10.3217/978-3-99161-014-4-015

PREDICTORS OF ECOG-BCI PERFORMANCES ACROSS SUBJECTS AND SESSIONS DERIVED FROM IDLE STATE CHARACTERISTICS

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ABSTRACT: Comprehension of performance variabilities across subjects and sessions is crucial for real life brain-computer-interfaces (BCI) applications. This study compared three subjects that underwent implantation of minimally invasive WIMAGINE ECoG recording implants. Three training strategies to discern best achievable performance, session drift, and variability were evaluated offline using datasets recorded during real-time closed-loop BCI experiments. Results revealed distinct BCI profiles across patients, consistent with qualitative observations made during online training. These performances were correlated with two indicators computed in feature space during idle periods of BCI sessions: Euclidean distance between the current session and the session of model creation in a low-dimensional UMAP embedding, and intrinsic dimension. Between sessions distances demonstrated statistically significant correlation with models' performances, then recalibration need may be potentially anticipated from the characteristics of idle state periods. Additionally, the intrinsic dimension was significantly correlated to subjects' overall BCI capabilities. The results are consistent with pre-implantation MEG-BCI experiments, which could make it useful for patient selection.

INTRODUCTION

Brain-computer-interface (BCI) technology has shown promising advances in the past years, in terms of rehabilitative potential, performances and usability [1], [2], [3]. Despite the progress, there are still challenges to overcome before BCI use in day-to-day scenarios. In particular, the need to regularly train / update decoders poses a significant obstacle to translate BCI into real-life applications [4]. Minimally invasive electrocorticography (ECoG) based BCI, provides a much higher signal stability than electroencephalography (EEG) based BCIs, or than highly invasive Microelectrode Array (MEA) based BCIs [5]. ECoG-BCIs showed their ability to properly decode brain activity without recalibration for several months [6], [7]. However, these studies included only one subject who was intensively trained to control the BCI. It is well known, however, that BCI control performances and motor imagery capabilities can vary significantly across subjects, 15-30% of patients even being described as BCI-illiterated or inefficient [8]. Furthermore, although studies [6], [7] showed globally stable performances over time, inter-sessions variability remained significant.

While the community widely acknowledges issues of inter- and intra-subject variability, characterization of good or poor BCI performance is still not well established. Several studies investigated potential neurophysiological EEG-based predictors of inter-subjects BCI performances variability, associating the frontal theta rhythm (4-8Hz) [9] and the amplitude of the motor cortex mu band peak in the power spectrum [10], [11] during a relax condition to the ability of the subject to control a BCI. At the subject level, it has been shown that quality of motor imagery within a session (assessed by classification of left and right motor imagery) was correlated with gamma power during the task [12]. While these studies presented promising results for patient selection, it also shows that a multitude of currently unknown brain processes most likely affects BCI performance, and may vary across experimental paradigms. Furthermore, none of these studies investigated the neurophysiological markers of session-to-session variability of subjects' performances. Recently, some studies explored transfer learning approaches to compensate for this drift over sessions in EEG [13] and MEA [14]. However, these methods performs systematic domain adaptation and model retraining which requires labelled data and computation time. In an online perspective with patients chronically implanted with ECoG recording implants, in which it is possible to keep the same decoder functioning for several

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sessions, establishing predictors that can be rapidly estimated on an idle state period could help determine if the decoder needs to be recalibrated and predict how well a previous decoder would fit the incoming data. Implementing predictors of day's performance of a subject using a former model is also crucial to develop better session-to-session variability compensation techniques, and to elaborate more effective and personalized training procedures.

In this study, we propose to compare BCI performances across sessions of three patients implanted with chronic ECoG implants, and relate them to data-driven characteristics extracted from idle state. We hypothesize that idle state signals recorded in motor and sensorimotor cortices are informative both on inter- and intra-subjects performances variability, and in particular that idle state characteristics can explain this variability. Interestingly, we relate these long-term ECoG-BCI results to MEG-BCI sessions that subjects performed before implantation, speculating that individual long-term performances was somehow predictable.

