Bachelor–Thesis

in

Allgemeine Informatik

A day in the life of our eyes

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Abstract

Using the eyes as input modality has a long history in human computer interaction. However, most eye-related work is focused on using gaze only. It is only recently that eye-movement is considered a context source and a possibility for activity recognition. Still eye-related research is bound to controlled laboratory settings and of short-term nature as existing video-based eye-trackers do not allow long-term data collection in a daily life setting.

In this work we built an experimental system, including an activity centric study design and technical implementation. The system is includes an electrooculography based eye-tracker, as well as a user interface and video based ground truth recording. We use this system to perform a user study with seven participants collecting data over a time of 86.7 hours in a daily life setting and verify the soundness and validity of the system by verifying existing findings using the recorded data. The experimental system and collected data form the base for future daily life eye-movement related work.

Keywords: *EOG, eye tracking, human computer interaction, activity recognition*

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Abbreviations

ACK	Acknowledge
ADC	Analog/Digital Converter
AIDL	Android Interface Definition Language
API	Application Programmer Interface
CRNT	Context Recognition Network Toolbox
EDA	Exploratory Data Analysis
EOG	Electrooculography
GUI	Graphical User Interface
HCI	Human Computer Interaction
I/O	Input/Output
IPC	Inter-Process Communication
MAC	Media Access Control
NDK	Native Development Toolkit
NiMH	Nickel-Metal-Hybrid
PIR	Passive Infrared Sensor
POJO	Plain Old Java Object
RTC	Real-Time Clock
SPP	Serial Port Profile
TMSi	Twente Medical Systems International
USB	Universal Serial Bus
UbiComp	Ubiquitous Computing

CHAPTER 1

Introduction

In the past few years, the way we use computers has changed drastically. They are no longer encased in laptops and desktop machines, but have turned into smartphones and game consoles. Traditional input devices such as mouse and keyboard have been substituted for touch-screens, motion sensors and gesture recognition. This new generation of computers is seemingly becoming intelligent by gathering context information about their environment using sensors and machine learning algorithms.

An emerging source of such context information are the eyes. Established applications in this regard are for example drowsiness detection using the blink rate [Sch08]. In the Human Computer Interaction (HCI) domain they're used as input modality [Cou11], but they can also be used for activity recognition [Bul11] and even contain markers for mental illnesses [Vid11].

However, all eye-related studies performed so far are of short length (up to four hours) and mostly within a controlled laboratory setting. In this work we recorded the eye-movements of seven participants during their daily life over a period of at least twelve hours; no such dataset existed as of yet. We devised activity centric recording procedures and built a system that supports such a recording.

1.1 Context and Objectives

We want record eye-movement data over a whole day and then exploratively look for patterns and trends. Until now, no such study has been performed as the technical

prerequisites were not available. Hence, we needed to build a system that supports such long runtimes and is unobtrusive enough to be worn during the period of twelve hours.

In addition to creating the technical prerequisites, we needed to design a study and devised proper procedures. We designed a user training introducing them to the system and their duties as participants, thus enabling them to perform a day-long data recording session. Within a months time, we performed that recording with seven participants.

Once the data is recorded, we process it and apply methods of exploratory data analysis in order to find interesting trends and patterns in the data. After segmenting the data into handleable chunks (also called windows), we go on to compute several features such as mean blink rate or mean fixation length.

1.2 Challenges

The 12h continuous recording length of the study poses several issues in a mobile environment. All technical components involved in the recording have to be able to run on battery for the required time. Additionally, the motivation and concentration of the participants might be diminishing over time, something the study design must account for.

When performing a study which involves sensible recording equipment, one is bound experience issues during data recording. As the habits of some participants might interfere with recording, we have to provide a participant training that guarantees good data quality. Such habits include touching ones face rather often resulting in signal artifacts or forgetting parts of the wireless recording equipment when leaving the room.

Analyzing the recorded data is a challenge itself. There is no established methodology for analyzing such a vast amount of eye-movement data. Although proper study design should ease the analysis, identifying proper statistical tools remains an open issue.

