Classifying Mental Tasks Using a Brain-Computer Interface

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Introduction

Electroencephalograms (**EEGs**) can record electrical activity in the brain. In conjunction with a **brain-computer interface** (**BCI**) they can be used to augment human sensory functions or control robotic devices.

In this project we use EEG inputs to classify which of three tasks a subject is performing :

- Thinking about moving their left hand
- Thinking about moving their right hand
- Thinking about words beginning with a certain letter.

Figure 1: A demonstration of a brain-computer interface.

Experimental Design

- EEG Data was collected for 3 subjects across 4 sessions each with sessions lasting 4 minutes.
- Subjects performed a task for 15-18 seconds before switching randomly at the operator's request.
- The first 3 sessions for each subject were used for model training, and the final session was used for testing.
- Models could be trained separately for each subject. In practice generalisation across subjects is not required.
- The data and the task are taken from dataset V of the "BCI Competition III", which provides 5 datasets with the aim of testing signal processing and classification methods for BCIs [2].

Feature Selection

- A validation set was used to assess the performance of models with different numbers of features.
- Dimensionality reduction using PCA reduced accuracy on the validation set.
- Instead, random forests were used to rank the importance of the variables in the classification task.
- The minimum number of features that had accuracy within one standard deviation of the max were kept.

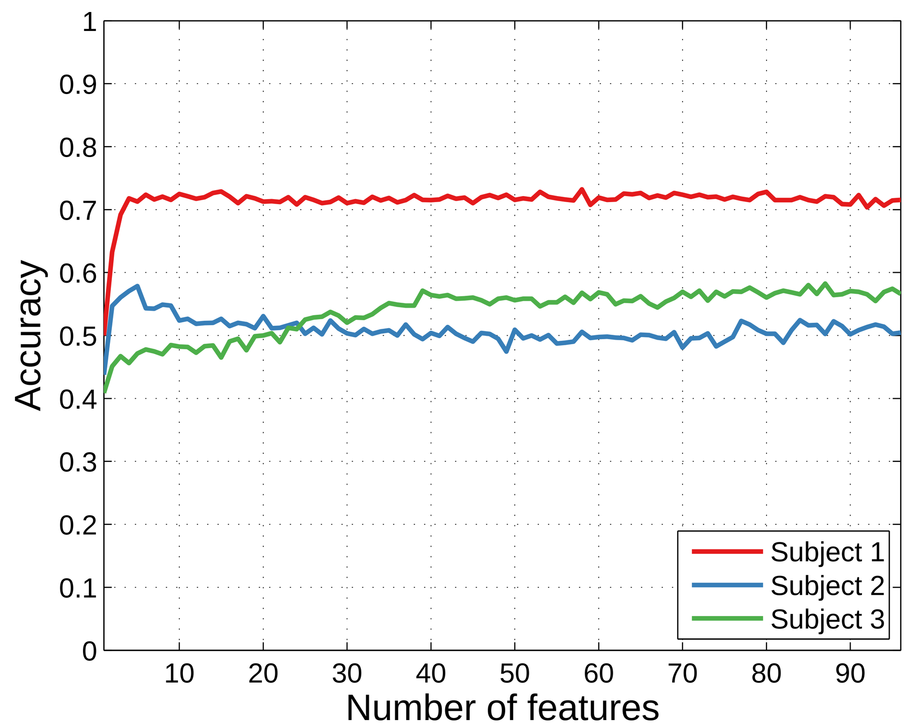


Figure 2: Classification accuracy vs number of features for each subject.

Features

- The raw data consists of 32 EEG potentials acquired at a rate of 512 Hz.
- The competition organisers provided processed features which consist of the power spectral density (PSD) in the band 8-30Hz for 8 centro-parietal channels.

