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BRIEF REPORT

How about taking a low-cost, small, and wireless EEG for a walk?

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Abstract

To build a low-cost, small, and wireless electroencephalogram (EEG) system suitable for field recordings, we merged consumer EEG hardware with an EEG electrode cap. Auditory oddball data were obtained while participants walked outdoors on university campus. Single-trial P300 classification with linear discriminant analysis revealed high classification accuracies for both indoor (77%) and outdoor (69%) recording conditions. We conclude that good quality, single-trial EEG data suitable for mobile brain-computer interfaces can be obtained with affordable hardware.

Descriptors: Mobile EEG, Wireless EEG, P300, Brain-computer interface, Walking

Noninvasive technologies for the study of human brain activity suffer from the requirement that subjects avoid gross movement during recording. Movement degrades signal quality, and this problem is commonly dealt with using one of two strategies. Firstly, signals recorded while subjects show explicit behavior are discarded, which results in asynchronous brain and behavior sampling (Gramann et al., 2011; Makeig, Gramann, Jung, Sejnowski, & Poizner, 2009). Secondly, only movement-constrained behavior is allowed. Accordingly, the validity of neurocognitive theories remains poorly understood in the context of unconstrained human behavior. Here, we investigate whether good quality electroencephalogram (EEG) recordings can be obtained while participants walk naturally outdoors.

EEG systems can be made small enough not to distract the user, and wireless signal transmission is possible (Dias, Carmo, Mendes, & Correia, 2011; Liao et al., 2012; Lin et al., 2011; Wang, Wang, & Jung, 2011). Moreover, small and wireless systems minimize movement of electrode wires, a major source of electromagnetic interference (Usakli, 2010) and electrode displacement, which dramatically degrades EEG signal quality. Dedicated mobile EEG systems should therefore be small, lightweight, and fully head-mounted. Additionally, systems should have no loose cables and comprise a sufficient number of channels to enable spatial filter-based biological artifact attenuation (Makeig et al., 2009).

Traditionally, brain-computer interfaces (BCI) have been developed as a communication tool (Birbaumer, 2006), but the focus recently has been widened. The passive BCI concept, for instance, aims at near real-time decoding of a person's cognitive or emotional state (Zander & Kothe, 2011). Ideally, mobile EEG should facilitate the decoding of mental states from brain activity (Wang et al., 2011). Technical reports introducing new EEG hardware provide the first initial evidence that BCIs can indeed be married with small and mobile EEG systems (Liao et al., 2012; Lin et al., 2008; Wang et al., 2011). Since available EEG systems may not meet all the requirements listed above, we merge small, consumer-EEG hardware with a state-of-the-art EEG electrode cap.

The P300 event-related potential (ERP) is a popular, flexible, and informative brain signal for BCI (Graimann, Allison, & Pfurtscheller, 2010). We therefore investigated whether the single-trial P300 could be reliably identified during natural behavior. To this end, auditory oddball data were obtained while participants walked around university campus, and the ERP and EEG single-trial data quality was compared to a seated, indoor recording condition.

Methods

Participants

Sixteen healthy volunteers free of past or present neurological or psychiatric conditions participated. The sample consisted of eleven females and five males (22–44 years of age; mean age, 27.9 years). Written informed consent was obtained from each participant, and the study was approved by the local ethics committee.

Stimuli and Task

Two pure tones (600, 1200 Hz) of 62-ms duration (10 ms rise/fall time) were presented binaurally with consumer in-ear headphones (Philips SHE2617/27) at a participant-controlled, comfortable level. Six hundred sixteen standards and 84 deviants were presented in randomized order at a fixed interstimulus interval (1,000 ms). Participants silently counted the rare tones. In the indoor recording condition, they sat in a quiet office room; in the

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outdoor recording condition, they walked slowly on Oldenburg campus. The route consisted of different surfaces (grass, asphalt), the crossing of curbs, and several turns, which were gestured by the escorting experimenter. No instructions were given for head and eye movements. The environment included substantial ambient noise, for instance, from nearby busy streets, while pedestrian traffic was moderate. The order of indoor and outdoor conditions was balanced across subjects. Stimulus presentation was controlled with OpenViBE (Renard et al., 2010).

