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A Step towards Neuro-Steered Hearing Aids: Integrated Portable Setup for Time-Synchronized Acoustic Stimuli Presentation and EEG Recording

Abstract: Aiming to provide a portable research platform to develop algorithms for neuro-steered hearing aids, a joint hearing aid - EEG measurement setup was implemented in this work. The setup combines the miniaturized electroencephalography sensor technology cEEGrid with a portable hearing aid research platform - the Portable Hearing Laboratory. The different components of the system are connected wirelessly, using the lab streaming layer framework for synchronization of audio and EEG data streams. Our setup was shown to be suitable for simultaneous recording of audio and EEG signals used in a pilot study ($n=5$) to perform an auditory Oddball experiment. The analysis showed that the setup can reliably capture typical event-related potential responses. Furthermore, linear discriminant analysis was successfully applied for single-trial classification of P300 responses. The study showed that time-synchronized audio and EEG data acquisition is possible with the Portable Hearing Laboratory research platform.

Keywords: Portable Hearing Laboratory, open Master Hearing Aid, openMHA, hearing aids, cEEGrid, around-the-ear EEG, EEG, portable setup, auditory Oddball

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1 Introduction

Inspired by recent neuroscientific findings, the idea of neuro-steered listening devices receives increased attention. Correlates in the electroencephalogram (EEG) related to mental acts such as auditory attention or listening effort can be measured to obtain electrophysiological feedback from brain activity. Such information may potentially be incorporated in advanced processing methods for hearing aids in order to optimize noise reduction or signal enhancement based on estimates of a users' attention or listening effort [1].

Making use of EEG, e.g., in a neuro-steered hearing aid, requires EEG and hearing related research questions to be explored in the field as part of realistic listening scenarios. For this, mobile systems are required. One successful approach to record data outside the laboratory is to use off-the-shelf Android devices. These can be combined with portable EEG amplifiers [2], thus enabling mobile data recording and processing. As done in [3], mobile Android smartphone-based systems can also be coupled with miniaturized EEG sensors, such as the cEEGrid, to perform long-term recordings of more than six hours. The cEEGrid is a flex-printed multi-channel EEG sensor array placed around the ear. Even though EEG sensor miniaturization usually leads to a reduced signal

Figure 1: Combined hearing aid - EEG research platform. The Portable Hearing Laboratory (PHL) presents acoustic stimuli to the subject via hearing aids. Brain responses are measured with the cEEGrid, used in combination with a mobile EEG amplifier.

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amplitude due to poorer spatial coverage, this technology may offer a viable option to be used together with hearing aids [4]. To develop EEG-assisted hearing aid algorithms, a measurement setup was implemented, combining currently available mobile EEG hardware with soft- and hardware components of the realm of hearing aid research (see Figure 1). For this, the Portable Hearing Laboratory (PHL, [5]), an integrated portable hearing aid research platform, is used. The PHL utilizes the open Master Hearing Aid software (openMHA, [6]) to conduct low-latency real-time audio signal processing. This device is combined with an EEG system (consisting of cEEGrid, a mobile EEG amplifier, and a smartphone). A crucial prerequisite for measuring EEG, such as event-related potentials, is the time synchronicity between audio data played back by the PHL system and the EEG data recorded by the EEG system. Thus, in addition to performing a physiological study, the system was evaluated with regards to the time synchronicity of the data acquisition. The setup was physiologically validated using a two-tone oddball paradigm.

2 Materials and Methods

2.1 Technical Setup

The PHL is used to present acoustic stimuli to the subject using hearing aids with receivers in the canal (RIC). In addition, the device collects and records both audio and EEG data streams. The data collection within the setup is based on sending data over the Wi-Fi network of the PHL using the lab streaming layer (LSL, [7]) framework. Two independent openMHA instances are employed for stimulus playback (“sender”) and data recording (“receiver”). While playing the stimuli, the sender instance is configured to simultaneously send out an LSL data stream of the stimulus signal. The brain response of the subject is captured with the cEEGrid and amplified using a small, wireless EEG amplifier (Smarting, sampling rate: 250 Hz). A corresponding Android application receives the EEG data via Bluetooth from the amplifier and streams the signal continuously as an LSL stream. The receiver configuration collects both LSL streams (audio and EEG) and writes them to the memory of the PHL.