MATERIALS AND METHODS

Subjects: Three subjects who underwent bilateral implantation of chronic wireless WIMAGINE implants on the motor and sensorimotor cortices were included in this study. Subjects 1 and 2 (S1 and S2) were respectively 28 and 29 years-old males (at the time of surgery), with traumatic sensorimotor tetraplegia which were included within the 'BCI and Tetraplegia' clinical trial (clinicaltrials.gov, NCT02550522) and implanted over the upper limb region of the cortex [15]. Subject 3 (S3) was a 38-year-old male who had sustained an incomplete cervical (C5/C6) spinal cord injury and was included within the 'STIMO-BSI' clinical trial (clinicaltrials.gov, NCT04632290) [1]. He was implanted more centrally to approach the legs motor regions.

Online experiments: During online BCI-sessions, the three subjects were trained to control different effectors. In the data considered in this study, S1 was controlling an avatar in a 3D virtual environment over eight continuous degrees of freedom (right and left hand 3D translations, and right and left wrist rotations) using motor imagery of both hands fingers. S2 controlled a virtual keypad in four directions, each of them being associated to a discrete state of the controller (up, down, left, right) using motor imagery of shoulders, legs and both hands. As for S3, he controlled directly his own legs independently through an epidural stimulator of the spinal cord allowing two discrete stimulation patterns (left leg and right leg) using direct motor imagery. For the three subjects, in addition to the controlled degrees of freedom, the decoders were trained to discern an idle class, corresponding to the periods of recordings in which the patient was relaxing. These periods were used to implement idle state indicators that are described below. ECoG was sampled at 585Hz. For each subject each BCI-session lasted approximately 2h, but only parts of data were labelled (rest of data was online testing). Prior to implantation, the three subjects performed a ~1h single magneto-encephalography (MEG) BCI session, sampled at 1kHz, in which they controlled a runner avatar through motor imagery of walking (2-states brainswitch control).

Offline dataset: In order to obtain comparable results, the online ECoG dataset of each subject was narrowed to three discrete states: idle for every subject and motor imagery of right and left hand for subjects 1 and 2 and right and left hip for subject 3. Since one subject had only one functioning implant due to an electronic dysfunction, only data from left implant were kept for all subjects, leading to 32 electrodes per subject. For S1 and S2 recorded electrodes were distributed following a checkerboard-pattern over the implant and for S3 more central electrodes were favored to get a better coverage of leg motor area [1]. Datasets were also balanced in terms of number of sessions and number of samples per states in each session. Finally, this led to a dataset comprising 15 sessions of 1800 labelled motor imagery samples per subject (one each 0.1s; 600 per state), acquired over 6, 10 and 5 months for subjects 1,2 and 3 respectively.

Feature extraction: Feature extraction procedure is described in details in [6]. After interpolation of missing points in the raw ECoG data, 1s-long epochs of neural signals with a 100ms sliding step, were mapped to the temporal frequency space using a complex continuous wavelet transform (CCWT) (Morlet) with a frequency range from 10 to 150 Hz (10 Hz step). The absolute value of the CCWT coefficients was then decimated along the temporal modality to obtain a 10-timepoints description of the epoch for each frequency band and each channel, resulting in the temporal-frequency-spatial neural feature tensor $X_t \in \mathbb{R}^{10*15*32}$. Same features were used during online experiments and offline analyses, except for subject 3 for which 0.2s-long epoch and 24 frequency bins were used in online experiments leading to $X_t \in \mathbb{R}^{2*24*64}$ (offline features were recomputed to match the other two subjects). Similar features were extracted from MEG experiments, with feature tensor $X_t \in \mathbb{R}^{10*9*105}$ (10 temporal steps, 9 frequency steps distributed between 1 and 40Hz, and 105 MEG channels).

BCI performances evaluation strategies and criteria: To assess subjects' performances across sessions, 3 classes classification models were trained offline for each subject. As previously explained, BCI performances were assessed offline on equivalent datasets to have a fair comparison between subjects that performed different online experiments. Similar to online experiments, Hidden Markov Models (HMM) combining emission and transition probabilities were trained and used for classification in a pseudo-online manner [6]. Emission probability was computed using REW-NPLS with one-hot encoded class labels, post-processed by softmax function [16]. Transition probability matrix was estimated by counting the number of transition in the training set. The class prior was established to ensure equal probability distribution among classes. In order to evaluate general performances but also their session-to-session variability, three training strategies were carried

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out:

- Within-session training: models were trained and tested on the same session, with a 5-folds cross-validation scheme.
- Session-1 training: models were trained only with data of session 1 and tested on every next sessions.
- Session-to-session training: models were trained each session, and tested on the following session.