EEG Recording

Exploration of a consumer 14-channel wireless EEG (128 Hz sampling rate; 0.16–45 Hz band-pass) from Emotiv (www.emotiv.com) led us to remove the hardware from its original bracket-like case and connect it to a state-of-the-art infracerebral electrode cap (www.easycap.de), resulting in three major improvements. First, the resulting EEG system was of small size ($49 \times 44 \times 25$ mm) and weight (48 grams) and could be tightly attached to the cap. Second, use of sintered Ag/AgCl electrodes improved EEG signal quality. And third, electrodes could be positioned at the 10-20 sites Fpz, F3, Fz, F4, C3, Cz, C4, TP9, Tp10, P3, Pz, P4, O1, and O2 (with reference sensors common mode sense and driven right leg at Afz and Fcz). After cap fitting, good conductivity was confirmed with Emotiv software. Data were acquired with a notebook running OpenViBE and, for outdoor recordings, carried in a backpack.

ERP and Single-Trial Analysis

Data were analyzed offline using EEGLAB (Delorme & Makeig, 2004) and MATLAB (Mathworks Inc., Natick, MA). Extended infomax independent component analysis (ICA) was used to semi-automatically attenuate eye blinks (Viola et al., 2009). EEG data were 20 Hz low-pass filtered, and trial epochs were extracted (−200 to 800 ms) and baseline corrected (−200 to 0 ms). Standard trials preceding deviants were selected to equalize the number of standard and deviant trials. After re-referencing to the average of Tp9 and TP10, ERPs were calculated for each recording (indoor, outdoor) and task (standard, deviant) condition. For single-trial P300 analysis data from 12 electrodes and eight 47-ms time bins comprising 250 to 617 ms served as the initial feature space and were ranked by means of biserial correlation. Shrinkage linear discriminant analysis (LDA) as implemented in BCILAB was used (Delorme et al., 2011; Lemm, Blankertz, Dickhaus, & Muller, 2011). The number of features was determined with a 5-fold cross-validation procedure applied to the training set (i.e., first half of trials). A model with 12 electrodes and six time bins applied to indoor and outdoor training data resulted in a mean accuracy of 88%. To mimic an online scenario, this model was applied to the validation set (second half of trials).

Statistical Analysis

ERPs were analyzed by a repeated measures analysis of variance (ANOVA) comprising the factors task (standard, deviant) and recording condition (indoor, outdoor). The effect sizes reported are η^2 (partial eta squared). Mean amplitudes from 250 to 617 ms were analyzed and used to calculate the signal-to-noise ratio (SNR), by dividing the ERP amplitude by the standard deviation in the prestimulus interval (Debener, Hine, Bleeck, & Eyles, 2008). ERP SNR and classification accuracies between indoor and outdoor conditions were evaluated with t tests. ERP analysis was limited to electrode Pz, where the oddball-P300 is prominent (Debener, Kranczioch, Herrmann, & Engel, 2002).

Results

Deviant ERPs evoked a centroparietal P300, which was evident for indoor and outdoor recordings (Figure 1). A significant main effect of task, $F(1,15) = 42.82$, $p < .001$, $\eta^2 = .74$, indicated larger amplitudes for deviant compared to standard ERPs. A main effect of recording condition, $F(1,15) = 14.11$, $p < .01$, $\eta^2 = .49$, revealed a larger indoor compared to outdoor P300. A marginal Task $\times$ Recording condition interaction, $F(1,15) = 3.97$, $p = .065$, $\eta^2 = .21$, was followed up by two t tests. For deviants, a significantly larger P300 was evident for indoor recordings, $t(15) = 4.55$, $p < .001$, but no significant effect emerged for standards, $t(15) = 1.23$, $p = .23$. Examination of the P300 ERP amplitude consistency between indoor and outdoor recording conditions revealed a strong association ($r = .85$, $p < .001$), which was driven by the deviant ERPs (deviants: $r = .87$, $p < .001$; standards: $r = .29$, *ns*). The P300 SNR was significantly lower for outdoor compared to indoor recordings, $t(15) = 2.78$, $p < .05$.

