Automatic Frequency Band Selection for BCIs with ERDS Difference Maps

M. Billinger[1], V. Kaiser[1], C. Neuper[1,2], C. Brunner[1]

[1]Institute for Knowledge Discovery, BCI Lab, Graz University of Technology, Austria
[2]Department of Psychology, University of Graz, Austria

martin.billinger@tugraz.at

Abstract

We present a new fully automated algorithm for frequency band selection in band power based brain-computer interfaces (BCIs). The algorithm performs a single pass and only requires information on the training data in the form of time-frequency ERDS maps, which visualize event-related desynchronization (ERD) and event-related synchronization (ERS). Frequency bands are selected by segmentation of ERDS difference images, similar to the way a human expert would manually select bands by inspecting these maps. We could show that bands selected by this approach perform almost as well as manually selected bands in an offline BCI experiment with data recorded from 18 users.

1 Introduction

Many brain-computer interfaces (BCIs) rely on a variety of different techniques to extract information from brain signals such as the electroencephalogram (EEG), which is often used in non-invasive BCIs. The instantaneous power of selected frequency bands (band power) has been successfully used to discriminate between different tasks in motor imagery (MI) based BCIs [1]. Band power can be estimated using filter banks [1] or autoregressive estimates of the spectrum [2].

Usually, frequency bands that contain discriminative information relevant to the BCI paradigm must be selected. This can be done using knowledge of the underlying physiological processes, or after analyzing a BCI user's specific task-related brain patterns. Selecting bands corresponding to fixed μ or β frequency bands may not be optimal for every user due to individually varying frequency components [1]. Automatic feature selection algorithms such as distinction sensitive learning vector quantization (DSLVQ) [1] or sequential floating forward selection (SFFS) [3] optimize bands for individual persons but do not have any knowledge about the nature of the features, which may lead to suboptimal or redundant band selection. Manual band selection by an expert can account for differences between individuals, as well as relevant physiological background.

An algorithm to select a frequency band for the common spatial patterns (CSP) approach is briefly mentioned in [4]. This method selects a single frequency band for all channels, based on a correlation score. We present a new algorithm based on image segmentation methods from the field of computer vision, which mimics an expert inspecting time-frequency maps of event-related desynchronization (ERD) and event-related synchronization (ERS) to select frequency bands. Multiple bands are selected for each channel separately, so that they discriminate between two different BCI tasks. In Section 2, we provide a detailed description of the algorithm and present possible extensions. In Section 3, we compare the performance of the algorithm to a human expert performing band selection on the same data set.

2 Methods

2.1 Manual Band Selection

ERDS maps show changes in the power spectrum (with respect to a reference interval) related to a recurring event such as MI. Power changes are averaged over many trials, and only if the change is significantly higher or lower than zero, the map is shaded in color. An increase in power is known as ERS (typically represented by blue color), whereas a power decrease is called ERD (represented by red color) [5].

After calculating ERDS maps corresponding to each MI task (class), an experts inspects these maps and selects those frequency bands where the maps differ most in a task-related way. However, the selected bands depend on the expert's subjective interpretation of the ERDS maps.

2.2 Automatic Band Selection

ERDS maps do not only produce visually appealing and informative images. On a lower level, the mean power change and associated confidence interval are obtained for each pixel in the map. Using this information from maps of two different classes, we can construct ERDS difference maps. The shading of these difference maps show where and how much the ERDS maps of the classes differ. Pixels with overlapping confidence intervals do not contain significant class differences and remain blank. One such difference map is created for each EEG channel.

Simply plotting ERDS difference maps would already provide a rough overview of which frequency bands could be selected to cover the most prominent class differences. Still, this would have to be done by a human supervisor. Thus, we attempt to automate this process.

