

# Developing a Brain-Computer Interface: principles and techniques

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## I. INTRODUCTION

*Brain-Computer Interfaces (BCI)* are a new kind of human-machine interfaces emerging on the horizon. They form a communication pathway between the brain and a machine. This can be achieved by measuring brain signals and translate them directly into control commands. Such a system allows people with severe motor disabilities to manipulate their environment in an alternative way. However there's still a lot of work to be done to make it usable in daily life. This article presents our prototype BCI. There are a lot of different types of BCI systems, but ours is based on *Event-Related Synchronisation and Desynchronisation (ERS and ERD)*, both physiological phenomena that occur in the brain when performing motor tasks (see section II and [1]). In order to detect these effects, we first construct spatial filters (see section IV and [2]) before building our classifier.

## II. NEUROPHYSIOLOGY

In our setup we want to discriminate single trial *electroencephalographic (EEG)* signals generated by left and right hand motor tasks. It's no coincidence we use these tasks because they are represented by different regions of the motor area of the cortex. For example, when we move our right hand the left hemisphere becomes active and starts to desynchronize while the neurons of the right hemisphere keeps firing at a synchronized idle rhythm. It's this rhythm that is attenuated in the contralateral

hemisphere when we start moving our hands. The rhythm varies strongly from person to person but is mostly situated around 10 and 20 Hz. The attenuation in power at these frequencies corresponds to a lower variance in the time domain. We use this property in the section IV to extract good features.

It's important to note that ERD and ERS effects not only occur in real movement tasks, but also in imaginary motor tasks. Herein conceals the power of the method to use it as alternative control input.

## III. PRE- AND POSTPROCESSING

Before calculating the spatial filters (see section IV) we go through two preprocessing steps. First we reject trials based on their outlierness. Outlierness is specified by the variance of the trial because artefacts induce higher variance than normal trials.

Second, we carefully select the passband of the temporal filter. Therefore we implemented a simple heuristic searching for frequencies with significantly different power between classes.

After calculating the spatial filters we select those that discriminate best between the two classes, figure 1 shows two such filters, focusing on the respective motor areas. In a last step we select the model trained on the time window which shows the best classification accuracy. In order to do that, we divide each epoch (typically one second before the movement onset and three seconds after) in overlapping windows of one second. The features and the classification model are then computed for each time window. The model and the time window with

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the best results are saved and used for validation on the test set.

#### IV. COMMON SPATIAL PATTERNS (CSP)

To detect these ERD/ERS effects in single trial EEG signals we construct *spatial filters* that maximize the variance (ERS) for one class and at the same time minimize it (ERD) for the other class. This can be formulated as follows,

$$W\Sigma_1W^T = D \quad \text{and} \quad W\Sigma_2W^T = I - D$$

With the rows of  $W$  the filters,  $\Sigma_1$  the covariance matrix of the signals from the first class and  $\Sigma_2$  the covariance matrix for the second class.  $D$  is a diagonal matrix of which the non-zero elements correspond with the relative variances of the signals. We use this insight in the postprocessing step, mentioned in section III, to select good spatial filters. For example, a filter that corresponds with a diagonal element near one for a particular class will produce a signal having a relative high variance for that class. At the same time a signal of the other class will have a relative low variance after application of this filter. The variances of these spatially filtered signals are then used as features for the classifier.

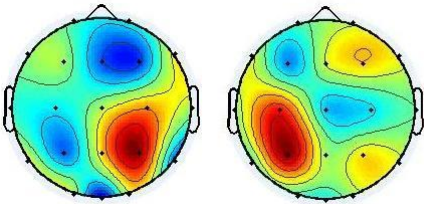


Figure 1. Two of the most discriminative spatial filters for the ‘Day 2’ set, selected based on their relative variance.

#### V. RESULTS

We test the procedure on three different datasets, one from the BCI Competition [3] and two of a colleague recorded on different days. Table 1 shows the average results on the different test sets. Each set is divided in two, the

first half is used for training, the second half for testing. The training set itself is randomly divided in 20% validation trials and 80% training trials. We run the algorithm five times per set. This results in five models and thus five different classification results which we average. We also reject 5% of the trials based on their outlieriness. A surprising result, but confirmed by the findings of other researchers, is the range of the selected time windows: a lot of them lie before the movement onset, meaning the brain prepares the movement before we actually execute it.

	Manually	Heuristic
Day 1	83%	88%
Day 2	82%	91%
BCI Competition	95%	95%

Table 1. The first column presents the results when we manually fix the passband between 8-12 Hz and 18-22 Hz (neurophysiologically most plausible), the second column presents the results when the passband boundaries are selected by the heuristic.

#### VI. CONCLUSIONS AND FUTURE WORK

We presented the usefulness of CSP for BCI and showed the importance of selecting the correct passband. However there’s still a lot of room for improvement. Removing a certain percentage of the trials can have a negative impact on the performance because it’s also possible that prototype trials are removed. Therefore we will try to remove these artefacts instead of rejecting the whole trial, which is obviously not possible in realtime applications of BCI.

#### REFERENCES

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