

Identification of Relevant Inter-channel EEG Connectivity Patterns: A Kernel-Based Supervised Approach

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Abstract. Extraction of brain patterns from electroencephalography signals to discriminate brain states has been an important research field to the develop of non-invasive applications like brain-computer-interface systems or diagnosis of neurodegenerative diseases. However, most of the state-of-the-art methodologies use observations derived from each electrode independently, without considering the possible dependencies between channels. To improve understanding of brain functionality, connectivity analysis have been developed. Nevertheless in those works, where connectivity measures are included, the total number of connections is high dimensional, and the relevance of connectivity values is not considered. To cope with this issue, we propose a kernel-based inter-channel connectivity relevance analysis (termed ConnRA), for such a purpose, linear dependencies between channel signals are extracted using coherence measures over specific sub-frequency bands, and a similarity criterion is implemented to rank the contribution of each channel-to-channel connection for a specific task. Experimental validation carried out on a database of brain-computer interfaces, demonstrate very promising results, making the proposed methodology a suitable alternative to support many neurophysiological applications.

1 Introduction

Description of separable patterns of brain activity has been a research field of interest to support the diagnosis of neurophysiological disease and to inferring

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about a person thoughts for the development of brain-computer-interface (BCI) systems. For this purpose, the monitoring of brain activity is commonly performed by the non-invasive measurement of the electrical activity projected over the brain scalp surface, (electroencephalogram – EEG). Because of high temporal resolution and low cost, EEG signals have been widely used in many neurophysiological applications related to brain-computer interfaces (BCI) [1], automated diagnosis of neurological diseases like epilepsy [2], neuromarketing [3], among others.

In practice, most of the approaches for brain activity discrimination are based on time-frequency representations of individual channels. Nevertheless, the dynamic behavior of neural activity can also be assumed as a combination of interactions among different brain areas [4]. Therefore, the patterns of brain connections should be included with the aim of analyzing all possible communicated networks between EEG signals measured from electrodes located in various areas of the scalp.

So far, connectivity methods have been applied on EEG signals, in order to estimate functional connectivity between scalp electrodes [5–9], however, reproduction of these interactions across spatial scales, by using EEG inter-channel connectivity measures, leads to high-dimensional spaces that may include redundant or worthless information for a specific task, not mentioning further computational cost issues. Hence, it is necessary to extract a set of the most relevant connectivity patterns that better encodes the main connection information to enhance discrimination performances for neurophysiological applications.

In this work, we propose to use the Magnitude Square Coherence as a measure of both linear dependencies (in amplitude and phase) to compute the degree of similarity between all possible pairs of EEG-channel signals, so that the interactions between the whole scalp areas can be detected. Also, we introduce a methodology to extract the most relevant EEG channel-to-channel connections for a specific task using prior information within a kernel-based analysis. This method may facilitate the physiological interpretation and improve the brain activity discrimination performance.

2 Methods

2.1 Magnitude Square Coherence

Magnitude Square Coherence. (MSC) is a large-scale measure of the underlying dynamic neural interactions, where higher coherence values indicate greater functional interplay between the two underlying neural networks [10]. Consequently, given a set of N EEG recordings $\{\mathbf{Z}_i \in \mathbb{R}^{C \times T}, i \in [1, N]\}$, where the i -th EEG is measured at C electrodes and $T \in \mathbb{N}$ time samples, the pair-wise MSC between two channels c and c' can be computed as [11]:

$$\gamma_{\mathbf{z}_i^c, \mathbf{z}_i^{c'}}(f) = \frac{|S_{\mathbf{z}_i^c \mathbf{z}_i^{c'}}(f)|^2}{S_{\mathbf{z}_i^c \mathbf{z}_i^c}(f) S_{\mathbf{z}_i^{c'} \mathbf{z}_i^{c'}}(f)}, \gamma_{\mathbf{z}_i^c, \mathbf{z}_i^{c'}}(f) \in \mathbb{R}^+ \quad (1)$$

where $\mathbf{z}_i^c \in \mathbb{R}^T$ is the c -th channel of i -th recording, $S_{\mathbf{z}_i^c \mathbf{z}_i^{c'}}(f) \in \mathbb{R}^+$ is the cross-spectral density between channels c and c' at the frequency bin f , and $S_{\mathbf{z}_i^c \mathbf{z}_i^c}(f) \in \mathbb{R}^+$ and $S_{\mathbf{z}_i^{c'} \mathbf{z}_i^{c'}}(f) \in \mathbb{R}^+$ are the auto-spectral density of \mathbf{z}_i^c and $\mathbf{z}_i^{c'}$, respectively.

