

# Brain-Computer Interface-Based Neurorehabilitation: From the Lab to the Users' Home



C. Escolano, E. López-Larraz, J. Mínguez, and L. Montesano

**Abstract** Most of the research in brain-computer interfaces (BCIs) to date is conducted using stationary electroencephalogram (EEG) equipment with high density recordings, and performed in controlled laboratory settings. Moving BCI-based neurorehabilitation or motor substitution applications from the laboratory to home settings will improve accessibility to these therapies while allowing a more intensive data collection to foster the scientific progress. One of the barriers for this is the EEG technology itself. We developed a new dry EEG system within the More-Grasp H2020 EU project to allow BCI home use for spinal cord injury patients. This paper describes the EEG activity measured with this new EEG system under well known experimental protocols such as resting-state, visual evoked potentials, and self-initiated reach-and-grasp movements.

## 1 Introduction

One of the aims of brain-computer interfaces (BCIs) is to improve the quality of life of people with difficulties to perform daily life activities, such as communication or mobility. Control of neuroprosthetics is one of the most studied BCI applications, as it can be used for neurorehabilitation and motor substitution for people suffering motor impairments due to a spinal cord injury (SCI) or stroke. The basic idea is

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that the modulation of brain activity can be used to control external devices that compensate the lost function [1] or facilitate functional recovery through their use [2].

Most of this research is done using stationary electroencephalogram (EEG) equipment with high density recordings in controlled laboratory settings (e.g., electromagnetically isolated rooms). These conditions, however, need to be reconsidered when transitioning to more ecological settings (such as the home of the users), which brings other factors such as usability and user acceptance. Indeed, this is not just a barrier for the transfer of results to real life. It also hinders the scientific progress since the amount of data and evidence that can be collected, analyzed and shared is limited to those that can be collected in research centers, which are usually expensive and difficult to scale up.

Bringing the technology to the end users' home will be a game changer for this type of applications: it will allow to reach more people that will potentially use the system for longer periods of time, with the potential to boost the results and the impact in their lives. This is, however, not an easy endeavour. Designing BCIs for home-use requires considering several usability factors to favor a frequent use (even daily), such as short set up times, easy to handle mobile devices, and gel-less electrodes that do not require to wash the hair and apply heavy hygienic afterwards. Notwithstanding, the signal quality needs to be in a similar range that the research-grade counterparts.

This study presents a new dry-EEG system developed within the MoreGrasp H2020 EU project [3], following a user-centered design methodology to be used for motor substitution and rehabilitation of SCI survivors at home. The main characteristics of the system are: (1) dry-EEG sensors that do not require any conductive substance and improve usability; (2) layout over the sensorimotor cortex; and (3) comfortable headset that can be set up in a few minutes without technical support. As mentioned, it is essential to provide reliable EEG signals with sufficient quality for the intended motor BCI applications. This paper reports the results of the wearable dry-EEG device (Hero, Bitbrain, Spain) used to record spontaneous activity, visual evoked potentials, and EEG-correlates of reach-and-grasp movements.

## 2 Methods

We conducted two separate experiments to cover the most typical EEG patterns used in BCI applications (right-handed able-bodied participants). The first one recorded resting state EEG and visual evoked potentials ( $n = 16$ , 20–35 age range); the second one, EEG correlates of self-initiated reach-and-grasp actions ( $n = 15$ , 15–30 age range).

The two experiments were conducted in Bitbrain (Fig. 1) using the wireless dry-EEG device (Hero, Bitbrain, Spain). The system has 11 sensors located over the sensorimotor cortex (FC3, FCZ, FC4, C3, C1, CZ, C2, C4, CP3, CPZ, and CP4) with the ground and reference sensors in the left earlobe, and a sampling rate of



**Fig. 1** Wireless dry-EEG device during the execution of the reach-and-grasp actions

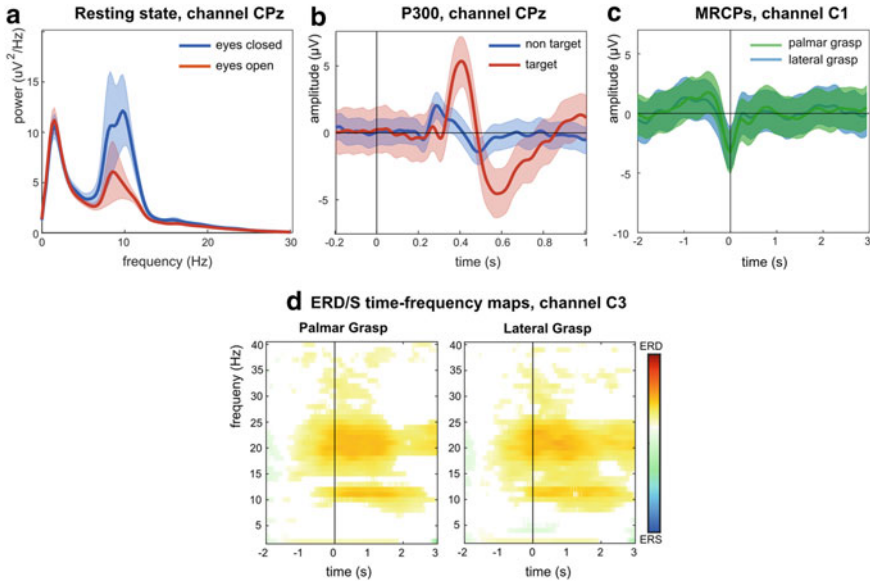
256 Hz. The software employed for stimulus presentation and data collection was a multimodal BCI programming platform (BCI Development Platform, Bitbrain).

