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Dendrite morphological neural networks for motor task recognition from electroencephalographic signals

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ABSTRACT

Brain–computer interfaces (BCI) rely on classification algorithms to detect the patterns of the brain signals that encode the mental task performed by the user. Therefore, robust and reliable classification techniques should be developed and evaluated to recognize the user's mental task with high accuracy. This paper proposes the use of the novel dendrite morphological neural networks (DMNN) for the recognition of voluntary movements from electroencephalographic (EEG) signals. This technique was evaluated with two studies. The first aimed to evaluate the performance of DMNN in the recognition of motor execution and motor imagery tasks and to carry out a systematic comparison with support vector machine (SVM) and linear discriminant analysis (LDA) which are the two classifiers mostly used in BCI systems. EEG signals from twelve healthy students were recorded during a cue-based hand motor execution and imagery experiment. The results showed that DMNN provided decoding accuracies of 80% for motor execution and 77% for motor imagery, which were significantly different than the chance level ($p < 0.05$, Wilcoxon signed-rank test) and higher when compared with classifiers commonly used in BCI. The second study aimed to employ the DMNN to recognize the intention of movement. To this end, EEG signals were recorded from eighteen healthy subjects performing self-paced reaching movements and several classification scenarios were evaluated. The results showed that DMNN provided decoding accuracies above chance level, whereby, it is able to detect a movement prior its execution. On the basis of these results, DMNN is a powerful promising classification technique that can be used to enhance performance in the recognition of motor tasks for BCI systems based on electroencephalographic signals.

1. Introduction

Brain–computer interfaces (BCI) have emerged as a new alternative to provide people suffering partial or complete motor impairments, with a non-muscular communication channel to convey messages or commands to the external world [1,2]. Consequently, these systems can help to improve the user's quality of life giving more independence and autonomy while constituting a novel research tool for understanding the brain. A BCI relies in the recording and processing the brain activity in order to obtain control signals or commands that are used to drive an external application [3,4], for instance, computer-based spellers [5], robotic wheelchairs [6], robotic arms [7], teleoperated mobile robots [8], games [9] or virtual environments [10]. The two basic elements in a BCI are the mental task performed by the user and the recording of the brain activity. On the one hand, the user's mental task is a specific mental action without physical output which induces recognizable patterns on the brain signals. The most common are selective attention (e.g. visual P300 potentials [11] or steady-state visual evoked potentials [12]), motor imagery of different parts of the body (e.g. event-related desynchronization/synchronization [13]) and self regulation of slow brain potentials (e.g. slow cortical potentials [14]). On the other hand, the brain activity can be acquired with invasive or non-invasive techniques. Invasive methods measure the electrical activity from electrodes placed in the brain tissue, therefore, they offer good signal-to-noise ratio, spatial selectivity, and a large bandwidth but they require surgery. Non-invasive methods on the other hand measure the electromagnetic or metabolic brain activity with sensors located outside the head. The most used technique for the recording of the brain activity in

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BCI systems is the non-invasive electroencephalogram (EEG) as it is inexpensive, innocuous and provides high temporal resolution brain signals [15].

The key in an EEG-based BCI is the recognition of the changes or patterns of the brain signals that are induced by the mental task, which is carried out by means of classification algorithms [16,17]. In order to perform this, the EEG-based BCI typically operates in cue-based synchronous protocols [18]. For example, in a motor imagery mental (MI) task the user imagines the movement of a limb during a well-establish period of time while the EEG activity is recorded [19]. After the MI is finished, a set of attributes (based on the power spectral [20,21] or common spatial patterns [22–24]) is computed from the recorded EEG signals which are provided to a classification algorithm to recognize the moved limb. Finally, the classifier output is used as a command in an application. Note that the accuracy in the recognition of mental tasks relies considerably on the classification algorithm. Hence, the application of BCI technologies in real situations and daily life activities with real users, i.e., patients with reduced communication and mobility, might benefit from novel and different classification algorithms [25]. In addition to this, synchronous BCIs requires a few seconds to collect brain signals while the user is carrying out the mental task. After this, the system recognizes the mental task, which takes a few milliseconds. Therefore, the user first performs the mental task and after it is finished the output command is generated, as a consequence, there is a noticeable time interval since the initiation of the mental task and the response produced in the application, which makes that output movements are not seen natural by the user.