1.3 Structure of the thesis

Chapters 1–2 introduce the reader to the thesis itself and give an introduction into the background theory necessary to understand the subsequent work. Chapter 3 describes the development of the experimental system in terms of study design and technical

implementation. In chapter 4 we describe the study preparation, data collection and preprocessing. Chapter 5 explains our analysis methodology and framework, but also gives evidence for the soundness of the experimental system. The thesis ends with its conclusion and a list of open questions in chapter 6. See below for an overview.

Chapter 1 serves as an entry point to this thesis. We'll introduce the context of the work and define its objectives, as well as give an overview of the challenges faced during this thesis.

Chapter 2 provides an introduction into topics necessary to understand this thesis. Thus it deals with the human eyes, ubiquitous computing and eye-tracking (with special focus on electrooculography).

Chapter 3 describes the development of the experimental system, including the study design as well as the technical implementation of the recording system.

Chapter 4 lists the circumstances under which we performed the study. We'll present the study preparation, challenges faced during execution and the data preprocessing.

Chapter 5 performs a first analysis of the data. We give descriptive statistics of the dataset and show a preliminary set of trends we found.

Chapter 6 summarizes the work and draws a conclusion. Further open questions and possible applications are presented.

CHAPTER 2

Related work and background

2.1 Human-computer interaction and ubiquitous computing

Human Computer Interaction (HCI) is the study of interaction between users and computers and represents the intersection of computer science, behavioral sciences and psychology [Car00]. Interacting with a computer is compromised of using software and hardware, with the two most prominent input devices being the computer mouse and keyboard.

Ubiquitous Computing (UbiComp) is a human-computer interaction model where the computer is no longer a dedicated device requiring explicit input, but is pervasive and seemingly intelligent by gathering context information and recognizing user activities using sensors. As Weiser defines it is [Wei91]:

> Machines that fit the human environment, instead of forcing humans to enter theirs [...]

A large amount of eye-related research in HCI (or UbiComp, for that matter) focus on using gaze as input modality. The first computer systems controlled using the eyes were gaze-based [Hut89], and fixations still remain a prominent way of implementing eye-movement based computer input [Zha99, Tur11].

Although it is long known that eye-movement contains more information than just the gaze, exploiting that information as a source of context and for activity recognition is a rather new trend. Some applications use the blink rate and blink length as metric for driver

attention [Caf03]. More complex oculographic features can even be used for activity recognition (e.g. if recognizing someone's reading [Bul11]).

There is information in eye-movement of which we know it exists – e.g. bio-markers for mental illnesses [Vid11]. However, there are no algorithms yet to automatically extract that information from measurement data. There might even be information in eye-movement of which we are completely unaware as of yet and it is the purpose of this work to potentially find such information.

2.2 Our eyes

As one of our five senses, our eyes provide several important functions. We use them for scene perception and navigation, for consuming information (i.e. by reading) and even communication. All of those activities have been studied to a great extend, with reading receiving the most attention [Ray98].

A great share of eye-movement related research has been done in psychology and neurobiology, where eye-movement was found closely linked to several cognitive processes [Duc02]. For example, attention and drowsiness can be measured using oculographic features [Liv00, Caf03].

Traditionally, eye-tracking applications were based on fixations, e.g. evaluating product placement strategies [Wed00] or using gaze as an input modality [Zha99]. It is only until recently, that other types of eye-movement are considered as a source of activity and context information. Table 2.1 gives an overview of the different types of eye-movements.

type of movement	**main function**
saccades	Bring images of interest onto the fovea.
fixations	Holds the image of a stationary image on the fovea.
vestibulo-ocular reflex	Stabilizes the image of the seen world during small brief movements.
smooth pursuit	Holds the image of a small moving object on the fovea; aids gaze stabilization during sustained head rotation.
optokinetic reflex	Tracks steady objects when in a moving reference frame.

