Performance Comparison of Functional Connectivity Evaluation for Graph-based Classification in Brain-Computer Interfaces

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Abstract – This work presents a classification performance comparison between different frameworks for functional connectivity evaluation aiming to distinguish motor imagery classes in the context of electroencephalography (EEG)-based brain-computer interfaces for nine subjects (BCI competition IV – dataset 2a). Two different theoretical scenarios for functional connectivity were studied: 1) classical Pearson correlation for estimating the adjacency matrix; 2) the spatial recurrence between each pair of electrodes at each time instant followed by recurrence frequency analysis for similarity inference. These strategies were followed by graph feature evaluation (cluster coefficient, degree, betweenness centrality and eigenvalue centrality), feature selection by Davies-Bouldin index and classification using least squares classifier. The obtained results revealed that the recurrence-based approach for functional connectivity evaluation was significantly better than the Pearson's framework, with the eigenvalue centrality being the best graph measure for distinguishing the 4-motor imagery classes, attaining 70% accuracy for the best subjects. When just the best pairs of classes were considered, accuracies higher than 90% were achieved for four subjects with the recurrence-based framework.

Keywords: *Brain-Computer Interface, Functional Connectivity, Complex Networks, Motor Imagery, Pattern Recognition.*

Introduction

A Brain-Computer interface (BCI) is a system that aims to extract information from central nervous system activity and translate it into output commands. BCIs have as main focus the development of solutions to restore communication and efficient control of assistive devices for people with disabling neuromuscular disorders, such as stroke, cerebral palsy, amyotrophic lateral sclerosis and spinal cord injury [1]. They have also been used for rehabilitation purposes [2].

Besides that, BCIs can also be employed to offer a better understanding of brain functioning and the cognition process itself, when mechanisms and variables are sought and investigated aiming at an efficient discrimination of mental tasks and their mapping in well-defined labels [1].

Among the techniques to study brain functioning, the functional connectivity [3, 4] seeks to characterize the observational similarity between different brain regions and how such similarity changes due to patient's pathology or even under different mental tasks. To accomplish that, the functional connectivity has been evaluated from time series obtained in different experimental frameworks: its most common application based on fMRI recordings and, more recently, on signals with a better temporal resolution, such as EEG, MEG, etc [3, 4]. In those cases, similarity is usually estimated based on classical statistical tools such as linear correlation (Pearson), covariance, spectral coherence, or phase locking between pairs of time series [4], which have been used in studies concerning schizophrenia [5], epilepsy [6] and depression [7].

Having these issues in mind, this work proposes to study the classification accuracy of functional connectivity measures obtained using classical Pearson correlation and also a recurrence-based quantification strategy with further characterization using classical graph metrics in the context of EEG-BCI motor imagery signals.

Methods

Database: A motor imagery (MI) database containing training and testing datasets of four tasks – left hand, right hand, feet and tongue – for nine subjects was analyzed (BCI Competition IV - dataset 2a). The trials (12 for each task per dataset) lasted around 8 seconds, with only 3 being related to MI tasks. More details in [8].

Preprocessing: The signals were bandpass filtered between 8 and 15 Hz and a common average reference spatial filtering was used [1]. After this, only the signals parts related to the MI tasks were taken into account in this analysis (second 3 to 6).

Functional connectivity quantification: functional connectivity evaluation leads to an adjacency matrix, which represents the similarity between all pairs of electrodes. Here, the adjacency matrix of all 22 electrodes available was obtained considering two different approaches: Pearson Correlation and the Space-Time Recurrence counting.

Pearson Correlation is a time-domain similarity measure which can detect linear dependency between two electrodes [9] as defined in Eq. 1, in which cov(*i*,*j*) is the covariance between electrodes *i* e *j*, and var(.) is the variance.

$$P_{i,j} = \frac{\mathrm{cov}(i,j)}{\sqrt{\mathrm{var}(i)\,\mathrm{var}(j)}} \tag{1}$$

In order to define binary connectivity matrices, graph edges were determined by a correlation threshold (ρ).

