M.Sc. Thesis proposal (SUPER EARLY DRAFT)

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

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CONTENTS

NOTES & TODOS

I. BACKGROUND

People spend more time than ever using computing devices. Work, entertainment, and services, have been steadily moving online over the last few decades, and this trend is expected to continue. While several studies have been tracking how people spend time on their devices a wider study of how people's app usage has changed over time and how it varies with demographics, is not publicly available.

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

- psychological well-being, such as depression and social anxiety [1][2], stress [3], self-esteem, life satisfaction, loneliness, and depression [4].
- the impact of screen time on children and adolescents [5].
- attention span among media multitasking adults [3].
- enhancing personal productivity [6].

Understanding device use and the underlying cognitive processes are essential when designing for motivation, engagement and wellbeing in digital experiences [7].

A. Automated time trackers

Automated time-trackers have been developed for computing devices for various applications such as tracking productivity, managing excessive use of social networking sites (SNSs).

1) Commercial use: Companies like RescueTime [8], Hubstaff [9], and others 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. Some of these services, like RescueTime and Hubstaff, are marketed towards teams and professionals, who want to keep track of individual and team productivity.

However, these services have some issues for use by researchers and individuals alike. Notably, their collection of detailed and non-anonymized behavioral data into a centralized system bring significant privacy concerns, especially in cases where the data is shared with a team or an employer.

Other limitations of these services, such as low temporal resolution and lack of detail, cause additional issues for certain tasks that are timing-sensitive (such as ERPs) or preprocessing steps that can take advantage of high level of detail (like classifying activity).

2) Research use: Previous research has been published which used automated time trackers, such as TimeAware [6] and ScreenLife [10]. However, the previous contributions are, like the commercial services, not open source or permissively licensed and therefore not suitable for use by external researchers.

3) ActivityWatch: As a solution to these privacy and data resolution issues we have build ActivityWatch, a free and open source automated time tracker [11]. ActivityWatch remedies issues with previous solutions around source availability/licensing, privacy, and cross-platform support.

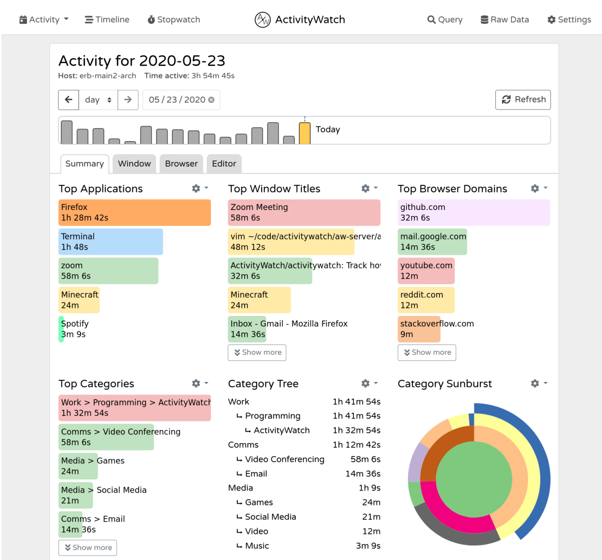

Fig. 1. ActivityWatch activity dashboard. Showing top applications, window titles, browser domains, and categories.

B. Low-cost functional brain imaging

Functional brain imaging methods such as fMRI, fNIRS, and EEG, have been used to study the relationship between cognitive or physical activity, and brain activity [12][13][14]. 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 [12], which has been replicated using EEG and low-cost biosensors [14].

But they are not without their limitations, among them a low signal-to-noise ratio [15], yet visual evoked potentials (VEPs) have been shown to be sufficient for high-speed BCI applications [16].

Convolutional Neural Networks (CNNs) have been successful in classifying time series in general [17], and EEG data in particular [18]. Additionally, Hierarchical Neural Networks (HCNNs) have been used for EEG-based emotion recognition [19].

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. This could be useful to future BCI applications where a command might be specific to a particular context.

A. Goals

- TODO

B. Questions

Can the OpenBCI system be used to...

- Classify which device activity the user is engaging in?

C. Challenges

- EEG data collection (limited time for data collection)
- Scope creep (hopefully resolved by the time this document is finalized)
- TODO

III. Methodology

We will collect EEG data from subjects while they are using their own computer with ActivityWatch installed. We will then categorize the activity that ActivityWatch recorded and use it to train an EEG classifier on device activity.

IV. Scientific Contributions

- The open source automated time-tracker ActivityWatch.
- A EEG classifier for device activity.
- Relationships found 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

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