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AUTO-ADAPTATION OF ECOG-BASED MOTOR BCI USING NEURAL RESPONSE DECODER: A CROSS-PATIENT STUDY

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ABSTRACT: Motor imagery brain-computer interfaces (BCIs) face challenges in practical application, notably in decoder training. Traditionally, decoders are trained in a supervised manner. This approach requires labeled data and restricts users to predefined actions during the training period. Moreover, regular decoder updates are needed. To address these issues, the auto-adaptive BCI (aBCI) infers training labels directly from brain signals using a neural response (NR) decoder, eliminating the need for supervised sessions. This study investigates the performance and replicability of the aBCI and explores labeling strategies using electrocorticography data from three spinal cord injured patients across diverse paradigms. Results demonstrate that aBCI can be used to significantly increase decoding performance above chance level in all three patients. Performance depended on patients and labeling strategy. The labeling strategy, focusing on correct neural responses (CNR), demonstrates significantly improved performance compared to correct/error neural responses (CENR) labeling strategy. Despite limitations of pseudo-online simulation, our findings underscore the aBCI's promise in advancing BCI technology.

INTRODUCTION

Motor brain computer interfaces (BCIs) come with a number of recognized limitations that hinder their practical use in everyday situations. Many of these limitations relate to the need for training of BCI decoders. Traditionally, motor control (MC) decoders in BCIs are trained using supervised learning. In such a framework, access to the neural data along with the labels is required. Labels are derived from the user's intention. Consequently, during MC decoder training, BCI users are constrained to perform predefined actions under the supervision of researchers or the dedicated environment [1] [2]. In addition, the MC decoder must be regularly updated due to the degradation of performance over time.

Facing these limitations, the use of neural responses (NR) to BCI task performance for unsupervised updating of BCI decoders has been explored [3] [4] [5]. The majority of studies use event-related NR, namely event-locked error-related potentials, e.g. [6]. Most studies focus on NR in brain areas outside the sensorimotor cortex using electroencephalography (EEG)-based BCIs [7]. A limited number of studies investigates NR within the sensorimotor cortex. Invasive electrocorticography (ECoG)-based [8] [9] or microelectrodes array-based BCIs [10] reveal detectable NR following discrete erroneous events in a sensorimotor cortex.

Continuous in time NR (in contrast to event-locked NR) is explored by Rouanne et al. [11] [12], demonstrating detectability of such NR in the sensorimotor cortex using ECoG recording device. For complex BCI auto-adaptation, access to continuous in time NR is powerful as it would provide performance assessments at each time point, whereas event-locked NR would have to extrapolate performance around measured points. On the bases of such continuous in time NR, an auto-adaptive BCI (aBCI) framework with the objective of training the MC decoder during the free use of ECoG-based motor BCI is proposed [11] [12]. The core idea is to infer the training labels directly from the brain signals rather than from the environment, thus removing the necessity for training sessions. Within this aBCI framework, the user can update the MC decoder at will, enabling greater user autonomy in determining their actions. This first proof-of-concept study demonstrated in offline simulation that aBCI can be used to train in an unsupervised manner a MC decoder from scratch, eliminating the necessity for precise label assignment. However, to evaluate the aBCI framework, Rouanne et al. worked on data from a single patient. In order to build a robust and replicable aBCI framework, several questions are still to be addressed. In this paper, we explore the replicability of the aBCI framework [11] [12] with three patients. In addition, we

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compared two aBCI labeling strategies to improve aBCI performance, and make the aBCI framework more versatile and compatible across different paradigms.

MATERIALS AND METHODS

Experimental recordings: To investigate the replicability, we tested the aBCI on datasets from three patients implanted with two ECoG-recording WIMAGINE implants, one on each hemisphere, on the sensorimotor cortex [1] [13]. Two of these patients, referred as BCI001 and BCI002, are involved in the “BCI and Tetraplegia” clinical trial at CEA/Clinatec (NCT02550522). Data for the third patient (BSI001) was collected in the STIMO-BSI clinical trial (NCT04632290). Both clinical trials focus on recording and decoding motor intentions with different effectors respectively. Consequently, experimental paradigms slightly differed between BCI and BSI patients.