Automation is based on the idea of eliminating differences caused by noise and fitting frequency bands to the remaining patches of differences. This is accomplished by first constructing a significance bitmap, in which 1 and 0 encode significant and non-significant differences at the corresponding point in the ERDS difference map. Groups of adjacent significant pixels are referred to as regions. Regions that are smaller than a threshold area A_{th} are considered as noise and can be removed by area-opening [6]. For each remaining region, a frequency band is created that ranges from this region's lowest to highest frequencies. Finally, overlapping frequency bands are merged. Figure 1 shows a summary of the algorithm. Note that the algorithm treats each channel individually. Thus, different bands may be selected for each channel.

Two parameters have direct impact on band selection: the Type I error probability of pixels in the ERDS map (α) and the area threshold for discarding small regions (A_{th}). Note that these parameters are not independent. A lower α leads to smaller regions, which causes more regions to be discarded with constant A_{th}.

2.3 Evaluation of the Algorithm

We used MI data from 18 persons to compare automatic with manual band selection. The data sets used are BCI Competition IV data sets 2A and 2B [7], each recorded from 9 different persons. From data set 2A, only three bipolar channels (C3, Cz, and C4) and two MI tasks (left versus right hand) were used to match the data available in data set 2B. All data available for each participant was separated into training and testing sets. Trials with artifact markers were removed. On average, the training set from participants of data set A consisted of 129 ± 9 trials, and 205 ± 29 trials from data set B. The testing set contained 131 ± 12 trials from data set A, and 360 ± 38 trials from data set B.

To test manual band selection, ERDS maps from the training data were inspected by an expert, who selected frequency bands for each participant that would allow classification of the MI tasks using band power features and linear discriminant analysis (LDA). The algorithm for automatic band selection was applied to the training data with parameters $\alpha = 0.01$ and $A_{tr} = 2$. If no bands were found, a wide frequency range from 5–30 Hz for every channel was selected.

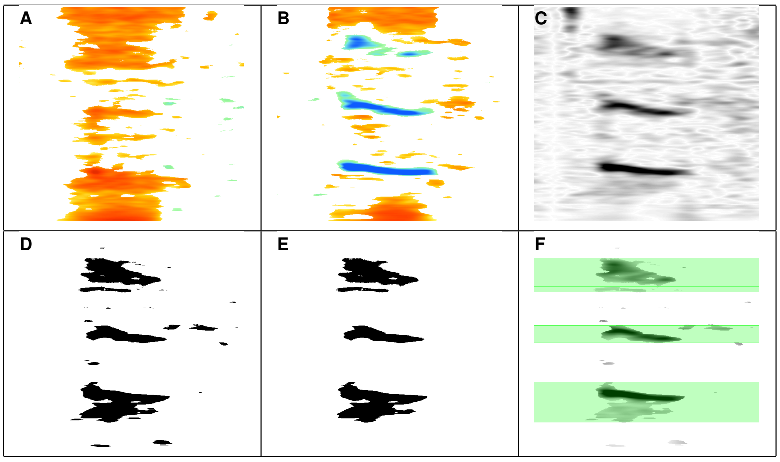

Figure 1: Processing steps of the band selection algorithm. (A) and (B) ERDS maps of each of the two MI classes, (C) ERDS difference map, (D) significance bitmap (E) significance bitmap after area-opening, (F) ERDS difference map with significance information and selected frequency bands. Axes are not labelled to emphasize that the algorithm treats these maps simply as images.

An LDA classifier was trained on the selected bands and subsequently tested with the same bands on the testing set. Classification accuracy was calculated from the continuous classifier output for each trial. The 0.9 quantiles of classification accuracy are reported as robust and comparable measures of classification accuracy for each participant.

2.4 Possible Extensions of the Algorithm

Extension of the band selection algorithm to an arbitrary number of N classes is straightforward by using multiple classifiers and assuming that each classifier has its own set of bands. Consider a three-class classification problem with classes A, B, and C. A pairwise classification scheme requires training three classifiers A–B, A–C, and B–C. Thus, our algorithm can be applied to each combination of classes to select the bands for each classifier. In a one versus the rest classification scheme, classification for class A versus the combined classes B and C is performed. To select bands for the A–BC classifier, our algorithm must be applied to the difference of the ERDS maps from class A and the combined ERDS maps from classes B and C.