Single-trial amplitudes for a single subject are illustrated in Figure 2a. A positive deflection was consistently evident in the deviant trials for outdoor and indoor recordings. The classification results for the validation data are shown in Figure 2b. The classification accuracy was significantly higher for indoor (mean: 77%, range: 59%–86%) compared to outdoor (mean: 69%, range: 54%–88%) recording conditions, $t(15) = 3.74$, $p < .01$. Five out of the 32 datasets revealed classification accuracies only slightly above chance level (< 60%), whereas eight performed well (> 80%), with the best performance of 88% evident for an outdoor recording dataset. Classification accuracy was significantly above chance for indoor, $t(15) = 14.9$, $p < .001$, and outdoor recordings, $t(15) = 7.7$, $p < .001$. A moderate positive correlation between indoor and outdoor classification accuracies failed to reach significance ($r = .42$, $p = .10$).

Discussion

We show that good quality EEG data can be obtained in such adverse recording conditions as naturally walking outdoors. All recorded trials were entered into the classification, after only moderate preprocessing that could be implemented online. Moreover, a chronological classification strategy that aimed at avoiding pitfalls in machine learning applications was chosen (Lemm et al., 2011). The drop in classification performance from training (88%) to testing (73%) revealed nonstationarities in the data, a common problem in EEG-based BCIs. Advanced feature selection strategies implementing spatial filters may be needed to optimize classification performance. However, the good across-subjects and across-trials consistency, in combination with the excellent ERP test-retest reliability, suggests that our results are robust and should generalize to other real-world scenarios. Accordingly, we present here a low-cost EEG platform that facilitates mobile EEG applications.

The hardware used was of sufficient quality to achieve competitive auditory P300 BCI classification performance (Halder et al., 2010), but consumer EEG systems cannot easily compete with certified, medical-grade lab devices in various aspects. Our hardware modifications aimed to minimize EEG signal deterioration caused by electromagnetic interference and electrode displacement. These two aspects cannot be removed by statistical artifact attenuation and thus inevitably cause data loss. Biological artifacts,

