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COMBINATION OF CONNECTIVITY AND SPECTRAL FEATURES FOR MOTOR-IMAGERY BCI

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ABSTRACT: In brain-computer interfaces (BCI), the detection of different mental states is a key element. In Motor Imagery (MI)-based BCIs, the considered features typically rely on the power spectral density (PSD) of brain signals, but alternative features can be explored looking for better performance. One possibility is the integration of functional connectivity (FC). These features quantify the interactions between different brain areas and they could represent a valuable tool to detect differences between two mental conditions. Here, we investigated the behavior of coherence-based FC features and PSD features, alone and in combination. For a better comparison, we characterized the network centrality of each brain area by computing the weighted node degrees from the estimated FC networks. Our findings show that in both alpha and beta frequency bands, and for almost all the subjects, the fusion of FC network indices and PSD features give better performance. This preliminary results open the way to the use for network-based approaches in BCIs.

INTRODUCTION

A brain-computer interface is a system that enables the interaction subject-external world without peripheral nerve or muscles [26]. It allows communication [17] and the control of real or virtual objects [4]. Nowadays, the performance of BCI appears to be inconsistent across subjects. Indeed, there is an non-negligible percentage of users who cannot use the interface [3], [24].
To face this problem, investigators historically searched for better brain decoders [18]. To do so, one possibility consists of working on the features extraction and selection and more specifically of looking for alternative features that could better discriminate the subjects' mental state.
Recently, a great interest was born in connectivity applied in brain-computer interfaces and in particular in motor imagery, giving promising results [22], [2]. The reason behind this choice is that brain mechanisms involved in BCI are complex and they could be better described by functional interactions changes. Indeed, connectivity describes the interaction between different brain areas that can reflect specific mechanisms such as synchronization in time-others in phase domain, or the causal interactions for instance [11]. Notably, a variation of inter hemispheric connections has been found using phase-locking value, but in other case the prominent mechanisms was the increase of information flow regarding the contralateral motor area [15]. The frequency band that appears involved in the task differs being alpha, beta or gamma and a completely changing behavior can be found in the different bands. These contradictory results motivated us to investigate more the subject.
Here, we hypothesized that features based on connectivity can provide relevant information to better discriminate the subjects' mental state. For this purpose, we first tested the feasibility of the use of connectivity-based features already identified as a feature with high discriminating potential in motor imagery task [7]. Then, we tested the combination of features based on power spectra and on connectivity to take advantage of their complementarity.

MATERIALS AND METHODS

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1. Experimental Protocol: Fifteen healthy subjects (aged 27.73 ± 4.45 years, 7 women) all right handed participated to our motor imagery-based BCI protocol. The users were seated in front of a screen. When the target was up, the subjects had to image to move the right hand (e.g. grasping) [27]. When the target was down they had to remain at rest. During the tasks, we recorded the electroencephalography (EEG) activity with 74 electrodes in a 10-10 standard configuration. We collected 64 trials for motor imagery and 64 for resting state. Each trial lasted 5s. EEG signals were recorded with frequency sampling of 1 kHz and then downsampled to 250 Hz. To remove those related to eye and cardiac artifacts in the sensor space, a pre-processing step consisted in an Independent Component Analysis (ICA) [10] with Infomax algorithm [1] performed with Fieldtrip toolbox [19]. The selection of the components was performed by a visual inspection of the signals.

2. Analysis: We can schematize our recording systems in the following way. N signal samples were acquired at frequency F_s in two different mental states, S_1 and S_2. EEG samples were recorded from M electrodes for each state, obtaining T_{S1} trials in S_1 and T_{S2} trials in S_2; the same procedure was replicated for I subjects.

