Summary

For most ERP-based BCI paradigms, the stimuli are presented with a predefined and constant speed. In order to boost BCI performance by optimizing the parameters of stimulation, this offline study investigates the impact of the stimulus onset asynchrony (SOA) on ERPs and the resulting classification accuracy. The SOA represents the time between the onsets of two consecutive stimuli. Therefore, a simple auditory oddball paradigm was tested in 14 SOA conditions. A great variability in simulated BCI performance was observed within subjects (n=17). This indicates a potential increase in BCI performance (≥2 bits/min), if the SOA is specified for each subject individually.

Experimental design

- Auditory oddball task, 16.6% target stimuli with high pitch
- Stimulus duration: 40 ms
- 61-channel EEG recording (Fast&Easy Cap, EasyCap GmbH) at 1000 Hz sample rate, band-pass filtered between 0.4 and 40 Hz
- 14 SOA conditions, 216 target epochs and 1080 non-target epochs for each condition
- Feature extraction: epochs were averaged at 12 intervals between 100 ms and 700 ms after stimulus onset
- Binary classification using a regularized LDA [1]

Simulating the ITR

Based on the empirically obtained binary classification accuracy (targets vs. non-targets) for each SOA condition, the corresponding BCI performance (in bits/minute) was assessed by simulating a BCI experiment with a 6-class ERP paradigm. Classifier outputs corresponding to target and non-target events were generated according to the assessed binary accuracy. Based on that, trials were simulated and a multiclass decision was made as soon as an early-stopping criterion was fulfilled, but latest after 15 presentations of each stimulus [2]. The duration of one trial thus depends on the SOA and the binary classification accuracy. The ITR (as defined in [3]) was computed based on the number of correct and incorrect decisions after the simulation of a BCI session lasting 60 minutes.

Results

Figure 1: ERPs (Fz) of one subject (VPkab) for 8 selected SOA conditions.

Figure 2: Target and non-target ERPs and discriminancy (signed ROC) maps for five subjects and each SOA condition at electrode Fz over time. Each row within one image represents data for one SOA condition. Color maps were kept constant for each column.

- The N100 component has the same latency for each SOA (Fig. 1,2)
- Fig. 1 shows diagonal patterns (especially for the non-targets), which represent the steady state evoked responses.
- General trend of increasing discriminability for N200 and P300 component with increasing SOA (Fig. 2)
- Positive correlation between binary classification performance and SOA (Fig 3a)
- Variability in binary performance and ITR for different SOA levels of a single subjects (Fig. 3a,b)
- Optimal (wrt. BCI performance) SOA for most subjects is in between 100 ms and 200 ms (Fig. 3b)
- Average potential increase in ITR is at least 2 bits/min (Fig. 3c) or 20% (Fig. 3d), if the individually optimal SOA is chosen.

Conclusions

In typical BCI paradigms based on ERPs like [4], the stimulation speed (here SOA) is predefined and thus equal for each subject. Changing the stimulation speed, one observes varying ERPs. Also in one of the simplest type of ERP paradigm, as it was used in this study (2-class auditory oddball), one can see that the ERPs, the discriminability of class-discriminative components and the resulting classification accuracy vary non-linearly. This study shows that an individual choice of the stimulus onset asynchrony is highly beneficial with respect to BCI performance. The analyses of a simulated online BCI experiment with 14 SOA conditions show that the BCI performance (assessed by the ITR) is on average at least 2 bits/min (or 20%) higher, if the SOA is defined for each subject individually.

The work by Sellers (2006) [5] already found that the choice of SOA greatly impacts the BCI performance, concluding that “it appears to be worthwhile to test multiple ISI values and thereby determine the optimal value for each user”. The presented study underlines these findings and quantifies the systematic error which is made due to the global selection of the SOA.

As the next step, machine learning methods will be elaborated to find the individually optimal SOA within a shot time.

References


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