Evaluating dry EEG technology out of the lab

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***Abstract*—Dry electroencephalography (EEG) electrodes have emerged as a promising solution for improving the ease of use of non-invasive Brain-Computer Interface (BCI) systems. Recently introduced dry helmets have been shown to be competitive to state-of-the-art gel-based ones. Here, we evaluate a dry EEG cap through BCI performance estimated on a very large population under extremely noisy conditions. Our results confirm the great prospects of dry EEG to help push BCI technology out of the lab for everyday use in homes, clinics and public spaces.**

***Index Terms*—EEG, dry sensors, brain-computer interface, evaluation**

I. Introduction

Non-invasive EEG brain imaging remains the most popular option for enabling BCI applications. However, the state-of-the-art "wet" EEG sensors (i.e., electrodes that require the application of non-abrasive gel to improve conductivity), despite shown to deliver the best currently possible EEG signal quality in terms of Signal-to-Noise Ratio (SNR), are the culprit of intense obtrusiveness reported by most subjects and of heavy logistic burden for the relevant application prototypes [1], thus posing a major barrier preventing the transfer of BCI and other EEG-based technologies [2]. Different dry EEG sensors have been introduced in the course of the last 15 years to address the shortcomings of gel-based systems. However, they have been often associated with inferior signal quality with respect to their wet counterparts.

As the industry rapidly develops, many recent studies have provided solid scientific evidence suggesting that some of the current, commercially available dry EEG caps are capable of delivering comparable performance to that obtained with wet systems [1]–[3]. Nevertheless, most of these investigations reported findings on relatively small subject samples, either in fully controlled laboratory conditions or only minimally cluttered environments, and often without estimating BCI performance. Here, we investigate the possibility to successfully operate a standard SensoriMotor Rhythms (SMR) BCI paradigm by means of a state-of-the-art dry EEG cap, with a sizeable sample of 100 participants extracted for preliminary analysis out of an unprecedentedly large database hosting EEG data by 530 volunteers. Importantly, EEG recording took place in the framework of a crowded, public exhibition and in the presence of numerous nearby electromagnetic sources. Our analysis indicates that dry technology has considerably advanced and may be sufficiently mature to enable unobtrusive, plug-and-play BCI applications even in extremely challenging, real-world settings.

II. Methods

We analyzed data of the first 100 registered out of the 530 total participants of the Mental Work event [4]. At Mental Work, a public, open-door exhibition that took place across several months in 2017 and 2018 at the premises of École Polytechnique Fédérale de Lausanne (EPFL), Switzerland, the public used research grade dry EEG helmets to connect to several different robotic machines/sculptures inspired by the industrial revolution, and activate them with a binary (2-class) Motor Imagery (MI) BCI developed by EPFL researchers. Participants were visitors of the exhibition who registered online and booked a Mental Work session.

Each session comprised a 30-minute training/calibration session to collect EEG data for supervised estimation of a machine learning decoder and to train the subject in performing mental imagery, followed by cued, closed-loop control of a conventional "feedback bar" graphical application on a screen; subsequently, participants would proceed with free-control of each of the three available robots through MI. Calibration took place in a non-isolated booth within the exhibition's space, accessible to observers and vulnerable to auditory and electromagnetic noise. It involved 30 10-s long trials for each MI class. The two mental tasks were kinaesthetic imagination of right and left hand movements. Here, we only report on the calibration data of each user.

A DSI-24 wireless, portable, dry, EEG cap (Wearable Sensing, San Diego, CA, USA) with on-board artifact elimination was used to acquire the signal from 19 EEG channels (10-20 system locations: Fp1, Fp2, Fz, F3, F4, F7, F8, Cz, C3, C4, C5,

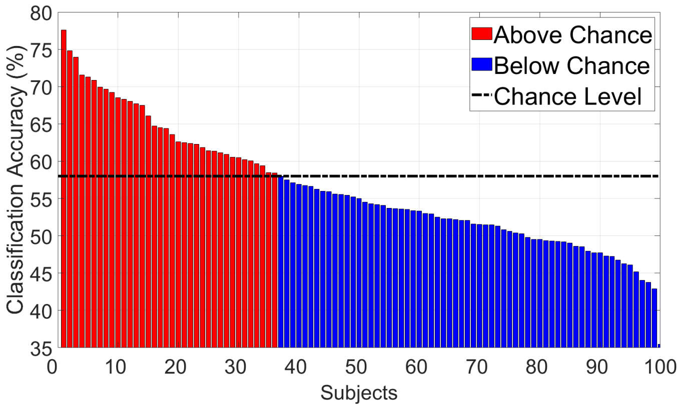

Fig. 1. Sorted classification accuracy for all subjects. The dashed black line indicates the 95% confidence interval for non-random classification in a binary classification problem with the amount of data available per subject here [5].

