HCI seminar 2 report: Brain computer interface to classify between two motor activities

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I. Introduction

This seminar is about implementing a brain computer interface to classify between two motor activities. The motor activities were chosen from a particular subject (**S053**) from the EEGMMI database [1], a database created for purposes of brain-computer interface research, available on PhysioNet. The 109 volunteers were asked to do 4 different tasks, which involved opening and closing, or imagining opening and closing both their fists and/or feet, depending on the task.

We will focus on trying to classify between two motor activities from task 1 - opening and closing left or right fist, and then separately task 2 - imagine opening and closing left or right fist. We will use the Common Spatial Patterns (CSP) method, and LDA and QDA classifiers.

II. Methods

As stated, we will attempt to classify between motor activities from task 1 and (separately) task 2, of the subject S053. The records corresponding to task 1 are 03, 07, and 11, and those corresponding to task 2 are 04, 08 and 12. In each of the records, the intervals where the subject opened and closed, or imagined opening and closing the left fist are marked as **T1**. The intervals where the subject did the same, but for the right fist, are marked as **T2**. For a given task, we need to extract all T1 and T2 intervals, so we can classify between them. Instead of reading the entire interval, we ignored the last 0.2 seconds, which we thought might slightly more accurately capture the corresponding motor activity interval, due to the change in subject's action (from doing or imagining the activity to relaxing).

To extract features in the component space, we used CSP as our spatial filter. The projection matrix for CSP was calculated based on the mean of first 5 T1, and first 5 T2 intervals. After applying CSP, we took the 2 signals with extreme variance, and passed them through an 8-13Hz band-pass FIR filter. Finally, to generate feature sets for both classes, we used the Var and log operators.

For classification, we used Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA).

III. Results

To evaluate our two classifiers, we used 10-fold cross validation, and used 4 metrics: sensitivity, specificity, classification accuracy, and AUC (Area Under ROC Curve). As we said, we attempted to classify between T1 and T2 intervals from task 1, and separately from task 2. We should point out here that, ignoring the last 0.2 seconds of each interval, as well as calculating the CSP projection matrix using the mean of first 5 T1 and T2 intervals, were empirically established as "best" values.

The only parameter of our model is the order of the 8-13Hz band-pass FIR filter. We experimented with order 20, 35, 50, 60, 75, 90, 100 and 115. For classification in task 1, the order that gave the best results for LDA was 75, and 100 for QDA. For classification in task 2, the order that gave the best results for LDA and QDA was 75.

The presented results can vary slightly, due to the randomness when generating folds for cross validation.

.	Se	Sp	CA	AUC
LDA (75)	68.18	69.57	68.89	75.96
LDA (100)	68.18	69.57	68.89	72.48
QDA (75)	54.55	69.57	62.22	72.16
QDA (100)	72.73	65.22	68.89	68.27

TABLE I
Results of classification between motor activities in task 1 (opening and closing left or right fist). The number in brackets corresponds to the order of the FIR filter used when extracting features. For this task, 75 was the order that gave the best overall results for LDA, while for QDA, it was 100.

.	Se	Sp	CA	AUC
LDA (75)	81.82	91.30	86.67	87.14
QDA (75)	81.82	91.30	86.67	85.45

TABLE II
Results of classification between motor activities in task 2 (imagining opening and closing left or right fist). The number in brackets corresponds to the order of the FIR filter used when extracting features. For this task, 75 was the order that gave the best results for both LDA and QDA.

IV. Discussion

As we can see from tables I and II, both LDA and QDA were way more successful for classification in task 2. No metric drops below 80% in that instance, while for classification in task 1, the best we can call our results is "decent". One solution of course, it to try a different classifier. While it may

perform better for classifying motor activities from task 1 for this particular subject (S053), it may not be so great applied to other subjects, or it may even be worse for classifying motor activities from task 2 for this subject (S053).

V. Conclusion

In this seminar, we implemented a brain-computer interface to classify between motor activities of a subject from EEG-MMI DB [1], originating from two different tasks (opening and closing left or right fist, and imagining the same). We used the Common Spatial Patterns (CSP) method, and used two different classifiers, namely LDA and QDA. We achieved varying results. Classification was way more successful in the case of imagining motor activities, than in the case where the subject actually performed them. An improvement might be to try different classifiers, and see how they compare to LDA and QDA.

References

[1] Schalk, G. and McFarland, D.J. and Hinterberger, T. and Birbaumer, N. and Wolpaw, J.R., "BCI2000: a general-purpose brain-computer interface (BCI) system," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 6, pp. 1034–1043, 2004.