Moreover, to quantify the dependencies, the averaged MSC, $\bar{\gamma}_{\mathbf{z}_i^c, \mathbf{z}_i^{c'}} \in \mathbb{R}^+$, is computed over a predefined frequency rank $f \in [f_1, f_2]$. Therefore, the feature representation matrix $\mathbf{X} \in \mathbb{R}^{N \times Q}$ is built by computing the connections between all the possible pair of channels, being Q the number of concatenated connections for the i -th trial.

2.2 Kernel-Based Relevance Analysis of EEG Channel-to-Channel Connections

With the aim of finding the most relevant channel-to-channel connections for a given task (i.e. Motor Imagery discrimination), we compute all relationships over pairs of feature vectors of \mathbf{X} , namely $(\mathbf{x}_i, \mathbf{x}_j) \in \mathbb{R}^Q$, through the introduced similarity kernel $\mathbf{K} \in \mathbb{R}^{N \times N}$ with elements defined like $k_{ij} = \kappa(d_A(\mathbf{x}_i, \mathbf{x}_j))$, $\forall i, j \in [1, N]$, where the distance $d_A : \mathbb{R}^Q \times \mathbb{R}^Q \mapsto \mathbb{R}$ is an operator related to the positive definite kernel function $\kappa(\cdot)$. Here, the Mahalanobis distance is used that defined in a Q -dimensional space with inverse covariance matrix $\mathbf{A}\mathbf{A}^\top$ computed as below:

$$d_A^2(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i, \mathbf{x}_j) \mathbf{A} \mathbf{A}^\top (\mathbf{x}_i, \mathbf{x}_j)^\top, \quad (2)$$

where matrix $\mathbf{A} \in \mathbb{R}^{Q \times M}$ holds the linear projection $\mathbf{y}_i = \mathbf{x}_i \mathbf{A}$, with $\mathbf{y}_i \in \mathbb{R}^M$, $M \leq Q$.

The matrix \mathbf{A} is computed by adding the available prior knowledge about the task of interest, in our case, the motor imagery paradigm with imagination of left or right motor action. The prior information is enclosed into the matrix $\mathbf{B} \in \mathbb{R}^{N \times N}$ with elements $b_{ij} = \delta(l_i - l_j) \in [0, 1]$, being $\delta(\cdot)$ – the delta function. Besides, the relationship between \mathbf{K} and \mathbf{B} is computed by the following kernel target centered alignment function [12]:

$$\rho(\mathbf{K}, \mathbf{B}; \mathbf{A}) = \frac{\langle \mathbf{H} \mathbf{K} \mathbf{H}, \mathbf{H} \mathbf{B} \mathbf{H} \rangle_F}{\|\mathbf{H} \mathbf{K} \mathbf{H}\|_F \|\mathbf{H} \mathbf{B} \mathbf{H}\|_F}, \rho \in [0, 1] \quad (3)$$

where $\mathbf{H} = \mathbf{I} - N\mathbf{1}\mathbf{1}^\top$ is a centering matrix, $\mathbf{I} \in \mathbb{R}^{N \times N}$ is the identity matrix, $\mathbf{1} \in \mathbb{R}^N$ is an all-ones vector, $\mathbf{K} \in \mathbb{R}^{N \times N}$ is the computed similarity kernel for a given matrix \mathbf{A} , and notations $\langle \cdot, \cdot \rangle_F$ and $\|\cdot\|_F$ stand for the Frobenius inner product and norm, respectively.