For the BCI001 and BCI002 patients, we used the dataset collected during the Runner paradigm experiments (Fig. 1A). Runner represents a binary classification test where the BCI user controls a human avatar to either walk or stand still. BCI001 dataset spans a period of 5 months, from September 2019 to January 2020, comprising 13 half-day sessions for a total of 142 minutes of recordings. BCI002 dataset spans a period of 12 months, from November 2019 to October 2020, comprising 34 half-day sessions for a total of 653 minutes of recordings. For the BSI001 patient, we used a dataset collected during the Gait paradigm (Fig. 1B). In this paradigm, the patient used the BCI system to modulate electrical stimulation of the spinal cord enabling walking. A 3-class decoder (left/right hip flexion and rest) was used to decode the intention to perform each independent step and modulate the amplitude of stimulation according to the decoder prediction [13]. This dataset spans a period of 4 months, from September 2022 to January 2023, comprising 19 sessions for a total of 518 minutes of recordings.

Figure 1: Experimental paradigms of datasets included to the study. (A) Runner paradigm, binary classification of human avatar to either walk or stand still. (B) Gait paradigm, 3-class classification of left/right hip flexion and resting to control spinal cord stimulator.

During real time BCI experiments, time–frequency information was extracted for each of the 64 electrodes used [1] from each 1s-long epoch (spaced by 0.1s, 90% overlap), using continuous complex wavelet transform (Morlet) with 15 central frequencies 10 Hz apart from 10 to 150 Hz for patients BCI001 and BCI002. 0.2s-long epoch (spaced by 0.1s, 50% overlap) with 24 central frequencies (2, 5:5:100, 125, 150, 200 Hz) were used in BSI001 patient sessions. Recursive Exponentially Weighted Markov-Switching multi-Linear Model (REW MSLM) was employed as MC decoder as in [2].

The aBCI framework have been evaluated across these three labeled datasets, shortly noted Runner BCI001, Runner BCI002 and Gait BSI001.

aBCI framework description: The overview of the aBCI framework [12] is given in Fig. 2. In the aBCI framework, the labels for the MC decoder training are not acquired through traditional training paradigm employed in supervised learning. Instead, they are estimated thanks to the auto-adaptive module. This module consists in a neural response (NR) decoder, also known as task performance decoder or satisfaction decoder. Its role is to interpret from the input features how well the effector’s actions match the user’s intentions. In other words, the NR decoder predicts from the brain signals whether the user is satisfied or dissatisfied with the action decoded by the MC decoder. The NR decoder is trained in a supervised manner. The MC decoder is then trained / updated in real time in an unsupervised manner, relying on the labels estimated by the NR decoder during the free use of the BCI.

In the current system, the same feature space described above is used by both decoders, which are trained using the REW MSLM algorithm [2].

aBCI labeling strategy: The process of automatic labeling of the training data for the MC decoder update is not a straightforward task. Indeed, the estimated labels are derived from the output of the NR decoder, noted $\hat{y}_{NR}$, which have not a perfect accuracy. Therefore, the derived labels cannot be expected to be perfect either. To limit this imperfection, the epochs with high level of uncertainty on the task performance estimation from the NR decoder are not labeled, and thus, discarded from the MC decoder update dataset. In this study, we compare two discarding strategies, resulted in two labeling strategies.

The first labeling strategy (Fig. 3A), proposed in [12], considers correct and error neural responses (CENR). It relies on the use of two thresholds, th_{corr} and th_{err}, for the classification of epochs respectively as correct and erroneous. Epochs are considered correct when $\hat{y}_{NR} > th_{corr}$ and erroneous when $\hat{y}_{NR} < th_{err}$. Epochs for which $th_{err} < \hat{y}_{NR} < th_{corr}$ are unlabeled and so not included in the MC training / update dataset. To evaluate the thresholds, the output of the NR decoder $\hat{y}_{NR}$ is modeled as a mixture of two Gaussians, $\mathcal{N}(\mu_{corr}, \sigma^2_{corr})$ for the correct class and $\mathcal{N}(\mu_{err}, \sigma^2_{err})$ for the error class. The parameters of the two Gaussians are estimated on the training data for each class. Then, the thresholds are defined as $th_{corr} = \mu_{corr} + a\ \sigma_{corr}$ and $th_{err} = \mu_{err} - a\ \sigma_{err}$, where a is a hyper-parameter to balance accuracy and data inclusion. Similarly to [12],

