A Comparison of Univariate, Multivariate, Bilinear Autoregressive, and Bandpower Features for Brain-Computer Interfaces

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Introduction

The signal processing toolchain in a brain-computer interface (BCI) consists of several components that influence the overall performance of the system. In general, raw electroencephalographic (EEG) signals are first preprocessed with temporal or spatial filters. Next, features are extracted before the final classification stage. After that, a control signal can be derived.

The aim of this offline analysis was to assess the influence of different feature types derived from autoregressive (AR) models on the overall performance of a BCI (measured by classification accuracy). We hypothesized that multivariate AR (MVAR) and bilinear AR (BLAR) parameters could yield higher classification accuracies because they contain more information about the underlying signals. In contrast to univariate AR (UVAR) parameters, MVAR parameters also describe the relationships between single channels, and BLAR parameters can model certain nonlinear signals.

Methods

We used data set 2A from the BCI Competition 2008 [1]. Nine subjects took part in two sessions on different days. The cue-based paradigm involved four different motor imagery tasks (left hand, right hand, foot, tongue). A session consisted of 6 runs with 48 trials each (12 for each of the four classes). We used signals from three bipolar electrodes C3, Cz, and C4. From those three EEG channels, we extracted different features:

(1) univariate AR (UVAR) parameters for each channel,

$$x_k = \sum_{i=1}^{p} a_i x_{k-i} + \varepsilon_k$$

(2) multivariate AR (MVAR) parameters for all three channels,

$$\mathbf{x}_k = \sum_{i=1}^{p} \mathbf{A}_i \mathbf{x}_{k-i} + \boldsymbol{\varepsilon}_k$$

(3) bilinear AR (BLAR) parameters,

$$x_k = \sum_{i=1}^{p} a_i x_{k-i} + \varepsilon_k + \sum_{i=1}^{q_1} \sum_{j=1}^{q_2} b_{ij} x_{k-i} \varepsilon_{k-j}$$

and (4) logarithmic bandpower (logBP) features.

In model (1), x_k is the value of one EEG channel at time k, p is the model order, a_i are the autoregressive parameters, and ε_k is white noise. Model (2) extends this model to the multivariate case, where $\mathbf{x}_k$ is an n-dimensional vector containing all n EEG channels at time k, $\mathbf{A}_i$ are the autoregressive parameter matrices, and $\boldsymbol{\varepsilon}_k$ is n-dimensional white noise. Model (3) extends the univariate model with a bilinear term, where q_1 and q_2 are the bilinear model orders, and b_{ij} are the bilinear autoregressive coefficients.

We first determined optimal parameters (model order and update coefficient) for the three different adaptive AR models with an exhaustive grid search. We optimized the frequency bands for the logBP features with a sequential floating feature selection algorithm. For this optimization stage, we used only the data from the first session. The optimization criterion was to maximize the 90% quantile of the classification accuracy. We optimized parameters both individually for each subject as well as globally over all subjects. In the case of logBP, we used default bands (10-12Hz and 16-24Hz) for comparison.

We evaluated the performance using the optimized parameters on the second session by calculating classification accuracy using a 10×10 cross-validation procedure. We used linear discriminant analysis (LDA) in all cases to classify the data.

Results

The optimization showed a great variability over subjects. Some subjects had their optimal parameters at low model orders, whereas others peaked at high model orders. In general, the model order was lower for the MVAR model than for the UVAR model. Moreover, choosing the optimal model order is not so critical for subjects with good brain patterns, since the area with good results is rather large (see Figure 1).