Consequently, the prior knowledge about the EEG trials can be used to highlight relevant features by learning the matrix \mathbf{A} that parameterizes a Mahalanobis distance between pairwise samples. Therefore, the function that implements the Centered Kernel Alignment can be formulated to compute the projection matrix \mathbf{A} as follows:

$$\mathbf{A}^* = \arg \max_{\mathbf{A}} \rho(\mathbf{K}, \mathbf{B}; \mathbf{A}), \quad (4)$$

From the obtained matrix \mathbf{A}^* , a relevant feature matrix $\mathbf{Y} \in \mathbb{R}^{n \times M}$ is estimated encoding a linear combination of EEG discriminative features according to the prior knowledge considered in \mathbf{B} .

At the end, the relevance for each input feature can be estimated by analyzing its contribution to building the projection matrix \mathbf{A}^* , resulting in the following feature relevance vector $\mathbf{q} \in \mathbb{R}^Q$:

$$\mathbf{q}_q = \sum_{m=1}^M |a_{qm}|; \forall q \in Q, a_{qm} \in \mathbf{A} \quad (5)$$

The main assumption behind the introduced relevance index is that the largest values of \mathbf{q}_q should point out to better input attributes since they exhibit higher overall dependencies to the estimated embedding. The M value is fixed as the number of dimensions needed to preserve some percentage of the input data variability [13]. So, the calculated relevance vector \mathbf{q} is used to rank the inter-channel connections.

3 Experimental Set-Up

3.1 Tested Dataset and Preprocessing

In order to assess the proposed methodology as a tool to support BCI systems, experimental testing is carried out over a two-class Motor Imagery (MI) Database¹. The EEG signals are provided by *Berlin Brain-Computer Interface group for a BCI* and include the 59-channel recording acquired for seven subjects who were instructed to perform the imaginary movement of the left or right hand indicated by a pointing arrow on a screen. All the recordings are band-pass filtered between 0.05 and 200 Hz and then submitted to a 10-order low-pass Chebyshev II filter with a stop-band ripple of 50 dB down and stop-band edge frequency of 49 Hz. All EEG signals are further digitized at 1000 Hz and down-sampled to supply the sampling frequency at 100 Hz. The whole session is performed without feedback, and 100 repetitions are recorded for each of two MI classes per person for a total of 200 trials per subject. The section of interest is 4 s during when the subject is instructed to perform the MI task. These periods, lasting 4 s, are interleaved with a blank screen and a fixation cross in the screen center.

The design procedure for the preprocessing stage is as follows: first, a 5-order band-pass Butterworth filter is implemented with bandwidth ranging from 30 till 30 Hz. Later, a data-driven supervised decomposition of the EEG multi-channel data is carried out based on the Common Spatial Patterns (CSP) algorithm. In this step, a spacial filter matrix is calculated projecting the original EEG signals to space where the differences in variance between the two labels of the MI task are maximized [14]. Finally, an empirical mode decomposition (EMD) is used, to extract adaptively components carrying MI information that better fits for the frequency band selection needed in the CSP method [15].

¹ <http://bbci.de/competition/iv/desc-1.html>. BCI competition IV 2008, Dataset 1.

3.2 Inter-channel Connectivity Extraction

In general, the EEG rhythms carrying out motor imagery interest include, mainly, the sub-bands Alpha ($\alpha, f \in [8, 13]$) Hz and Beta ($\beta, f \in [14, 30]$) Hz [16]. Consequently, the underlying dynamic interactions are computed across those frequency bandwidths by filtering each preprocessed EEG trial \mathbf{Z}_i using a 5-order band-pass Butterworth filter. Moreover, to obtain a holistic view of the information transfer using this linear metric, MSC is also calculated for the entire range ($f \in [8, 30]$) Hz. As a result, MSC is computed over all EEG trials for each frequency range.

Consequently, all row channel vectors are considered in pairs over which coherence measurement is calculated as explained in Sect. 2.1, building the channel-to-channel connection matrix for each trial $\mathbf{Y}_i \in \mathbb{R}^{C \times C}$ with elements $v_i^{c,c'} \in \mathbb{R}[0, 1]$ defined as follows: $v_i^{c,c'} = \overline{\gamma}(\mathbf{z}_i^c, \mathbf{z}_i^{c'})$, $\forall c, c' \in [1, C]$ with $v_i^{c,c'} \in \mathbb{R}^+$.