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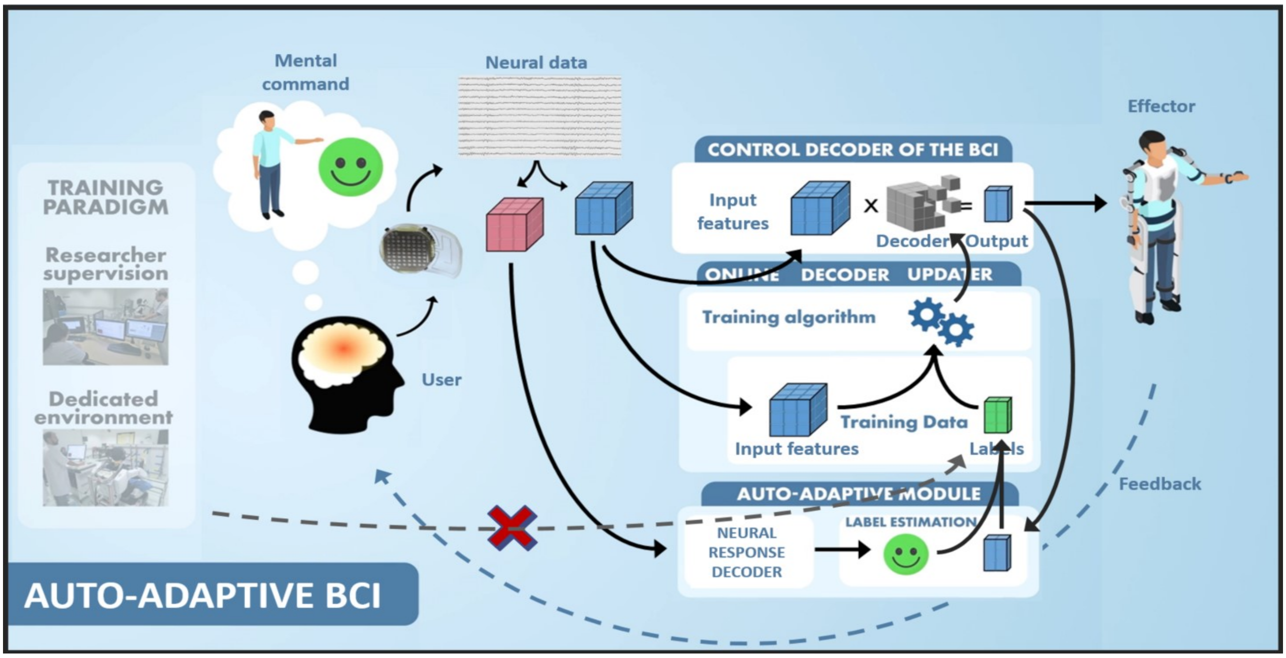

Figure 2: Diagram of the aBCI framework. An extra auto-adaptive module is added to the classic BCI framework, which is usually composed of a (motor) control (MC) decoder and an updater. The aBCI module includes a neural response (NR) decoder aiming at detecting continuous in time NRs to task performance and estimating the labels to update the MC decoder, instead of using the ones supplied by the researcher's supervision or the dedicated environment as it is commonly done in a classic BCI framework.

we set $a = 1$ in this study. Finally, the fixed thresholds are used during the update of the MC decoder. When the epoch is estimated correct, the true MC label is the most probable MC output, while when it is estimated erroneous, the true MC label is the second most probable MC output.

The second labeling strategy (Fig. 3B), that we propose, is more restrictive and focuses exclusively on correct neural responses (CNR). It relies on the use of only one threshold for the classification of epochs as correct when $\hat{y}_{NR} > th_{corr}$ and unlabeled when $\hat{y}_{NR} < th_{corr}$. The rest of the conditions and parameters employed with the CNR labeling strategy were consistent with those from the CENR one. We have headed for the CNR labeling strategy to make the aBCI framework more generic and adapted to multiclass classification, regression problems or combinations, where wrong decoded motor actions are very hard to relabel.

Pseudo-online simulation: We conducted a pseudo-online simulation to evaluate the performance of the aBCI framework, aiming to replicate conditions closely resembling online uses. To achieve this, we divided each dataset into three non-overlapped splits containing approximately the same number of recording sessions. The first split was dedicated to train the NR decoder. The second split was allocated to train the MC decoder from scratch within the aBCI framework, i.e. without knowledge of the real labels for the MC decoder. The third split was reserved for evaluating the performance of the newly trained MC decoder. The training data for the NR decoder were labeled according to the decoded MC outputs obtained during the online experiment: an epoch with a decoded MC output being consistent with the desired MC output was labeled correct, while it was labeled error when inconsistent. We chose to train the MC decoders from scratch, meaning that no prior training was required, using solely the aBCI framework to highlight its capacity in training MC decoders.