Table 2.1: A classification of eye-movement types (based on [Lei99])

2.2.1 Types of eye movements

When viewing a visual scene, the eyes perform rapid movement to increase the visual resolution as only a small part of the retina, the fovea, is capable of high accuracy perception. Those rapid eye-movements are called *saccades*, have a typical duration of 10ms to 100ms and reach speeds up to 600deg/sec [Duc07].

When holding our gaze on a specific location within the virtual scene, we perform so called *fixations*. Those fixations are what a lot of the traditional eye-tracking applications are based upon. Fixations can also be used to discriminate certain tasks [Can09], such as reading, talking and counting.

As the eyes are firmly attached to the head, they need to compensate the heads movement; otherwise we would be unable to produce a steady image. Compensating those head perturbations is especially important during locomotion [Gro88] as otherwise we would have to hold still every now and then in order to get a non-blurred image of our surroundings.

The *vestibulo-ocular reflexes* provide such an image stabilization mechanism based on perceived head acceleration. Combined with *smooth persuit* tracking and the *opto-kinetic reflex*, we are able to produce a steady point of gaze on an object, independent of our heads movement.

The eye-movement necessary to follow a moving object is called a *smooth pursuit*. Smooth pursuits are voluntary in a sense, that we can decide to shift our gaze away from the moving object and thus end the pursuit (as opposed to say the optokinetic reflex which is involuntary). We do however, require a moving signal to perform a smooth pursuit and can not produce it without a moving object. Such a moving object can also be our own finger in complete darkness [Gau76].

Tracking stationary objects when ones reference frame is moving (e.g. following street posts from within a moving car), is performed using the *optokinetic reflex*. Although very similar to smooth pursuits this type of eye-movement is involuntary.

2.3 Eye-tracking

When conduction studies or otherwise researching eye-movement one needs a device to measure the movement of the eyes. Some devices can measure the point of gaze on the

plane, as well as the pupil dilation in centimeters. Others can even measure the depth of vision (read, the point of gaze in three dimensional space). The maximum sample frequency is also an important property of an eye-tracking device.

The most common kind of eye-trackers are video-based ones. They record the perceived scene – the so called scene video – and have a camera, paired with an infrared light-source pointing, at the eye. Based on the reflections of the infrared light-source, one can compute the rotation of the eye using video processing gear. Prominent examples of video-based eye-trackers are build by SensoMotoric Instruments GmbH[1] and the Ergoneers GmbH[2] Dikablis (figure 2.1).

Video-based eye-trackers have a maximum sampling frequency of roughly 30Hz, whereas sampling the eye-movement frequency content of 0 – 30Hz requires at least 60Hz (considering the Nyquist-Shannon sampling theorem [Sha49]). Additionally, due to the computational intensity of video processing, the runtime of such eye-trackers when running on battery is limited to a few hours. Both considerations make render them unsuited for long-term studies outside of a controlled laboratory environment.

Figure 2.1: SMI Eye Tracking Glasses (courtesy SensoMotoric Instruments GmbH, Dikablis (courtesy Ergoneers GmbH)

1 http://www.smivision.com/
2 http://www.ergoneers.com/

2.3.1 Electrooculography

A more lightweight eye-tracking approach, by measuring the resting potential of the eye, is Electrooculography (EOG). The eye can be considered a dipole, with its positive pole being at the cornea and the negative pole placed by the retina (figure 2.2). Change in potential of that electric field corresponds to eye-movement and can be measured by placing electrodes on the opposite sides of the eye and a reference electrode on the forehead. EOG signal typically ranges from 5μV/deg to 20μV/deg and has an essential frequency content between 0Hz to 30Hz [Mar11].

Due to the small amplitude of the potential, performing accurate EOG is a challenging task. Several solutions have been developed in Academia, as well as by commercial vendors. The solutions developed in research focus on certain aspects of the device, such as unobtrusiveness e.g. Bulling's EOG Gogles [Bul09] or Vehkaoja's wireless head cap [Veh05], but sacrifice signal quality for their form factor. Commercial devices (such as the Twente Medical Systems International (TMSi) Mobi8) tend to be more rugged and have better signal quality, but are also bigger and more obtrusive.