If we wanted to select the same frequency bands for multiple channels, the difference maps of individual channels have to be merged into a single map. With this modification applied, and the selection process restricted to select only the single most important frequency band, we expect our approach to be suitable also for CSP-based classification.

Furthermore, our algorithm does not necessarily rely on ERDS difference maps. Any measure in time-frequency space that provides information about class discrimination and significance can be subject to band selection. The most obvious example is using the difference of power maps directly instead of ERDS maps.

3 Results

Automatic band selection failed for 3 out of 18 participants (A2, A6, and B3). For these participants, broadband features were used instead, as described above. Table 1 lists classification accuracies for each participant for both automatic and manual band selection. Average accuracy was $68.1 \pm 13.5\,\%$ with automatic and $70.5 \pm 14.5\,\%$ with manual band selection. According to a paired t-test, the difference between both methods was not significant ($p = 0.198$).

Participant	A1	A2	A3	A4	A5	A6	A7	A8	A9
Automatic	73.8	*57.0*	70.8	64.4	54.8	*59.3*	66.4	91.0	89.2
Manual	83.7	58.5	65.0	58.3	58.5	60.2	54.3	94.8	88.5
Participant	B1	B2	B3	B4	B5	B6	B7	B8	B9
Automatic	54.6	53.2	*53.2*	94.1	85.8	67.3	61.4	64.3	65.8
Manual	63.6	53.2	54.6	95.4	84.5	65.0	78.1	82.7	70.8

Table 1: Classification accuracies for all participants with automatic and manual band selection. The 0.9 quantiles of classification accuracy (in %) are listed in the table. Note that A1–A9 are different persons than B1–B9.

4 Discussion and Conclusion

The main disadvantage of applying feature selection algorithms like SFFS or DSLVQ to the band selection problem is that these algorithms do not have knowledge about the nature of the features. When applied to band selection, a subset of pre-defined frequency bands is selected. To allow these methods enough flexibility and accuracy in band selection, a sufficiently large number of bands has to be provided, which can dramatically increase computational requirements.

The band selection method we present in this paper does not suffer from these disadvantages. Instead of selecting bands from a pre-defined set, band limits are fitted to statistically significant class differences in the time-frequency domain. This approach closely resembles the way a human expert selects frequency bands and yields comparable results. Segmentation of significant regions is very efficient. The computationally limiting factor is the calculation of ERDS maps.

Although automatic band selection performed slightly worse than manual selection, the null hypothesis that both methods perform equal could not be rejected. Thus, we conclude that the difference between the two methods (if there is any) is too small to expose a significant effect in the available data.

Depending on the application, a small loss of classification accuracy may be preferrable over the need of a human expert to interact with the BCI setup process. This may be the case especially with BCIs for home use, where the whole BCI process should run as automated as possible.

References

[1] G. Pfurtscheller and C. Neuper. Motor imagery and direct brain-computer communication. *Proceedings of the IEEE*, 89:1123–1134, 2001.

[2] D. J. McFarland and J. R. Wolpaw. Sensorimotor rhythm-based brain-computer interface (BCI): model order selection for autoregressive spectral analysis. *Journal of Neural Engineering*, 5:155–162, 2008.

[3] P. Pudil, J. Novovičová, and J. Kittler. Floating search methods in feature selection. *Pattern Recognition Letters*, 15:1119–1125, 1994.

[4] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K. R. Müller. Optimizing spatial filters for robust EEG single-trial analysis. *IEEE Signal Processing Magazine*, 25:41–56, 2008.

[5] B. Graimann, J. E. Huggins, S. P. Levine, and G. Pfurtscheller. Visualization of significant ERD/ERS patterns in multichannel EEG and ECoG datas. *Clinical Neurophysiology*, 113:43–47, 2002.

[6] S. T. Acton and N. Ray. Biomedical image analysis: Segmentation. *Synthesis Lectures on Image, Video, and Multimedia Processing*, 4(1):1–108, 2009.

[7] BCI Competition 2008 - Graz data sets 2A and 2B. *http://www.bbci.de/competition/iv/*.