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 inter-subject 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 epoching). Then, the signal was also splitted in blocks of one second, every 16th second (time based epoching), 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.

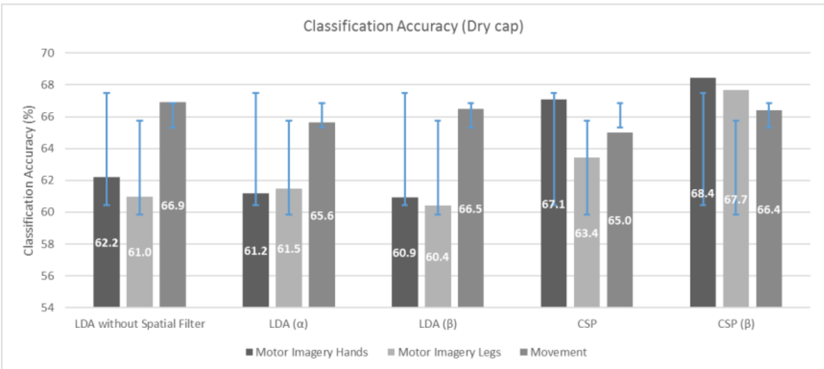

Chart 1- Classification accuracy for different tasks and methods (dry cap)

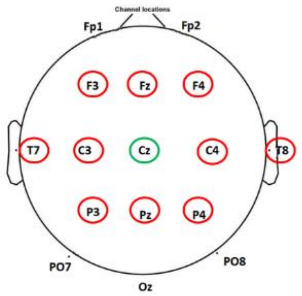

Figure 1 - Channels locations for the dry cap with channels represented in red and reference represented in

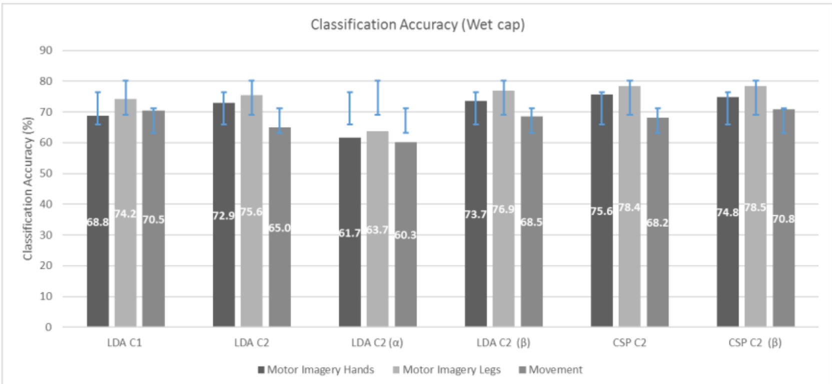

Chart 2- Classification accuracy for different tasks and methods (wet cap)

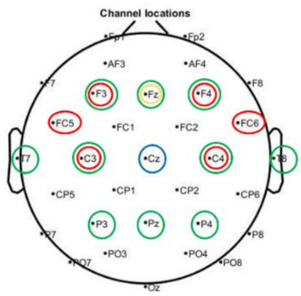

Figure 2 - Channels locations for the wet cap. Configuration 1 (in red and yellow) and configuration 2 (in green and blue)

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

[1] M. Jeannerod, “The representing brain: neural correlates of motor intention and imagery,” *Behavioral and Brain Sciences ,* vol. 17, pp. 187-245, 1994.

[2] T. Hanakawa, I. Immisch, K. Toma, M. Dimyan, P. Van Gelderen and M. Hallett, “Functional Properties of Brain Areas Associated With Motor Execution and Imagery,” *Journal of Neurophysiology,* vol. 89, pp. 989-1002, 2003.

[3] S. Page, P. Levine, S. Sisto and M. Johnston, “A randomized efficacy and feasibility study of imagery in acute stroke,” *Clinical Rehabilitation,* vol. 15, p. 233–240, 2001.

[4] M. Bakker, J. Stevens, I. Toni and B. Bloem, “Motor imagery of gait: a quantitative approach,” *Experimental Brain Research,* vol. 179, pp. 497-504, 2007.

[5] R. Dickstein, E. Marcovitz and A. Dunsky, “Motor Imagery for Gait Rehabilitation in Post-Stroke Hemiparesis,” *Physical Therapy,* vol. 84, p. 1167–1177, 2004.

[6] K. Oostra, G. Vanderstraeten and G. Vingerhoets, “nfluence of motor imagery training on gait rehabilitation in sub-acute stroke: A randomized controlled trial,” *J Rehabil Med,* vol. 47, pp. 204-209, 2015.

[7] Z. Wang, C. Wang, G. Wu, Y. Luo and X. Wu, “A Control System of Lower Limb Exoskeleton Robots Based on Motor Imagery,” in *International Conference on Information and Automation (ICIA)*, Macau, China, 2017.

[8] I. Navarro, B. Hubais and F. Sepulveda, “A Comparison of Time, Frequency and ICA Based Features and Five Classifiers for Wrist Movement Classification in EEG Signals,” in *Engineering in Medicine and Biology Society*, Shanghai, China, 2005.

[9] F. Ghani, H. Sultan, D. Anwar, O. Farooq and Y. Khan, “Classification of Wrist Movements Using EEG Signals,” *Journal of Next Generation Information Technology (JNIT),* vol. 4, pp. 29-39, 2013.

[10] G. Pfurtscheller, C. Neuper, G. R. Müller, B. Obermaier, G. Krausz, A. Schlögl, R. Scherer, B. Graimann, C. Keinrath, D. Skliris, M. Wörtz, . G. Supp and C. Schrank, “Graz-BCI: state of the art and clinical applications,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 11, no. 2, pp. 1-4, 2003.

[11] D. H. Brainard, “The Psychophysics Toolbox,” *Spatial Vision,* vol. 10, pp. 433-436, 1997.

[12] D. G. Pelli, “The VideoToolbox software for visual psychophysics: transforming numbers into movies.,” *Spatial Vision,* vol. 10, pp. 437- 442, 1997.

[13] M. Kleiner, D. Brainard, D. Pelli, A. Ingling, R. Murray and C. Broussard, “What's new in psychtoolbox-3,” *Perception,* vol. 36, pp. 1-16, 2007.

[14] Y. Renard, F. Lotte, G. Gibert, Congedo M., E. Maby, V. Delannoy, O. Bertrand and A. Lécuyer, “OpenViBE: An Open-Source Software Platform to Design, Test and Use Brain-Computer Interfaces in Real and Virtual Environments,” *Presence : teleoperators and virtual environments,* vol. 19, 2010.

[15] J. Andreu-Perez, F. Cao, H. Hagras and G. Yang, “A Self-Adaptive Online Brain Machine Interface of a Humanoid Robot through a General Type-2 Fuzzy Inference System,” *IEEE Transactions on Fuzzy Systems,* no. 99, p. 1, 2016.