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Automated identification of neural correlates of continuous variables

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HIGHLIGHTS

- A new method for identifying EEG correlates of continuous independent variables.
- Our method outperforms canonical correlation analysis and common spatial patterns.
- When applied to real EEG during music it finds known correlates of music tempo.
- The method also identifies novel neural correlates of music induced emotion.

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ABSTRACT

Background: The electroencephalogram (EEG) may be described by a large number of different feature types and automated feature selection methods are needed in order to reliably identify features which correlate with continuous independent variables.
New method: A method is presented for the automated identification of features that differentiate two or more groups in neurological datasets based upon a spectral decomposition of the feature set. Furthermore, the method is able to identify features that relate to continuous independent variables.
Results: The proposed method is first evaluated on synthetic EEG datasets and observed to reliably identify the correct features. The method is then applied to EEG recorded during a music listening task and is observed to automatically identify neural correlates of music tempo changes similar to neural correlates identified in a previous study. Finally, the method is applied to identify neural correlates of music-induced affective states. The identified neural correlates reside primarily over the frontal cortex and are consistent with widely reported neural correlates of emotions.
Comparison with existing methods: The proposed method is compared to the state-of-the-art methods of canonical correlation analysis and common spatial patterns, in order to identify features differentiating synthetic event-related potentials of different amplitudes and is observed to exhibit greater performance as the number of unique groups in the dataset increases.
Conclusions: The proposed method is able to identify neural correlates of continuous variables in EEG datasets and is shown to outperform canonical correlation analysis and common spatial patterns.

1. Introduction

The electroencephalogram (EEG) is a method for measuring changes in electro-potential in the cortex related to the activation levels of cortical neuronal populations (Niedermeyer and Silva, 2005). It is a popular method for studying neuro-electrophysiological correlates of cognitive processes and behaviour.

The EEG has a high temporal resolution and a wide spectral range and may, therefore, be described by a very large number of features. These include, for example, the band power within specific frequency ranges, amplitudes over specific regions of the cortex, or measures of interactions between different spatial regions (Rahman et al., 2012). However, EEG has very poor signal to noise ratio (SNR), which often means that many repeated trials are required before cognitively relevant information emerges from the background noise present in the signal (Niedermeyer and Silva, 2005).

Due to practical limits on the numbers of repetitions of cognitive events participants in cognitive experiments may perform, an

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investigative researcher is often faced with a very large potential feature space and a very small number of trials. Thus, identification of reliable task-related features is a considerable challenge.

A number of approaches may be taken to tackle this problem. Where particular cognitive processes within the EEG are phase-locked to the trial commencement time and stationary, a time-averaging approach may be adopted to attempt to identify features related to specific neural correlates. However, in cases where physiological responses are not phase-locked (for example band-power measures Pfurtscheller and Lopes da Silva, 1999) an approach from machine learning may be adopted (Alpaydin, 2004).

One such approach which has gained considerable traction in recent years is common spatial patterns (CSP), which is based upon eigen-decomposition of the covariance matrices of each group in the dataset (Koles et al., 1990). This method was used originally in the brain-computer interface (BCI) (Wolpaw et al., 2002) community to identify optimal features for separating two groups of events in the EEG and has since gained growing popularity for a range of uses, for example, identifying neural activity related to motor imagery (Friedrich et al., 2012). Extensions of the method have also been proposed for multiple group cases (Grosse-Wentrup and Buss, 2008).

However, while CSP is able to identify features which may be applied to optimally separate discrete groups of tasks, it is less effective in the case of continuous variables. Thus, in the case of correlation studies, where neural correlates are sought relating to a continuous independent variable, it may not be the most suitable method.

An alternative approach, which may be applied in this case is canonical correlation analysis (CCA) (Knapp, 1978). CCA attempts to find relationships between sets of independent variables, for example between two or more time series, and may be used to identify neural correlates of continuous variables (Hardoon et al., 2004). However, CCA is only able to identify sets of variables which linearly correlate with the independent variables and, therefore, may be limited in its applications (Hardoon et al., 2004).

To tackle these problems with CSP and CCA we have developed an alternative automated feature selection method that is able to identify neural correlates of continuous independent variables. The proposed method is based upon eigen-decomposition of the coarse-grained (rescaled) combined matrix of features and the continuous independent variable.

We first describe the method. We then compare the method to CSP and CCA on a synthetic test dataset before using it to attempt to find feature sets which correspond to a continuous independent variable in a study of neural correlates of music-induced emotions and neural correlates of music perception.