In a typical online use, the neural data corresponding to the second split would be gathered during free use of the BCI. However, in our simulation study, we utilized pre-existing labeled datasets. The MC decoder training process was emulated in a pseudo-online fashion, where neural data was iteratively fed into the algorithm to mimic online acquisition. Labels are continuously estimated and training of the MC decoder were conducted using the aBCI framework every fifteen seconds, corresponding to the acquisition of labeled data. Notably, the newly updated MC decoder did not influence BCI actions, as the datasets were pre-recorded.

Performance evaluation: Cross-validation with the three splits by permuting their roles, which leads to six performance measures, was used to evaluate aBCI performances. For the Runner paradigm (binary classification), the performance was evaluated using the AUC of the ROC curve of the MC decoder. For the Gait paradigm (3-class classification), the performance was evaluated using a generalized version of the AUC of the ROC curve for multi-class classification [14]. The final performance of the aBCI for each paradigm was assessed with the mean AUC of the ROC curves over each test split. For a comparative evaluation, the MC decoder trained from scratch using the aBCI framework was compared to MC decoders trained in two other ways. The

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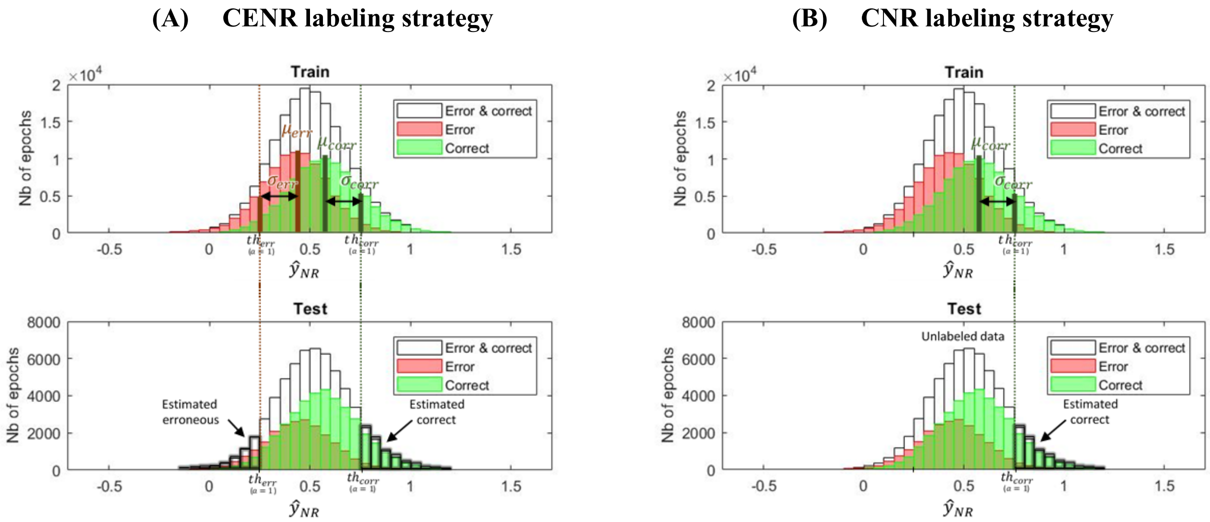

Figure 3: Two aBCI labeling strategies, one (A) focusing on correct/error neural responses (CENR) and the other (B) on correct neural responses (CNR). These histogram examples show the outputs of the neural response (NR) decoder, $\hat{y}_{NR}$, on one training fold (top) and its associated test set (bottom). The thresholds for the inclusion of epochs in the training set of the aBCI-based motor control (MC) decoder are based on a tradeoff parameter a and the means and standard deviations of the Gaussians fitted to the correct and error class (for the CENR labeling strategy) or only the correct class (for the CNR labeling strategy) on the training set.

first one was a supervised training of the MC decoder using the true labels of each epoch from the recorded dataset. The second one was a MC decoder trained following the aBCI framework, but with random outputs of the NR decoder (chance level). For each dataset, the three training strategies were tested against each other through two-sided Wilcoxon Mann Whitney tests.

RESULTS

Fig. 4 shows the mean AUC of the ROC curves for the MC decoding of the three compared training methods (random aBCI training / aBCI training / supervised training), across the three examined datasets (Runner BCI001 / Runner BCI002 / Gait BSI001) and using both labeling strategies (CENR / CNR).