C6, T7, T8, Pz, P3, P4, O1, O2, two earlobe clip references, ground electrode at FPz) at 300 Hz sampling rate. EEG signals are processed within each trial with linear detrending, DC removal, second order Butterworth band-pass filtering with low/high cut-off frequencies at 2 Hz and 40 Hz, respectively, and large Laplacian spatial filtering. We extracted Power Spectral Density (PSD) features from all 19 EEG channels with 0.5 Hz frequency resolution between [0.5, 30] Hz, in sliding 1 s windows with 0.5 s overlapping/shift using the Welch method (internal windows 0.5 s long with 50% overlapping). This yields 1140 samples (60 trials $\times$ 19 samples/trial, 570 per class) and, incidentally, 1140 candidate features (60 bands $\times$ 19 channels) for each subject. Classification accuracy is estimated with 5-fold cross-validation individually for each subject using a Quadratic Discriminant Analysis (QDA) classifier, selecting within each fold the 10 best features in terms of r^2 separability from a candidate feature subset consisting of channels Cz, C3, C4, C5, C6 and the μ (8-14 Hz) and β (18-24 Hz) bands, known to be relevant to SMR BCI. Data from the same trial are kept in the same cross-validation fold to avoid overestimating accuracy due to data dependence.

III. Results

Fig. 1 shows that 34 out of 100 subjects were able to reach above-chance classification accuracy in open-loop with the dry EEG helmet after only 30 minutes of training under difficult circumstances. Six participants obtained accuracies over 70%. It must be highlighted that the presented single-sample accuracy estimate refers to samples derived from 1 s data segments, as opposed to the single-trial estimates usually reported in the literature that reflect information from 4–5 s of EEG data. Fig. 2 confirms that high classification accuracy is fueled by the anticipated SMR patterns that can be precisely captured by the dry system used. Specifically, contralateral activation associated with MI of both hands is observed for S1 in the μ band, and for the left hand in the β (S1, S2) and μ band (S2). SMR modulation is stronger in the μ band as is most often the case for able-bodied users.

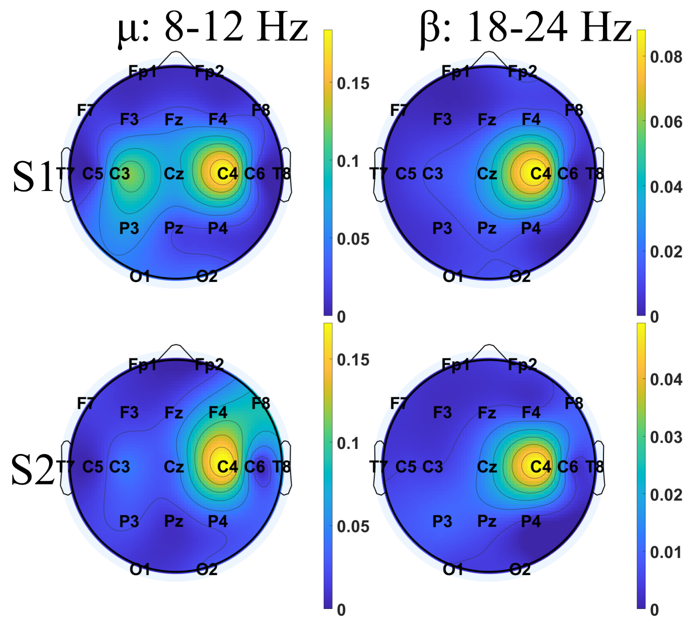

Fig. 2. Topographic distribution of r^2 feature separability averaged within the μ (left) and the β band (right) for subjects S1 (top) and S2 (bottom) exhibiting the highest classification accuracy in this sample.

IV. Discussion

This partial, preliminary analysis of the Mental Work exhibition dataset shows that state-of-the-art dry caps hold great promise for enabling brain control in realistic application scenarios, while also greatly improving ease of use, the Achilles' heel of current BCI prototypes. The accuracy results may improve through user training, as shown in research conducted with wet systems [6]. Our future work will focus on extracting several additional measures of signal quality, processing the entirety of the Mental Work dataset, and performing explicit comparisons with wet systems.

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