Dry versus Wet EEG electrode systems in Motor Imagery Classification

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Abstract
Motor imagery (MI) classification performance is important in developing robust brain computer interface environments for neuro-rehabilitation of patients and robotic prosthesis control. To bring this technology to everyday use relatively new EEG acquisition systems have been developed. These systems are highly portable, wireless and they are based on dry, active electrodes, which does not require the use of conductive gel. As a result they are more prone to interference via noise sources that are commonly around and their signal-to-noise ratio may be low. Here, we device a number of motor imagery tasks along with actual movements of the limbs and compare the classification performance of a dry 16-channel and a wet, 32-channel, wireless EEG system. Our results demonstrate the feasibility of home use of dry electrode systems with a small number of sensors.

Introduction
The Motor imagery in Brain Computer Interface (BCI) is defined as the activity of mentally simulating a given action without the actual execution of the movement. Several studies have shown that performing a motor imagery session activates partially the same brain regions as the performance of the real task and it can increase motor performance [1] [2]. Therefore, it is widely used in rehabilitation, for example, for persons with Parkinson disease, stroke or any other motor deficit [3]. The first studies regarding motor imagery focused mainly in hand and arms movements [3]. Recently, those studies started to embrace also the leg and feet movements, in order to study the neurophysiology of human gait. In 2007, Baker et al. demonstrated a high temporal correlation in EEG signal between imagined and actual walking patterns, which confirmed that MI uses similar cerebral resources as the ones used during actual gait [4]. Several studies, has showed that MI practice improves walking in patients with hemiparesis and stroke [5], [6]. This means that the motor imagery promotes learning by reinforcing processes at the cortical level [6]. Research teams are also trying to combine BCI with exoskeleton robots. Recently, Zhouyang Wang et al. proposed a lower limb exoskeleton robot controlled with MI to walk forward, sit down, and stand up [7].

There are several challenges associated with detecting motor intention in imagery movement tasks of the legs/hands even for just two classes [8] [9]. These challenges result in long training sessions and large intersubject variability in the performance. The number, placement and type of EEG channels/electrodes play a critical role. The use of fewer channels helps to decrease the computational complexity and develop methods that allow real-time feedback to the user, which can substantially increase the learning rate. Electrodes can be either wet or dry. Wet electrodes require the application of conductive gel that improves the signal quality. However, they require long preparation times and impede the use of the technology at everyday scenarios. Dry electrodes may overcome this problem, reducing montage times and subject discomfort but the signal quality is poorer.

In the present study, we contrast several two-classes experiments that include MI of the hands, legs and actual movements of the legs based on a graz-BCI stimulation paradigm. We have acquired data from both a dry 16-channel and a 32-channels wet system and compare their offline classification performance.

Methods
Experimental Setup: EEG data was recorded from six healthy participants (3 males and 3 females, 25.5 ± 6.7453 years). None of the participants had previous motor imagery experience. We used two g.tec Nautilus, EEG wireless acquisition systems with active-electrodes: i) a 16-channels dry, g.Sahara electrodes, cap and ii) a 32-channels, wet g.ladybird cap. The EEG caps were placed accordingly to the 10-20 system. Note that out of the six participants only two repeated the experiments with the wet system.

The study comprised of i) a two-class MI task that involved imaginary movements of the left and right arms, ii) a two-class MI task that involved imaginary movements of the right and left legs and iii) a task with actual movements of the left and right leg while the subject was sited. We followed a Graz-BCI stimulus paradigm to collect data for offline classification (30 randomised trials per class) [10]. The cues were displayed with Psychtoolbox-3 (Matlab R2017b) and the EEG acquisition/analyss was performed with OpenVibe 1.3 [11] [12] [13] [14].
Feature extraction and classification: The signal was temporally filtered in the alpha (8-12Hz) and beta bands (12-30 Hz). For the feature extraction, we selected four seconds of the signal, half a second after the cue (stimulation based epoaching). Then, the signal was also split into blocks of one second, every 16th second (time based epoaching), and the logarithmic band power was calculated. Features were also extracted based on a Common Spatial Pattern (CSP) filter, which increases the signal variance for one condition while minimizing the variance for the other condition. For classification, we used Linear Discriminant Analysis (LDA) which exploits hyperplanes to separate the data representing different classes, assuming a normal distribution, with equal covariance matrix for both classes. The LDA classifier was trained to detect left/right movements based on a seven-fold cross-validation procedure. Both of the classifiers used are linear classifiers, since nonlinear classifiers are not as widespread as the first ones in BCI applications.

Results

In table 1-2, we show results obtained from the dry and wet cap, respectively. Feature extraction is based on five scenarios: LDA and CSP are based on the standard motor imagery tasks implemented with Openvibe, whereas LDA (Alpha), LDA (Beta) and CSP (Beta) have been modified to bandpass the signal in alpha or beta bands, respectively. The combination of a beta bandpass filter with a CSP filter has shown the best classification rate. This method shows a better performance, since it relies on a decomposition of the raw EEG signal into spatial patterns, which are extracted from two distinct populations (left and right).

Firstly, we re-reference all the channels to the reference channel and subsequently we selected channels based on their location with respect to the motor cortex. For the dry cap, the reference channel selected was the Cz and the channels were F3, Fz, F4, T7, C3, C4, T8, P3, Pz, P4, Figure 1. For the wet cap, it was used the same electrode configuration as the dry cap and a different configuration according to [15], where we selected the channels F3,F4,FC5,FC6,C3,C4 with Fz as the reference, Figure 2.

Conclusions

Our results show that careful selection of electrode location is more important than having a dense map of electrodes. Dry systems are more sensitive to interference and their signal-to-noise quality is low. Nevertheless, with an appropriate sensor selection process and feature extraction, their classification performance can increase. This would make EEG systems user-friendly and more reliable. Future work should focus on how to dynamically select the optimum EEG sensor configuration.
References


