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Pole tracking of EEG signals for BCI applications

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Introduction: Autoregressive (AR) models have been widely used in brain-computer interfaces (BCI) for frequency domain characterization of the electroencephalogram (EEG) signals. The coefficients of the AR models have also shown high discrimination capabilities. Time-varying AR analysis is usually achieved by segmenting the EEG into quasistationary epochs. Subsequently the estimated coefficients or the AR power spectral densities are used for classification or analysis purposes. This approach, although very popular, is limited by the selection of an optimal window length. A small window could lead to high estimation variance, whereas a large window would smoothen out fast/abrupt changes. To overcome this challenge, recursive techniques such as Kalman filtering (KF) and Recursive Least Squares have been proposed to track the evolution of the AR coefficients. The main issue with these techniques, however, is stability as well as interpretability of the model coefficients. A more intuitive approach would be the direct tracking of the poles of the AR model. The frequency and the magnitude of the poles describe in a compact manner the spectral characteristics of the analysed signal. Pole tracking (PT) relies on reformulating the AR model as a cascade of first- and second-order filters. This allows independent monitoring of the poles of each filter. However, the model becomes nonlinear in its coefficients and therefore, we have previously used the unscented KF (UKF) for its time-varying estimation [1].

Materials, methods and results: We applied PT on the Graz data set A of the BCI competition 2008 [2], consisting of 22-channel EEG signals obtained during cue-based movement imagination of the left hand, right hand, tongue and both feet. Our goal was to explore the possibility of classifying these movements using as features the frequency and the magnitude of the tracked EEG poles. For each subject and each trial, we extracted five poles from channels Fz, Cz, C3, C4 and Pz (one pole per channel). The UKF hyperparameters were optimized based on only one trial (from each subject) and then kept fixed for the rest of the trials. The average testing classification accuracy over time for four representative subjects can be found in Fig.1A. At each time point we applied shrinkage Linear Discriminant Analysis classification [3] based on a 10-fold cross-validation scheme. As features we included the instantaneous amplitude and frequency of the tracked poles from each channel (i.e., overall 10 features). The time evolution of a representative pole for different imagined movements can be seen in Fig.1B,C.

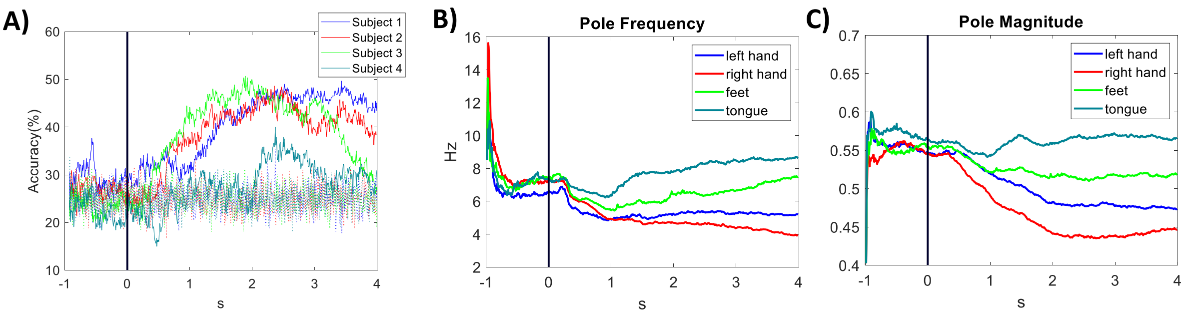

Figure 1: **(A)** Classification accuracy throughout time in four subjects and average (over all trials) evolution of the **(B)** frequency and **(C)** magnitude of the C3 pole from one representative subject for the different types of movement imagination. The black vertical line denotes the cue onset. In (A) dotted lines (around ~25% level) represent the chance level obtained by permuting randomly the input feature vector.

Discussion and Significance: We have proposed the use of AR PT for spectral characterization of EEG signals in a BCI dataset. This technique allows for real-time monitoring of the poles of the EEG without the need of applying sliding windows. We observed that one pole for each channel was found to be sufficient to describe the underlying dynamics and this could be projected on the classification results. However, in future work we will investigate the impact of a larger number of poles. UKF hyperparameter tuning was achieved using only one trial, which is a highly favorable attribute when calibration time is required to be minimum. Most importantly, however, the time-varying pole features can be further used to understand in more detail the EEG characteristics that different imagined movements give rise to.

References

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