Reading The Mobile Brain: From Laboratory To Real-World Electroencephalography

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MUM 2017, November 26–29, 2017, Stuttgart, Germany
ACM 978-1-4503-5378-6/17/11.
https://doi.org/10.1145/3152832.3156560

Abstract
It is increasingly viable to measure the brain activity of mobile users, as they go about their everyday business in their natural world environment. This is due to: (i) modern signal processing methods, (ii) lightweight and cost-effective measurement devices, and (iii) a better, albeit incomplete, understanding of how measurable brain activity relates to mental processes. Here, we address how brain activity can be measured in mobile users and how this contrasts with measurements obtained under controlled laboratory conditions. In particular, we will focus on electroencephalography (EEG) and will cover: (i) hardware and software implementation, (ii) signal processing techniques, (iii) interpretation of EEG measurements. This will consist of hands-on analyses of real EEG data and a basic theoretical introduction to how and why EEG works.

Author Keywords
EEG; Signal Processing; Mental Workload; Notifications; Neuroergonomics;

ACM Classification Keywords
H.5.2 [User Interfaces]: Evaluation/methodology

Figure 1: Participant wearing a mobile EEG device whilst performing a spatial navigation task in a CAVE-like virtual environment. Photo: Lewis Chuang.

Introduction

Measurements of cortical activity are increasingly accessible. Recent years have witnessed a rapid decrease in their cost, both in terms of purchase price and physical encumberance. This has resulted in their integration, amongst other implicit and physiological signals, as an input device in mobile and ubiquitous computing [17]. One notable example is electroencephalography (EEG), which refers to the attachment of skin electrodes to the scalp in order to measure changes in the electrical potential of neurons in the brain. The fundamental motivation for doing so is the belief that EEG measurements reflect cognitive processes that take place in the brain. In other words, EEG measurements could provide us insight into: (i) how sensory stimuli might be perceived by users, (ii) hidden mental states (e.g., focused attention) that could be induced by interface devices, (iii) the amount of *mental resources* required to perform the same task equally well under different scenarios, amongst other reasons.

Besides lowered costs, EEG is increasingly viable as a tool for “reading” the human mind because of advances in: (i) signal processing algorithms that increase the cortical signal to non-cortical noise in EEG recordings, and (ii) a better understanding of how the mind works. While we are far from a complete understanding of how the human mind works, or how 100 billion neurons might interact with one another in order to give rise to our conscious experience of the world we inhabit [9], technological advances have facilitated our understanding by ensuring that we are indeed measuring cortical activity. The miniaturization of amplifiers, sometimes housed within the local electrodes itself, boost the signal at the recording site and allow for more user mobility. Besides this, signal processing algorithms are constantly improved upon to filter out non-cortical activity in the EEG recordings.

Improvements in signal processing methods and the hardware design of EEG recording have also facilitated its deployment in everyday settings [6, 3]. The introduction of dry electrodes have drastically reduced preparation time by removing the need to apply wet electrolyte gel as a conductive medium [4]. More recently, novel electrode montages have been proposed to render EEG electrodes inconspicuous. In-ear electrodes and electrodes placed around the ear allow users to wear EEG throughout the day without appearing out of place [1, 8]. These developments, and others, have lowered the barrier for integrating EEG recordings as an input modality for real-world computing applications.

Although technology has made it easier to record the cortical activity of users engaged in real-world activities, the appropriate application and interpretation of EEG recordings will be an issue. For instance, it is common for researchers with the objective of *reading* the minds of their targeted users to be sorely disappointed when they are greeted by undecipherable squiggly lines, namely changes in the electrical potentials of EEG electrodes. Some manufacturers might provide read-out indices for operational concepts, such as *mental workload* and *task engagement*. Nonetheless, generic off-the-rack measures rarely serve the purpose of expressing the bespoke purposes that a given scenario or interface is designed for.

Therefore, we will address the practical concerns relating to the use of EEG and their theoretical fundamentals.

Program

This half-day tutorial will consist of short lectures on EEG theory, interspersed with practical sessions. Participants will be introduced to open-source software tools that they will use to analyze datasets alongside the instructors. The supplied datasets were collected in two different studies (see