Subjects' performances were assessed with the accuracy of classification (total number of correct predictions divided by the total number of samples). They were also evaluated in prior MEG experiments with two states classification models using within-session training strategy. As the different states were balanced, the chance level was of 1/3 for all classifications.

Idle state variability evaluation: All idle state samples of the three patients were projected together in an unsupervised manner from the feature space into a low dimensional (2D) space using Uniform Manifold Approximation & Projection for dimension reduction (UMAP [17]). The centroid of each session for each patient was identified, and idle state variability was evaluated through the Euclidean distance between each session's centroid and the centroid of session 1, and between each pair of consecutive sessions' centroids (Fig. 2). Measure of distances in a 2D UMAP embedding was chosen to investigate variability over sessions because we showed in a previous study on a comparable dataset that the projected patterns were remarkably stable over time [18].

Idle state dimensionality: Intrinsic dimension (ID) was computed in the feature space for idle state samples of each session. ID can be defined as the minimum number of parameters needed to describe the data with a minimal loss of information. This was done using two widely used classical estimators, MLE and DANCo [19]. ID was also assessed in MEG experiments to evaluate to what extent the dimensionality is predictable before implantation.

Correlations: To investigate if idle state characteristics could explain inter-sessions and inter-subjects variability, linear regressions were estimated between BCI performances, both distances in the UMAP embedding as well as the ID. Specifically, we investigated relationships between 1) within-sessions training performances and idle state ID indicators, 2) session-1 training performances and distances between each session's centroid and the centroid of session 1, and 3) session-to-session training performances and distances between each pair of consecutive sessions' centroids. Goodness of fits were estimated using the Pearson correlation coefficient R.

Statistical tests: Differences in performances, distances and ID between subjects (mean across sessions) were assessed using one-way analysis of variance (ANOVA), followed by post-hoc Tukey's honestly significant difference tests when ANOVA were significant. Statistical significance threshold was set to $p < 0.05$.

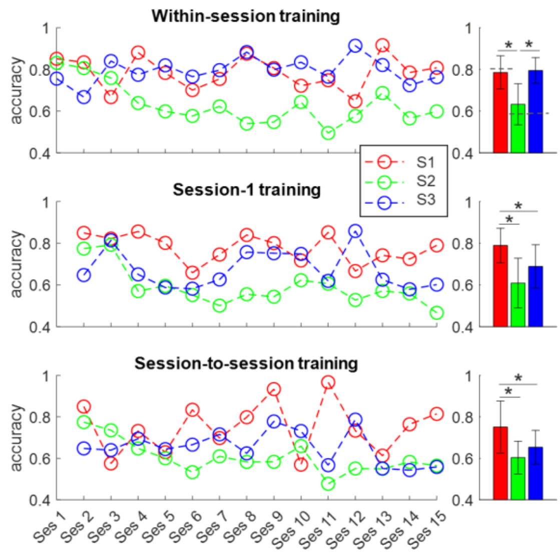

*Figure 1: Models' decoding accuracies over sessions (left) and average across sessions (right) with the three training strategies. Bar graph are presented as mean ± standard dev. * reports significant differences. For comparison purposes, grey dotted lines on the top bar graph represents models' decoding accuracies in MEG experiments.*

RESULTS

BCI performances: BCI performances (models accuracy on test sets) of the three subjects with the three training strategies are presented in Fig. 1. S1 and S3 had significantly better performances than S2 in the within-session training (p<0.001; S1: 0.79±0.08; S2: 0.63±0.10; S3: 0.79±0.06). When model was trained on day 1 only, performances of S1 were significantly better than S2 and S3 (p<0.001 and p = 0.02 respectively; S1: 0.79±0.08; S2: 0.61±0.12; S3: 0.69±0.10). Only performances of S3 dropped in this scenario compared to within-session training, For session-to-session training, S1 performances were significantly better than S2 and S3 (p<0.001 and p = 0.03 respectively; S1: 0.75±0.13; S2: 0.60±0.08; S3: 0.65±0.08). Again, performances of S3 dropped particularly with this training strategy compared to within-session training. Regarding prior to implantation MEG experiment, BCI performances were better for S1 in comparison to S2 and S3 (S1: 0.80; S2: 0.58; S3: 0.59).

