Cross-Subject EEG Channel Selection for the Detection of Predisposition to Alcoholism

Selezione Generalizzabile tra Soggetti di Canali EEG per l'Identificazione di predisposizione all'alcolismo

Michela Carlotta Massi, Francesca Ieva

Abstract ElectroEncephaloGram (EEG) is a powerful technology for the early detection, among others, of alcoholism. However, multiple electrodes placed on the scalp to record brain signals may introduce noisy and redundant information, hinder performance and increase computational times in the task of automated decoding of EEG signals. In this work we propose a novel end-to-end Representation Learning-based algorithm to select the most relevant EEG channels to perform detection of predisposition to alcoholism, in a subject-agnostic way. Indeed, EEG signals are characterized by strong subject-specific variance potentially affecting the generalizability of the selection. Results are promising, especially compared to the very limited literature on cross-subject EEG channel selection.

Abstract *L'Elettroencefalogramma è una tecnologia potente per la diagnosi precoce di alcolismo. Tuttavia, la presenza di molteplici elettrodi sullo scalpo per la registrazione dei segnali cerebrali può introdurre informazione ridondante e rumorosa, penalizzare la resa ed aumentare i tempi computazionali di approcci automatici alla classificazione di segnali EEG. In questo lavoro proponiamo un nuovo algoritmo end-to-end basato su Representation Learning, per selezionare i canali più rilevanti per il riconoscimento della predisposizione all'alcolismo in modo agnostico al soggetto. Infatti i segnali EEG sono caratterizzati da forte variabilità tra soggetti, che aumenta la complessità di ottenere una selezione generalizzabile. I risultati ottenuti sono promettenti, specialmente comparandosi alla letteratura molto limitata nel campo della selezione canali EEG indipendentemente dal soggetto.*

Key words: Representation Learning, Signal Processing, Feature Selection, EEG Channel Selection

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1 Introduction

One of the main difficulties in early detection of alcoholism is the unreliability of the information presented by patients with addiction [10]; this hampers diagnosis and reduces the effectiveness of treatment. However, alcohol affects the Central Nervous System (CNS) directly, causing changes in brain functions. One way to check the changes caused by alcohol is through an EEG exam which can identify different types of brain activities through electrodes placed on the scalp. Automatically decoding EEG signals call for novel Statistical and Machine Learning approaches [4], to reduce time and efforts on the clinicians side. A typical EEG exam foresees the recording of signals from multiple sites of the head. However, applying a large number of EEG channels may present several drawbacks: it could (i) include noisy and redundant signals; (ii) induce longer preparation times and (iii) lead to higher computational time and lower performance in the automated processing of signal data for early detection of alcoholism. The development of effective channel selection algorithms is one of the most relevant strategies to overcome all the aforementioned issues at once [6]. However, EEG data is known to be highly subject variant. To the best of our knowledge, only a very limited number of studies devoted to subject-independent channel selection can be found in literature. One recent example can be found in [5], with very poor results ($\sim 61\%$ average accuracy).
In this work we propose an algorithm to diagnose a predisposition to alcoholism by exploiting only a subset of the available channels, selected in a subject-agnostic fashion. Moreover, the algorithm here proposed is end-to-end, meaning that it does not require preprocessing of raw signals, which is oftentimes a cumbersome and knowledge-intensive procedure.

2 Materials: EEG Database

The dataset used in this work is a large public EEG database, available through UCI Machine Learning Repository[1]. This dataset was developed to examine genetic predisposition, through EEG signals, to alcoholism. To elicit the Event-Related Potential (ERP), a modified delayed Visually Evoked Potential (VEP) matching-to-sample task was used, in which two picture stimuli (i.e. objects chosen from the 1980 Snodgrass and Vanderwart picture set [11]) appeared in succession: a first picture stimulus (S1) was followed by a second stimulus (S2) either matching or non-matching the first picture. The database includes 122 subjects, equally splitted between two classes, alcoholic and controls. Each subject completed 120 trials. The signal acquisition is performed according to the 10–20 International System with 64 electrodes placed on the scalps of the subjects and recordings were sampled at 256 Hz (3.9-msec epoch) for 1 second. In this experiment we aimed at classifying trials (the class was determined by the subject associated to each trial) on the basis of the brain signals produced as response to the first visual stimulus (S1).

