Brain Computer Interfaces for Mobile Interaction: Opportunities and Challenges

Mariam Hassib
University of Stuttgart
Stuttgart, Germany
mariam.hassib@vis.uni-stuttgart.de

Stefan Schneegass
University of Stuttgart
Stuttgart, Germany
stefan.schneegass@vis.uni-stuttgart.de

Abstract

As Brain-Computer interfaces are getting less complex and more portable, they provide opportunities to be used in mobile interaction. Collecting information about the users' mental states passively, or actively providing signals for hands-free interaction with various systems and applications, are among the rising uses of BCIs of the future. However, many challenges still exist in the design, aesthetics, and reliability of BCIs to be used in everyday life. In this paper, we introduce challenges hindering BCIs from becoming mainstream in our lives and explore several use cases in which BCIs can be used to enrich the mobile interaction.

Author Keywords

Brain Computer Interface; Wearable; Mobile Interaction.

ACM Classification Keywords

H.5.2 [Information interfaces and presentation]: User Interfaces. - Graphical user interfaces.

ACM 978-1-4503-3653-6/15/08. http://dx.doi.org/10.1145/2786567.2794309

Introduction

Brain Computer Interfaces (BCIs) are currently making the transition from being high complex lab-only devices to mass-market products (cf., Table 1). During this transition, the ease of use, mobility, and usability increase. New devices utilize Bluetooth as an easy way for connecting the device to the computer and run several hours on battery.

	Emotiv EPOC+	Neurosky Mindwave Mobile	Myndplay Brainband	Muse	OpenBCI
Chip	Emotiv	Neurosky	Neurosky	InteraXon	TI ADS1299
Electrodes	14 (+2 ref) wet	1 dry	1 dry	5(+2 ref)	8 per board
Senses	7 emotional states	2 mental states, 4 EEG signals	2 mental states, 8 EEG signals	2 mental states	Raw EEG
Connectivity	Bluetooth 4.0 LE	Bluetooth 2.1	Bluetooth 2.1	Bluetooth 2.1	Bluetooth 4.0 LE
Battery	6h	8h	8h	5h	external batteries

Table 1: Overview of the most common consumer BCIs and their EEG chip, type and number of electrode, connectivity, and battery.

Although the number of channels is mostly reduced compared to medical devices, off-the-shelf BCIs provide information about the mental state of the user including level of focus, or meditation. This information and the raw EEG signals provided by BCIs may be used in several ways. On the one hand, by implicitly sensing the user's mental state, provide rich data the can be utilized in the area of personal informatics (PI), such as tracking the user‘s mental activity and trends through the day and providing feedback. On the other hand, explicitly where users utilize their raw brain signals to interact with mobile devices.

Nevertheless, even the current commercial BCIs are mostly used in the lab rather than used in everyday life, making most of them so far rather useless for the average user. The reasons for this include the lower signal resolution, low usability, the mostly futuristic look and thus the reduced social acceptability. The usefulness for healthy users is to this day limited. Although APIs are available, the number of applications providing a benefit for the user is still low.

In this work, we discuss the challenges that need to be tackled for BCIs allowing their usage in everyday life in explicit and implicit interaction, as well as discuss possible application scenarios in the mobile domain.

Related Work

There are many techniques to measure brain signals ranging from invasive to non-invasive ones. Although invasive techniques provide more accurate and less noisy signals, they are risky and not suitable mobile applications for healthy users. Non-invasive techniques such as functional near infra-red spectroscopy (fNIRS) and electroencephalography (EEG) have recently become more available to the masses and affordable with the emergence of more commercial devices (cf., Table 1).

EEG signals from the brain can be used for explicit and implicit interaction. For instance, they can be used for explicit control tasks such as selecting a contact on a mobile phone [1] or controlling a smart home [3]. Scenarios for implicit interaction include neurofeedback applications for giving feedback to the user about their mental state. For example, for retaining focus during reading tasks [7] or personalizing computer games by adapting the content and difficulty depending on the player‘s state of mind [9]. Additionally commercial BCIs are used for recognizing different cognitive activities such as reading and listening to music [6] or annotating videos by detecting their highlights [5].

Figure 1: Examples of consumer BCI: the Emotiv EPOC and the Myndplay Mindband.

Challenges of Everyday Life BCIs

A multitude of challenges stand in the way before BCIs can be used as everyday wearables. These challenges mainly fall into three categories: (1) signal quality and artifacts, (2) usability and integration, and (3) aesthetics.

EEG signals are typically weak signals measured in microvolts, which makes them highly susceptible to noise from various sources. Head movements and eye blinks introduce motion artifacts to the EEG signal which should be removed prior to emotion extraction [8]. Any excessive movement while wearing the EEG sensor also adds further motion artifacts to the signal. Various algorithms for artifact removal currently exist. However, it is still a challenge to obtain a noise free EEG signal [4]. Reduced signal reliability due to electrode drift and dryness over time is also an issue. Finally, machine learning and algorithmic complexity pose significant challenges for an everyday BCI. Additionally, the signal classification requires a considerable amount of training to be able to provide valid information.

