M.Sc. Thesis proposal

Classifying brain activity using low-cost biosensors and automated time tracking

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CONTENTS

I. BACKGROUND

A. Device use

People spend more time than ever using computing devices[**TODO**]. As services, entertainment, and work, moves online this trend is expected to continue. While several studies have been tracking how people spend their screen time, and how that varies with demographics, is not publicly available [**TODO**].

Furthermore, how different computer activities affects the user behaviorally and neurologically is of interest for many areas of research, including:

- the impact of screen time for adolescents [**TODO**]
- attention span among media multitasking adults [**TODO**]
- psychological well-being [4].

Companies like RescueTime, HubStaff, etc. offer automated time tracking as a service. These services let the user track their screen time by installing a program on their device which tracks the active application and sends the data to their servers for storage and analysis. The user can then view their data in a dashboard on the service's website. There services are marketed towards teams and professionals, who want to keep track of individual and team productivity.

However, by collecting detailed and non-anonymized behavioral data on the user these services bring significant privacy concerns, especially in cases where the data is shared with a team or an employer.

B. Low-cost functional brain imaging

Functional brain imaging methods such as fMRI and fNIRS, have been used to study the relationship between cognitive or physical activity, and brain activity [1][3]. The more accurate methods such as fMRI are costly and inflexible/impractical for many uses. However, the recent availability of low-cost biosensors such as EEG, HEG, and fNIRS, enables studying brain activity during real-life tasks.

Functional brain imaging techniques hold the promise of relating cognition to physical activities and brain structures. As an example it has been shown that it is possible to classify what task a participant is undertaking using fMRI[1], which has been replicated using EEG and low-cost sensors[2]. EEG-based BCIs are not without their limitations [5], yet visual evoked potentials (VEPs) have been shown to be sufficient for high-speed BCI applications [6].

II. PROBLEM DESCRIPTION, RESEARCH GOALS AND QUESTIONS

We want to investigate whether EEG and other low-cost biosensors can be used to accurately classify device activity in a broader context than previous studies.

III. Methodology

IV. Scientific contributions

- The open source automated time-tracker ActivityWatch.
- Relationships between device activity and brain activity, as measured by EEG.

V. Resources

- ActivityWatch, an open source automated time tracker (already developed by the author, but never before used in a scientific publication)
- OpenBCI Cyton biosensing board (8 channel) and Ultracortex headset
- HEGduino

VI. References

References

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