The signal Acquisition Stage (AS) in the two mental states S_1 and S_2 for the i-th user, t-th trial, m-th channel, n-th signal sample yields the real measurements' sets:

$$X^{(S_1)} = \{x_m^{(i,t)}[n]\},\ S_1 \text{ AS}\} \tag{1}$$

$$X^{(S_2)} = \{x_m^{(i,t)}[n]\},\ S_2 \text{ AS}\} \tag{2}$$

We reported the framework of this study (Fig. 1). The first step consisted of recording brain signals from a given subject i followed by the features extraction. Here, we considered two types of features: PSD, that reflects the local activation of the cortex, and connectivity, describing interactions of brain areas. The last step is the evaluation of compact metric (node degree) that synthetically quantifies the connectivity of each node. In the next sections, a detailed description of each step is given.

2.1 Features estimations: For both the ASs, the following power spectral estimates are computed:

$$P_{x_m}^{(i,t)}[k] = \frac{1}{L_W}\sum_{l=0}^{L_W}\left|\sum_{n=0}^{N-1} w_l[n]x_m^{(i,t)}[n]e^{-j2\pi nk/N}\right|^2 \tag{3}$$

$$P_{x_{m_1}x_{m_2}}^{(i,t)}[k] = \frac{1}{L_W}\sum_{l=0}^{L_W}\left(\sum_{n=0}^{N-1} w_l[n]x_{m_1}^{(i,t)}[n]e^{-j2\pi nk/N}\right)\cdot \left(\sum_{n=0}^{N-1} w_l[n]x_{m_2}^{(i,t)}[n]e^{-j2\pi nk/N}\right)^* \tag{4}$$

where $w_l[n]$, with $l = 0,\cdots L_W - 1$ and $n = 0,\cdots N-1$ are real windows L_W , depending on the estimation method. In the case of Welch method, a set of time orthogonal functions are used [25].

For each subject i, each trial t, each frequency bin we evaluated the two features. Specifically, Welch method is used for the evaluation of the auto and cross-spectrum. Hanning time windows characterized by a length of 1s and an overlap of 50% are used. To this aim,we narrowed the frequency set, to select features from 4 to 40 Hz in steps of 1 Hz.

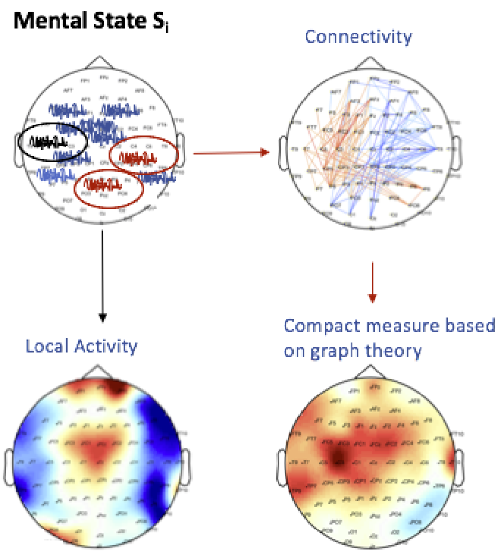

Figure 1: Schematic representation of different steps of our analysis. EEG signals are recorded from each channels. Signals vary in time and frequency domain. Since we collected all the signals, we can extract features, which can be local features (as PSD) or connectivity (as coherence). We can use compact measures based on graph theory (as weighted node degree).

The connectivity estimator that we use in this work, is the spectral coherence [6], defined as:

$$C_{m1\,m2}^{(i,t)}[k] = \frac{\left|P_{x_{m_1}x_{m_2}}^{(i,t)}[k]\right|}{\left(P_{x_{m_1}}^{(i,t)}[k]\cdot P_{x_{m_2}}^{(i,t)}[k]\right)^{1/2}} \tag{5}$$

This quantity reflects in the frequency domain the synchronization in amplitude between two signals. The advantage compared to the simpler cross-correlation is that it is possible to separate different frequency bands. This aspect is important in EEG applications where, the response changes in different frequency bands.

We defined a graph as a set of vertices (or nodes) and edges (or links)[5]. In our case, nodes represents the EEG-electrodes and the edges are the connectivity estimate, without thresholding or binarizing [11].