2. Methods

2.1. Proposed method

The proposed method aims to identify features which covary with an independent variable by first redistributing, then coarse-graining, performing principal component analysis (PCA), and clustering the set of available features. This can be summarized as follows.

1. Prepare the data set by first uniformly redistributing the values each feature takes.
2. Then coarse-grain the values each feature takes across all trials.
3. Calculate a covariance matrix from the coarse-grained feature matrix to measure relationships within the dataset.
4. Perform principal component analysis (PCA) to identify directions of maximum variance.
5. Calculate the participation index, sort and extract the top q index values. These index the features of interest.

For a data set $\boldsymbol{D} \in \mathbb{R}^{M\times N}$ of N trials, each trial may be represented by M features. Features may describe the data in a number of different ways, for example, representing them in the time and/or frequency domains. A feature vector comprises the values of that feature for all trials in the dataset $\boldsymbol{D}$. A feature vector is defined as

$$\boldsymbol{F}_i = [D_{i,1}, \ldots, D_{i,N}], i \in [1, \ldots, M], \quad (1)$$

where i denotes the i'th feature in the data set. An additional vector is concatenated to the set of feature vectors, resulting in a total of $M+1$ feature vectors. This additional vector will contain the values taken by the continuous independent variable across the N trials. We will refer to this additional variable as the independent covariate vector.

In order to improve the robustness of the selection of features related to the independent covariate vector, the range of values in the set of all feature vectors is uniformly redistributed over the range $1, \ldots, u$, where u denotes the number of unique values in the independent covariate vector, and coarse-grained into u partitions. This is done by first z-scoring the coordinates of each feature vector to a mean of zero and a standard deviation of 1.

To improve the robustness of the feature selection in subsequent steps, the complementary error function (1 – the error function) is then applied to the normalised feature vectors (Hunter and Regan, 1972). Consequently, this allows us to use PCA to identify features in the data. Finally, the coarse graining is completed by affine-mapping the entries in each feature vector so that they fall into the range $1, \ldots, u$ and rounding the values in the feature vector in order to ensure that the number of discrete values taken by the members of each feature vector is equal to u. This is done by dividing the values within each feature vector by the maximum value in the feature vector, multiplying them by u, and adding 1.

This results in a set of coarse-grained feature vectors $\overline{\boldsymbol{F}}_i = [\overline{D}_{i,1}, \ldots, \overline{D}_{i,N}]$, where $\overline{D}_{i,n}, n \in 1, \ldots, N$, $i \in 1, \ldots, (M+1)$ denotes the coarse-grained value of feature i, trial n.

It is now possible to identify informative features by employing techniques related to finding clusters in multivariate datasets. One of the clusters obtained as a result will contain the independent covariate vector. The elements of this grouping therefore define the features that are most closely related to it. Thus, these features are taken to be the features that optimally relate to the independent covariate vector.

To this end we adapted a form of spectral clustering introduced in (Allefeld et al., 2007). The $(M+1)\times(M+1)$ covariance matrix $\boldsymbol{\Sigma}$ is calculated from the coarse-grained collection of feature vectors. Eigen decomposition is applied to the covariance matrix $\boldsymbol{\Sigma}$ to find a set of eigenvalues and eigenvectors defined as

$$\boldsymbol{\Sigma}\boldsymbol{V}_k = \lambda_k \boldsymbol{V}_k \quad (2)$$

where λ_k denotes the eigenvalues and $\boldsymbol{V}_k$ the eigenvectors.

Eigenvalues are then sorted in descending order and the q eigenvalues in the top 5th percentile are identified. The corresponding eigenvectors explain the majority of the variance in the set of feature vector projections onto the linear subspace spanned by these eigenvectors $\boldsymbol{V} = [v_{i,k}], k \in [1, \ldots, q], \forall i \in [1, \ldots, (M+1)]$.

The Participation Index ($\boldsymbol{PI}$) (defined in (Allefeld et al., 2007)) provides a measure of the involvement of each feature vector in each cluster

$$PI_{i,k} = \lambda_k * v_{i,k}^2, \forall i = [1, \ldots, (M+1)], \forall k = [1, \ldots, q], \quad (3)$$

where the eigenvalues λ_k and their corresponding eigenvectors have been pre-sorted in descending order of eigenvalue.

We first inspect the column of $\boldsymbol{PI}$ corresponding to the independent covariate vector ($PI_{(M+1),:}$). The largest $\boldsymbol{PI}$ in this column