Given that the coherence is a measure that assumes linear relationships, the square matrix \mathbf{Y} becomes symmetric with ones on the main diagonal and zeros elsewhere. Accordingly, only the values of the upper diagonal of \mathbf{Y} are contemplated to create a feature representation matrix \mathbf{X} with the minimum possible redundant information. As a result, each row vector of \mathbf{X} comprises $Q = 3 \times C(C-1)/2$ features, corresponding to the $C(C-1)/2$ possible connections over the three studied frequency ranks of interest.

3.3 Classifier Training and Validation

The proposed approach is used as a tool to select the most relevant channel-to-channel connections, providing a better understanding of the relations of brain electrical signals projected over the scalp in a specific task as MI paradigm. Hence, the approach generates by feature transformation, new composites of the input feature set to improve overall brain activity discrimination performance. Consequently, the accuracy of the approach for an MI task is carried out.

Prior to classification, the feature relevance analysis is performed as stated in Sect. 2.2. As a result, the estimated relevance vector $\boldsymbol{\rho}$ is employed to rank the original features. Further, the k -Nearest-Neighbor (k -nn) classifier is trained. The number of nearest neighbor is fixed automatically for each subject according to the training set accuracy. Finally, the accuracy curve performed for the MI classification is computed through the 10-folds cross-validation scheme, adding one by one the features ranked by the relevance vector. Also, the average of each feature relevance for all the cross-validation iterations is computed, aiming to obtain a representative relevance vector of the complete features set.

4 Results and Discussion

As described before, we consider the relevance analysis as a channel-to-channel connections selection tool. Thus, Fig. 1a shows the coherence matrix for subject labeled as #6 obtained in the three considered frequency sub-bands: Alpha,