To extract information about the connectivity of each electrode and following the approach in [7], we defined the Coherence-based Node Degree (CND), as follows:

$$\text{CND}_m^{(i,t)}[k] = \sum_{c=0}^{M-1} C_{mc}^{(i,t)}[k] \tag{6}$$

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This measure describes in compact way the connectivity of each node. In fact, it is evaluated for each node and it represents how much one node is connected to all the others [11].
To take into account the neurophysiology aspects underlying the task used here [21],[20], we decided to restrict our study on the set of electrodes located in the controlateral motor area (Fig.2). Nevertheless, the CND is evaluated taking into consideration all the possible connections including the selected nodes.

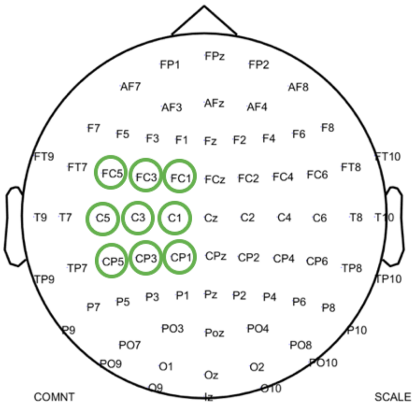

Figure 2: Representation of 74 electrodes in 10-10 standard configuration as used in our experiments. Electrodes in left central are circled in green

2.2. Features fusion: To understand if a combination of different information would better discriminate between two conditions, different approaches have been proposed in the literature [23]. Notably, the fusion of features from different modalities in motor imagery BCI has already been studied, with promising findings [9]. In particular, the fusion can be performed at the classifier level, by attributing a specific weight to the output of each classifier, or at features level. Here we used the latter with a concatenation of the trials of different features.

2.3 Classification: To classify the subjects' mental state, we used the linear discriminant analysis (LDA) method [12]. Our classifier operates on single subject, single frequency bin and single channel. More specifically, for a given subject, for the k -frequency bin and the m-channel we randomly chose the 80% of the trials for the training set. The total number of trials for the training set is 103. The remaining 25 trials, related to the other 20%, are used for the testing part. Performances of the classification were evaluated during the testing part. We repeated this operation 50 times and the performances reported here corresponds to the average in all the repetitions. For i -subject, k -bin, m -channel, we measured classification performances, in terms of accuracy, sensitivity, specificity, and area under curve (AUC). For a necessity of representation, we only reported here the most significative results in terms of accuracy, defined as follows:

$$ACC = \frac{TP+TN}{P+N} \tag{7}$$

Where TP are the true positives, TN the true negatives and P and N are positives and negatives respectively.

RESULTS

We performed the classification test as explained before and we repeated the operation for each subject, each frequency bin and each channel. For each subject, we selected the best value in terms of classification performances (e.g. accuracy) comprised in the central left area. The best accuracy value is associated with a given (electrode; frequency bin) couple. In the Fig 3, we represented the maximum accuracy obtained for each subject and each modality. In particular, we reported in a bar plot the maximum value of accuracy. In order to make the results clearer, we associated to each frequency bin, the related frequency band.
To be more precise, the frequency band that we use are: $B_{theta} = 4-7$Hz, $B_{alpha} = 8-13$Hz, $B_{beta} = 14-29$Hz and $B_{gamma} = 30-40$Hz.

In Fig. 3, when we compare the PSD with coherence, we can notice that 9 on 15 subjects reached higher accuracy with PSD, while for the remaining 6, the coherence is better. If we compare coherence with the fusion, the latter is better in 9 over 15 subjects. The last comparison is between fusion and PSD. The fusion of the two features is better in 13 over 15 subjects. The mean values of accuracy with the associated standard deviations are: 0.66$\pm$ 0.03 for PSD, 0.66$\pm$ 0.02 for coherence and 0.68 $\pm$0.02 for the fusion. The frequency bands associated with the reported results vary according to the subject, but the most selected bands are alpha and beta.
We reported a set of figures to represent the most frequently chosen channels (Fig.4) The associated plots represent the occurrences on the scalp for each explored mode, Coherence-based Node degree, PSD and fusion and for each frequency band. In each picture, the dimension of the circle is proportional to the occurrence of each electrode as the one related with the highest accuracy. C5 and C3 channels are usually the most involved in the task, have a high representation, especially in alpha and beta band. Interestingly, the occurrences associated with these two channels, in the case of coherence feature, are also high in gamma band. For sake of completeness, in Fig.5, for each subject and each feature we report the standard deviation related to the cross validation. Specifically, we evaluated the standard deviation of the accuracy across the 50 random repetitions for the best couple channel-frequency bin.

