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EEG classification for the detection of mental states

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ABSTRACT

The objective of the present work is to develop a method that is able to automatically determine mental states of vigilance; i.e., a person's state of alertness. Such a task is relevant to diverse domains, where a person is expected or required to be in a particular state of mind. For instance, pilots and medical staff are expected to be in a highly alert state and the proposed method could help to detect possible deviations from this expected state. This work poses a binary classification problem where the goal is to distinguish between a "relaxed" state and a baseline state ("normal") from the study of electroencephalographic signals (EEG) collected with a small number of electrodes. The EEG of 58 subjects in the two alertness states (116 records) were collected via a cap with 58 electrodes. After a data validation step, 19 subjects were retained for further analysis. A genetic algorithm was used to select a subset of electrodes. Common spatial pattern (CSP) coupled to linear discriminant analysis (LDA) was used to build a decision rule and thus predict the alertness of the subjects. Different subset sizes were investigated and the best compromise between the number of selected electrodes and the quality of the solution was obtained by considering 9 electrodes. Even if the present approach is costly in computation time (GA search), it allows to construct a decision rule that provides an accurate and fast prediction of the alertness state of an unseen individual.

1. Introduction

Over the last decade, Human–Computer Interaction (HCI) has grown and matured as a field [1,2]. Gone are the days when only a mouse and keyboard could be used to interact with a computer. The most ambitious of such interfaces are Brain-Computer Interaction (BCI) systems. The goal in BCI is to allow a person to interact with an artificial system using only his brain activity. The most common approach towards BCI is to analyse, categorise and interpret Electroencephalographic signals (EEG), in such a way that they alter the state of a computer.

In particular, the objective of the present work is to study the development of computer systems for the automatic analysis and classification of mental states of vigilance; i.e., a person's state of alertness. Such a task is relevant to diverse domains, where a person is expected or required to be in a particular state. For instance, pilots, security personnel or medical personnel are expected to be in a highly alert state, and a BCI could help to confirm this or detect possible problems. However, this task is by no means a trivial one. In fact, EEG signals are known to be non-stationary, highly noisy, irregular and tend to vary significantly from person to person, making the development of general techniques a very challenging scientific endeavour [3]. Therefore, it is important to develop robust methods, adaptable to different persons, that can give a rapid and accurate prediction of the alertness state.

EEG signals are almost always pre-processed before any further analysis is performed. The main goal of pre-processing methods is to perform feature extraction and pose a classification problem. To obtain these features, signal processing tools such as the Fourier transform or discrete wavelet decomposition (DWT) can be applied. For example, a DWT can be used to select the wavelet

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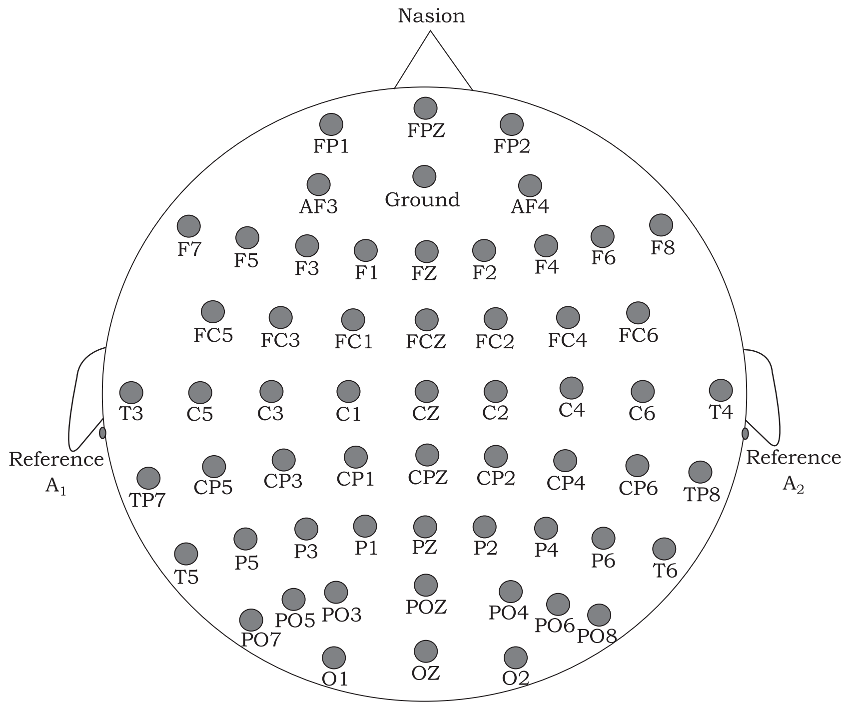