In general, EOG based eye-trackers provide longer runtime as they do not require powerful video-analysis equipment. Just because they're not video-based, they also don't provide a video of the perceived scene which makes interpreting the eye-tracking data harder. However, combined with their small form factor and ease of use, they are suitable for our purpose.

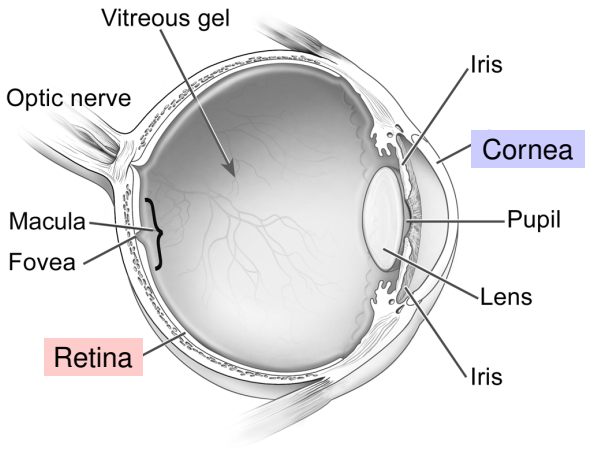


Figure 2.2: The eye forms a dipole between the cornea and retina. Adapted from [NEI].

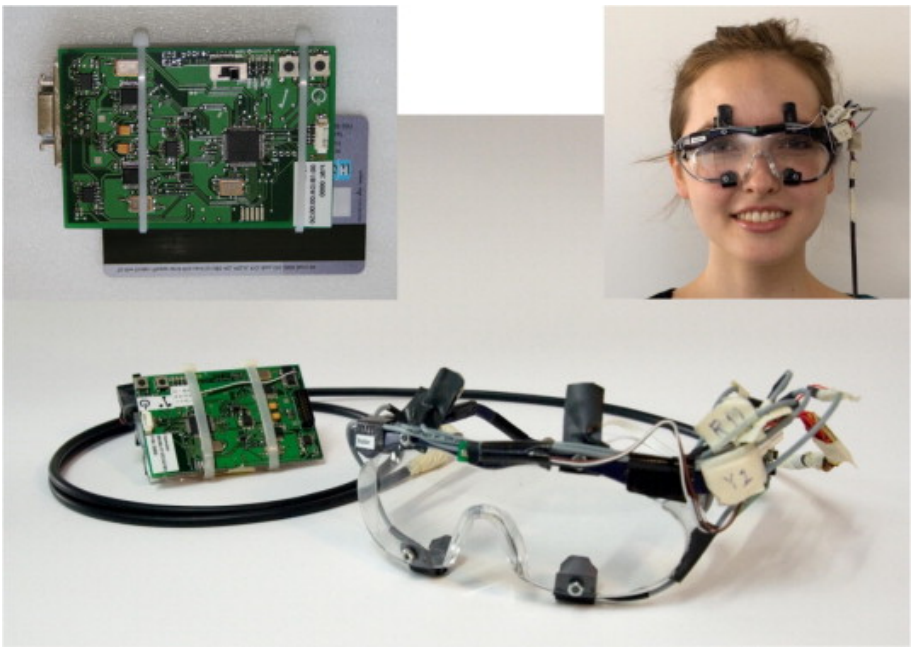


Figure 2.3: Wearable EOG gogles [Bul09]

CHAPTER 3

Development of the experimental system

3.1 Requirements

We had to design a study that records eye-movement data alongside with reference data (ground truth). Once the study is laid out, a technical system has to developed according to the requirements dictated by the study design. The study design described in this chapter, as well as the technical implementation fulfill the following requirements:

- capable of continuously recording eye-movement data with a sampling rate of at least 60Hz for at least 12 hours,
- provides the means for recording proper ground truth in terms of high-level activity labeling and scene video,
- the system respects the participants privacy and provides means for participants self-determination,
- is unobtrusive enough and easy enough to use so that participants are willing to wear it over the anticipated 12 hour recording time,
- after training the participants they set up by the the recording system themselves.