2.2 Time Synchronization Test

To evaluate and quantify the temporal precision of the setup a method described in [2] in detail was employed:

The audio signal is fed directly into the EEG amplifier (using the Smarting DJ Test Box), such that the stimulus onset

Figure 2: Core idea of the experimental procedure to test the audio-EEG data stream synchronicity. A square wave test signal is fed directly into the EEG amplifier. By that, the onset times extracted from the audio LSL stream can be compared to the actual playback onset time [2].

markers extracted from the audio LSL stream can be compared to the actual playback onset time extracted from the amplifier’s LSL stream (see Figure 2).

For this, a 60 ms square wave signal with a mean temporal distance of 1 s between the square’s onsets was used. The sound signal was recorded on a single EEG channel. The marker time was defined as the onset time of the audio signal’s square wave and was set to 0 ms as reference. The amplifier signal could be epoched from –100 ms to 150 ms and baseline corrected from –100 ms to –50 ms relative to the extracted marker (at 0 ms). The latency of a single trial was set to the time difference between the marker and the amplitude exceeding the half-maximum of the trial averaged response. The marker time points extracted from the audio LSL stream are only an estimate of the “true” time and can therefore occur before the actual physical response, leading to a negative latency.

2.3 Physiological Validation

For the physiological validation a two-tone oddball paradigm was used. The resulting EEG data were analyzed using the event-related potential technique and assessed further in a single-trial classification.

Participants Five volunteers with self-reported normal hearing participated in the study (two female, three male, 20–39 years of age; mean: 26 years). The experiments were in accordance with Covid-19 hygiene and safety measures.

Stimulus and Task The oddball stimulus was implemented similarly to [4] consisting of two pure tones (600 Hz, 900 Hz) of 60 ms duration with a 10 ms rise/fall time. The 600 Hz tone was the standard tone; the 900 Hz tone was the target/deviant tone. On average, 717 standard and 179 deviant tones were

presented in a pseudo-randomized order (20% deviant probability) with a mean inter-stimulus interval of 1000 ms (± 200 ms). The experiment took place in a quiet office room and was conducted while the participants were sitting. During the experiment, the participants were instructed to focus on a fixation cross displayed on a computer screen. The participants' task was to silently count the high deviant tones and report the number of counted tones at the end of the experiment.

Pre-Processing The data were analyzed using custom scripts (cf. Github-repository: <https://git.io/Jnx3Y>) implemented in Matlab (Version: R2020a) and EEGLAB (Version 2020.0, [8]). Filtering (low-pass filter at 10 Hz (order: 330) and high-pass filter at 0.1 Hz (order: 8250)), artifact correction (Artifact Subspace Reconstruction (ASR) using the function "pop_rejchan"), and EEG channel rejection ($SD=2$) were adopted from [3]. Rejected channels in the remaining dataset were spherically interpolated, which occurred once for one channel in one session.

Event-related potentials (ERP) Epochs were extracted from -0.2 s to 0.8 s and baseline-corrected from -200 ms to 0 ms. By using ASR it was assumed that the data had been sufficiently "cleaned" from artifacts. Thus, no individual trials were excluded from the analysis. As done in [3] for the analysis of the ERPs, the vertical bipolar cEEG channels were used, i.e., the mean of the channels R2 and R3 re-referenced to the mean of channels R6 and R7.

