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On Modern Neurofeedback Solutions based on Brain-Computer Interfaces in Uncontrolled Real-World Settings

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Abstract— **This study reports a feasibility analysis that encompassed 83 participants, demonstrating how modern Neurofeedback procedures based on BCI technology can be deployed in uncontrolled real-world scenarios. The results obtained were comparable to those acquired in controlled research studies.**

I. INTRODUCTION

Brain-Computer Interfaces (BCIs) are real-time systems that translate brain signals into commands for communication and control, motor substitution, and entertainment, among other applications. To this date, most of these applications have been demonstrations of proof-of-principle, carried out in laboratory settings [1]. **Neurofeedback** (NF) is a specific BCI application that has been traditionally used outside laboratories, in clinical settings, for the last three decades. However, there is a gap between modern NF research studies based on BCI technology (usually confined to clinical settings) and the widespread classical NF, with classic EEG equipment, reduced number of sensors, and generic signal processing that do not take into account inter- and intra-subject variability (feedback must be adapted to the participant on the fly [2]).

This study presents a commercial **NF technology for cognitive enhancement based on BCI tech**, aimed at reducing the aforementioned gap by introducing: (i) a lightweight and reliable gel-less EEG technology, and (ii) state-of-the-art BCI signal processing methods (artifact filtering, subject-specific feature extraction). These methods are fully automatized for online operation as well as for offline reporting of results. From a BCI and signal processing point of view, the results of 83 participants are presented herein. Signals were recorded in five different clinical centers (Spain) by non-expert personnel in the EEG field. Fifty-nine participants underwent a five-session program and the remaining 24, a ten-session program.

II. BCI-BASED NF TECHNOLOGY

The technology implements a widely used protocol to date, which focuses on the **up-regulation of the upper part of the alpha frequency band** (upper alpha, UA) in posterior locations of the scalp [3]. This band is determined for each subject using the Individual Alpha Frequency (IAF) as an anchor point to address inherent inter-subject variability [4]. This NF protocol is supported by the relationship between increased parieto-occipital alpha activity and cognitive function, related to inhibitory mechanisms of task-irrelevant brain regions [5].

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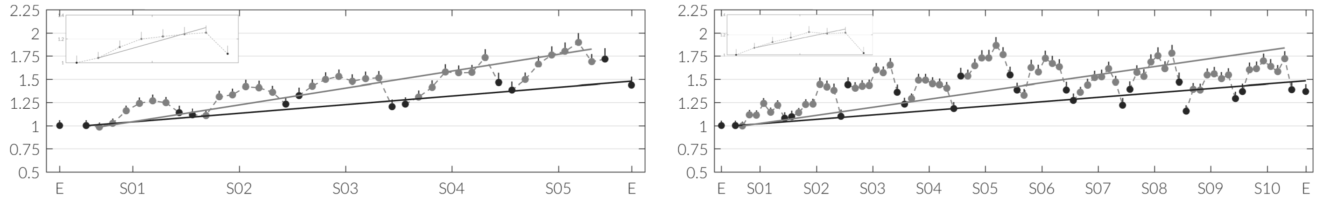
Fig. 1. The two types of portable EEG recording systems. Left) Versatile system with 16 channels and water-based sensors, located on FP1, FP2, F3, Fz, F4, C3, Cz, C4, P7, P3, Pz, P4, P8, O1, Oz and O2. Right) Minimal headset with 12 channels and dry sensors, located on AF7, FP1, FP2, AF8, F3, F4, P3, P4, PO7, O1, O2, and PO8. In both cases the ground and reference electrodes are placed on FPz and left earlobe, respectively.

The solution consists of three main elements: (i) portable, lightweight, and wireless EEG recording systems by Bitbrain [6] (Figure 1); (ii) software that fully automatizes the online NF procedure using state-of-the-art signal processing methods; and (iii) cloud service that automatically reports the NF effects on the trained parameter for all sessions performed. The online and offline signal processing methods have been extensively reported in previous publications [3] and are briefly summarized next.

