wet*), with better performance observed when selecting the 8-channel gold-standard subset compared to the X.on-like 7-channel subset. This finding aligns with previous studies that evaluated the effects of spatial channel selection on classification performance [13]. Indeed, supplementing the midline P300 recording locations (i.e., Fz, Cz, Pz [8]) with posterior regions significantly improves the classification performance of the P300-speller [13].

Posterior-occipital electrodes (i.e., PO7, PO8, Oz) capture additional information reflecting visual processing in both focal and peripheral fields. This contributes to P300 response detection and improves classification performance when used in conjunction with the classical P300 feature space at Fz, Cz, Pz [13]. The posterior features are hypothesized to contribute to classification due to the differences observed in visual evoked responses depending on the target location (i.e., in the focal or peripheral field): a prominent event-related negativity between 200 and 250 ms can be found in posterior-occipital target responses reflecting the focal field [12]. In the 7-channel X.on configuration, Fz was replaced by F3 and F4, only Cz was retained among midline electrodes, and posterior-occipital sites (i.e., PO7, PO8, Oz) were omitted, explaining the observed reduction in classification performance compared to the 8-channel montage. These results highlight that electrode spatial configuration can be as critical as electrode type for effective BCI performance.

Taken together, these findings provide a comprehensive perspective on the interplay between electrode technology and montage design. Semi-dry electrodes have been confirmed as a reliable alternative to wet electrodes, offering comfort, ease of setup, and practical suitability for extended use. However, the limitations associated with fixed montages not specifically designed for P300-applications, as demonstrated with the 7-channel X.on headset, indicate that adequate spatial coverage, particularly including posterior-occipital sites, is essential for maximizing P300 classification performance. This highlights the need for customizable headset designs that can combine the practical advantages of semi-dry technology with flexible electrode placement, supporting both research applications and real-world AT deployments. Collaboration between researchers and commercial developers will be key to achieving these solutions and ensuring that BCIs provide reliable, user-friendly communication channels for people with severe motor disabilities. This will expand access to BCI communication and promote autonomy, social participation, and inclusion.

CONCLUSION

This study investigated the effects of electrode type and montage on the performance of a P300-based BCI. Semi-dry electrodes were confirmed to provide signal quality comparable to traditional wet systems, while offering increased comfort, faster setup, and ease of use, making them a practical option for both laboratory and real-world applications. In contrast, electrode montage significantly influenced classification performance, with the 8-channel gold-standard configuration outperforming the 7-channel fixed semi-dry montage, highlighting the importance of adequate spatial coverage, particularly including posterior-occipital sites. These findings suggest that future BCI systems for AT should combine semi-dry electrodes with montages optimized for P300-applications, to balance usability, comfort, and classification accuracy.

Such designs could enable reliable, efficient communication for individuals with severe motor impairments, supporting daily interaction and social participation. Optimizing both electrode type and montage is crucial for translating laboratory BCI research into practical, user-friendly assistive solutions, helping to reduce barriers and enhance autonomy for users with severe disabilities.

ACKNOWLEDGMENT

This work was partially supported the Italian Ministry of Health (PNRR POC-2023- 12377627) and Sapienza University of Rome (LEAF 2023- RM123188F229EC72; Avvio alla Ricerca 2025- AR125199BE5D0A07).

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