Influence of spatial filters on the performance of EEG-based BCIs using autoregressive models

C. Brunner[1], M. Billinger[1], C. Neuper[1,2], and G. Pfurtscheller[1]

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

Introduction

The performance of brain-computer interfaces (BCIs) depends, among other factors, on the type of spatial filters used for preprocessing the recorded monopolar electroencephalographic (EEG) signals. Depending on the subsequent feature extraction and classification stages, suitable spatial filters should be chosen to maximize the classification performance of the system. For example, McFarland et al. [1] have compared monopolar data with three different spatial filters and found significant differences when using bandpower-like features. Here, we use autoregressive parameters as features instead and assess the impact of different spatial filters.

Methods

Nine healthy subjects participated in the study and performed four different types of motor imagery (left hand, right hand, foot, and tongue) in a randomized order. The data was published as part of the BCI Competition IV [2], data set 2a. Two sessions from different days were recorded. Each session consisted of 72 trials per class, thus yielding 288 trials per session. One trial lasted 7.5 s, no feedback was provided. The EEG was recorded from 22 Ag/AgCl electrodes with inter-electrode distances of 3.5 cm. All signals were acquired monopolarly with the left mastoid as reference and the right mastoid as ground. The signals were sampled with 250 Hz and prefiltered between 0.5 Hz–100 Hz with an additional notch filter at 50 Hz to suppress line noise. The amplifier sensitivity was set to 100 µV.
Spatial filtering can be considered as a linear combination of the original monopolar EEG channels:

$$\boldsymbol{y}_t = \boldsymbol{W} \cdot \boldsymbol{x}_t$$

In this equation, $\boldsymbol{x}_t$ represents the original monopolar EEG signals with K channels ($K \times 1$), $\boldsymbol{W}$ is an $M \times K$ weight matrix, and $\boldsymbol{y}_t$ contains the spatially filtered EEG signals. The spatial filters used and compared in this study are common average reference (CAR), bipolar derivations and Laplacian derivations (see Figure 1 for more details). CAR is obtained by subtracting the mean of all electrodes from individual channels.

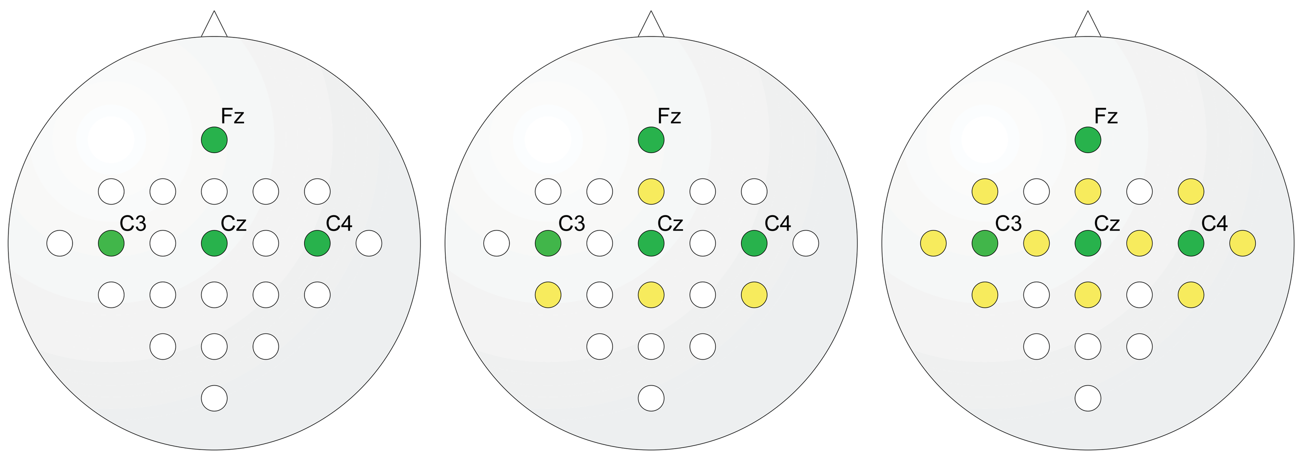

Figure 1: Left: Monopolar electrodes C3, Cz, C4, Fz. Middle: Corresponding four bipolar derivations (from green to yellow electrode). Right: Corresponding four Laplacian derivations (the average of the surrounding four yellow electrodes was subtracted from the green center electrode). Note that the Laplacian of Fz involves only one surrounding channel and that the surrounding electrodes of C3, Cz, and C4 are overlapping.

