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Real-time artifact correction enables EEG-based feedback inside the fMRI scanner

C. Zich[1], S. Debener[1], M. De Vos[2], C. Kranczioch[1], I. Gutberlet[3]
[1] Neuropsychology Lab, University of Oldenburg, Germany.
[2] Methods in Neurocognitive Psychology, University of Oldenburg, Germany.
[3] BlindSight GmbH, Schlitz, Germany.
catharina.zich@uni-oldenburg.de

Abstract

The aims of this contribution were (1) to investigate the feasibility of motor imagery (MI) electroencephalogram (EEG)-based online feedback during continuous functional magnetic resonance imaging, and (2) to examine the validity of electric MI signatures by comparing EEG MI data obtained inside and outside the MRI scanner. Participants (N=22) imagined hand movements, which led to an event-related desynchronization (ERD) of the contralateral sensorimotor rhythm. The contralateral ERD of the online corrected as well as of the offline corrected EEG data correlated strongly with the EEG data recorded outside the MRI scanner. We provide a proof-of-principle demonstration that meaningful EEG-based feedback inside the MRI scanner is possible for MI.

1 Introduction

As both movement execution and motor imagery (MI) decrease the amplitude of sensorimotor rhythms, termed event-related desynchronization (ERD), MI electroencephalogram (EEG)-based neurofeedback seems a promising intervention supporting the recovery of motor impairments. For the improvement of MI practice it is highly relevant to investigate the neurophysiological correlates of MI EEG-based feedback using high spatial resolution imaging. Combining MI EEG-based feedback with functional magnetic resonance imaging (fMRI) allows addressing several important aspects, such as a) a investigation of the role of feedback; b) a better understanding of individual differences in MI; and c) an identification of the brain patterns underlying the neural correlates of EEG MI feedback.

However, to successfully implement MI EEG-based neurofeedback inside the fMRI scanner good EEG signal quality must be achieved, which requires the online correction of the gradient artifact (GA) and the ballistocardiogram (BCG) artifact. As a first step we investigated the feasibility of real-time EEG-based MI feedback during fMRI, as this would open the door to address the above stated aspects. The validity of the MI EEG data collected inside the MRI scanner was verified by comparing the ERD after online and offline artifact correction with the ERD obtained outside the MRI scanner.

2 Methods

2.1 Subjects and Task

Twenty-four healthy individuals (11 females, 20-30 years of age, mean age: 23.9 years) with no MI experience participated in this study, which was approved by the local ethics committee. The data from two subjects had to be excluded because of noncompliance with task instructions. Participants were

measured twice with a six-week interval in between. During the first session concurrent EEG-fMRI was recorded and during the second session the same experiment was recorded outside the scanner in the EEG lab. Each session consisted of four blocks and each block comprised 40 trials (20 left and 20 right hand). Subjects were instructed to execute a finger tapping movement in the first block and to imagine the same movement in the last three blocks. Two imagery blocks were performed without feedback and in the last one online feedback was provided. Stimulus presentation was controlled with OpenViBE and followed the standard Graz MI protocol [1], except that we employed longer inter-trial intervals (4.5 to 9 sec) to accommodate the fMRI protocol timing.

2.3 EEG and fMRI Data Acquisition

EEG data were collected from 64 equidistant scalp sites, with Cz as reference, Iz as ground and ECG at the lower back, using an MR-compatible BrainAmp system and the BrainVision Recorder software 1.20.0506 (Brain Products GmbH, Gilching, Germany). Raw EEG was sampled at 5kHz, both GA and BCG artifacts were corrected online and corrected data were passed on to OpenViBE via a direct network link. FMRI data acquisition was performed on a 3T Siemens MRI scanner (Siemens AG, Erlangen, Germany). During functional measurements 420 $T2^*$-weighted gradient echo planar imaging volumes (3.1 x 3.1 x 3.0 mm voxels, 0.75 mm gap, TR = 1.5s, FoV = 200 * 200, Flip Angle = 90°, 27 transversal slices) were obtained within each block. The EEG data obtained outside the scanner were acquired using the same paradigm and EEG setup, except for a lower sampling rate of 500 Hz.

