# A Platform for the Detection of Brain Activity Changes in Patients Diagnosed With Disorders of Consciousness

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*Abstract.* A set of tools and methods for the analysis of electrophysiological signal acquired in patients diagnosed with Disorders of Consciousness (DOC) are here outlined. They allow to process data from several different devices and relative to different protocols, thus facilitating the sharing of data, protocols and the evaluation of results across different laboratories and in a homogenous way. Evaluation tools are also provided to detect brain activity in DOC patients.

Keywords: Brain-Computer Interface, Consciousness, Methods, Evaluation, Detection

## 1. Introduction

Since now, Brain-Computer Interface (BCI) technology main aim has been to provide a mean for restoring communication capabilities to patients who have lost their motor capabilities, such as those affected by severe neuromuscular disorders (e.g. Amyotrophic Lateral Sclerosis). Most of the studies described in the literature focuses on the implementation of new methods, algorithms, protocols, devices for maximizing the information flow from the brain to the external environment without using the normal pathways of nerves and muscles and a wide set of technology has been developed. This last, however, can also be applied in other contexts, such as the one described in this paper, in which BCI expertise has been used for detecting brain activity changes in those patients diagnosed with Disorder of Consciousness (DOC), that fall into two states, Vegetative State (VS) and Minimally Conscious State (MCS) that can be really difficult to discriminate [Lulè et al., 2013]. The main difference among them is that MCS patients preserve some cognitive ability which is hard to detect and that is unavailable in VS: several times, as described in [Monti et al., 2010], MCSs were erroneously diagnosed as VSs. For this reason, the idea of applying protocols aimed at detecting some brain activity that requires awareness or understanding (e.g. P300, N400, etc.) arose. However, the evoked response are in these patients somehow destructured, different across subjects and with respect to those usually described in the literature. For this reason, BCI classifiers represent a valuable instrument which, in most cases, are able to adapt to each subject to detect and discriminate among different brain states: in this case it is not important for example to fully describe in time and amplitude two ERPs, but just that they are different. There is, however, a relevant difference with typical BCIs: these last are usually tuned to maximize the amount of information extracted from the brain, whereas in this study the primary goal is to maximize the accuracy and reliability of the detection process. Thus, it is necessary to implement new tools and methods for answering new questions. Another problem is that this new approach lacks of a standardized procedure and methodology and large reference datasets are missing or hard to obtain. To overcome this and other problems, a set of tools belonging to the BF++ framework [Bianchi et al., 2003] has been implemented or adapted to allow different laboratories to share their data, to use the same evaluation methods regardless on the adopted experimental paradigm thus allowing a faster and coherent growth of this research field and to measure how reliable are the classification results.

## 2. Material and Methods

Despite classical BCIs, the process for classifying different brain states in this new class of experiments is usually performed offline: this allows to better optimize the evaluation process in order to maximize its robustness. The proposed BF++ platform, which can be downloaded from www.brainterface.com, includes several tools (mostly for free) for the processing and analysis of data. The NPXLab tool, for example, is a complete EEG/ERP reviewer and analysis system which allows filtering signals either in the time or in the spatial domain with methods such as Laplacian, Independent Component Analysis (ICA), Common Spatial Patterns (CSP), etc., to compare, even statistically, evoked responses, to perform spectral analysis and brain mapping and much more. It can read several different file formats (EDF, BCI2000, g.Tec, GDF, ASCII, etc.), thus allowing a wide range of labs to adopt it.

The BCIClassifier is a powerful tool which implements 8 different classifiers (SWLDA, FLDA, BLDA, SRLDA, RLDA, KNN, SVM, ANN), operates on raw or filtered signals (including, ICA and CSP components) and automates training/testing/classification/validation procedures. It also provides confusion matrices to evaluate classification performance and metrics to evaluate protocols/systems. More importantly, a statistical procedure has been also implemented to assess if classifications are due to chance or not: a chi-squared test computes the probabilities (p-values) of making errors stating that the results are not due to chance. Thus, the lower the p-value, the more reliable the results. It is important to underline that, because the test is performed on classification results and not on the signals, they are protocol independent: not only ERPs, but also motor imagery, SSVEP, and fMRI based protocols can be evaluated in this way. This guarantees a wide usability of this procedure.

The way this last tool can be used in the study of DOC patients is simple: subjects are asked to perform a series of cognitive tasks, in which they have to categorize two classes of stimuli. If they are able to perform the task then it is possible to correctly classify it, otherwise the results are due to chance: the statistical test will check this exactly this. In this way, it is possible to deduce if residual cognitive abilities are present in a patient and therefore support the clinical assessment of his/her state.

# 3. Results

For its simplicity, support of a wide range of file formats and protocols and completeness in either the reviewing or the analysis process, the proposed platform has been adopted by the EU DECODER project: it has been successfully used to analyze data from several protocols from 6 different laboratories. In another report in this conference [Quitadamo et al., 2013] promising results show agreement among the complete processing pipeline of the NPXLab Suite with MCS diagnosed patients, whereas brain activity related to a cognitive task was reported in one VS patients, thus suggesting a misdiagnosis.

# 4. Discussion

Classifiers can represent a powerful tool to help clinicians to make diagnoses. However, their output is subject to mistakes, false positives (FP) and false negatives (FN), and these may have several causes and consequences.

False positives may be due to systematic errors in the experiment, such as stimuli related artifacts, or statistical random noise. Their occurrence can be easily reduced by repeating the experiment, increasing the number of trials/classifications, which increases the signal to noise ratio, and improving the design of the experiment, as in every cognitive task. The consequences of such errors are to diagnose a VS patient as MCS.

False negative may have different causes and then are much harder to be removed. Possible causes are: subject is sleeping, the task/protocol is too difficult to be performed (e.g. he is not able to recognize familiar voices), activity is not detectable, classifier fails, signal is too noisy, statistical test fails, etc. Repeating the test only increases the probability to find the subject in an awaken state and to reduce the probability of statistical test failure. The consequences of such errors are to diagnose a MCS patient as VS.

Thus, these tools should not be used to perform a diagnosis, but to support it. They include a fully functional EEG/ERP system with advanced filtering techniques such as ICA and CSP, procedure for automating and validating classifications (8 different classifiers are provided), methods for evaluating protocols and to measure the reliability of the results. They are easy to use, support a dozen of different file formats and most of them available for free.

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#### References

Bianchi L, et al. Introducing BF++: A C++ framework for cognitive bio-feedback systems design. Meth Inf Med, 42:104-110, 2003.

Lulé D, et al. Probing command following in patients with disorders of consciousness using a brain-computer interface. *Clin Neurophysiol*, 124(1):101-106, 2013.

Monti MM, et al. Willful modulation of brain activity in disorders of consciousness. New Eng J Med, 362(7):579-589, 2010.

Quitadamo LR et al. Detecting brain responsivity in disorders of consciousness: a Brain-Computer Interface-based methodology. Fifth International BCI Meeting, CA, 2013.