DISCUSSION AND CONCLUSION

Functional connectivity is a valuable tool to describe and

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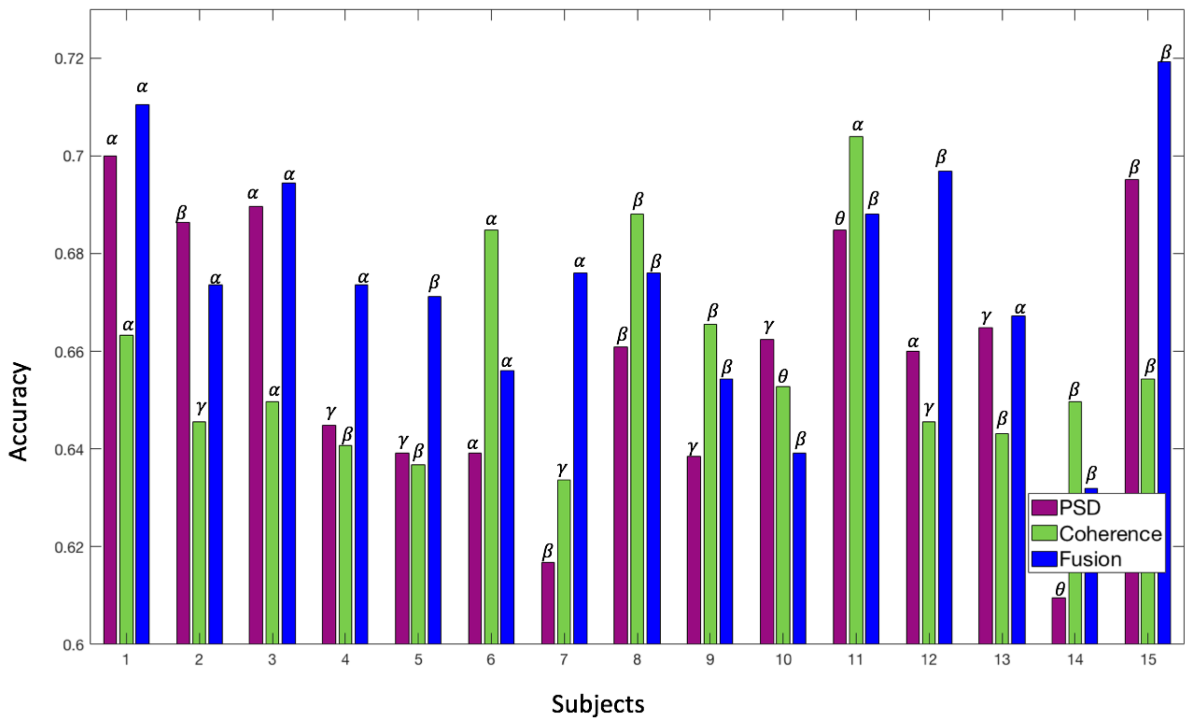

Figure 3: Bar plot with the best accuracy level for each subject. Each value is related to a specific couple frequency bin-electrode. For each subject we have three bars that refer to the three modes: PSD (in pink), Node Coherence (in green) and Fusion (in blue). On the top of each bar we report the frequency band associated to the selected bin.