Space-Time Recurrence (STR) counting consists on the evaluation of a recurrence plot [10] in the electrode space for each time instant and their further density analysis. This implies in evaluating which electrodes are close or not to a distance ε and building a three-dimensional $\mathrm{M}\times\mathrm{M}\times\mathrm{T}$ data recurrence structure, being M being the number of electrodes and T the number of time instants. The Space-Time Recurrence (STR) matrix between electrodes *i* and *j* for *n* samples can be defined as:

$$\mathrm{STR}_{i,j}(\varepsilon,n) = \Theta\{\varepsilon - \| x_i(n) - x_j(n) \|\} \tag{2}$$

with $\Theta\{x\}$ denoting the Heaviside function and ε an arbitrary distance chosen to indicate proximity. The edges between nodes *i* and *j* in the adjacency matrix (A) can be set by means of Eq. 3, in which ψ is a counting threshold:

$$A_{i,j}(\psi) = \Theta\left\{\left(\frac{1}{N}\sum_{n=1}^{N}\mathrm{STR}_{i,j}(\varepsilon,n)\right) - \psi\right\} \tag{3}$$

This threshold (ψ) can be obtained from the minimum density of recurrence plus a percentage (φ) of the distance between the minimum and maximum densities to define the adjacency matrix used in the subsequent steps:

$$\psi = \min(den_{i,j}) + \varphi(\max(den_{i,j}) - \min(den_{i,j})) \tag{4}$$

The distance threshold (ε) and percentage (φ) for were defined after an exhaustive search, as in the case of the correlation threshold (ρ), aiming to compare the best classification performances of these techniques. It is also important to highlight that the use of a recurrence plot to estimate the adjacency matrix has already been reported in [11] and [12], but out of the context of space recurrence plots between different sensors or even functional connectivity.

Graph theory metrics: To evaluate the functional connectivity matrix obtained by both approaches, four graph metrics were chosen: degree, clustering coefficient, betweenness centrality and eigenvector centrality.

The node degree (Eq. 5) is a measure that quantifies the number of links, or neighbors, of a given node, which allows identifying the network hubs [13]:

$$D_i = \sum_{j=1}^{n} A_{ij} \tag{5}$$

in which *n* is the number of nodes and A_{ij} is the adjacency matrix value between nodes *i* and *j*. The clustering coefficient (Eq. 6) is a segregation metric that represents the fraction of triangles around a node and is equivalent to the fraction of the node's neighbors that are also neighbors of each other [13]:

$$CC_i = \frac{2t_i}{D_i(D_i - 1)} \text{ for } \mathrm{D_i} \geq 2 \tag{6}$$

in which t_i is the number of triangles around a node *i* and D_i the node degree. The betweenness centrality (Eq. 7) quantifies the network information flow by means of the shortest path between two nodes *s* and *t* (σ_{st}) and how many of these include node *i* ($\sigma_{st}(i)$) [13]:

$$BC_i = \sum_{s\neq t\neq i} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{7}$$

Finally, eigenvector centrality evaluates nodes interaction considering the whole network structure, since it considers the connection of the neighbors of the node to quantify the centrality [14]. It can be defined as:

$$EC_i = \frac{1}{\lambda}\sum_{j=1}^{n} A_{ij} x_j \tag{8}$$

in which λ is the greatest eigenvalue of *A* and x_j the respective eigenvectors. The computed metrics were used as features and were selected by the Davies-Bouldin index [15, 16]. Lastly, a least squares classifier [17] was used to discriminate the classes based on the best 22 ranked attributes and the accuracy was obtained based on training and testing datasets as established in BCI Competition IV [8].

After a preliminary investigation, the chosen correlation threshold was $\rho = 0.16$, which aimed to provide the best classification performance for Pearson scenario. In the STR framework, the best scenario was attained for $\varepsilon = 2.2$ and $\varphi = 0.5$ after exhaustive search, being the best Pearson and STR compared in this work.

Results

Table 1 and 2 show, respectively, the classification accuracy for Pearson correlation and STR approaches considering the 4 classes (1-left hand, 2-right hand, 3-feet and 4-tongue) and each pair of classes for all subjects.

Table 1. Classification accuracy considering all 4 classes (All) and pairs of classes using Pearson correlation with $\rho = 0.16$.