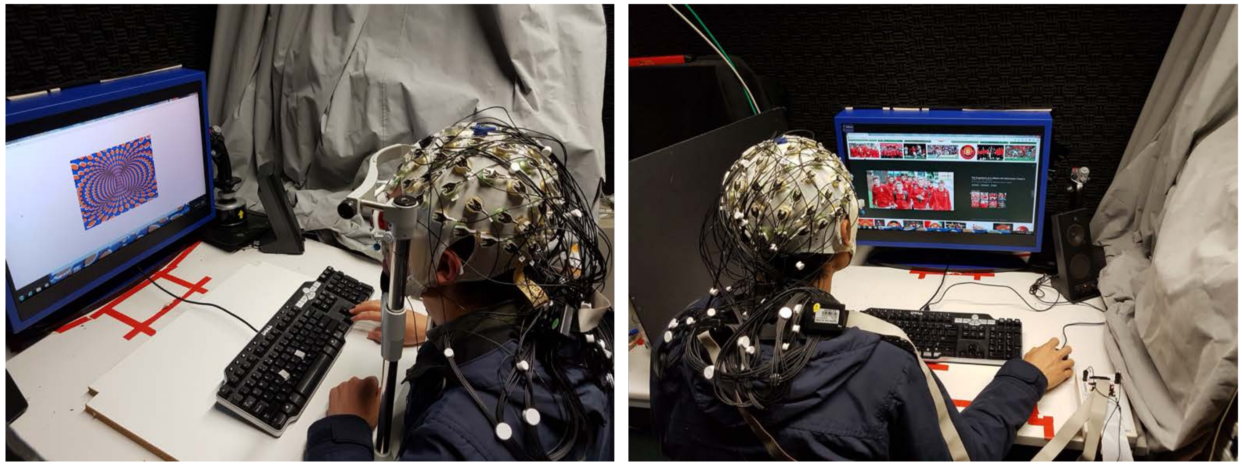

Figure 2: In this image, a participant is shown wearing a cap with high-density 64 EEG channels. On the left, the participant is performing a visual psychophysics task (i.e., *volumetric shape perception from texture gradient*) in a traditional setup, which tries to minimize muscle-induced EEG artifacts by ensuring that the participant is fixed in a chin-rest and that response movements are kept to a minimum (i.e., button presses). On the right, the participant is performing an internet image search task (i.e., *find the best football team in the world*), which requires copious and diverse arm and finger movements. Image: Lewis Chuang.

next section). These datasets were collected with three EEG systems: a 14-channel low-cost system, a 24-channel system with mobile phone integration, and a 64-channel medical-grade system.

By the end of the tutorial, participants will understand how EEG recording devices could be integrated with other devices, pre-processing steps for preparing EEG data for subsequent analyses, the use of independent component analysis for the removal of non-cortical artifacts, and the derivation of some established metrics of EEG data for inferring user states.

Table 1: Program Overview

Time	**Topic**	**Format**
1300 hrs	Introduction to EEG	Lecture
1330 hrs	Setting up an EEG system	Demonstration
1415 hrs	Frequency-Based Analyses	Hands-On
1500 hrs	*Break*	
1530 hrs	Signal Pre-processing	Hands-On
1600 hrs	Independent Component Analysis	Hands-On
1630 hrs	Interpreting EEG Responses	Lecture
1700 hrs	Event-Related Analyses	Hands-On
1745 hrs	Questions	
1800 hrs	*End of Programme*	

Use Case Scenarios

Mental workload

EEG data were collected from twenty-two participants who performed a standardized *mental workload* task on a mobile phone [10]. More specifically, they performed a visual single matching digit recall N-back task with two levels of task difficulty (i.e., N=0 vs N=2), whereby *mental workload* was varied by increasing the number of numeric digits that they had to maintain in short-term working memory. Digits were visually presented one after another (duration=1 sec). In the 0-back task, participants had to compare each presented digit with the target digit presented at the start of the experiment. They had to respond whenever a match was detected. In other words, they only had to maintain one digit in their short-term working memory. In the 2-back task, participants had to respond whenever a presented digit matched an item presented two digits before. Thus, they had to maintain two digits in short-term working memory at any given time and to update their memory with every new digit presentation. The N-back task is an established paradigm for manipulating *mental workload* and is highly robust in yielding discriminative EEG recordings, e.g., [2]. This dataset will be used to demonstrate frequency-based analyses for inferring the level of *mental workload* experienced by the user. This dataset was collected with a 14-channel low-cost system. In addition, we provide a comparison data sample that was collected independently and with a 24-channel EEG system with mobile phone integration.

Auditory in-vehicle notifications

EEG data were collected from thirty participants who responded to auditory notifications that were designed to alert drivers to changes in driving conditions or to cue them to perform certain tasks [5]. This dataset is sub-divided into one that was collected under in a highly controlled psychophysics laboratory and another that was collected in a virtual reality vehicle simulator. With this dataset, we will demonstrate how environment variables could induce differences in the raw data. More importantly, we will demonstrate how signal processing techniques can significantly clean up the recording data. This dataset will also be used to demonstrate event-related analyses. Specifically, this paradigm allows us to make inferences on how different types of auditory notifications (i.e., verbal vs. icons) might be processed by the brain differently.

