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Classification algorithms analysis for brain–computer interface in drug craving therapy

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ABSTRACT

This paper presents a novel therapy to recover patients from drug craving diseases, with the use of brain–computer interfaces (BCIs). The clinical protocol consists of trying to mentally repel drug-related images, and a Stroop test is used to evaluate the blue therapy effect. The method requires a BCI hardware package and a software program which communicates with the device. In order to improve the BCI detection rates, data were collected from five different healthy subjects during the training. These measurements are then used to design a better classification algorithm with respect to the default BCI classifier. The investigated algorithms are logistic regression, support vector machines, decision trees, k-nearest neighbors and Naive Bayes. Although the low number of participants is not enough to guarantee statistically significant results, the designed algorithms perform better than the default one, in terms of accuracy, F1-score and area under the curve (AUC). The Naive Bayes method has been chosen as the best classifier between the tested ones, giving a +12.21% performance boost as concerns the F1-score metric. The presented methodology can be extended to other types of craving problems, such as food, pornography and alcohol. Results relative to the effectiveness of the proposed approach are reported on a set of patients with drug craving problems.

1. Introduction

The term *craving* refers to the impulsive desire for a psychoactive substance, food or any other rewarding thing [1–4]: this supports the "additive" behaviour and the compulsion aimed to avail oneself of the object of desire. Initially used by the dependent subjects to describe a strong and irrepressible opiates urge during abstinence periods [1,2,5], it has assumed subsequently the meaning of a longing for whichever psychotropic substance, in any situation [2,5]. Some authors have highlighted strong differences between the meaning that patients give to the term, and the interpretation given by the clinical staff [1]. In this work, craving is considered as a strong desire or an intense longing, as suggested by [2]. Two models have been proposed to explain the mechanism with which the craving would contribute to cause a relapse. The first one suggests that this need shares common characteristics with the obsessive-compulsive disorder (OCD) [3]. The second model tries to explain the craving as being induced by conditioning phenomena with positive and negative reinforcement mechanisms [4]. In the drug or alcohol abuse therapy, it is very important to detect craving, in order to intervene as soon as possible [5]. However, usually the patient must face alone the craving condition and it is of paramount importance that he/she is able to take the correct actions. In this view, reinforcement of will could be an important tool.

Brain–computer interface (BCI) systems can be used to train the patient's will and enhance his/her capability of overcoming a craving condition. In this work, a BCI system is used as a tool in drug addiction therapy. This aims to increase the ability of autonomously dealing with craving situations. The use of BCIs can be beneficial for both clinical purposes, as in case of people suffering from amyotrophic lateral sclerosis (ALS) [6], and for playful ones [7]. Brain–computer interfaces are composed by sensors (the headset) and algorithms that perform pattern identification and classification. According to the brain activities that have to be detected, two main approaches exist to control a BCI [8]. In the first approach, subjects are exposed to a sequence of stimuli, while focusing on a particular one of them. When this target is recognized, an event related potential (ERP), which represents an electrophysiological response to a specific stimulus, can be detected. Appearing 300 ms after a surprising or task-relevant event, and observed in EEG signals, the P300 is an example of such brain patterns [9]. Other

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examples of ERPs consist of steady-state visual evoked potentials (SSVEPs) [10] and motor-related potentials (MRPs) [11]. The BCI system therefore has to identify when the target stimulus has happened. The second approach consists of imagine a specific mental task, for example a hand movement or other actions. These activities are reflected by oscillatory brain waves in EEG data, such as the delta [0.5–4 Hz], theta [4–8 Hz], alpha and mu [8–13 Hz], beta [13–30 Hz], and gamma [31–40 Hz] rhythms. The BCI system must correlate the mental tasks with the features of the brain waves. Other types of signals, resulting from the focus on mental task, are slow cortical potentials (SCPs) [6] and neuronal ensemble activity [12]. Although scalp-recorded EEG represent the majority of adopted signals for BCI systems, other types of recordings can be used, such epidural, subdural or intracortical. For a survey on the topic, see [13].

Machine learning algorithms are strongly used during the signal processing stage in BCI applications, mainly for feature extraction, pattern recognition and classification. The term "machine learning" refers to the scientific discipline of "learning from data using machines", which traces its origins from computer science, statistics, engineering and artificial intelligence [14]. In BCI applications, machine learning techniques are often used [8,11,13,15]. In fact, it can be assumed that different brain activities lead to different actions. So, there are patterns, i.e. there is a relationship between signals and actions. However, the analytical function which maps this relationship is hard to be described analytically. But there are data available, i.e. the BCI signal measurements, so the mission is to tame this numbers and retrieve something useful from them to solve a specific problem. In the view of a BCI system, a machine learning algorithm is expected to distinguish between different mental statuses. This is accomplished by training a classification algorithm with data measured from the BCI electrodes. Since the subject knows what he/she was thinking, this information can be used to drive the algorithm training. This is known as supervised learning; otherwise the tuning is done in an unsupervised way.