To address these issues, we propose the use of dendrite morphological neural networks (DMNN) to recognize motor tasks directly from EEG signals. The novelty in the DMNN relies upon its architecture, which incorporates dendrites in the model of the artificial neural networks [26,27]. The processing in the dendrites allows to obtain closed separation surfaces offering higher classification accuracies. This novel classification method has been recently applied in the diagnosis of diseases using biomedical images [28,29], however, it has not been applied to the problem of recognizing motor tasks from EEG signals. This might suggest that DMNN can also be a good alternative in the context of BCI systems. Therefore, here we investigated the recognition of motor execution, motor imagery and motor intention using EEG brain signals recorded in BCI settings.

This work consists of two experimental studies. The first study evaluates the performance of DMNN in the recognition of motor tasks from EEG signals recorded in a classical cue-based synchronous BCI experiment and presents a systematic evaluation to compare its performance with Fisher Linear Discriminant Analysis (FLDA) and support vector machines (SVM). EEG signals were obtained from twelve participants performing hand motor execution and motor imagery which were used to evaluate the two-class classification scenarios *relax* versus *motor execution* and *relax* versus *motor imagery*. The results showed that the proposed DMNN provided classification rates that were significantly different and higher than the chance level. In addition, DMNN yielded on average a classification accuracy of 80% and 77% in the two classification scenarios, which were higher than the accuracies achieved with FLDA and SVM. The second study applies the DMNN for the recognition of motor tasks from EEG signals recorded in an asynchronous BCI experiment. To do so, EEG signals were recorded from eighteen healthy subjects performing self-paced reaching movements and the DMNN classification algorithm was applied to recognize between movement states in the following two-class classification scenarios, *relax* versus *intention*, *relax* versus *execution* and *intention* versus *execution*. The results showed that the DMNN provided on average classification accuracies of 65, 69 and 77% respectively, moreover, classification rates were significantly different and higher than the chance level. These studies and their results extend those presented in [30,31]. First, a detailed description of the architecture, training procedure and classification process of the DMNN is presented. Second, a more elaborate analysis of the DMNN performance in the recognition of motor execution and motor imagery tasks using brain signals along with a systematic evaluation to compare performance with other classification algorithms is presented. Third, the recognition of motor intention using brain signals is studied with the DMNN over a much greater set of participants with a deeper evaluation process that includes more classification scenarios and significance tests.

This work contributes in two aspects. First, it is demonstrated that DMNN is a powerful classification model to recognize motor execution and motor imagery tasks from EEG signals, whereby, it can be incorporated as a novel neural decoder in synchronous BCI systems. Second, DMNN is successfully applied to recognize the intention to move a limb from EEG signals acquired in self-paced reaching movements, which is an important feature to attain BCI technologies with a reduced delay between the mental task and the system output. The rest of the work is organized as follows. Section 2 presents the technical details of the DMNN classification algorithm. Section 3 describes the two studies designed and executed to evaluate the DMNN algorithm in the classification of motor tasks from EEG signals and to compare its performance with other classifiers. Section 4 presents the results of the two experimental studies. Sections 5 and 6 discuss the results and presents the conclusions, respectively.

2. Dendrite morphological neural networks (DMNN)

The most common classification models used in EEG-based BCI are Fisher Linear Discriminant Analysis or FLDA and support vector machines or SVM [16,32]. These classifiers learn a discriminant function [33] whose effect is to establish linear or non-linear separation surfaces [34,35]; however, the regions created by such discriminant function are not closed and may include examples from different classes. To produce closed separation surfaces to discriminate data from different classes, novel artificial neural networks (ANN) such as dendrite morphological neural networks (DMNN) have been proposed [27,26]. The novelty in these models is the incorporation of a computational structure in the dendrites of the neurons [36]. This is important because dendrites are relevant computational units in a biological neuron, but they have not been considered in most of the current models of ANN [37]. The use of dendrites in the neural network model has several properties [38], first, no hidden layers are required as the processing of information is performed in the dendrites, second, produces closed separation surfaces between classes, thus, it offers a different solution for multi-class classification problems.

2.1. Architecture

The architecture of a DMNN is illustrated in Fig. 1. The model consists of n input neurons (number of attributes), m class neurons (number of classes) and a selection unit (final output). All input neurons are connected to each class neuron through d dendrites $D_1, \ldots, D_d$. Note that each input neuron has at most two weighted connections on a given dendrite, one excitatory and other inhibitory, which are represented as black and white dots, respectively. The weights between neuron N_i and dendrite D_k in the class neuron M_j are denoted by ω^l_{ijk}, where $l = 1$ represents excitatory input while $l = 0$ represents inhibitory input. The value of these weights is unknown and has to be learned from a training dataset. The output of dendrite D_k in the class neuron M_j is $\tau^j_k(\mathbf{x})$, which depends on the vector of attributes and the weights. Each class neuron provides an out-