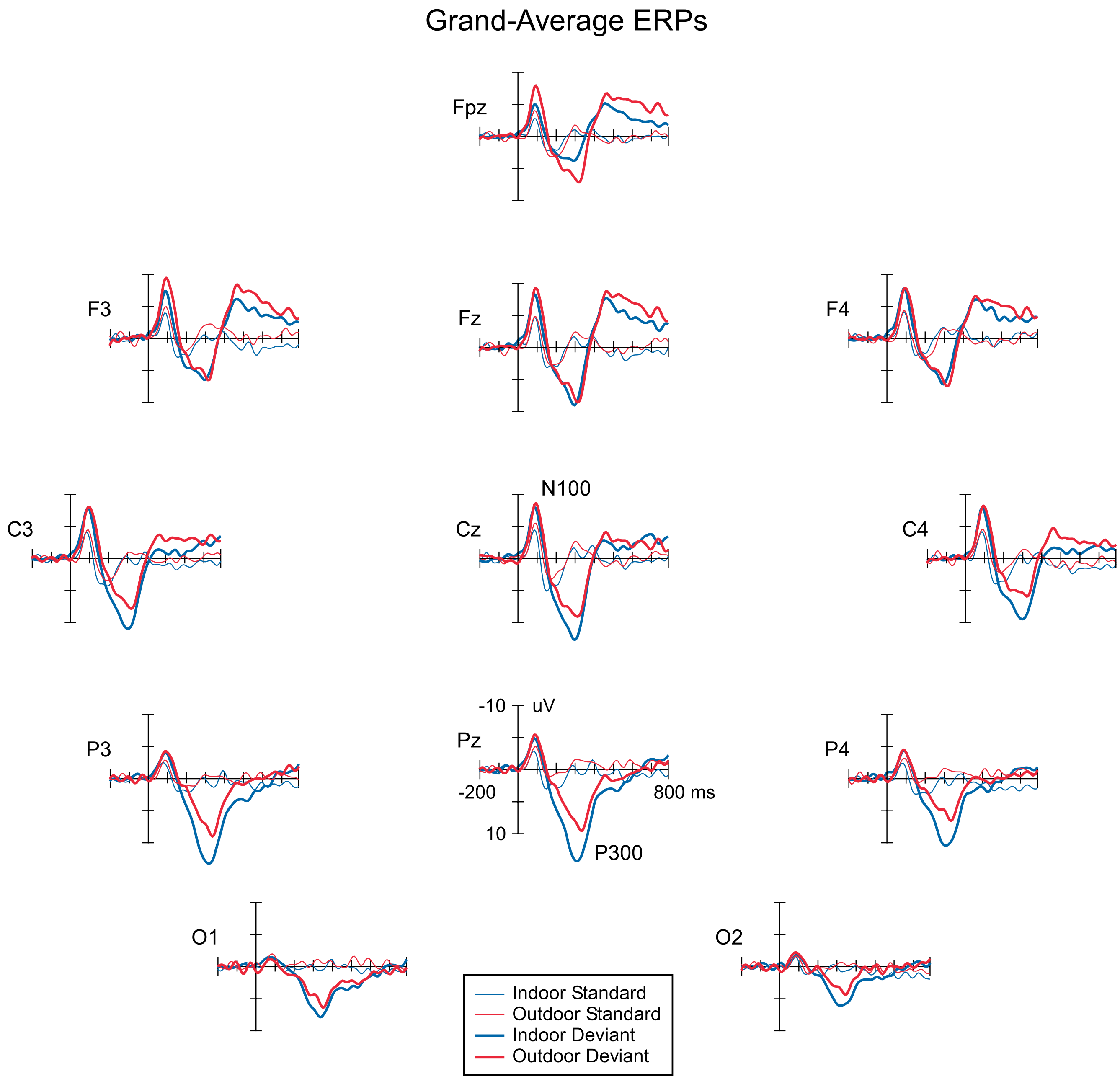

Figure 1. Grand average ERPs at 12 electrode sites. Negative voltage is plotted upwards.

on the other hand, can be tackled with spatial filter strategies (Makeig et al., 2009) and seem a less dramatic problem. Avoidance of long and loose cables and tight fitting of the small and lightweight amplifier, in combination with wireless signal transmission, led to a reduction of otherwise notoriously difficult technical EEG artifacts to an extent that subjects could freely and naturally behave during data acquisition.

Another interesting result is the smaller P300 ERP and lower single-trial classification accuracy observed for outdoor recordings. Whether this reflects residual noise or a difference in cognitive processing resources invested (Debener et al., 2002) remains open. Since cognition likely depends on the concurrent active behavior expressed by individuals (Gramann et al., 2011), future mobile EEG studies will be necessary to shed light on this issue.

Various fields may benefit from wireless EEG technology, such as EEG recording from individuals who have difficulties in sitting still. More fundamentally, mobile EEG enables the truly simultaneous acquisition of brain activity and natural behavior, which may be of interest in social neuroscience and emotion research. Finally, the development of small, wireless, and cost-effective EEG systems is necessary to achieve ubiquitous BCIs (Graimann et al., 2010), but present evidence for successful online neural decoding in real-world situations is scarce (Wang et al., 2011). By demonstrating that low-cost mobile EEG is possible, we hope to spark enthusiasm towards more ecologically valid EEG experimentation. In the future, mobile BCIs could predict, and thereby prevent, maladaptive human behavior in everyday life.

