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Towards Aphasia Rehabilitation with BCI

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Abstract

Cognitive states can be monitored and exploited in real-time by brain-computer interface (BCI) systems. Comparable to motor rehabilitation after stroke, we propose a simple BCI-supported paradigm for the cognitive rehabilitation of speech production deficits in aphasia patients. The paradigm thrives to close the loop between top-down execution and bottom-up perception, while constraining the execution of a rehabilitation trial to BCI-detectable attention patterns. In an offline study, the basic characteristics of the novel paradigm were explored with n=9 normal hearing healthy students in a free-field spatial auditory setup. Event-related potentials (ERPs) of the electroencephalogram were analyzed and the possibility for an online classification of target vs. not-target words was explored. Despite differing in delay from ERP components evoked by artificial tones, the ERPs evoked by words can be classified on a comparable level in single trial, encouraging future tests of the attention-constraint paradigm in closed-loop.

1 Introduction

The inability to speak certain words (e.g. after stroke) can have different causes, ranging from a lesion within the dual loop model of language [4, 6] to disturbed attention mechanisms [1, 3]. Several cognitive models propose that word production may derive from high and rapid online interaction between top-down and bottom-up processing at different levels (i.e. formulation of conceptual representation into a linguistic form and an articulation level).

It is intriguing to engage both interaction directions in a rehabilitation approach. Practically this requires to close the loop from (1) the willful attempt of a word production or at least the concentration onto a word to (2) producing the sound of the intended word and thereby providing sensory feedback of the (artificially) spoken word. Transferring methods from spatial auditory BCI paradigms, we make a first attempt towards such an attention-constrained rehabilitation paradigm: a BCI system, detects attention onto a difficult-to-produce target word among a sequence of several words. Upon detection, a trial ends by playing the target word, which closes the loop via auditory feedback.

2 Methods

2.1 Participants

Two pilot sessions were performed. Data thereof was used to fine-tune experimental parameters, but excluded from further analysis. After providing written informed consent, N=9 healthy students (5 male and 4 female, age 22–26 yrs, no history of hearing defects, native German speakers) participated in the study.

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2.2 Experimental Setup

Subjects were seated in a ring of six speakers (AMUSE paradigm, [5]). A screen provided a fixation cross, indicated periods for relaxation and active trials. At trial start, subjects received static visual and auditory information about the current target direction.

Stimuli and Trial Structure. The following one-to-one relation between sentences and end-of-sentence words had been learned by subjects during a familiarization phase:

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Wir müssen putzen, überall ist ...  Dreck.
Komm, wir gehen raus an die frische ...  Luft.
Zum Frühstück mache ich mir ein belegtes ...  Brot.
Wir machen Picknick auf der Wiese im ...  Gras.
Alle Kinder trinken gerne ...  Saft.
Er hat schon wieder gewonnen - er hat so viel ...  Glück.
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Prior to presenting a rapid stimulus sequence consisting of the six end words, one of the sentences was cued from a loudspeaker. It indicated the target direction of the current trial. (Target directions were pseudo-randomized between trials.) The last word of the sentence was missing, and subjects were instructed to focus their attention to complement the missing word. The subsequent rapid sequence of 90 word stimuli per trial was presented with a stimulus onset asynchrony (SOA) of 175 ms. Comprising 245 ms each, word stimuli slightly overlapped in time. During a run, the six words were tied one-to-one to the loudspeakers. This mapping was changed between runs and balanced over runs.

Structure. Subjects were familiarized with a six-class AMUSE spatial auditory setup by first slowly. During the familiarization phase only, subjects had to count and indicate by finger movements when they had perceived target stimuli. Subsequently, three main blocks were performed with an SOA of 175 ms and one last block with 300 ms. Only data recorded with 175 ms SOA entered the analysis. Each block consisted of six runs, every run of six trials. A trial contained 90 stimuli (15 iterations of the six stimuli). As each iteration contained only one target stimulus and five non-target stimuli, this procedure totaled to an amount of $3 * 6 * 6 * 15 * 1 = 1620$ target epochs and $3 * 6 * 6 * 15 * 5 = 8100$ non-target epochs.

Electroencephalogram Recordings. During a single session, electroencephalogram (EEG) was recorded from 63 passive Ag/AgCl electrodes (EasyCap / BrainAmpDC amplifiers). The electrodes were placed according to the 10-20-system and referenced against the nose. In addition, one channel was placed below the right eye. Signals were sampled at 1 kHz, band-filtered between 0.01 Hz and 250 Hz and stored for offline processing.

2.3 Offline Data Analysis

Data of one subject had to be removed due to excessive eye blinks. Data of the remaining eight subjects was bandpass-filtered between 0.5 Hz and 20 Hz. For each stimulus, an epoch was windowed at [-175 ms , 1200 ms] relative to stimulus onset. Epoch offsets were corrected based on the interval [-175 ms , 0 ms]. Epochs were removed, if the variance of their amplitude exceeded three standard deviations or if max-min amplitudes exceeded $80\,\mu V$. On average, 37 target epochs and 182 non-target epochs were dropped per subject. Remaining epochs were averaged over subjects, but separately for target- and non-target stimuli to reveal the grand-average ERP structures (time courses and scalp maps) of the word paradigm.

