ONLINE CLASSIFIER ADAPTATION IN HIGH FREQUENCY EEG

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SUMMARY: In recent years a number of non-invasive Brain-Computer Interfaces have been developed that determine the intent of a subject by analysing the Electroencephalograph(EEG) signals up to frequencies of 40Hz. The use of high frequency EEG features have recently been proposed as alternative or additional features in EEG-based BCIs. In this paper we examine the performance of several feature bands, and evaluate the performance on online classifier adaptation on these features. Our analysis shows that the higher frequency band perform very well under online classifier adaptation for all the frequency bands, particularly for the higher bands.

INTRODUCTION

EEG-based BCIs have inherent instability due to the variation in EEG signals over time. Choosing more stable features is one way of reducing this variation. A different approach is to continually adapt the classifier as it is being used, in order to keep it tuned to the signals of the current session. Of course, ideally we would like the features that we are using to be as stable as possible so that the minimum possible adaptation is used. To this end we are investigating frequency bands higher than those traditionally used in BCIs. A comparison between different frequency bands has been performed by Ferrez et al[1]. This paper investigates the performance of high frequency features in an adaptive classifier.

MATERIALS AND METHODS

This experimental setup is described more thoroughly in [1]. The data analysed in this paper were recorded from four healthy subjects performing three mental tasks (imagination of left and right hand movement and a language task), with EEG being recorded at 512 Hz from 64 scalp electrodes. The subjects were asked to perform each task for 5.5 seconds, of which the last 3 seconds was used in the analysis. The subjects received no feedback in order to prevent a bias towards one particular feature set. Each subject performed 15 sessions on two consecutive days, where each session comprised 18 trials with a delay of about 2.5 seconds between them.

Offline analysis was performed to determine the best feature bands as described in [1]. Fifteen feature bands of varying width were constructed by calculating the PSD over the given band, with narrower bands at low frequencies, covering the full range of frequencies from 2Hz to 250Hz. For each subject the 30 sessions were divided into six groups of five sessions. Feature selection was performed for each frequency band in each group to select the best electrodes. From the 64 electrodes the 10 with the highest discriminative power were chosen, creating a 10-element frequency-specific feature vector. For each group a Gaussian classifier was trained on the data from one group and tested on the five sessions of the next group.

From this analysis three frequency bands were chosen for further analysis with online classifier adaptation: 8-14 Hz, 72-90 Hz and 212-230 Hz. The online adaptation was performed on the Gaussian classifier by stochastic gradient descent (for details, see [2]). Each sample in turn was classified by the classifier, then used to update the classifier. In this analysis only the first second of every three was used to update the classifier in this way. This method of assessing the results gives us an idea of how the classifier would have performed online.

The Gaussian classifier outputs the posterior probabilities of the three classes. In general we set a minimum probability threshold level and reject samples that do not reach this confidence level. However, for the purpose of this study we are not rejecting any samples, so all samples are either classified correctly or incorrectly, making the chance level of good classifications 33.3%.

RESULTS

Table 1 gives the classification results of the static classifier (trained on the sessions in the previous group) and the adapted classifier (initialised as the static classifier, then updated throughout the sessions) averaged over all 25 test sets of each subject, and the overall average. For all subjects and frequency bands, the adapted classifier significantly outperforms the static classifier. However, the statistical significance of comparisons between different frequency bands is less clear. When looking at the static classifier, the classification rates are similar for the three bands (the only statistically significant difference is between 8-14Hz and 72-90Hz), but the lower band has much smaller variation. When the adaptive classifier is used the lower band is more constantly outperformed by the higher bands (statistically significantly over the whole data set, and almost always significantly over the individual subjects), but the variation in the lower band is again much smaller than in the higher band.

Table 1: Average % correct classifications of the static classifier (S) and the adapted classifier (A) for each subject (1-4), and averaged

		8-14 Hz	72-90 Hz	212-230 Hz
1	S	37.6 ± 6.1	45.9 ± 16.7	49.9 ± 20.5
	A	54.6 ± 5.8	70.1 ± 18.0	59.7 ± 22.9
2	S	51.2 ± 3.7	51.3 ± 13.0	49.3 ± 16.8
	A	58.9 ± 7.1	69.1 ± 23.5	77.7 ± 17.4
3	S	51.2 ± 3.7	47.6 ± 15.4	49.7 ± 18.0
	A	64.1 ± 8.0	78.5 ± 16.0	76.1 ± 17.7
4	S	46.0 ± 6.7	45.9 ± 14.8	49.3 ± 11.2
	A	59.0 ± 8.0	72.7 ± 17.8	83.7 ± 13.5
Av	S	45.4 ± 8.2	47.7 ± 15.0	49.5 ± 16.7
	A	59.2 ± 7.9	72.6 ± 19.1	74.3 ± 20.0

Figure 1 shows the average correct decisions of the adaptive classifier over the five groups of five sessions that were used for testing. This shows the lower but more constant performance of the lower band, and the higher but more variable performance of the two higher bands.

Since the data was recorded over two days the first two groups are from the first day and the following three groups from the second day. As we are using the data from the previous group to train the classifier, this means that the third group was trained on data from the previous day, a situation which generally results in poorer classification rates due to changes in the EEG signals. Interestingly, results obtained with online adaptation seem quite robust to this. Without online adaptation, classification rate of the low band on average decreased by 4.3 percentage points and the highest band dropped by 6.1 percentage points. With online adaptation the classification of the low band increased by 5.2 percentage points from the second to the third session, and the highest band dropped by only 0.2 percentage points on average (the figures for 72-90Hz have not been quoted because of the distorting effect of the second subject on this band, where both the static and adaptive classifiers had the same very low classification rate on the third group). This indicates that the adaptive classifiers are able to incorporate quickly the signals in the new session and adjust themselves accordingly.

It is also interesting to note that the classification of the last group is often higher than the first group, especially in for the 72-90 Hz band, which might be an indication that the subject is becoming more used to the experiment and is generating more stable EEG.

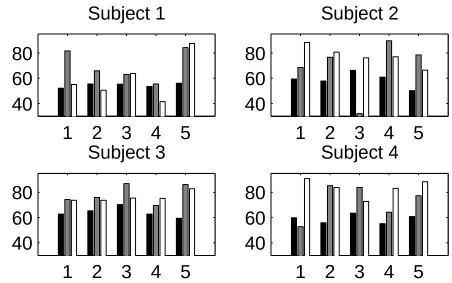

Figure 1: Performance of the adaptive classifier by group (average over 5 sessions), where the black bar is 8-12 Hz, the grey bar is 72-90 Hz and the white bar is 212-230 Hz.

DISCUSSION

The analysis in this paper demonstrated that online classifier adaptation was very effective when applied to high frequency features, as shown by the improvement in classification rates over the static classifier and the robustness to the difference in signals caused by the test and training data being from different days. The use of higher frequencies as features has potential and warrants further investigation. This analysis considered only the use of one frequency band at time and should be extended to using multiple bands together. However, while this analysis indicates that the average classification rates of the higher frequency bands are higher, particularly when used in conjunction with online classifier adaptation, the variation in the classification rates between sessions is much greater. Unless this variation is reduced it might make higher frequencies less desirable for a BCI than lower frequencies, despite their apparent promise.

REFERENCES

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