Idle state variability: Distances between centroids of idle state features projected into the 2D UMAP embedding are presented in Fig. 2. Whether comparing distance to first session or session-to-session distances, it appeared that idle state features of S1 remained more stable over time, with a smaller average distance and a smaller variability of distances. Distance to session 1 was significantly lower for S1 than for S2 and S3 (p = 0.01 and p = 0.02 respectively; S1: 0.73±0.41; S2: 1.99±1.78; S3: 1.33±1.13), while session-to-session distance was significantly lower for S1 in comparison to S3 only (p<0.01; S1: 1.11±0.58; S2: 1.49±1.07; S3: 1.95±1.38).

Idle state dimensionality: ID was globally stable over ECoG sessions for the three subjects with a gradation between them (Fig. 3). Whether computed with MLE or

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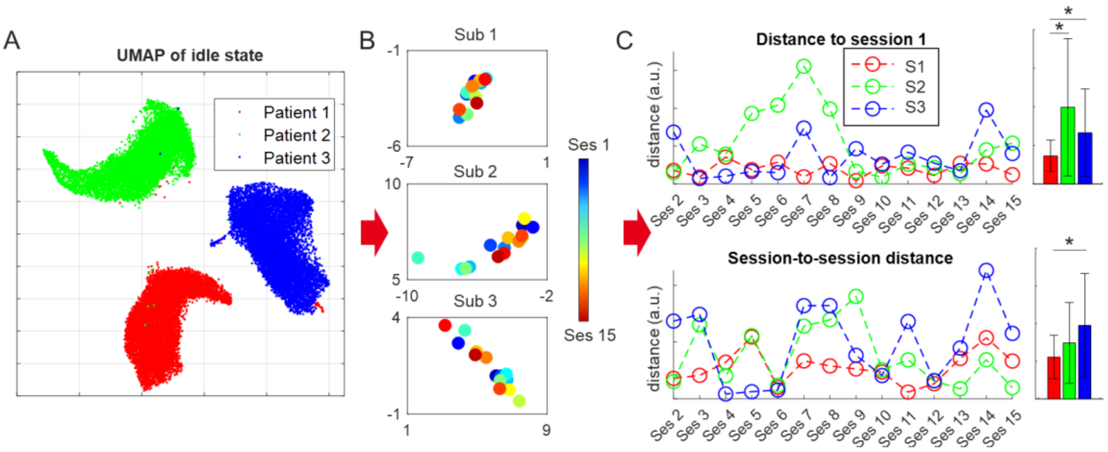

*Figure 2: (A) Unsupervised UMAP of all idle state features of the three patients in a 2D-space; (B) Representation of the centroids of each BCI-ECoG session for each subject separately; (C) Euclidean distance between centroid of session 1 and centroids of the following sessions (top) and distance between each session and the previous one (bottom) in the UMAP embedding. Average across sessions is presented as bar graphs on the right (mean ± standard dev). * reports significant differences).*

DANCo estimator, ID was significantly lower for S1 compared to S2 and S3, and significantly lower for S2 than for S3 ($p<0.001$ for all cases; MLE-ID: S1: 15.3±1.8; S2: 31.3±4.8; S3: 24.7±2.9; DANCo-ID: S1: 19.2±4.5; S2: 53.7±11.4; S3: 39.9±7.4). ID was also evaluated during prior to implantation BCI-MEG experiments, and seemed to follow a similar pattern between subjects, especially with DANCo estimator (MLE-ID: S1: 34.0; S2: 36.3; S3: 36.8; DANCo-ID: S1: 27.2; S2: 43.3; S3: 37.2).