Outlook

We seek to address many of the issues that one can expect to encounter when first implementing EEG recordings. We introduce many of the software tools for processing EEG data and the main approaches for deriving principled inferences from EEG data. This tutorial does not cover brain-machine interfaces, which is a specialized research area that focuses on how EEG recordings can be employed as a real-time control input or as a passive indicator of the user's mental state [12, 11, 14]. Also, other neuroimaging devices that are suitable for mobile use are not covered here, in particular functional near-infrared spectroscopy [13, 7].

EEG measurements can be a reliable measure of a user's mental state. One particular advantage that it offers is that it provides an estimate of the mental capacity of a user without requiring an explicit response from the user. For example, we can measure the involuntary response of the brain to task-irrelevant stimuli in the environment, in order to evaluate how engaged users are with their given task [15]. In other words, it is a non-obtrusive approach that complements explicit interviews and/or performance measures, by filling a gap that such methods leave behind. Thus, it is an approach with the potential to ubiquitously assess and facilitate the implicit interactions between humans and their mobile computing systems [16].

Biographies

Christiane Glatz is a researcher at the "Cognition and Control for Human-Machine Systems" group at the Max Planck Institute for Biological Cybernetics in Tübingen, Germany. Her research investigates the neural mechanisms that underlie how auditory warnings cue and sustain visual attention during steering. She studied Cognitive Science at the Universities of Osnabrück (BSc) and Neural and Behavioral Sciences at the International Max Planck Research School for Cognitive and Systems Neuroscience, University of Tübingen (MSc). Currently, she is pursuing her PhD in Cognitive Neuroscience at the University of Tübingen.

Thomas Kosch studied Software Engineering at the University of Stuttgart in Germany with a focus on signal processing algorithm design, analysis of physiological sensory data, and the implementation of context-aware computing systems. He is currently a PhD student of the Human-Centered Ubiquitous Media group under the supervision of Albrecht Schmidt at the Ludwig-Maximilian University of Munich. His research encompasses the analysis and interpretation of physiological sensory data to explore its usage in adaptive computer environments. This includes the interpretation of cognitive processes to design workload-aware user interfaces. This is complemented by the development of interactive assistive systems in home and workplace settings. Furthermore, his interests comprise eye tracking, electroencephalography, electromyography, machine learning, and image processing.

Marie Lahmer is a Master student in Cognitive Science at the University of Tübingen, where she graduated as Bachelor in Cognitive Science in 2015. She has been working as a research assistant at the Max Planck Institute for Biological Cybernetics in Tübingen since 2016. For her Master thesis, she uses EEG to research auditory warnings for emergency braking situations.

Jonas Ditz is a Master student in Bioinformatics at the University of Tübingen. He received a Bachelor of Science in Bioinformatics form the Freie Universität Berlin in 2014. He worked as a research assistant at the University of Upsala and joined the Max-Planck Institute for Biological Cybernetics as a research assistant in 2015. He works on mobile eye tracking and researches on auditory-induced alpha-band lateralization for BCI control.

Albrecht Schmidt is a professor of the Human-Centered Ubiquitous Media Group at the Ludwig-Maximilian University of Munich. His central research interests are novel user interfaces and innovative applications enabled by Ubiquitous Computing. Prior to this appointment, he was a professor at the Universities of Stuttgart and Duisburg-Essen. This was preceded by a joint position between the Fraunhofer Institute for Intelligent Analysis and the University of Bonn. He studied Computer Science in Ulm and Manchester. Afterwards, he worked as a researcher at the University of Karlsruhe and at the Lancaster University. In 2003, he completed his PhD thesis on the topic "Ubiquitous Computing - Computing in Context". Before he became a professor at the B-IT-Center, he headed the DFG-funded "Embedded Interaction Research Group" at the Ludwig-Maximilians University in Munich. His teaching and research interests are in Media Informatics and in particular in the areas of user interface engineering, pervasive computing, and mobile interactive systems.

Lewis Chuang leads research on "Cognition and Control for Human-Machine Systems" at the Max Planck Institute for Biological Cybernetics in Tuebingen, Germany. He employs gaze tracking and physiological sensing (i.e., EEG) methods to understand how humans seek out and process information when interacting with closed-loop machine systems (e.g., vehicle handling). He read Psychology at the Universities of York (BSc) and Manchester (MPhil) and received his PhD in Neuroscience at the University of Tübingen. He is currently a principal investigator within the SFB-TRR 161 for "Quantitative Methods for Visual Computing". Previous projects include "myCopter-Enabling technologies for personalized aerial vehicles (www.mycopter.eu)".

Acknowledgements
ML and JD would like to thank mBrainTrain for their travel scholarships. The remaining authors would like to acknowledge the support from the German Research Foundation within projects C02 and C03 of SFB/Transregio 161, as well as the Amplify project which received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement no. 683008).

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