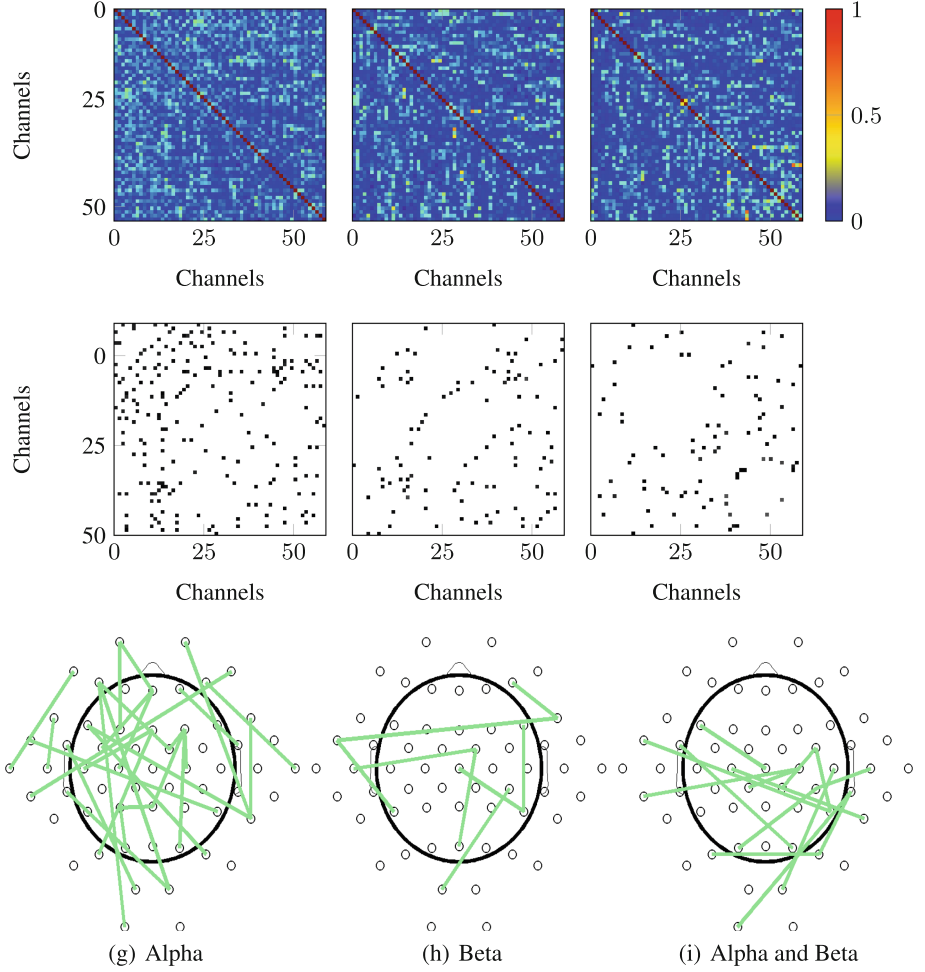


Fig. 1. Estimated values of the connectivity measure and the most relevant connections for subject # 6 for the subfrequency bands: Alpha, Beta, and the interval that holds both frequency ranges.

Beta, and the interval that holds both frequency ranges. Each matrix position designates the connection weight between channels c and c' . Further, Fig. 1b shows with black points the inter-channel connections that are selected as the most relevant for the discrimination between left-right motor imagery classes.

For the sake of visual representation, Fig. 1c displays only the 50 most relevant connections, drawn as linked lines between electrode locations. As seen in Fig. 1b and 2, the majority of relevant connections for the discrimination of the contemplated MI tasks is extracted from α sub-band. This behavior holds for the majority of subjects of this study (in five of seven). Also, different patterns for each frequency band are noticed in Fig. 1c.

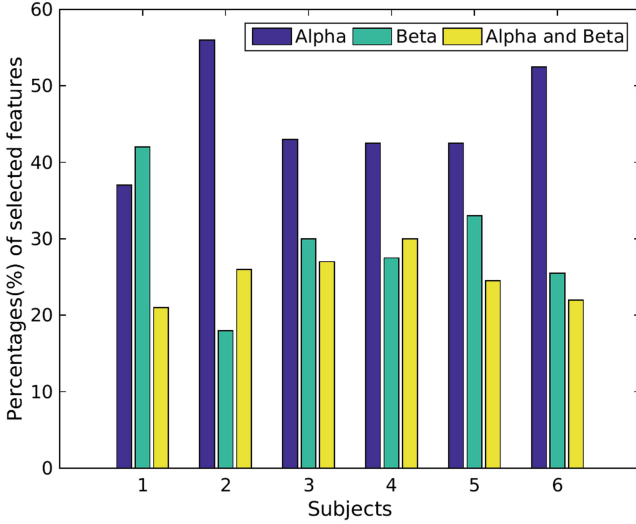


Fig. 2. Contribution of the considered sub-bands of frequency to the MI discrimination performance.

In the discrimination of MI classes, we just select a training set containing the minimum amount of channel-to-channel connections that achieves the maximum classification accuracy. For this purpose, the relevant connections are fed one by one into the k -nn classifier in accordance with the decreasing rank of relevance. Results for the performed classification accuracy are shown in Fig. 3 and Table 1. It can be seen that classification accuracy improves selecting just the most relevant features compared against the accuracy when all computed connections are considered.

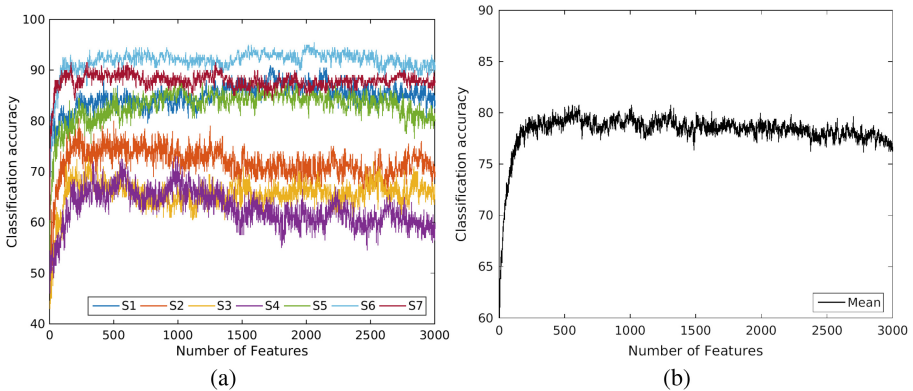


Fig. 3. Learning curves for classification accuracy.