On the aspect of usability, current commercial BCIs are trying to achieve an integration into the microcosm of the user's devices by providing mobile APIs and Bluetooth connectivity. However, battery life, device weight, and form factors are still important issues. A trade off between the cost of high sampling rates, an 'always-connected' state, and battery life has to be made to sustain the long hours required for robust day-to-day usage. Additionally, users should not have to equip themselves with complicated hardware or long setup times. Many devices currently use wet electrodes dipped in gel or saline solution which is not suitable for everyday life. Nevertheless, recent research shows that dry electrodes are capable of producing similar results compared to wet ones [2].

A final aspect that needs to be considered is the visual aesthetics of such a device. While most current systems rather look futuristic (cf., Figure 1) and may not be socially accepted, everyday life BCIs should be able to weave themselves into the clothing of the user, for example, by integrating into hats, ice caps, glasses, or other head worn garments. In this way, users can wear the BCI on a daily basis.

BCI Opportunities for Ubiquitous Interaction

In this section we discuss use cases for using BCIs for both implicit and explicit mobile and ubiquitous interaction in everyday life.

Enriching Interaction with Mobile Devices

Hands-free interaction with mobile devices, smart-watches could be made possible using BCIs. Brain signals such as Event Related Potentials (ERP) or Visual Evoked Potentials (VEP) which can currently be sensed by off-the-shelf BCIs can be used for explicitly control. Applications such as hands-free calling a contact, navigation, zooming, or other control functions can be realized. Concentration or meditation levels or can be utilized as implicit input that helps providing an adapted user interface depending on the current capabilities of the user. For instance, if the user gets stressed, the interface might be simplified.

Implicit Quantified Self

The most common source for Quantified Self (QS) data nowadays comes from fitness tools such as bracelets and mobile phones. These tools mainly provide motion data such as actual step-count or motion type. We envision the usage of BCI to get knowledge about the mental and emotional state of the user communicated through mobile devices. This can be either used stand alone or support the classical QS data, for example, by handing out advices on what activity needs to be done to increase the happiness of the user. This can be achieved by correlating positive states with performed activities.

Enriching Mobile Social Interaction
BCIs gather emotional data from the user. While this data is relevant for self-reflection, it may also help to better understand others. Recently, the mood of the user can be added to social media posts. By using BCIs, this can be automated. Furthermore, this information can be communicated to remote persons such as the partner or friends (e.g., during chatting or automatically). This will generate awareness of the emotional condition.

Conclusion
In this work, we present challenges and use cases for an everyday life BCI. We present recent off-the-shelf BCI systems and discuss related work in explicit and implicit interaction using BCI. We argue for the use of BCIs in the future in everyday life for a in controlling other systems in the user's microcosm (mobile phones/smart watches) and collecting rich data about the user's mental state implicitly.

Acknowledgments
The research leading to these results has received funding from the European Union 7th Framework Programme ([FP7/2007-2013]) under grant agreement no. 323849.

REFERENCES
1. Andrew Campbell, Tanzeem Choudhury, Shaohan Hu, Hong Lu, Matthew K Mukerjee, Mashfiqui Rabbi, and Rajeev DS Raizada. 2010. NeuroPhone: brain-mobile phone interface using a wireless EEG headset. In *Proc. workshop on Networking, systems, & applications on mobile handhelds*. ACM, 3–8.
2. Yu Mike Chi, Yu-Te Wang, Yijun Wang, Christoph Maier, Tzyy-Ping Jung, and Gert Cauwenberghs. 2012. Dry and noncontact EEG sensors for mobile brain–computer interfaces. In *IEEE Transactions on Neural Systems & Rehabilitation Engineering,*. IEEE, 228–235.
3. Wei Tuck Lee, Humaira Nisar, Aamir S Malik, and Kim Ho Yeap. 2013. A brain computer interface for smart home control. In *Proc. ISCE*. IEEE, 35–36.
4. Vojkan Mihajlovic, Shrishail Patki, and Bernard Grundlehner. 2014. The impact of head movements on EEG and contact impedance: An adaptive filtering solution for motion artifact reduction. In *Proc. EMBC*. IEEE, 5064–5067.
5. Alireza Sahami Shirazi, Markus Funk, Florian Pfleiderer, Hendrik Glück, and Albrecht Schmidt. 2012. MediaBrain: Annotating Videos based on Brain-Computer Interaction. In *Proc. MuC*. Oldenbourg Verlag.
6. Alireza Sahami Shirazi, Mariam Hassib, Niels Henze, Albrecht Schmidt, and Kai Kunze. 2014. What's on your mind?: mental task awareness using single electrode brain computer interfaces. In *Proc. AH*. ACM.
7. Daniel Szafir and Bilge Mutlu. 2012. Pay attention!: designing adaptive agents that monitor and improve user engagement. In *Proc. CHI*. ACM, 11–20.
8. Jonathan R Wolpaw, Niels Birbaumer, Dennis J McFarland, Gert Pfurtscheller, and Theresa M Vaughan. 2002. Brain–computer interfaces for communication and control. In *Clinical neurophysiology*. Elsevier, 767–791.
9. Myeung-Sook Yoh, Joonho Kwon, and Sunghoon Kim. 2010. NeuroWander: a BCI game in the form of interactive fairy tale. In *Proc. Ubicomp, Adj.* ACM, 389–390.