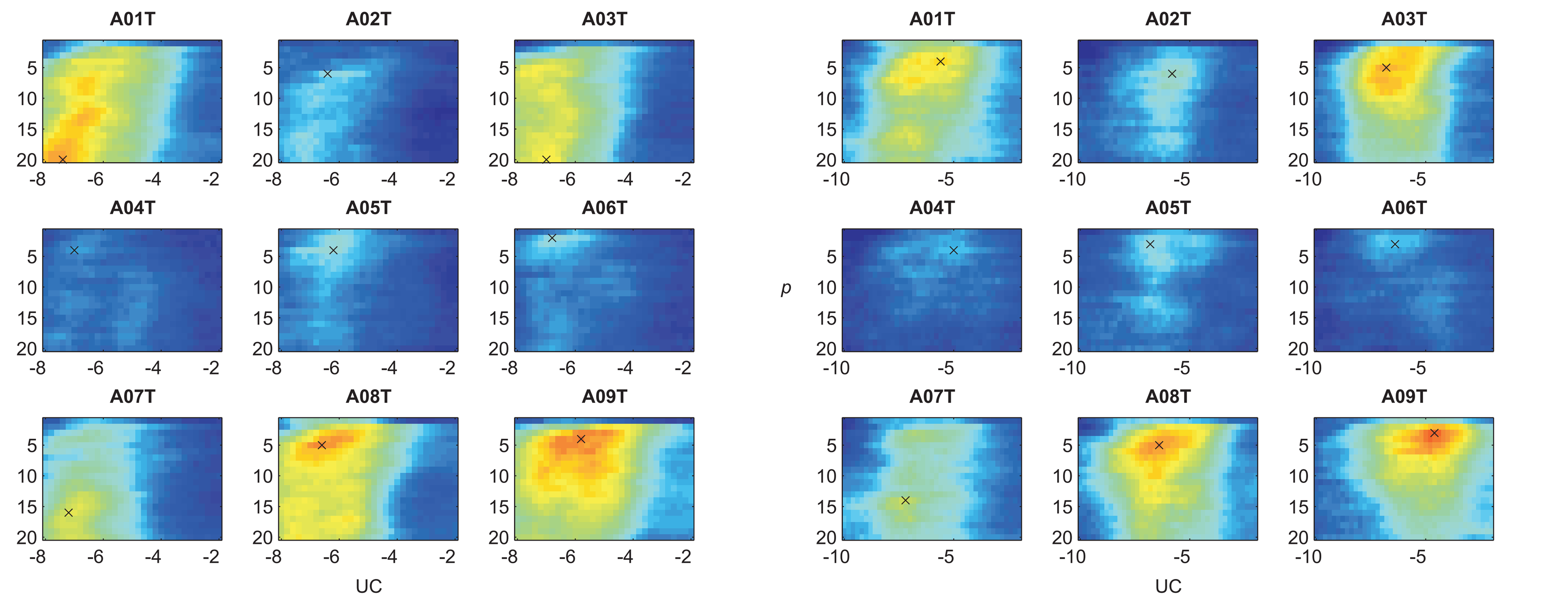

Figure 1: Results from parameter optimization for the UVAR (left) and MVAR (right) models for all subjects. The *x*-axis shows the UC (logarithmic scale), whereas the *y*-axis shows the model order *p*. The highest classification accuracy for each subject is marked with a cross. Blue denotes low and red high classification accuracies.

Using a two-way repeated measures ANOVA with factors „feature type“ (four levels) and „optimization“ (two levels), we found no significant differences between the different feature types (see Figure 2). MVAR parameters and BLAR parameters could not exploit their theoretical advantages over the univariate AR model. Moreover, the frequently used logBP features did not differ significantly from the AR methods.

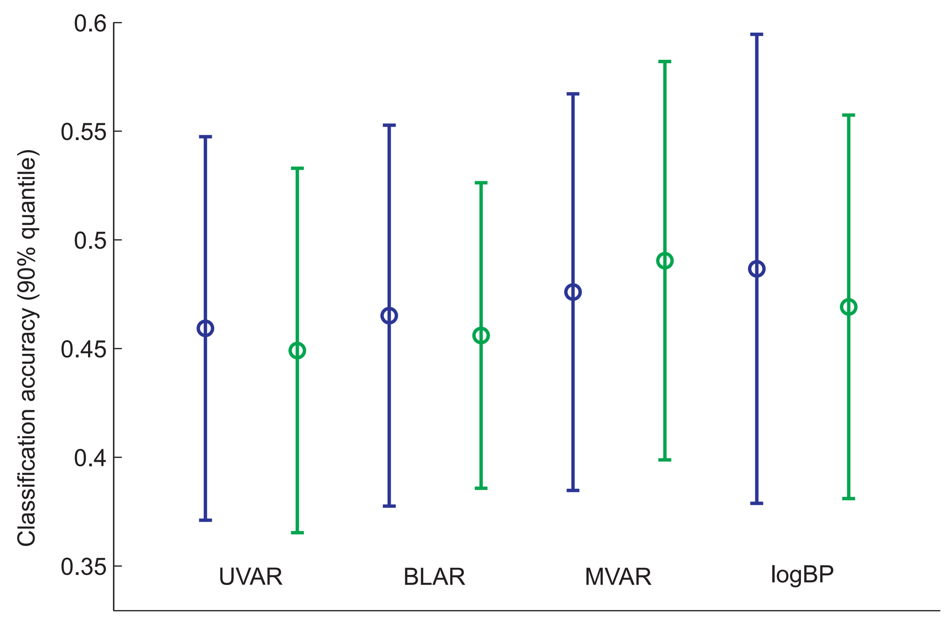

Figure 2: Cross-validated classification accuracy (90% quantile) from unseen session for all four feature types. Blue denotes features optimized for each subject individually, whereas green denotes features optimized globally over all subjects.

Surprisingly, there was also no difference between parameters optimized for each individual subject and globally optimized (or default) parameters.

Conclusion

In conclusion, we reported the following two findings. First, there is no significant difference between AR and BP features. This occurred because both methods describe the spectrum of the signals, and therefore result in similar BCI performance. However, the AR-based features might be improved by choosing a model better suited to the statistical properties of the EEG signals or by decreasing the sample rate [2]. Second, optimizing parameters individually for each subject was not necessary for the analyzed data set; using default parameters yielded equally high results.

References

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[2] M. Billinger, C. Brunner, C. Neuper. Classification of Adaptive Autoregressive Models at Different Sampling Rates in a Motor Imagery-Based BCI. Fourth International BCI Meeting, Asilomar, USA, 2010.

Support

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