Besides, we analyze the suggested Kernel-based relevance analysis of inter-channel connectivity selection concerning the classification accuracy achieved for the contemplated MI task, where the proposed methodology reaches an averaged accuracy 84.64 ± 0.544 as shown for all subjects in Table 1. With the aim of comparing our methodology, we add the accuracy estimated by the approach submitted in [14] where spatio-temporal features are selected and a non-linear regression for predicting the time-series of class labels is applied. The work in [17] that employs spatial preprocessed features and an SVM classifier is also compared. Note that either examined training approach does not take in account spatial dependencies between brain electrical signals, underperforming the proposed *ConnRA* method.

Table 1. Classification accuracy [%]. Figures remarked in bold are the best performed for each subject. Notation # is the subject label. (–) Results not provided

#	He [14]	Zhang [17]	ConnRA
#1	67.7±2.20	77.2±0.03	91.0±6.00
#2	70.7±1.20	70.8±0.02	80.5±9.27
#3	83.9±1.30	-	73.0±7.54
#4	93.0±1.20	-	73.0±9.48
#5	93.2±1.20	-	88.0±5.38
#6	-	76.8±0.03	95.5±5.00
#7	-	80.0±0.03	91.5±5.83
Mean	81.7±12.1	76.2±3.87	84.6±6.92

5 Discussion and Concluding Remarks

In this work, we discuss a novel methodology for selecting the most relevant EEG channel-to-channel interactions to enhance the automatic identification of brain connectivity patterns. For such a purpose, a similarity criterion to rank the contribution of inter-channel connectivity values for classifying two tasks of brain activity in an MI paradigm is proposed. So, experimental results are carried out on real EEG Data in motor imagery paradigm, i.e., a real BCI application.

The values calculated for connectivity over the sub-frequency band Alpha are more relevant for the discrimination of the considered MI task; this fact can be seen in Fig. 1. Furthermore, the classification accuracy of the proposed methodology outperforms the accuracy presented in works where dependencies between the EEG signals are not considered explicitly. This behavior can also be noticed in Fig. 3 showing that the highest accuracy rates are obtained for a low amount of features (connections). In turn, the accuracy rate considerably decreases when the entire set of connections considered (See also Table 1). Consequently, we can

conclude that the selected features are the most relevant ones to discriminate between MI tasks. Moreover, the proposed approach is a suitable alternative to support straightforward BCI systems.

The proposed methodology is tested through the 10-folds cross-validation scheme, but due to the phenomenon is not universal for all subjects as a future work new data can be used and hypothesis tests can be implemented.

The feature extraction in [14] is made by measuring signal dynamics both in time and frequency over each channel. Hence, this dynamics could also create a favorable representation for the label discrimination given specific subjects and conditions, and this might explain the outcomes of this method for some subjects in the considered dataset. Therefore, as a future work, we propose to implement both feature extraction: to represent the individual channel dynamics and to find channel-to-channel relations, to lately use the feature selection stage based on the similarity criterion applied in this work to rank the contribution of each set of features. Also, it is suitable to compare different methods of connectivity selection, including supervised and unsupervised schemes.

Given that the electrical brain activity measured over the scalp is affected by volume conduction factors and do not faithfully represent the information in the brain source space, neurophysiological interpretation in EEG channels spaces is difficult and no accurate [18]. Therefore, as a future work a EEG source imaging stage can be included to implement the proposed methodology over the estimated brain source signals.

Recently, connectivity analysis has been used as a biological marker to the support of the diagnosis of Attention deficit hyperactivity disorder, using evoked response potentials [19, 20]. Consequently, also as a future work we propose to use the proposed methodology to find the most relevant inter-channel connections in the support of diagnosis of this disorder.

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