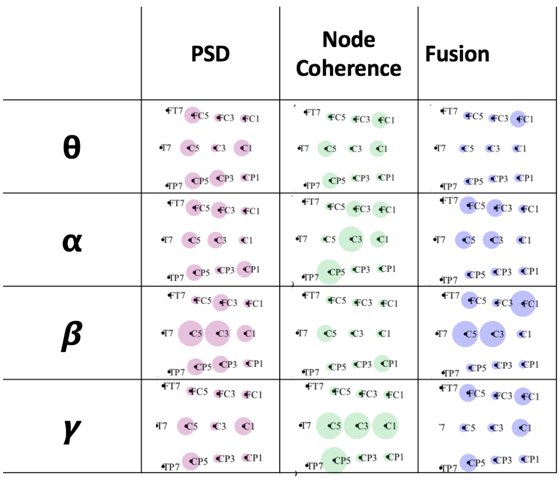

Figure 4: Table with occurrences of electrodes related to the highest accuracy. The size of the circles is proportional to the number of subjects for which that channel was the best. Each frequency band and each mode is considered separately: PSD in pink, coherence-based node degree in green and the fusion in blue

explain the organization and functionality of the brain during the tasks. For these reasons, we believe that it can be an important feature for brain computer interface applications, in which the user has to perform difficult tasks, involving different portions of the brain. In this work, we presented a mental state classifier based on connectivity features and we compared its performances with those achieved using local spectral features. Most importantly, we considered the classification results with the combination of the two features.

Our findings demonstrated that alpha and beta frequency bands are usually more involved during the task. In fact, the accuracy obtained in those bands are higher.Another interesting result is that the fusion between connectivity feature and a local one gives higher accuracy than PSD alone for the majority of the subject, for 13 over 15. This means that the integration of features reflecting different brain mechanisms can be useful for the discrimination of different mental states.

We notice that in general our accuracy values are higher than the actual chance level that in this configuration corresponds to 63% [8]. In addition, we reported a relatively high variance in the accuracy across the cross-validation that is explained by the high inter-trial variability.

From our findings, we can notice that there is a high variability between subjects concerning the best feature to use. This is reflected by the high standard deviation, 0.02 for coherence and fusion and 0.03 PSD. The inter-subjects variability is also evident in terms of frequency band of interest [16]. However, the most selected

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	Subjects														
	1	2	3	3	5	6	7	8	9	10	11	12	13	14	15
PSD	0,1	0,1	0,07	0,09	0,09	0,08	0,1	0,12	0,09	0,1	0,08	0,08	0,1	0,09	0,08
Coherence	0,08	0,09	0,09	0,09	0,09	0,08	0,09	0,09	0,07	0,11	0,09	0,09	0,13	0,11	0,06
Fusion	0,08	0,11	0,08	0,1	0,09	0,1	0,08	0,08	0,08	0,08	0,09	0,1	0,09	0,08	0,1

Figure 5: Table with values of standard deviation of the accuracy associated to cross validation folds. For each subject and each feature, for the best couple channel-frequency bin, we evaluated the standard deviation related to the 50 random repetitions

bands are alpha and beta as expected because they are usually related to motor tasks. Interestingly, in the case of coherence, the gamma frequency band is intensively involved. One possible explanation is that connectivity mechanisms during motor imagery tasks happens also in high frequencies [13].

In this preliminary work, we did not put a constraint on the frequency band in the fusion case. Indeed, for each case, we selected the best frequency bin independently from all the other cases. For instance, it could be interesting to put a constraint on the frequency band associated to the fusion on the basis of the selected frequency band for the other two ways. Alternatively, it could be possible to select the same frequency for all the features. These changes could help in the interpretation of the results.

For the fusion between two different features, another possibility is to perform a fusion of the classifiers output. In this case, the advantage will be a better control of features contribution and it can be helpful for the interpretation. Indeed, for each subject it will be possible to determine which feature contributed the more to the fusion [9]

Another possible improvement would be to increase the number of selected features. Indeed, in this work, we only considered the single feature case, or the combination of one of each class to obtain the fusion. One option to integrate more features could be the ranking of the features on the training set, based for instance of statistical tests performed between conditions [14].

This preliminary work confirmed our hypothesis that connectivity features bring relevant information on brain functionality. Notably, the integration of these features with standard one could increase BCI performances and be a valuable tool to reduce the inter-subject variability.

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