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Features reduction for P300 Spellers

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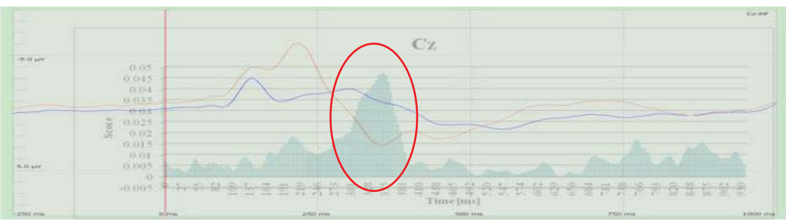
Introduction: The detection of brain state changes plays a fundamental role in the neuroscience research field because it can dramatically improve the comprehension of cerebral functioning. In this field, it may result extremely useful the support of machine learning based automatic tools able to correctly classify different brain responses. The performance of these tools depends on both the features and the classification algorithm employed. In order to select the most appropriate classifier for a given BCI system it is essential to single out a subset of significant features from the original data set, due to the poor signal-to-noise ratio [1] of the EEG signal, and to the small number of training data compared to the number of features. It is well known that distinguishing relevant features is fundamental to improve the predictor's performance. More importantly, it can provide a better understanding of the underlying cerebral processes that generated the data. The aim of this study is twofold: on the one hand to choose the most appropriate features selection strategy in order to maximize the predictor's performance applied to a visual evoked potential based BCI. On the other hand, we aim at showing how the features ranking can be used to support scientific hypotheses or diagnoses.

Material, Methods and Results:
Data were recorded during several training sessions from nine healthy subjects using the P300 Speller paradigm. EEG was recorded using a cap embedded with 19 electrodes according to the 10-20 International System, sampled at 256 Hz and averaged for 800ms after the visual stimulation. Five features selection methods were analyzed: IG, CFS, ReliefF, Consistency and 1RR [2]. All of them belong to the class of filter methods for feature selection. A support vector machine with Gaussian kernel (RBF SVM) was used as classifier for several reasons: first, it is able to handle high dimensional data sets; second, it has few hyper-parameters that need to be defined by hand; third, it has already been successfully adopted in BCI providing very good results [1]. Grid Search was used for hyper-parameters optimization. The data processing was carried out with Weka. All feature selection methods were able to select smaller subsets of features improving the quality of the results. The range of features reduction was between 62 % (IG) and 99.78 % (Consistency). Table 1 shows the classification results in terms of accuracy and Cohen's Kappa on test sets for each subject, using ReliefF [3] which turned out to be the best among the five methods. We compare our result with CFS-FLDA, the embedded feature selection method implemented in Weka that is closer to the SWLDA, a common approach for P300. CFS-FLDA is a correlation based feature selection method embedded into a Fisher's Linear Discriminant Analysis. The results show how ReliefF outperforms CFS-FLDA since the mean value of accuracy is 88.5%, which is significantly better (paired t-test < 0.5) than the one of the LDA method (79.6%) and the Kappa is almost always higher or comparable.

Subjects	**PC**	**LQ**	**FG**	**VP**	**MA**	**LB**	**NL**	**ZI**	**IG**
CFS-FLDA: A(%)/K	93.4/0.78	89.9/0.67	87.92/0.62	84.25/0.53	75.1/0.33	71.82/0.25	77.92/0.43	56.52/0.006	70,66/0.25
ReliefF-RBF SVM: A(%)/K	95.35/0.83	93.02/0.73	91.35/0.66	88.69/0.57	88.67/0.37	88.24/0.48	84.59/0.42	83.41/0	83.21/0

Table 1. Prediction result

Discussion and significance: The most important result is that the subset of selected features is physiologically correct: ReliefF was able to detect physiological components elicited during the protocol either in space (e.g. Cz, Pz, O1, O2, ..) or in latency (e.g. P300). As an example, in Picture 1 we draw the scores assigned by ReliefF versus the evoked P300 potential on Cz, showing how the scores follow the signal behavior. This kind of information may furnish relevant insights to identify which brain areas and when are involved during certain cerebral activities, thus improving the comprehension of brain functioning.



Picture 1. ReliefF scores of subject PC compared with the P300 potential on Cz

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