[1] https://archive.ics.uci.edu/ml/datasets/EEG+Database

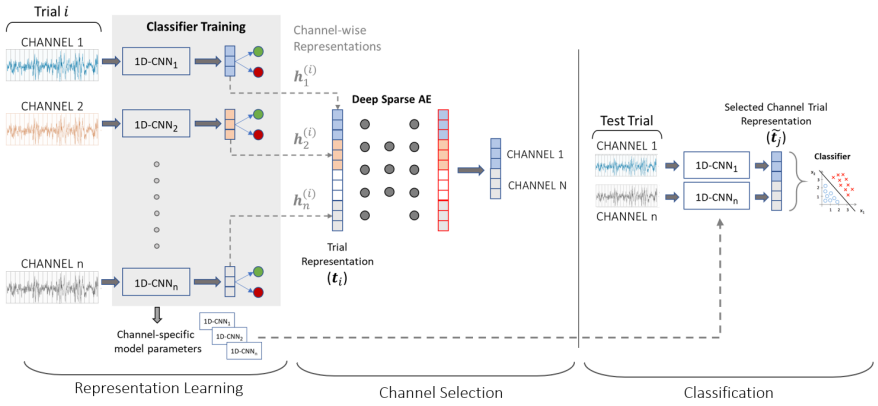

Fig. 1 Algorithm process flow

3 Proposed Methodology

To detect predisposition to alcoholism by exploiting the least number of EEG channels we propose an End-to-End Representation Learning (RL)-based algorithm that reduces signal dimensionality in a channel-wise fashion and selects the most relevant electrodes across subjects. The algorithm is composed of modules tailored to address different parts of the process and provide a variety of advantages for the task at hand. Its multi-step process is depicted in Figure 1.

The algorithm is designed to learn channel-specific 1-Dimensional Convolutional Neural Networks (1D-CNN) to embed signals grouped by electrode in a latent space of small dimensionality that maximizes intra-class separability. To do that, we consider each 1DCNN as composed of an *encoder* and a subsequent *classifier*. The encoder maps the signals from the J-dimensional input space, into an M-dimensional embedding space, where $M < J$. The whole model is then parametrized with supervised training to classify the signals as originating from alcoholics or controls. After training, the embedded M-dimensional vectors from each of the C channels are extracted from the *encoder*, and the algorithm builds a unique representation of each trial by concatenating the C embeddings into a trial vector $\mathbf{t} \in \mathbb{R}^{1\times(\mathrm{M}\times\mathrm{C})}$.

After that, the Channel Selection (CS) module relies on a Feature Selection method developed in [8]. This method exploits Deep Sparse AutoEncoders (DSAE) in an ensemble-like fashion to select the most relevant features to discriminate between minority and majority class. In particular, it analyzes the feature-wise average *difference* in Reconstruction Error (Δ RE) between classes after training each component on majority class only. In this context of application, the algorithm is adapted to select channels instead of single features. Indeed, Channels are ranked in terms of average channel Δ RE, and top K channels are selected.

At test time, our algorithm transfers the parametrized subgroup of selected channel-specific 1D-CNNs to embed new signals, obtaining new trial vectors $\tilde{\mathbf{t}} \in \mathbb{R}^{1\times(\mathrm{M}\times\mathrm{K})}$ of small dimensionality and high predictive power that can be fed to any classifier.

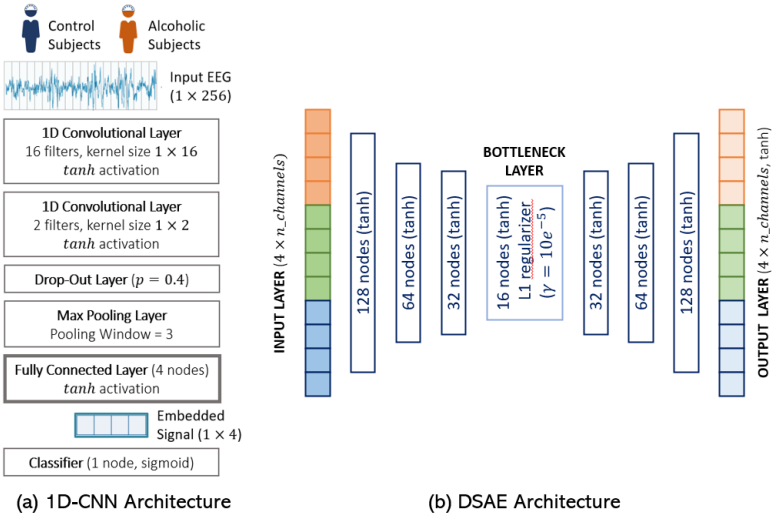

Fig. 2 (a) Architectural details of the 1D-CNNs employed for the described experiment. (b) DSAE components' architectural details. DSAEs are exploited for channel selection from embedded trial vectors.