In this study, adaptive autoregressive (AR) models were used to extract features from the raw EEG by utilizing a Kalman filter algorithm, as described in [3]. Specifically, we compared the performance of univariate (UV) AR models with the more general case of multivariate (MV) AR models. Basically, both models can be described with the following equation:

$$\boldsymbol{y}_t = \sum_{i=1}^{p} \boldsymbol{A}_i \cdot \boldsymbol{y}_{t-1} + \boldsymbol{\varepsilon}_t$$

In this equation, $\boldsymbol{y}_t$ represents the M EEG channels at time t (so the dimension is $M \times 1$), p is the model order, $\boldsymbol{A}_i$ is the i^{th} autoregressive parameter matrix ($M \times M$), $\boldsymbol{y}_{t-1}$ are the EEG signals at time $t-1$, and $\boldsymbol{\varepsilon}_t$ is a white noise process at time t ($M \times 1$). In the UV case, all $\boldsymbol{A}_i$ become scalars a_i because each of the M channels is modeled by a separate model. In both cases, the features used for classification were the AR parameters $\boldsymbol{A}_i$ (total number $p \cdot M^2$) or a_i (total number $p \cdot M$).
The AR parameters were estimated continuously in an adaptive way. This was achieved by implementing a Kalman filter algorithm, and the parameters of the UV model were determined by setting $M = 1$. From previous preliminary studies, the model order was chosen to be $p = 3$ for the MV case and $p = 6$ for the UV case. In both models, the other free parameter, namely the update coefficient was set to be $10^{-5.5}$.
Analyses were performed for each subject and spatial filter type, separately with a UV and an MV AR model, in the following way. First, a spatial filter was applied to the monopolar signals, thereby reducing the dimensionality to four channels C3, Cz, C4, and Fz. Next, either UV or MV AR parameters were estimated continuously for the entire session. Finally, the AR parameters at each time step were used as features and concatenated into feature vectors and used as input for continuous classification based on Fisher's linear discriminant analysis (LDA).
Two types of evaluation schemes were employed: first, a 10×10 cross-validation procedure was implemented on each of the two sessions available for each subject. Second, the performance on unseen data was estimated to analyze the session-to-session transfer. To this end, the classifier was trained with the data from one session and tested with the data from the other session. The classification accuracy was measured by the data at the 90[th] percentile of the accuracy time course over a trial (which is the highest accuracy over the trial after discarding the highest 10 % of the values). In total, 144 different results were obtained for both types of evaluation schemes (18 sessions, 4 spatial filters, 2 AR model types) for each subject and statistically assessed with an analysis of variance (ANOVA) for repeated measures with factors "filter" (monopolar, CAR, bipolar, Laplace) and "model" (UV and MV). Bonferroni-corrected t-tests were used as post-hoc tests.

Results

The results of the ANOVA show a highly significant main effect "filter" with $F(1, 3) = 22.72$, $p = 0.000$ and $F(1, 3) = 8.75$, $p = 0.000$ in both the cross-validated and session-to-session case, respectively. There is no significant difference between the UV and MV models, although there is a trend in the cross-validated case. The interaction between filter and model was found to be not significant.

	Cross-validation			Session-to-session		
	df	F	p	df	F	p
Filter	3	22.72	0.000	3	8.75	0.000
Model	1	2.78	0.098	1	1.86	0.175
Filter × Model	3	1.13	0.339	3	0.58	0.627

Table 1: Results of the ANOVAs showing degrees of freedom (df), F-values and p-values for the factors "filter", "model" and the interaction.

The mean classification accuracies are listed in Table 2, separately for each model type (upper half) as well as spatial filter type (lower half). Clearly, the MV model yields higher classification accuracies in both the cross-validated as well as session-to-session case. Comparing the three spatial filters and the monopolar recordings, Laplacian derivations perform worst in both analyses. CAR performs very good in both cases, this filter yields the best results in the session-to-session case and the second best results in the cross-validation. Bipolar derivations outperform all other filters in the cross-validated analysis, whereas the performance in the session-to-session analysis drops even below monopolar data. The data from this table is also visualized in Figure 2, which shows boxplots of the individual classification results. The whiskers denote the minimum and maximum, the edges of the box are the 25[th] and 75[th] percentiles, and the red line in the box marks the median. The notches of the boxes are the endpoints of confidence intervals that, if they do not overlap, denote a difference between the medians at a 5 % significance level.

	Cross-validation	Session-to-session
UV	0.422	0.338
MV	0.444	0.355
Monopolar	0.428	0.352
Bipolar	0.482	0.341
Laplace	0.344	0.300
CAR	0.478	0.393

Table 2: Mean classification accuracies (as measured by the value at the 90[th] percentile) of the different models as well as different spatial filter types.