Subj.	All	1-2	1-3	1-4	2-3	2-4	3-4
S1	0.50	0.74	0.71	0.76	0.79	0.79	0.67
S2	0.34	0.63	0.57	0.52	0.62	0.58	0.52
S3	0.49	0.85	0.73	0.70	0.75	0.80	0.56
S4	0.46	0.67	0.65	0.70	0.67	0.70	0.57
S5	0.35	0.59	0.55	0.60	0.59	0.50	0.57
S6	0.32	0.63	0.61	0.53	0.62	0.56	0.58
S7	0.29	0.54	0.56	0.62	0.55	0.52	0.61
S8	0.55	0.88	0.76	0.77	0.74	0.72	0.67
S9	0.47	0.75	0.81	0.78	0.63	0.74	0.60

Table 2. Classification accuracy considering all 4 classes and pairs of classes using STR with $\varepsilon = 2.2$ and $\varphi = 0.5$.

Subj.	All	1-2	1-3	1-4	2-3	2-4	3-4
S1	0.60	0.83	0.93	0.91	0.96	0.97	0.62
S2	0.33	0.50	0.57	0.53	0.67	0.63	0.60
S3	0.67	0.94	0.88	0.90	0.80	0.92	0.64
S4	0.45	0.62	0.73	0.75	0.69	0.69	0.53
S5	0.33	0.57	0.60	0.61	0.56	0.65	0.62
S6	0.33	0.55	0.63	0.58	0.60	0.58	0.58
S7	0.35	0.52	0.56	0.61	0.63	0.63	0.63
S8	0.70	0.94	0.83	0.79	0.79	0.86	0.77
S9	0.67	0.89	0.90	0.94	0.74	0.74	0.83

Table 3 shows the comparison between these strategies revealing the significant STR better performance (paired *t*-test, *p*-value = 0.04).

Additionally, in order to identify the network metric that most influenced performance, the data were classified using each of the four metrics individually. Figure 1 shows the accuracy obtained by the metrics for each similarity measure.

Table 3. Classification accuracy comparison between Pearson and STR strategies.

	Pearson	STR
mean ± st. deviation	0.42 ± 0.09	0.49 ± 0.16

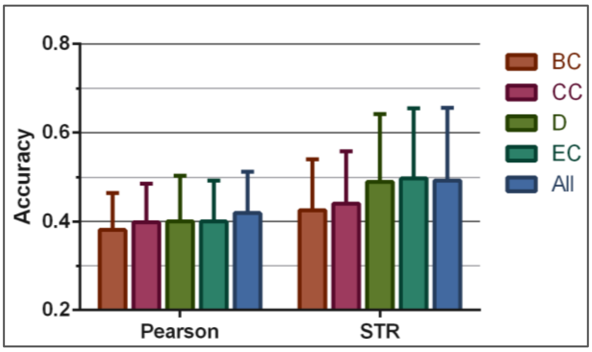

Figure 1. Accuracy obtained when separately using BC, CC, D and EC for each similarity measure.

Also, the kappa value, which is a measure of performance that considers also the hit rate of a random classifier, was computed and compared to those obtained by the BCI Competition participants. Table 4 presents the results of the first three places and the results obtained by correlation and STR approaches.

Table 4. Kappa obtained by participants of BCI Competition IV and by STR and Pearson correlation.

	1st	2nd	3rd	STR	Pearson
mean kappa	0.57	0.52	0.31	0.33	0.23

Discussion and Conclusions

The idea of applying recurrence-based methods for BCI applications was introduced in [18]. In the present work, it has been shown that spatial recurrence between EEG electrodes can offer an interesting tool for estimating functional connectivity and distinguishing MI tasks in the BCI context, reaching an accuracy around 70% for the best subjects considering all 4 MI classes and higher than 90% for the best pair of classes for 4 subjects.

Comparing the similarity measures evaluated, STR exhibited a significantly better performance than Pearson's approach considering all subjects and classes (*p*-value = 0.04 – paired t-test). STR also obtained a kappa value of 0.33, showing a result superior to the third place of the BCI competition, which employed a complex combination of benchmark techniques (e.g. common spatial patterns, support vector machines), as reported in [8].

Finally, this work has also shown that the EC measure presents the best discriminant potential. In fact, previous findings with a similar approach (but using a different method for estimating the adjacency matrix) found similar results [19, 20]. This strongly motivates applying EC features in online BCI systems, something that outlines a natural perspective of this study.

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