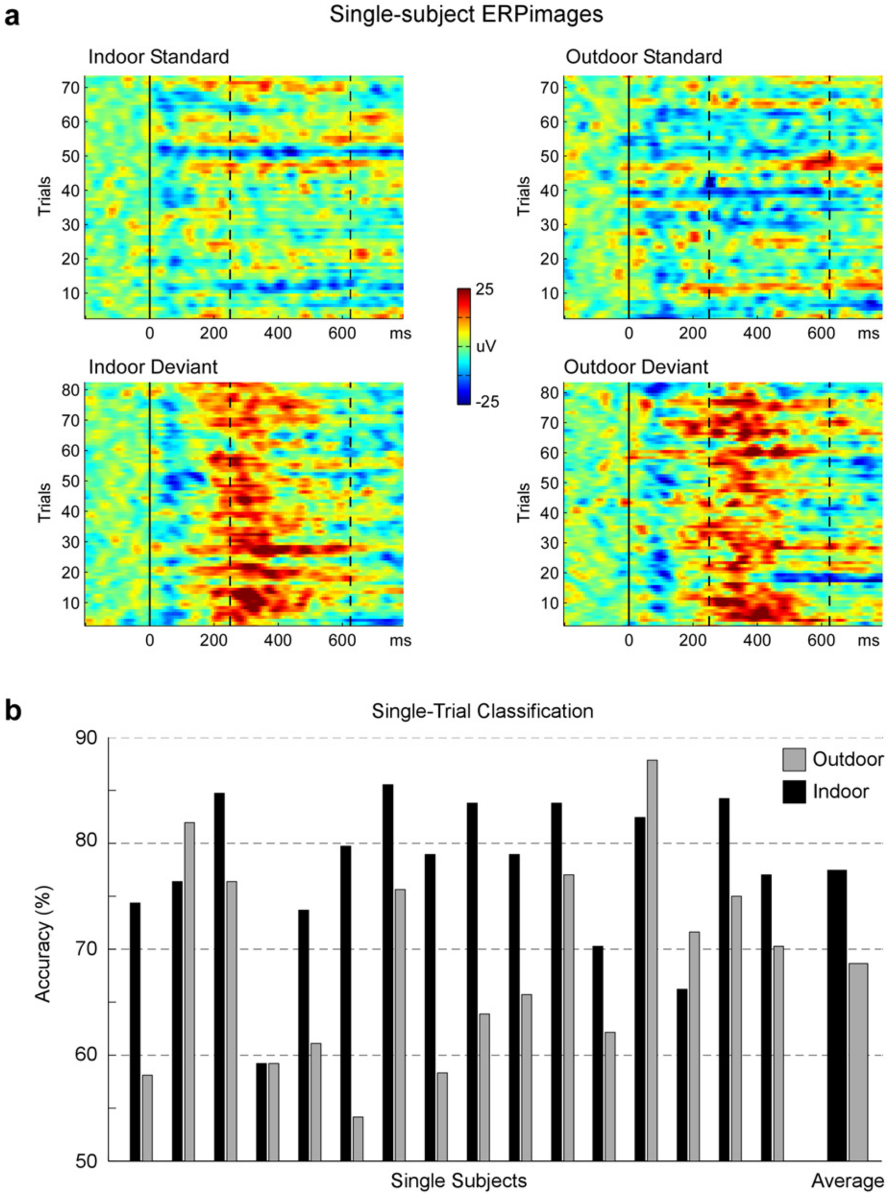

Figure 2. a: Single-trial amplitudes from a single subject for standard and deviant trials recorded indoors and outdoors (averaged across P3, Pz, and P4). Black vertical line indicates stimulus onset, dashed lines the P300 interval. A moving average of size 3 was used for vertically smoothing. b: Single subject and group average EEG single-trial classification results plotted as percent accuracy for indoor and outdoor recordings. Chance level is 50%.

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