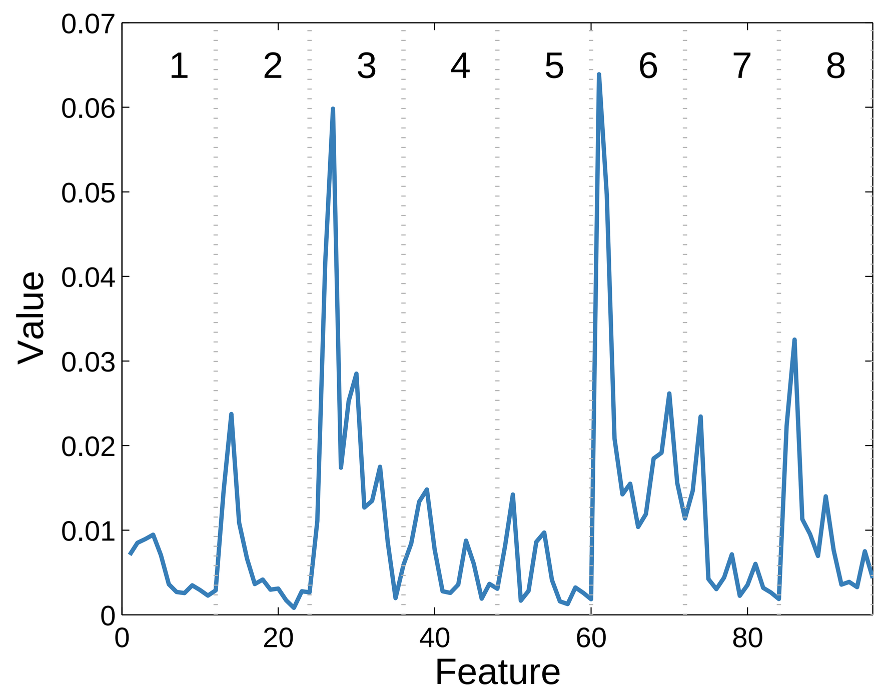
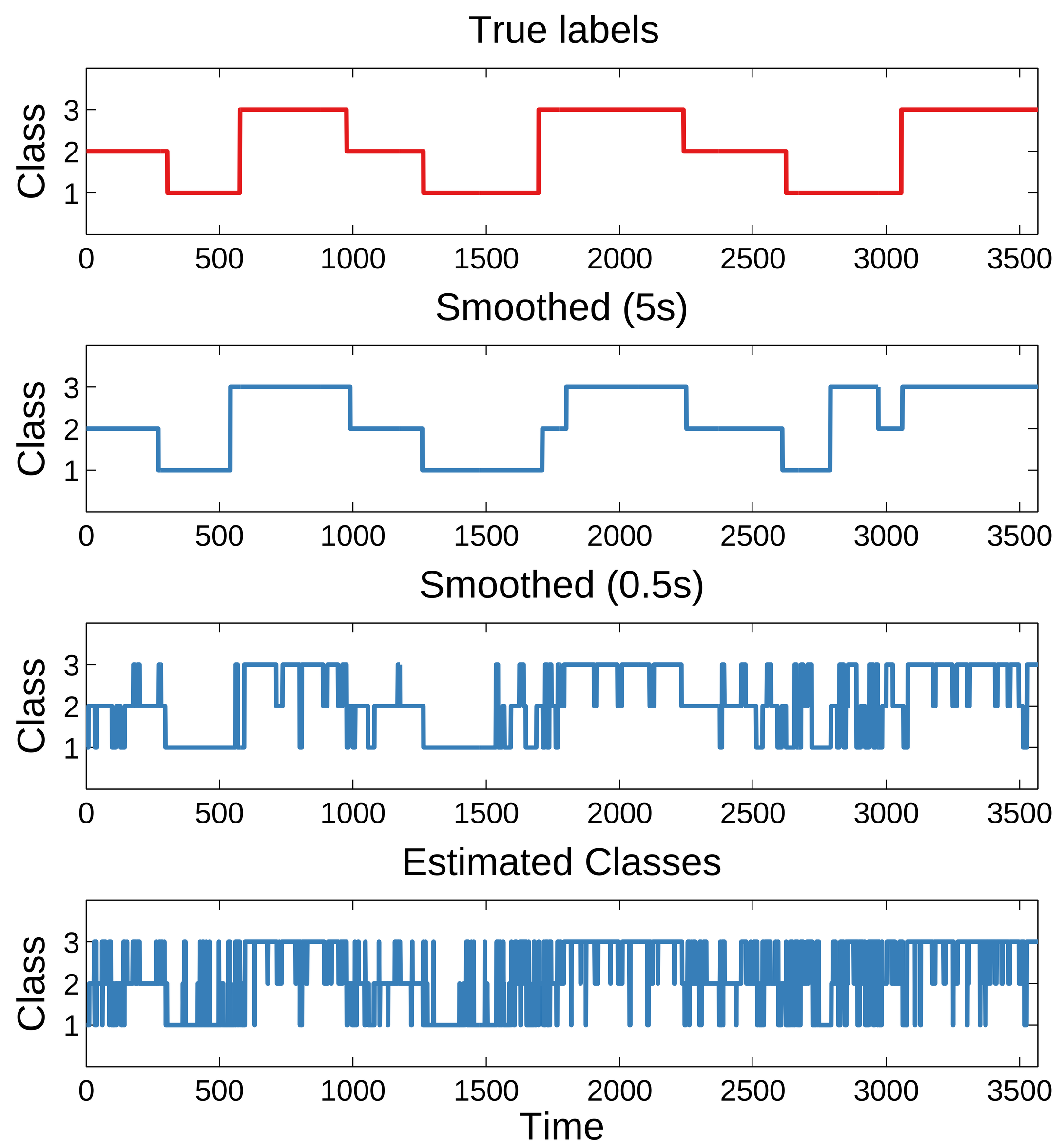