1. *Resting state EEG*: EEG was recorded in resting state conditions (eyes closed and eyes open, 3 min each).
2. *Visual oddball P300 task*: The task consisted of two blocks, where each block had 30 target and 90 non-target stimuli (1/4 target probability). A red (target) or blue (non-target) dot was displayed on the screen during 250 ms. The inter-stimulus interval was random in the [1.25–1.75] s range. Total time for each block was 3.5 min.
3. *Self-initiated reach-and-grasp actions*: Participants were instructed to perform reach-and-grasp actions with their right hand towards two objects: a glass (palmar grasp) and a spoon within a jar (lateral grasp). We asked them to focus their gaze on the object to grasp for at least 2 s before starting the movement. A total of 80 trials per condition were recorded, distributed in four runs (20 trials each). The location of the objects were switched between runs.

## 3 Results

### 3.1 Resting State EEG

EEG data from resting state conditions were transformed to the frequency domain using a short-term FFT transform. Figure 2a shows the group-level power spectra in both eyes closed and open conditions for the CPz sensor (mean and standard error of the mean), which shows the typical alpha-blocking phenomenon reported in literature.



**Fig. 2** EEG correlates for the dry-EEG device in **a** resting state conditions, **b** a visual evoked P300 paradigm, and **c–d** a motor task involving reach-and-grasp actions (MRCPs and ERD/S time-frequency maps)

### 3.2 Visual Oddball P300 Task

EEG data from the P300 task was bandpass filtered in the [1–10] Hz range. Data was epoched using a [−0.2 1] s time window relative to stimulus onset. For each condition (target, non-target) the average across trials was computed, and the 95% confidence interval of a bootstrap procedure (1000 permutations) using the mean as the statistic. Figure 2b shows the group-level visual-evoked potential for the CPz sensor. There is a clear difference between target and non-target conditions, depicting a visual P300 waveform in agreement with literature in this domain [5].

### 3.3 Self-initiated Reach-and-Grasp Actions

We analyzed low-frequency movement-related cortical potentials (MRCPs) and event-related (de)synchronization (ERD/S) time-frequency maps. For the MRCPs, a low-pass filter with a cut-off frequency of 3 Hz was applied. Then, EEG data was epoched into trials with a [−2 3] s time window relative to the movement onset. We determined a 95% confidence interval for each condition using non-parametric *t*-percentile bootstrap statistics and computed the grand-average across participants. Regarding the ERD/S time-frequency maps, we applied a [1–60] Hz bandpass filter

and computed the ERD/S for each frequency bin (range [2–40] Hz, 1 Hz resolution) using a reference interval of  $[-2 -1]$  s with respect to the movement onset. To obtain grand-average ERD/S maps, we computed the average and confidence intervals (non-parametric  $t$ -percentile bootstrap statistics,  $\alpha = 0.05$ ), and the non-significant time-frequency points are not shown in the maps.

Figure 2c–d shows the group-level MRCPs and ERD/S time-frequency maps in contralateral sensors. A negative deflection can be observed in the MRCPs waveform at movement onset that starts around 0.5 s before the movement onset. Desynchronization patterns can be observed in the time-frequency ERD/S maps, with larger values in alpha (8–12) Hz and beta (15–25) Hz frequency bands. For a detailed comparison with other type of electrodes see [4], which also shows that, using the same number and location of sensors, the decoding performance is not statistically different from widely spread and standard EEG research systems.

## 4 Conclusion

EEG systems are the cornerstone for the effective introduction of BCIs in real-world applications outside the lab, as well as for the effective adoption in user-centered fields. In recent years, there have been strong R&D efforts in developing new EEG technologies with enhanced usability and comfort, without sacrificing reliability and accuracy. This paper briefly described how one of these new dry-EEG devices was able to reliably measure the most typical brain patterns used for BCIs in practical scenarios.

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