Replicability study across patients: First, we could remark performance variations among patients, especially looking at the supervised trainings with mean AUC of the ROC going from 0.650 to 0.894. The aBCI decoding performances follow a similar trend. Second, we could also note that the aBCI decoding performances consistently exceed chance levels (50%, whatever the number of classes) and almost always in a significant manner (p-values < 0.05), except for the CENR labeling strategy on the Runner BCI002 (p-value > 0.05).

Comparison of labeling strategies: First, one should note that the aBCI decoding performances for the CENR labeling strategy always fall short of the gold standard performances achieved through supervised training, sometimes very significantly as for the Runner BSI001 and the Gait BSI001 (p-values < 0.01). Second, a direct comparison of aBCI decoding performances using both labeling strategies reveals a discernible improvement when exclusively using correct neural responses. Notably, this enhancement is particularly pronounced in the case of the Runner BCI001 dataset, with the AUC of the ROC increasing from 0.637 to 0.819. Although not displayed on the figures, a p-value of 0.0022 for this dataset means significance when comparing the results of both labeling strategies through a two-sided Wilcoxon Mann Whitney test. No significant difference were observed when comparing CENR and CNR for the other datasets. Third, CENR presents high AUC variabilities in terms of standard deviation compared to low AUC variabilities for CNR.

DISCUSSION

Replicability across patients: We showed over three patients that the aBCI control decoding performances are significantly higher than the random auto-adaptive trainings. This result demonstrates the potential of the aBCI framework for replication across different patients and its capacity to train / update MC decoders. aBCI performance is lower than supervised BCI, with essential cross-patient differences observed for the CENR labeling strategy (-29%, -12% and -15%, respectively). However, the cross-patient results are rather consistent for the CNR labeling strategy with smaller differences, down to -8%, -0.3% and -9% for the three patients respectively.

Improvements using CNR labeling strategy: The CNR labeling approach resulted in an improvement of 29%, 13%, and 8% in AUC compared to the CENR labeling approach, also reducing drastically AUC variabilities as indicated by lower standard deviations. These improvements brought aBCI decoding performance closer to supervised ones in terms of mean AUC and standard deviation of AUC. Several reasons may explain

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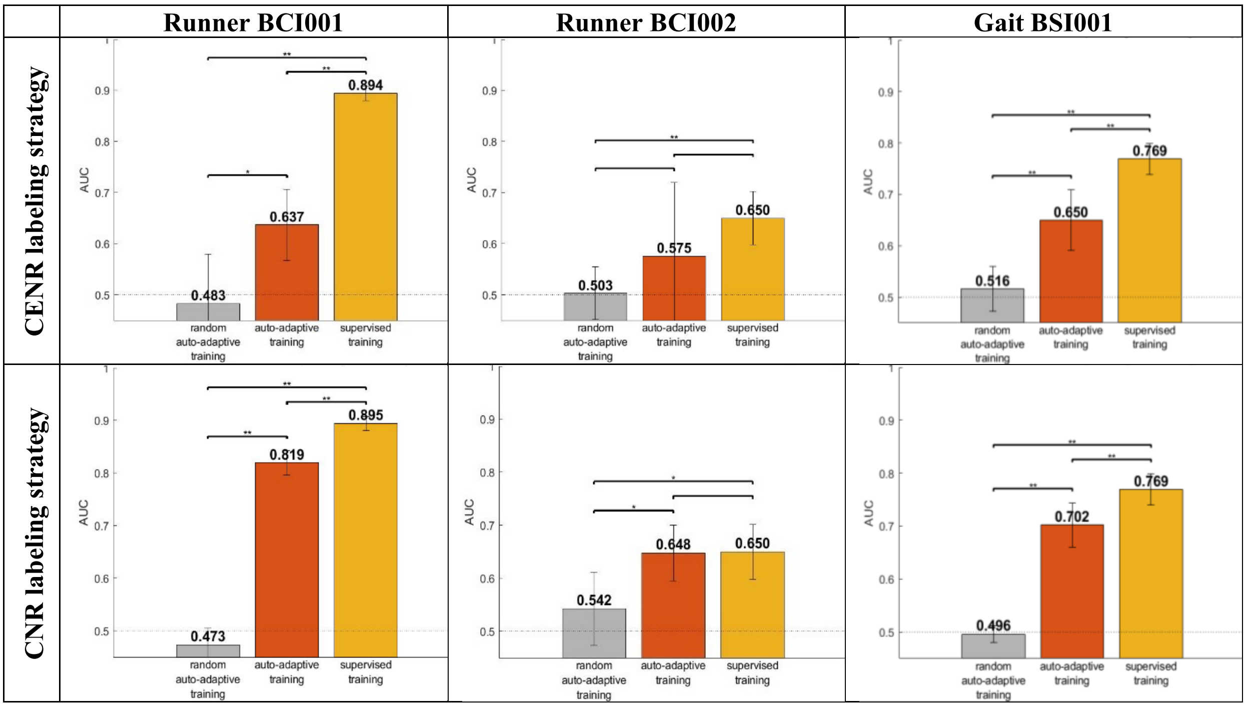