Correlations: When pulling subjects' together, significant correlations between cross-sessions models' accuracies and variability of idle state between sessions as well as between subjects' performances and intrinsic dimensions were found (cf. Fig. 4 – Pearson correlation coefficient and associated p-values are indicated in the figure). These correlations remained insignificant for individual subjects.

DISCUSSION

The main objective of this study was to investigate if markers of inter and intra-subjects' BCI performances could be unraveled from idle state. To do so, we compared different indicators of idle state brain signals between sessions and patients, and related them to the BCI performances. BCI performances were assessed offline, with three training strategies to disentangle subjects' best achievable performance (within-session training), drift over time (session-1 training) and session-to-session variability (session-to-session training). Note that for the purpose of this study, subjects' best achievable performance were assessed with relatively small training sets (5 folds of 1440 features, i.e. 2.4 min of data) and do not reflect the best performances they could achieve with a longer training.

The three training strategies allowed us to observe that the patients presented distinct BCI profiles. S1 showed high BCI capabilities with no drift and only low variability over sessions. S2 performances were lower, but we did not observe strong drift or variability between sessions either. Regarding S3 high BCI performances were observed, with an important drop of performances when the model of a previous session was used, indicating a drift and/or variability over sessions. Interestingly, these observations are consistent with what was noticed in online experiments. Indeed, S1 was able to control accurately up to 8 continuous degrees of freedom without recalibration of the model for up to 6 months [6], while S2 controlled models with 5 discrete states with fluctuant performances even in the same session. As for S3, he was somewhere in between, and controlled with good performances 7 continuous states [1], although regular model recalibration (approximately every 2 weeks) was necessary.

This more frequent need for recalibration was also coherent with more fluctuations of idle state, measured as distances between centroid features of sessions in a low-dimensional projection. Indeed, S2 and S3 presented higher variability in idle state features over sessions. Furthermore, the performances in a session using a decoding model of another session was significantly negatively correlated with the distance between these sessions. Thus, measuring the distance with model's calibration session through an idle state recording acquired prior to the BCI experiment could be a good predictor of session expected performances, and of the need to recalibrate the model. Although this has to be confirmed on more sessions, we believe to have obtained here a session-to-session predictor of subjects' performances, in contrast to previous studies that investigated only inter-subjects predictors of performance [10], [11], [20]. In addition, this distance is a data-driven indicator that is not based on neurophysiological hypotheses, and then could be adapted to other recording techniques.

Regarding ID of the idle state in features space, we observed a clear gradation between subjects, with a lower ID for S1, higher for S2, and relatively stable across sessions. Crosschecking this result with subjects'

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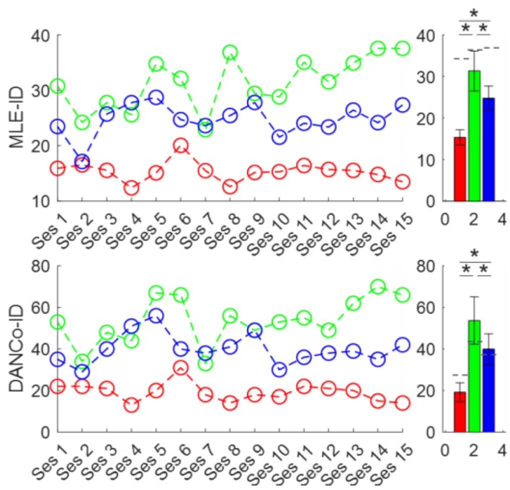

*Figure 3: ID of idle state features over sessions (left) and average across sessions (right) with MLE (top) and DANCo (bottom) estimators. Bar graph are presented as mean ± standard dev. * reports significant differences. For comparison purposes, grey dotted lines on the bar graphs represents ID of idle state features in MEG experiments.*

performances indicated that ID could be a good global predictor of subject BCI capabilities: the lower ID, the more decodable and stable brain signals. This was confirmed by correlation between model's accuracy and ID. This is in agreement with previous results that reported the same relationship in images dataset [21].