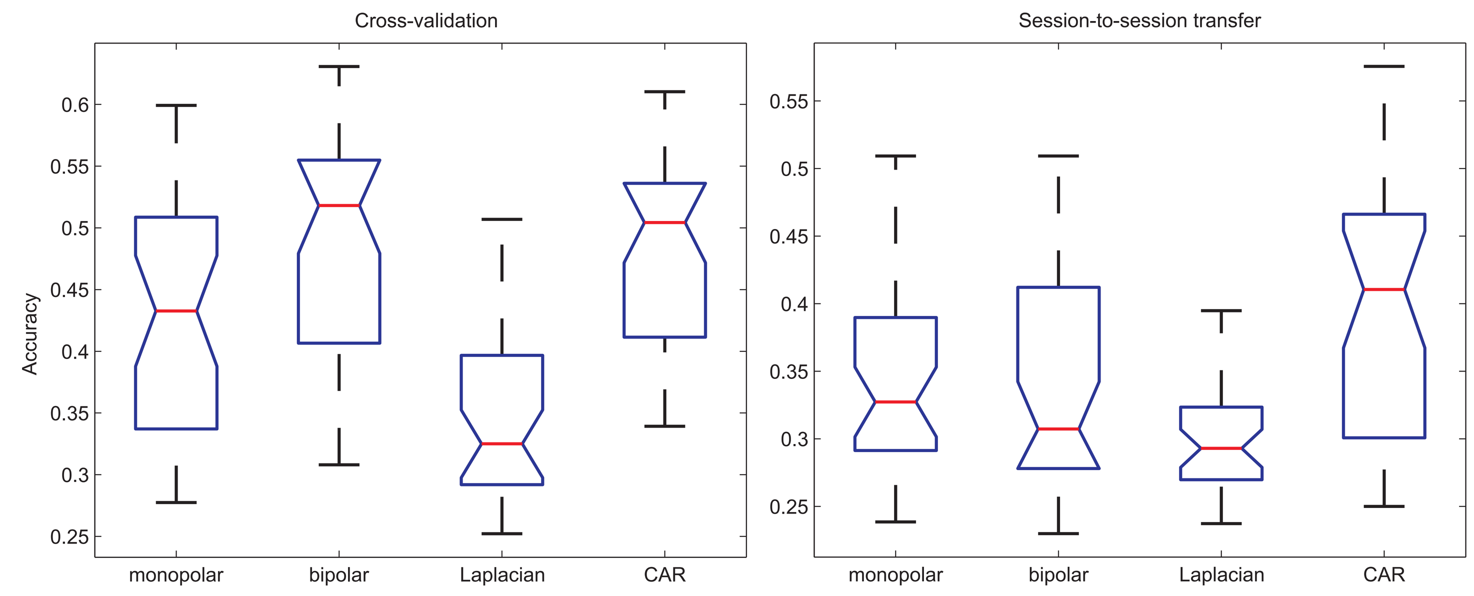

Figure 2: Left: Boxplots of the four spatial filter types in the cross-validated case. Right: Same as left, but for the session-to-session transfer. For an explanation of the plots, see main text.

All spatial filters were compared to the results obtained with the original monopolar data by conducting multiple Bonferroni-corrected t-tests. The results are summarized in Table 3. All differences are significant, except for bipolar filters in the session-to-session transfer case. Together with the results from Table 2, it can be stated that Laplacian derivations performed worst in both cases (cross-validation and session-to-session). Bipolar recordings were only better in the cross-validated case, whereas CAR-filtered data yielded better results in both cases.

	Cross-validation	Session-to-session
Bipolar	0.008	0.817
Laplace	0.000	0.008
CAR	0.015	0.034

Table 3: Results of the t-tests (all filters were tested against monopolar data). All p-values were Bonferroni-corrected to avoid spurious false positives. The table contains the p-values scaled by the correction factor, which was 3 in this case.

Discussion

Significant differences were found between the different spatial filter types. From the results, CAR can be recommended as a suitable preprocessing technique because it yielded improved results for both the cross-validated as well as the session-to-session transfer case. Based on the results of this study, Laplacian filters cannot be recommended for use with AR parameters.
Although the difference between UV and MV models were not significant, it is still interesting to note that MV yielded better results than the UV model. Optimized model parameters (model order and update coefficient) could further improve the performance.

References

[1] D. J. McFarland, L. M. McCane, S. V. Davis, and J. R. Wolpaw. Spatial filter selection for EEG-based communication. *Electroencephalography and Clinical Neurophysiology*, 103:386–394, 1997.

[2] `http://ida.first.fhg.de/projects/bci/competition_iv/index.html`

[3] A. Schlögl, D. Flotzinger, and G. Pfurtscheller. Adaptive autoregressive modeling used for single-trial EEG classification. *Biomedizinische Technik*, 42:162–167, 1997.