2.4 Online processing of EEG Data

To enable real-time EEG-based neurofeedback inside the MRI scanner, EEG data had to be immediately corrected for MRI artifacts in all MI blocks. Online artifact corrections of GA and BCG were performed stepwise using the BrainVision RecView software 1.42 (Brain Products GmbH, Gilching, Germany). The online GA correction method employed is based on the average artifact attenuation method proposed by [2] with the notable difference that online corrections can only incorporate the already recorded data into the GA correction template. An artifact subtraction template of 1500ms was built, based on the MR system TR events and the corrected data were down sampled to 500 Hz using a block down sampling algorithm. Subsequently the data were filtered using a Butterworth low-pass with an edge frequency of 35 Hz (48 dB slope).

Online BCG correction first performed a search for the most suitable BCG template within the first 30 seconds of GA-corrected EEG data. This prototypical BCG template was then used in a moving template matching approach to identify subsequent valid BCG episodes. Minimum correlation threshold for BCG detections was 0.7, with an allowed average amplitude ratio range from 0.6x to 1.4x relative to the prototypical BCG data. The total BCG correction window length varied between 800 (-100 to 700ms post R-wave) and 900 ms (-100 to 800 ms post R-wave) depending on the average inter-beat-interval of the subjects as determined before the main recordings commenced. The BCG artifact subtraction template was based on a moving window comprised of 21 subsequent BCG episodes.

The two MI blocks without feedback were concatenated and filtered from 8-30 Hz. MI intervals were extracted using EEGLAB. Artifactual segments were rejected and a common spatial pattern algorithm was applied to train a linear discriminant analysis classifier [3]. During the feedback block data were preprocessed online in OpenViBE, keeping the parameter settings identical to those used in EEGLAB. The output of the classifier was translated into the length of a light blue horizontal bar (updated at a frequency of 16 Hz).

2.5 Offline processing of EEG Data

For offline analysis standard preprocessing steps were applied on the uncorrected raw EEG data. Offline corrections of GA and BCG artifacts were performed in separate steps using the BrainVision Analyzer Professional software package 2.0.4 (Brain Products, Gilching, Germany). The GA correction time window was placed from -35 to 1465 ms relative to the MR system TR marker to accurately capture

all MR gradient activity. All other GA correction parameters were the same as for online GA correction (see above). Analysis of the BCG artifact structure in the (GA corrected) data showed that the ECG channel data was afflicted with strong additional artifacts related to respiratory cycle chest movements. Since even strict filtering of the ECG data (3 to 12 Hz - 48 dB slope Butterworth filter) typically did not remove these artifacts, a spatio-temporal matching approach was employed that detected BCG episodes based on spatial and temporal BCG signatures in all EEG channels. This method resulted in near perfect detection of valid BCG episodes. All other parameters were the same as for online BCG correction, with the notable exception that offline BCG correction automatically determined the optimal position and length of the BCG artifact subtraction window relative to the R-markers detected.

After offline correction, data were re-referenced to the common average. All three MI blocks were concatenated, filtered from 8 and 30 Hz, segmented into consecutive time intervals of one second and gross artifactual segments rejected. The remaining data were submitted to extended infomax ICA to identify and subsequently attenuate eye-blink, eye-movement and heart-beat artifacts. Artifact-corrected EEG data were segmented to extract task-related event-related desynchronization (ERD). The ERD time course was computed following the procedure proposed by [4].

Online and offline analysis of the EEG data recorded outside the MRI scanner was exactly the same except for the necessity of MRI artifact correction in the former.

