**Power spectral density or functional connectivity indices? A comparative study regarding feature selection for motor imagery-based brain-computer interfaces**

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**Introduction:** In this study, a multi-layer perceptron (MLP) neural network was used to classify fist MI tasks from electroencephalography (EEG) data. The classifier’s performance was analyzed regarding the use of distinct features, as well as different feature selection (FS) approaches.

**Materials and Methods:** All 64 channels EEG data were provided by an open online database [1] containing records of 109 healthy subjects, from which data from only ten were analyzed. An estimate of the power spectral density (PSD) in two bands of interest (mu and beta) and elements from a functional connectivity matrix (FCM) were tested as features for the classifier. The FCM was estimated using the motifs method [2]. Pre-processing included using a common average reference (CAR) filter. FS was done in one of three ways: (1) a wrapper was designed to add new features from a single electrode, until no improvement in classification accuracy could be observed after four consecutive iterations. This approach was only used for the PSD inputs, as using it with elements from the 64 x 64 FCM would take too much processing time. The other two forms of FS were tested for the two types of inputs, and combined with the wrapper described in (1): (2) Pearson’s and (3) Fisher’s filters [3]. A total of 10 runs were done for each subject, with data from left and right fists MI being randomly assigned as training, validation and testing ensembles. Validation error was used as a criterion for defining the architecture of the MLP to be used on the test data.

**Results:** Table 1 displays average results in the form (mean ± standard deviation). Standard deviation was calculated considering only variations across subjects.

*Table 1. Average classification accuracy results between all ten subjects for different types of input features*

|  |  |
| --- | --- |
| Frequencyband | Classification accuracy (%) |
| PSD | FCM elements |
| (1) | (2) | (3) | (1) | (2) | (3) |
| Mu | 70 ± 11 | 82 ± 8 | 76 ± 11 | - | 72 ± 7 | 69 ± 12 |
| Beta | 62 ± 7 | 67 ± 12 | 73 ± 14 | - | 79 ± 6 | 73 ± 9 |

**Discussion:** As expected, the use of filters for FS significantly increased classification accuracy rates. Average results increased 12% when the PSD was used as feature for the classifier with Pearson’s filter (Table 1). Using Fisher’s filter also increased accuracy, but to a lesser extent (mu band). Classification rates for the mu band using FCM elements were comparable to using (1). On the other hand, in the beta band, FCM elements provided the best rates when Pearson’s filter was used, and an equal average value to PSD features with Fisher’s filter. However, in both cases, the standard deviation for FCM features was considerably smaller, indicating that this method can produce more accurate results across subjects.

**Conclusion:** The present work confirmed that the use of FS filters can significantly increase classification accuracy rates. Also, we found that even though MI-BCI studies have focused on extracting features mainly from the mu band, connectivity patterns were more distinguishable in the beta band. This indicates that there may be non-straightforward relations between the manner event related synchronizations and desynchronizations alter functional connectivity in the brain across distinct frequency bands that can be recorded with EEG. Better generalization remarks may be achieved after further data analysis, such as increasing the subjects’ sample and investigating other frequency bands.

**References:** [1] Physionet online database: https://www.physionet.org/pn4/eegmmidb/; [2] Rosário RS et al., Physica A 439: 7-19, 2015; [3] Duch W, “Filter Methods”, in Guyon I, “Feature Extraction: Foundations and Applications”, Springer, 2006.