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Re(con)volution: accurate response prediction for BBVEP-based BCI

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Introduction: Evoked potentials can be subdivided in three classes: transient, steady-state, and broad-band responses. The extent to which these responses reflect qualitatively different types of neural activation is still debated. Here, we employed the superposition hypothesis, which states that the response to a sequence of events is a linear summation of the transient response to each individual event. We modeled EEG responses to rapid visual stimulation to be the summation of overlapping time-shifted versions of basic transient responses to a flash. The transient responses were estimated from data, using deconvolution. Modeled responses were generated by convolution of the estimated transients with a signal, representing the onset times of the flashes. This linear framework is called reconvolution as it combines both deconvolution and convolution.
With reconvolution, evoked responses to flash sequences can be predicted accurately given relatively small amounts of training data. Therefore, this technique is suitable as a framework for Brain Computer Interfacing. In a visual matrix speller, we have achieved high classification accuracies with short single-trials, resulting in fast and robust communication rates. Additionally, because of the availability of a generative model and optimized stimulation, pilot results reveal the possibility for high-class BCI, zero-training BCI, and asynchronous BCI.

Material, Methods and Results: We presented modulated Gold codes as rapid non-periodic visual stimulation in a matrix speller. While participants gazed at a target, EEG data were recorded from 32 water-based scalp electrodes, amplified by a TMSi Mobita amplifier. A Canonical Correlation Analysis (CCA) based reconvolution was applied, in which single-trials (X) were spatially filtered (XW_X) with a weighting vector over electrodes (W_X), in order to maximize the correlation with the convolution (YW_Y) of a design matrix (Y) and the transient responses (W_Y). This CCA based reconvolution simultaneously learns the temporal as well as the spatial distribution of the transient responses embedded in broad-band responses. This method allows for accurate generation of evoked responses, explaining up to 50% of the variance for bit-sequences used to fit parameters during calibration, as well as for novel bit-sequences. These generated responses can serve as templates in an evoked response BCI. Because of the generative framework, less training data is required to calibrate the classifier, with a retained possibility of using many classes concurrently.
In offline analysis of data acquired in [1], we achieved an average classification accuracy of 88%, with single-trials of 3 seconds (N=12). In online experiments, we have achieved a robust classification accuracy of 95% with single-trials of 1.5 seconds, both using a 6 x 6 matrix as well as using a 5 x 13 matrix speller (N=1).
We investigated the possibility of a zero-training setup by applying CCA based reconvolution to each bit-sequence, on single-trial level. The BCI selected the bit-sequence that revealed highest explained variance in the linear framework. In an online experiment, we found robust classification accuracies (90%) with single-trials starting at 40 seconds, decreasing to 1.5 seconds within approximately 5 single-trials (N=1).
Gold codes are pseudo-random bit-sequences generated in sets, which exhibit a minimized cross-correlation (i.e., the correlation between pairs within the set), as well as minimized auto-correlation (i.e., the correlation of a bit-sequences with a delayed version of itself). Therefore, high correlations would only occur at zero time-lag of a targeted code. This makes Gold codes appropriate for asynchronous BCI, where time-lock information is lost (e.g., in low-end headsets that do not have external trigger inputs to synchronize stimulation and data-analysis). In the asynchronous setup, the number of templates is increased by including time-shifted versions of all templates. In a 6 x 6 matrix speller with 60 time-lags, a classification problem with 36*60 classes is created. Still, the BCI detected the target using 4.2 seconds of EEG data with a classification accuracy of 80% (N=1).

Discussion: The proposed setup allows for high-class, asynchronous, and zero-training BCI. In the case of asynchronous BCI, the calibration phase does require synchronization. An asynchronous zero-training method would overcome this issue, though the methods are not yet combined and rely on results from pilot studies.

Significance: This BCI setup allows robust BCI. Use of low-end headsets is possible, trading signal quality for detection time. Further, only few electrodes are required, no external trigger input for data synchronization is needed, and high classification accuracy is possible even with a high number of classes and short single-trials. This assures to high communication speeds, enabling communication without the need of the peripheral nervous system, with a user-friendly system.

References
[1] Thielen, J, van den Broek, P, Farquhar, J, & Desain, P (2015). Broad-Band Visually Evoked Potentials: Re (con) volution in Brain-Computer Interfacing.*PloS one*, *10*(7), e0133797.