3 Results

As reported previously MI caused an ERD prominent above the contralateral sensorimotor areas [e.g. 1, 5, 6]. This effect was evident for all three conditions (Figure 1), online, offline and outside the MRI scanner. Descriptively, the relative power decrease of the contralateral ERD at electrode sites corresponding to C3 and C4 was on average -18.5% ± 15.1% for the online corrected EEG signal, -31.1 ± 14.9% for the offline corrected signal and -28.7% ± 13.5% for the data obtained outside the scanner. Analysis of the ERD time course using a one-way ANOVA with factor condition (online corrected, offline corrected, EEG recorded outside the MR) revealed a significant main effect ($F_{2,42}$=12.47, p<.001, η^2=.37). Subsequent paired sample t-tests revealed no significant difference in ERD amplitude between offline corrected data and those recorded outside the MRI scanner (t_{21}=-.83, p=.42) but a significantly lower ERD amplitude in the online compared to offline corrected (t_{21}=5.83, p<.001) data. The standard deviation within the MI interval across trials was significantly higher for online corrected compared to offline corrected data, t_{21}=-3.5, p=.003.

Examination of the association between the online as well as the offline corrected EEG data recorded inside and outside the MRI scanner revealed strong correspondences for the contralateral ERD (r=.56, p=.007; r=.53, p=.01). Analysis of the overall spatial ERD pattern was performed for the 30 electrodes

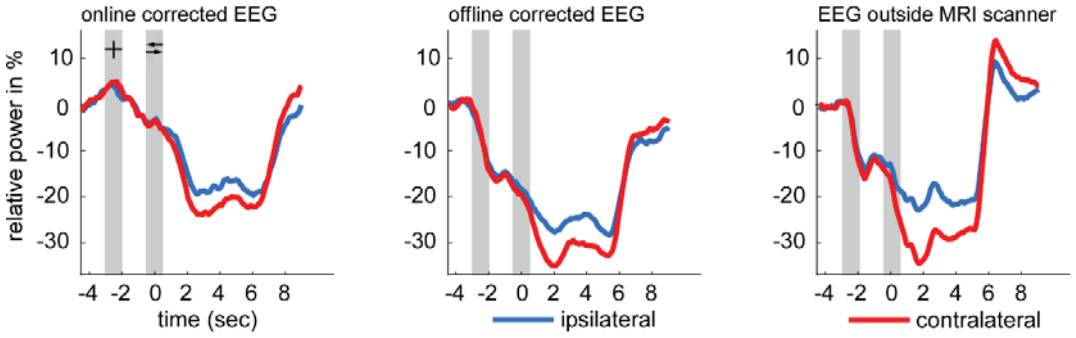

Figure 1: Grand average ERD from N=22 for online and offline corrected EEG data and data obtained outside the scanner at C3 and C4. Blue indicates contra- and red ipsilateral electrode sites, with respect to stimulus direction.

on the top of the scalp. Between the offline corrected data and the data acquired outside the scanner high associations for right and left hand MI ($r=.87$, $p<.001$; $r=.88$, $p<.001$) were found, weather no significant correspondences could be obtained for online corrected data and data obtained outside the MRI scanner.

4 Discussion

Motivated by our interest in the spatial underpinnings of MI EEG-based neurofeedback, the possibility of EEG-based feedback during fMRI acquisition for MI was explored and the validity of MI EEG data after online and offline artifact correction examined. Although the procedure is technically challenging, it offers the unique possibility to investigate in detail the brain patterns involved in EEG-BCI operation. This may help to further develop effective MI EEG-based feedback.

For the first time we provide a proof-of-principle demonstration that EEG-based feedback during continuous MRI scanning is possible for MI. This is illustrated by high associations of the contralateral ERD, for EEG data obtained inside and outside the MRI scanner. The contralateral ERD was significantly lower for online versus offline corrected data, however as EEG data and artifact correction protocols were identical for online and offline corrections, the differences can only be attributed to the vastly reduced efficacy of the ECG detection method used in online versus offline corrections. A possible adaptation of the spatio-temporal matching algorithm used for the offline ECG detection thus holds excellent promise for a further improvement of the efficacy of online EEG-fMRI based MI protocols. Furthermore the development of more efficient online artifact correction procedures can accelerate the correction process and thereby reduce the delay of feedback inside the MRI scanner. However, even with the currently implemented methods, we were able to show that it is possible to remove MRI related artifacts in real-time, which is necessary to provide online feedback.

The present findings open up new possibilities to investigate the neurophysiological underpinnings of MI, which seems necessary in light of the promising role of MI for stroke recovery.

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