Figure 4: Motor control (MC) decoding performances for three MC training methods, on three datasets (as columns) and using two aBCI labeling strategies (as rows). Performances are given in terms of mean AUC of the ROC curves of the MC decoders trained using the aBCI (in red) compared to MC decoders trained using supervised learning (in yellow) or using random outputs of the neural response decoders (in gray). CENR stands for correct/error neural response and CNR stands for correct neural response. Stars denote significant differences between training methods (two-sided Wilcoxon Mann Whitney test, * p-value < 0.05, ** p-value < 0.01).

this performance improvement. First, the distribution of class ‘correct’ is possibly better evaluated as it is better presented in the recordings. Therefore, the model of class ‘correct’ may have better generalization ability compared to the model of class ‘error’. Second, in case of detection of class ‘error’ by the NR decoder, supplementary relabeling is needed: the second most probable class is used as label in the CENR labeling strategy. In case of more than two classes in the MC decoder, it may increase the probability of erroneous labeling.

In addition, we suggest that using the CNR labeling strategy, the aBCI becomes more versatile and compatible across different paradigms, including classification, regression problems and combinations. On the other hand, the CNR labeling strategy is more selective and keeps less data for the model update compared to the CENR labeling strategy. It may result in a slower MC decoder adaptation.

Limitations and perspectives: By modifying the aBCI labeling strategy to the only use of correct neural responses, we get rid of the uncertainty on relabeling error ones but we also reduce the quantity of data used for updating the MC decoder. This reduction of data could be dramatic for cases with lots of error neural responses. The labeling strategies should be further explored.

According to the results of this study, on simple BCI paradigms with three patients, the aBCI framework seems highly promising. However, it remains essential to validate this approach on more complex datasets, featuring additional degrees of freedom and a combination of discrete and continuous tasks, through classification and regression. Such paradigms will be tested with our aBCI framework in the near future.

A significant limitation of the study lays in the pseudo-online simulation rather than actual online use. While pseudo-online simulation studies allow for greater parameter exploration, they may not fully capture the variability of online experiments, even if it was designed to closely mimic the online use. In the near future, we will test the online version of the proposed aBCI framework.

On another hand, a more in-depth cross-paradigm and cross-patient study of features extraction should be conducted in terms of frequency and spatial characterization, for NR decoders. Indeed, the NR decoder is of critical importance in the aBCI framework and features extraction have not been optimized yet. For now, extracted features are the same as for the MC decoder. Therefore, studying other feature extraction methods would allow better interpretation of the aBCI performance results.

CONCLUSION

The aBCI framework addresses critical limitations associated with traditional BCIs, especially the need for

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supervised retraining sessions by allowing MC decoders to be updated during the free use of the BCI. This innovation not only offers greater user autonomy but also the potential for more natural and intuitive control.

In the continuation of the initial work of Rouanne et al. [12], the present paper provides valuable insights into the replicability and performance of the aBCI framework. Our investigation into using data from multiple patients and diverse paradigms with varying number of degrees of freedom, demonstrates the framework's adaptability. However, the variation of performance observed across patients and paradigms, highlights the need for further research to enhance the framework's robustness and generalizability.

Furthermore, we delved into refining the labeling strategy for training the MC decoder, emphasizing the use of correct neural responses exclusively. This approach yielded significant improvements in aBCI control decoding performance, showcasing the potential of this labeling strategy for future development.

In summary, the aBCI framework represents a promising avenue for advancing BCI technology, offering the potential for greater user autonomy and more natural control. Current and further exploration of the framework's capabilities and optimization strategies will undoubtedly contribute to its continued development for real-world applicability.

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