4 Experimental and Implementation Details

To test the cross-subjectivity of our channel selection procedure, we splitted the 122 subjects in training (102 subjects, equally subdivided between alcoholics and controls) and test group (20 new subjects, 50% alcoholics and 50% controls). The former group with all its trials was exploited for channel-wise 1DCNNs training and channel selection, while the latter was supplied to the algorithm to test the classification performance.

To perform the channel-wise embedding of the EEG recordings we had to train several channel-specific models. We opted for a shallow 1D-CNN and the specific architectural details are reported in Figure 2.(a). Hyperparameters were chosen by randomly sampling 10,000 training signals irrespectively of the channel - to make the tuning generalizable across electrodes - equally splitted between classes, and performing random search of the best combination. After setting hyperparameters, each channel-specific 1D-CNN was trained for 200 epochs with a batch size of 1,000 signals. For what concerns the channel selection module, details are reported in Figure 2.(b). Each DSAE model in the ensemble (30 components in total) was trained for 300 epochs with a batch size of 500 training trials. The whole algorithm was implemented in Python 3.7, exploiting Keras framework with Tensorflow backend and scikit-learn. To evaluate the performance on test set we adopted several classifiers, but we report here results for the best performer only, i.e. Support Vector Machines (SVM). We evaluated whether the channel reduction would impact the performance of the classifier by first trying to classify trials using all 61 channels (after their embedding via 1DCNNs and transformation into trial vectors) and then with smaller

subsets of 30, 20, 15, 10 and 5 most relevant channels. The performance of the classification was measured using the Area Under the ROC curve (AUROC) and Accuracy metrics by cross-validating 10 times.

4.1 Results

Results for this experiment are reported in Table 4.1. This experimental setting is lightly comparable to [9, 10] and benchmark algorithms therein, even though performance measurements and data splitting criteria are not always clear from the original papers. Our algorithm obtains a satisfactory accuracy, and a very high AUROC performance, indicating a great precision in identifying the positive class (i.e. *alcoholics*). Our best classifier (SVM) with only 5 electrodes surpasses the performance in [9] with 4 channels (75.13% average accuracy). However, in this work the authors exploit PCA for channel selection applied to the whole dataset, and the lack of information on splitting criteria or performance standard deviations suggest that they are reporting training accuracy measures, which are overestimated compared to our test values. The average accuracy reported more recently in [10] with 11 channels ($\sim 93\% \pm 3.3$ with the best proposed approach and SVM classifier) is therein defined as the state-of-the-art on this data. Their performance is higher compared to ours with a similar number of channels. However, in their work they perform channel selection evaluating the mean-variance of each channel for all subjects in the dataset before proceeding with feature extraction and classification, therefore their selection is not comparable to our subject-agnostic approach.

	AUROC		**Accuracy**	
N Ch.	**Mean**	**Std**	**Mean**	**Std**
61	0.905	0.013	0.807	0.015
30	0.895	0.018	0.816	0.017
20	0.879	0.020	0.798	0.023
15	0.862	0.016	0.793	0.024
10	0.872	0.021	0.786	0.025
5	0.858	0.018	0.762	0.015

Table 1 Trial Classification Results with SVM classifier in terms of AUROC and Accuracy

5 Discussion and Conclusions

In this work we proposed an algorithm to perform cross-subject EEG Channel selection for the task of detecting predisposition to alcoholism. The reduction of EEG channels have several statistical and practical advantages as mentioned in Introduction. Moreover, the algorithm here presented was applied to the very specific clinical task of early diagnosis of predisposition to alcoholism. This clinical application could greatly benefit by more efficient and effective decoding of brain signal recordings, but EEG technology finds application in several other medical fields, s.a. clinical and neurological diagnosis of diseases and disorders like Alzheimer's disease [7], depression [2], traumatic brain injuries [1] and in the recently spotlighted field of Brain-Computer Interfaces (BCI) [3], all heavily relying on EEG technology because of its high portability, relative low cost, high temporal resolution and few

risk to users. All these fields share the same needs and complexities of the context discussed in this work, therefore would take advantage of an effective cross-subject selection of the most relevant electrodes to aid EEG decoding tasks. Clinical trials could turn more efficient by cutting set-up times, and novel portable BCI technologies could benefit by a generalizable reduction of electrodes that effectively satisfy the needed tasks. In addition, the end-to-end approach of our algorithm makes it more easily transferrable to different tasks, as it avoids long and seldom highly task-specific signal preprocessing procedures. For this reason, this first application and its promising results can open up a stream of further developments to apply our methodology to several other medical EEG decoding domains.

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