Fig. 1. Representation of the distribution of electrodes in the international system 10/10.

sub-band frequencies δ (1–3.5 Hz), θ (4–8 Hz), α (8–12 Hz) and β (19–26 Hz) that are given as an input to a neural network classifier [3]. Another approach that uses coefficients of a discrete wavelet decomposition as features to describe the EEG signal can be found in [4]. An artificial neural network is then used to determine if the EEG record comes from a schizophrenia patient, an obsessive-compulsive disorder patient or a healthy subject. In [5], the EEG signal is decomposed into 23 bands of 1 Hz (from 1 to 23 Hz) and a Short Term Fast Fourier transformation (STFFT) is used to calculate the percentage of the power spectrum of each band. In [6], a Fourier transform is used between hidden layers of a convolutional neural networks to switch from the time domain to the frequency domain analysis in the network.

Another common method to obtain features from EEG signals is the common spatial pattern (CSP). This method was introduced by Funkunaga and Koontz [7]. The CSP method was used to analyse EEG signals and to extract features for different classification tasks; for example to differentiate between normal and abnormal EEG signals [8] or for movement classification [9–11].

Once features are extracted, a classification method is applied to achieve the classification task. When a Fourier transform or DWT is used as pre-processing, the most common classification method is neural network (see for example [3] or [12]). However, the disadvantage of this approach is that it requires having a large set of test subjects relative to the number of predictive variables. To avoid this problem, it is possible to split the EEG signal into several segments of a few seconds, called "epochs" (see [3] and [12]). Other approaches use different statistical methods. For example, [13] uses Support Vector Machine (SVM), [14] Autoregressive Models (AR) and [15] hidden Markov chains.

When the CSP is used to extract features, the most common classification method is Linear Discriminant Analysis (LDA) as described in [16] or [11], even if other classification methods can be used, such as neural networks [17].

Main contributions. The aim of this work is to construct a model that is able to predict the alertness state of a human using the smallest possible number of EEG electrodes. That is why, the two main objectives are:

- Reduce the time needed to install the EEG cap on a subject using a variable selection method to determine the best compromise between the number of variables (electrodes) kept and the quality of the solution (based on classification rate). In fact, in real world applications, it is necessary to reduce the number of electrodes needed because the cap installation process has to be short. Moreover, a long installation of the EEG cap can cause a disturbance of the mental state of the person that we want to study.
- Obtain a model (decision rule) which is able to give a reliable prediction of the alertness state of a new subject.

In this paper, the CSP method coupled to LDA will be used to construct the decision rule and thus predict the alertness of the subjects. Moreover, a genetic algorithm selects a subset of variables on which the CSP method will be executed. In this work, the CSP method is used to extract features from EEG data signals of different individuals. It represents one of the most important contributions of this work because usually the CSP is used on a single subject to obtain subject specific discriminative spatial filters.

The remainder of this paper proceeds as follows. Section 2 presents the data acquisition procedure that was applied to record EEG signals. Section 3 deals with the CSP method and the genetic algorithm that is used to perform variable selection is detailed in Section 4. Finally, the results of this work are discussed in Section 5.

2. Data acquisition

This section describes the data acquisition process that was used to record the EEG signals and details how the data is validated.

2.1. Procedure

EEG signals are recorded using a cap with 58 electrodes placed according to the international system 10/10 defined in [18] and shown in Fig. 1.

During the data acquisition procedure, the subject is alone in a soundproof room, comfortably seated in front of a computer screen. It takes approximately two hours and a half to place the EEG cap on