Although predicting the global long-term performances of implanted patients through ECoG experiments could be of interest, it would be much more valuable to assess it before implantation. With this in mind, we examined prior to implantation MEG-BCI experiments that were performed by the three subjects. This session was the first BCI experiment of patients and was performed to assess their adhesion. While S1 and S2 presented similar MEG-BCI performances than in ECoG-BCI, S3 presented much lower performances (in comparison to within-session training, which is the same strategy than in MEG). This tends to indicate that, if high MEG-BCI performances would ensure high ECoG-BCI performances, lower MEG-BCI performances does not necessarily leads to lower ECoG-BCI performances. This is not surprising as the patients certainly have a different BCI learning potential, which cannot be estimated within a single session. Thus, MEG-BCI sessions seems to be an important step for subjects prior to the implantation to assess their BCI "compatibility" (in addition to their adhesion), but we strongly suggest to perform more than one BCI sessions (ideally, enough to observe a learning curve). Interestingly ID of idle state during these MEG-BCI experiments was also estimated and showed the same gradation between patients than in ECoG-BCI experiments (especially with DANCo estimator). Since ID seems to remain relatively stable and discriminating across subjects after implantation, it could be a strong predictor of subjects' global BCI long-term performances. Although this need to confirmed on more patients, this could be an important finding as it could help identifying BCI-inefficient patient for whom an

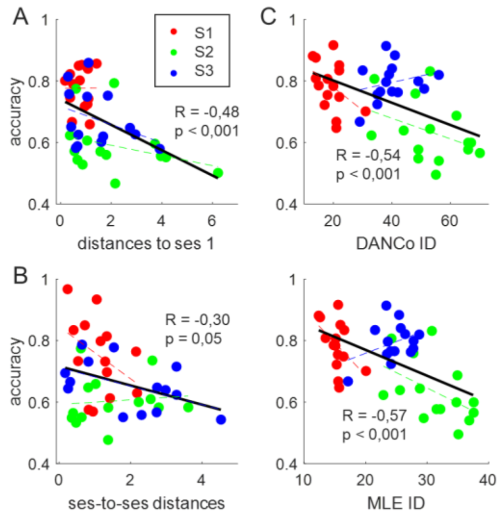

Figure 4: Correlations analyses: (A) between models' accuracy (session-1 training strategy) and distance to session 1 in idle state UMAP embedding, (B) between models' accuracy (session-to-session training strategy) and session-to-session distances in idle state UMAP embedding and (C) models' accuracy (within-session training strategy) and idle state features ID (DANCo and MLE).

implantation would be an unnecessary risk in addition to a waste of time and resources. A simple assessment of subject's brain signals complexity in MEG (or EEG) in a relax state could participate to reveal these patients before implantation.

CONCLUSION

To our knowledge, this work is the first study investigating session-to-session BCI performance predictors on implanted ECoG patients. Even though this was based on offline analysis, on patients that used different motor imagery, effectors and online decoding models, the conclusions drawn here on narrowed comparable datasets are reflecting our experimental observations done during the online experiments. Based on idle state features variability over sessions, we first uncovered a predictor of the performances of a previous decoding model on current session. Then, analyzing the dimensionality of brain signals in idle state, we revealed a more "long-term" indicator, which predicted the global BCI-capabilities of the patients. Furthermore, although this must be confirmed on more subject, the latter followed the same pattern between patients in MEG-BCI experiments performed before implantation. These results are of particular importance on one hand to anticipate the need of model recalibration in ECoG-BCI training experiments, and on the other hand for selecting patients to be implanted with BCI neuroprosthesis.

ACKNOWLEDGMENTS

This study was Supported by Translational Medical Research Award 2021 from the Leenaards Foundation, the Swiss National Science Foundation, the Lead Agency Program with the French National Research Agency

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10.3217/978-3-99161-014-4-015

(Think2Move SNF-32003BE-205563, ANR-21-CE19-0038), the European Commission (ERC-2019-PoC Braingait 875660, EIC 2021-TransitionChallenges-01-01 ReverseParalysis 101057450, Horizon-EIC-2021-Pathfinderchallenges-01-02 NEMO-BMI 101070891), Fonds Clinatec (WIMAGINE implant development, BCI4Grasp) and Institut Carnot Leti.

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