Single-trial classification Linear Discriminant Analysis (LDA) was employed to further evaluate the data. The procedure and the code were taken from [9] and adapted accordingly. The epochs were grouped according to the class labels (C_0 : standard, C_1 : deviant). Feature extraction was done by computing the temporal mean amplitude of successive

windows of 48 ms for each epoch and channel. The data's dimensionality was reduced by applying a Principal Component Analysis. Only the principal components which corresponded to 99 % of the variance were retained for further analysis. Two classification approaches were employed. In the first scenario a 10-fold cross-validation on all sessions for every subject was computed. For the second approach the cross-session performance of this classifier was investigated by training on the first session data to classify the data from the second session from the respective subject. The classifier performance was evaluated using the area under the curve (AUC) extracted from the receiver operating characteristic curve.

3 Results and Discussion

3.1 Time Synchronization Test

The latency, i.e., the temporal distance between the extracted marker position and the rising edge of the EEG amplifier response, was measured over 15 minutes of recording time in 8 sessions resulting in approximately 900 epochs per session. A negative latency corresponds to the case that the EEG signal's rising edge was detected temporally before the associated marker.

The lag of these eight measurements ranged from -23.60 ms to 11.74 ms (mean = -1.27 ms). All measurements featured a similar jitter of 1.32 ms ($SD: 0.23$ ms). A linear drift of 0.24 ms/min ($SD: 0.02$ ms/min) was observed for all measurements. This compares to current Android-based systems, such as [2], which reached a jitter of less than 3 ms.

3.2 Physiological Validation

For the physiological validation a total of approximately 150 minutes of recording data were collected (approx. 15 minutes per session, 2 sessions, 5 participants). In order to achieve comparability between the subjects the data sets were truncated to contain the same numbers of rare and frequent events. This resulted in 13.5 min per session used in the analyses.

Event-Related Potentials The single-subject ERP plots for the vertical bipolar channel are depicted in Figure 3. As indicated by the results from the previous section the lag varied across sessions. Thus, no grand average (across all subjects) is shown. Because of the low number of participants ($n = 5$), all results are reported purely descriptively by visual differences and no statistical analysis was conducted. In the case of the

Figure 3 Single-subject event-related potential plots for the vertical bipolar channel (red: deviants, blue: standards). The shaded areas indicate the 95 %-confidence interval.

deviant tones, an N100 deflection is visible for all subjects. For standard tones an N100 deflection is still visible for most subjects but reduced in amplitude. The N100 peak positions were extracted in the range of 50 ms to 150 ms after the onset. For the rare condition a mean latency of the N100 response, expected around 100 ms after stimulus presentation, of 99 ms (range: 60 ms to 120 ms) was observed; for the frequent condition a mean latency of 102 ms (range: 64 ms to 148 ms). This indicates that the setup's latency jitter was sufficiently small to detect an N100 response in the averaged signal. The latency of the N100 peaks for most subjects occurred at approx. 100 ms, being in line with the setup's lag and literature [10]. For 7 out of 10 sessions a P300 response is visible. Differences in the observed characteristics of N100 and P300 components could have occurred due to individual differences such as age [11] and the positioning of the cEEGrid [4]. For our small group of pilot subjects the results suggest conformity with previous studies such as [4].

Single-Trial Classification The AUC for both cross-validation and cross-session analysis are depicted in Figure 4. In the first session the AUC ranged from 0.73 to 0.83, in the second session from 0.69 to 0.93. In the cross-session validation the AUC ranged from 0.65 to 0.85. Overall, the single-trial classification revealed above chance-level classification ($AUC > 0.5$) into rare and frequent stimuli, being in line with results obtained in [4].

Figure 4: LDA classification results for the cross-validation and the session-transfer evaluation. The AUC values are depicted as single bars for every subject, the error bars correspond to the standard error across cross-validation iterations.

4 Conclusion

The analyses show that typical event-related potential responses were captured reliably using the setup implemented in this work. Single-trial analyses of the oddball data revealed that classification was possible above chance level. These results provide the first proof of concept that the Portable Hearing Laboratory can be used together with the portable EEG system described in this work to serve as a combined hearing aid-EEG research platform. Taking advantage of the

online processing capabilities of openMHA, we will further develop the setup towards an online processing system for auditory attention decoding.

Author Statement

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