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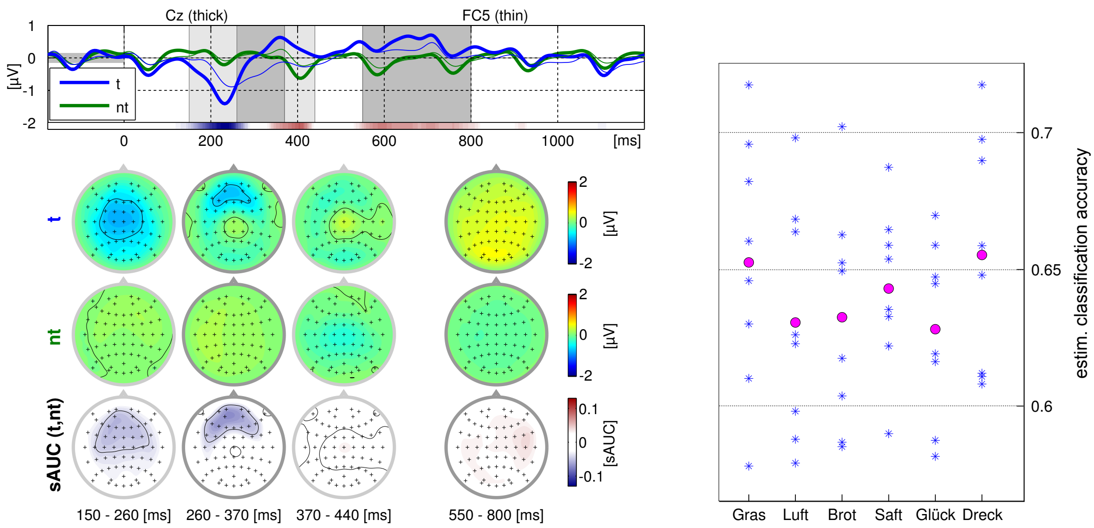

Figure 1: **Left:** evoked ERP components (grand average, n=8). TOP ROW: average time series of EEG channels Cz and FC5 for target (blue) and non-target (green) epochs. A color bar below the time series indicates the class-discriminative information (signed AUC) values contained over time in the Cz channel. MIDDLE ROWS: average potential maps evoked by target stimuli (t) and non-target stimuli (nt) of three earlier intervals and a later one (see corresponding light and dark gray shadings of top row). BOTTOM ROW: maps of channel-wise class-discriminative information content as indicated by signed AUC values of the same intervals. **Right:** Classification accuracies estimated for six classifiers trained separately for each word. Asterisks indicate the eight subject-specific accuracies, grand average results are indicated by colored circles.

Prior to classification with a shrinkage-regularized linear discriminant analysis (LDA), 15 average potentials (six intervals of 20 ms duration between 170 ms and 290 ms and nine intervals of 60 ms length between 290 ms and 830 ms) were extracted from each EEG channel, resulting in $15 * 63 = 945$ dimensions per epoch. Classification values are given relative to a chance level of 0.5 and were estimated by five-fold chronological cross-validation.

To get an overview over the novel paradigm and to estimate its single-trial classification level, a binary target vs. non-target classifier was trained for each subject. The average performance over all subjects is reported.

In addition, six separate binary classifiers were trained per user. For each classifier, only epochs from one of the six words were included. Though this strategy reduced the available amount of data by a factor of 1/6 and thereby lead to classifiers of decreased performance, it allowed us to investigate systematic differences between words.

3 Results

The evoked ERP components for target- and non-target words varied strongly between users. For this reason, the left plot of Figure 1 must be taken with caution. It shows the grand average ERP response for two channels and four selected time intervals. Over subjects, the word stimuli elicited an attention-modulated, class-discriminative fronto-central to fronto-bilateral negativity

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around 230 ms post stimulus onset, and a subsequent class-discriminant central positivity ending at approx. 800 ms with peak amplitudes at more (right-) lateralized electrodes. Compared to the original AMUSE setup, which also shows these two class-discriminative features, the latencies on average are longer for the word stimuli. The excessive length of the class-informative late positivity in fact is caused by averaging over shorter corresponding intervals of single subjects, which strongly differ in latency and duration.

Classification analysis reveals, that the word stimuli can be classified with accuracies between 65 % and 77 %. The grand average performance over subjects is 71.2 %, which slightly improves over the brisk AMUSE tone stimuli [5] (68.5 %).

Direction-related performance differences with word stimuli by and large replicate findings of the AMUSE reports (not shown). Thus it is interesting to see, if the six words, which have been randomized over the loudspeaker directions, result in similar classification performances. The right plot of Figure 1 shows the results of six classifiers trained specifically on epochs of one word each. Fortunately the spread of binary classification accuracies between words is small (between 0.625 and 0.655).

4 Discussion and Future Work

The data presented is an indicator for the effectiveness of the proposed attention-constrained word paradigm to elicit target and non-target responses, such that profound problems are not expected when transferring the paradigm to an online setup. As next steps, the trade-off between delayed high-quality feedback (cp. to current auditory BCI routines) and immediate, but more unreliable feedback must be addressed. Furthermore, the feasibility of the paradigm with individually chosen word sets needs investigation, as well as the use of longer words. The far goal is to test the potential effectiveness of the attention-constrained aphasia rehabilitation training procedures, which of cause can only be verified in randomized, blinded online studies with the target user group of chronic stroke patients. Tight time budgets in clinics or for home-use should be accommodated for by reducing the calibration time to a minimum. A combination of the attention-constrained paradigm with recently proposed transfer learning approaches in combination with unsupervised adaptive classification [2] may provide a solution.

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