Figure 4: Input features for subject 1 at the first time point. The numbers 1 - 8 correspond to the 8 centro-parietal bands.

Classification and Smoothing

Figure 3: Classification using random forests with varying degrees of smoothing. Plots produced using subject 1 and RF classification with the full feature set.



Random Forests

- Random forests were used to classify each data point in the test set.
- Smoothing these predictions by choosing the most commonly occurring classification in a certain time window is a straightforward way of improving accuracy.
- In order to guarantee fast response times, the competition insists that the classifier only averages over the last half second of data.
- Figure 3 shows that smoothing over a longer time window (5s) is beneficial.

Hidden Markov Model

- Hidden Markov Models were used as an alternative classifier: HMMs with two hidden states were trained for each class c.
- sequences $(\mathbf{x}_t, .., \mathbf{x}_{t+k})$ can be classified as $\arg\max_c p(\mathbf{x}_t, .., \mathbf{x}_{t+k} \mid c)$.

Results

		Subject			
	Classifier	1	2	3	Overall
F	RF	0.75	0.61	0.40	0.59
	RF 0.5s	0.76	0.65	0.42	0.61
	RF 5s	0.86	0.68	0.50	0.68
	HMM 0.5s	0.50	0.39	0.37	0.42
	HMM 5s	0.52	0.37	0.34	0.41
R	RF	0.72	0.60	0.42	0.58
	RF 0.5s	0.76	0.65	0.41	0.61
	RF 5s	0.86	0.79	0.53	0.73

Table 1: Classification accuracy on the test sets for each classifier. Classifiers are divided into those using all the features (**F**) and reduced feature sets (**R**). Overall accuracy is the mean subject accuracy for a classifier. Top performing classifier in red, top performing classifier within competition spec in **blue**.

- Classifier accuracy is quite variable across subjects: Subject 1 produced good results for most of the classifiers whereas subject 3's activities were more difficult to classify.
- The greatest overall accuracy was achieved by the random forest classifier with the reduced input features and with smoothing on 5 second blocks.
- For classifiers within the specification of the competition, random forests on both the full feature and reduced feature space had the best performance.
- The performance of the hidden markov models on 0.5s and 5s blocks was poor. A next step is to use priors to regularize the emission and transition distribution parameters in an attempt to improve generalisation.

References

[1] **Millán, J. del R.** On the need for on-line learning in brain-computer interfaces *Proc. Int. Joint Conf. on Neural Networks.*, 2004.

[2] **BCI competition III - Dataset V webpage**, http://www.bbci.de/competition/iii (accessed Dec. 1, 2014)