A. Signal processing

EEG power was calculated through a short-term Fast Fourier Transform (FFT) analysis with 1s hamming window, 30 ms overlapping, and zero-padded to 1024 points (0.25 Hz resolution). Online signal processing uses the EEG collected immediately before the NF procedure (resting state and task-related activity screenings), to compute the Independent Component Analysis (ICA) matrix for the online filtering of the blinking component, the IAF as the frequency bin with the maximum power value in the extended alpha range 7-13 Hz, and the training baseline (and lower and upper limits) using the mean (and the 5th-95th percentiles) of the UA power distribution. Offline analysis uses a three-step automatic procedure: filtering out of the blinking component by the FastICA algorithm, epoch rejection by a time-domain threshold ($> 200\mu V$) at any electrode, and epoch rejection by a frequency-domain threshold. In the latter, the power values for each epoch in the bands (1-3 Hz) and (20-30 Hz) were computed, commonly affected by ocular and muscular artifacts. The log-transformed



a) Five-session program

b) 10-session program

Fig. 2. Individual UA power (mean + SEM) averaged across the feedback electrodes for the task-related EEG screenings (black dots) and NF trials (gray dots). Data was normalized to the power in the initial screening. The upper-left boxes display the power enhancement within sessions, where EEG data of the NF sessions were averaged across sessions. The gray line depicts the relevant trend measurements.

power values were then converted to z-scores and outliers (> 2.5) were removed for any electrode.

III. DATA ANALYSIS AND RESULTS

Fifty-nine and 24 participants underwent five and ten training sessions, respectively, with pre- and post- cognitive evaluation sessions on the first and last days.

A. Electrophysiological metrics

Power EEG analysis was conducted in the trained parameter: power in the individual UA band, averaged across the feedback electrodes. Pre-post enhancement was defined as the power change between the initial and final EEG screenings in task-related activities. Across- and within-session enhancements were also measured. Across-session enhancement was assessed by a linear trend analysis between the power values in the pre-NF screenings of all sessions and the final screening. Within-session enhancement comprised two measurements, computed in the power values averaged across the NF sessions: a power change comparison between the pre- and post- EEG screenings, and a linear trend analysis of the power values in the six training trials. A t-test for dependent samples was applied to log-transformed power values to determine statistical significance of pre- and post- comparisons. Trend analysis consisted of the computation of the slope of a fitted regression line for each participant, and a t-test to test the hypothesis of a null slope. Type I error was set at $\alpha = .05$.

B. Electrophysiological results

Figure 2 displays the EEG results. Regarding the five-session programs, analysis of the pre-post enhancement in the trained parameter revealed a significant increase ($t_{58} = -4.8, p < .005$; medium effect size, $d = .45$), with an average increase of 40.2%. Trend analysis showed a significant UA power increase across the NF sessions ($t_{58} = 3.3, p = 0.002$). Regarding the within-session enhancement, no significant power increase was found between pre- and post-NF screenings. Trend analysis indicated a significant power increase across NF trials ($t_{58} = 4.6, p < 0.005$). Regarding the 10-session programs, analysis of the pre-post enhancement in the trained parameter demonstrated a significant increase ($t_{23} = -4.1, p < .005$; medium effect size, $d = .54$), with an average increase of 36.3%. Trend analysis revealed an increase in UA power across NF sessions at a statistical trend ($t_{23} = 1.9, p = 0.059$). For within-session enhancement, no significant power increase was found between the pre- and post- NF screenings. Trend analysis showed a significant power increase across NF trials ($t_{23} = 2.8, p = 0.010$).

IV. CONCLUSIONS

This study provided the results of 83 participants that underwent NF programs of either five or ten sessions, producing 350 hours of EEG data. The EEG results show consistent pre-post enhancement in the trained parameter and power increase across NF sessions. It must be highlighted that this across-session increase was statistically significant for the 10-session program ($t_{23} = 1.9, p = 0.059$). This could be due to the lower number of subjects (and consequently lower statistical level) and also because of a saturation phenomenon of the UA power that is not well captured by a linear trend. Both conditions demonstrated increased 'trainability', i.e., a consistent enhancement across training trials is visible. The electrophysiological results are comparable to those obtained in research literature using similar NF procedures [3], [7], i.e., pre-post and across-session enhancements in the trained parameter.

Data were collected by non-technical personal in a completely uncontrolled scenario. Five independent Spanish centers acquired the technology and obtained data during normal, day-to-day operations. Obtaining similar results to those of research studies carried out in controlled scenarios indicates the feasibility of using this **BCI technology in real-world settings**.

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