As a *first contribution* of this paper, a therapy for drug craving dependency using BCIs is introduced and its protocol developed. The therapy is intended to be personalized for each patient, feasible at their homes and outside the clinic. This can accustom patients to enacting the behavioural intervention even outside the place in which they are assisted, making the BCI an enabling technology as discussed in [5]. As a *second contribution*, various types of classification algorithms have been investigated, comparing their performance between multiple subjects and with the default algorithm of the headset device, in order to find the best one for therapy in consideration. Related work on the selection of features and classification methods on BCI systems is presented in [15]. Algorithms such as Logistic Regression [16], support vector machines [17], decision trees [18], K-nearest neighbors [19] and Naive Bayes [20] have been compared. These classifiers have been chosen as representatives of different categories: linear, non-linear, tree models, instance-based and probabilistic. A preliminary version of the work in this paper appeared in [21] by the same authors. However, this paper goes beyond that work by analyzing the developed algorithms for more than one subject, and comparing their performance with that of the BCI default software.

The remainder of the paper is organized as follows. In Section 2, the use of BCIs for the therapy of drug addiction diseases is explained. In Section 3, the steps involving the data acquisition and experimental setup are described, while Section 4 highlights the preprocessing and feature extraction methodology. Section 5 shows a comparison between different classifiers for each subject, with indications about the algorithms implementation details. Section 6 analyzes the various algorithms performance by looking at common metrics, and presents an assessment of the therapy effectiveness on patients suffering from drug craving. Section 7 discusses the experimental results and limitations of the approach. Finally, Section 8 is devoted to concluding remarks and future developments.

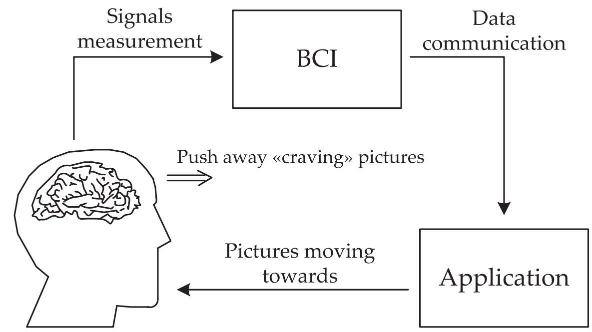

Fig. 1. Use of BCI for craving treatment.

2. Drug craving therapy

In this section, the therapy protocol and rationale are outlined, describing how and on which tasks the device has been trained. This work proposes the use of the BCI as an instrument to recover patients from drug craving diseases. The therapy consists of two consecutive moments: during the first activity, depicted in Fig. 1, the subject performs first a training of the device, and then uses the BCI in an active way, by trying to push away pictures which have a link with his disease. The second moment of the therapy is related to the treatment assessment. This is done via the emotional Stroop test (see [22] for a review of the topic).

The training operation is done at the beginning of every treatment session, in order to make the algorithm more reactive to the patient current mental state. It was experimentally observed, on healthy subjects, that the time of response and accuracy (for a given task) was higher on a freshly trained BCI, with respect to an algorithm trained even a few days before the test. This condition implies that the training session cannot be bore for too much time. Therefore, the experiments done in Section 3 consisted in trying to replicate the exact procedure to which patients will be exposed. The training is done on the basis of two mental tasks: a *neutral task* and a *push task*. In the neutral task, the subject does not have to focus on a particular activity, while in the push task he is required to think about pushing further away an object. The choice of focusing on this two tasks is due to the fact that most BCI systems require the user to train a neutral action first. Furthermore, concentrating on only one of the two tasks makes the training phase lighter and faster, which can be beneficial for patients. Then, other actions could be trained. The ability to train correctly the BCI for two classes is not time consuming. Relying on the experiments carried out with the BCI equipped software, few minutes are required to perform a full training. Just by only adding a third action, the training time grows in the range of hours. This is not acceptable in terms of a treatment of people who could be mentally unstable. By considering the neutral activity as a proper mental task, this problem has been overcome. During the treatment, via the developed software which interacts with the BCI (Fig. 2), the patient undergoes to a series of different images, loaded through it. These pictures could represent images related with his personal craving disease, or, instead, pictures of relaxing landscapes and not harmful scenery. If a picture of the former type appears, the subject has to actively try to repel it, thinking the push task: the picture then will be visually pushed away from the screen. If the patients succeeds to dwindle enough the image, with respect to a set threshold level, a new picture will be prompted. In case of pictures which represent "good" scenes (these are, as the craving scenes, subject dependent) the subject