3.2 Ground truth

In order to validate a remote sensor based system, one needs to record sensor independent data of ”what's really going on”. This data is referred to as *ground truth*[1], a term which is very common in the ubiquitous computing community. It has widespread use and is even transformed into other forms, e.g. recording ground truth is called ground-truthing.

While preparing a study, designing proper ground truth collection is a very important task. Poorly designed ground truth does not provide enough information to interpret sensor data or might lack certain details required for an intended analysis. When deciding what kind of ground truth should be recorded by which means, one has a wide range of options to chose from. All methods represent a trade-off between precision, monetary costs and effort for the participant, see table 3.1 for an overview.

One important aspect of recording ground truth is proper time synchronization with the remote sensor data. It is a major design goal for any recording system to ensure that synchronization which can be achieved by either synchronizing the ground truth and sensor recorders before collecting data, or by correcting the different time-bases in post processing. We choose to do the latter, due to technical issues with the SenseCam (see section 3.3.2).

3.2.1 Labeling

A very important kind to ground truth are *labels*. Labels are simple tags/markers describing what's going on, either denoting continuous tasks or points in time. Typically labels are grouped by the task they describe and can be mutually exclusive within their group. Designing a set of labels (also called a coding scheme) is part of the ground truth design process. The coding scheme implicitly defines the expectations of the study as it limits what information the ground truth can contain. Thus, deciding upon labels is a delicate and important task.

We identified the high-level activities we wanted to recognize in the eye-data and made them part of our coding scheme. Most of those activities are pair-wise exclusive (one

1 The term originates from cartography and aerial photography where it refers to data that is collected on the ground vs. the data collected remotely

	Detail	Accuracy	Costs	Effort
A **dedicated observer** follows the participant and annotates their activity	very high	high	very high	very low
Complementary sensing employs sensors to overdetermine the systems state	high	high	low - high	low
Post annotation is performed using video material recorded during the study	medium	high	medium	low
With **self annotation** the participant applies labels themself	low	low	low	high
Experience sampling asks the user at fixed time-interval to answer some questions	very low	very low	very low	high
Legend	very good	good	medium	bad	very bad

Table 3.1: Overview of ground-truthing methods

can not be in- and outside at the same time) with the respective pairs forming mutually exclusive label groups. Additionally, we add free-text point labels to give the participant the chance to mark special events – such as reattaching electrodes or eating (which is likely to induce motion artifacts in the data). Table 3.2 shows the coding scheme used for this work.

We employed *self-annotation* during the study. As there is a trade-off between the descriptiveness and the effort that goes into applying the coding scheme precisely, the amount of labels had to be kept to a minimum. It turned out, that labeling just those four groups correctly is already challenging. To improve the participants motivation to apply the correct labels, each label application was rewarded with £0.1 (10 pence). However, the final amount rewarded was subject to labeling quality, in order to prevent participants from ”overlabeling”.

3.2.2 Video recording and spatial location

Solely relying on self-annotated labels as ground truth is not precise enough for pattern matching and similar techniques. Applying the labels correctly is a challenging task as it is prone to inaccuracies due to the vast amount of attention such labeling requires.

To allow for later correction of those labels (*post annotation*), we made video part of our ground truth. Constant video recording is perceived as very intrusive in terms of privacy,

	vs.
(visually) **interacting** – the participant is currently interacting with a person face to face (incl. video chat). E.g. talking to someone, checking out at a cashier or buying a bus ticket.	**not interacting** – at the moment the participant is not engaged in any form of visual interaction with another individual. One can still be chatting with someone or writing an email.
concentrated – concentrated work is everything the participant actively produces or consumes, such as working at his job, reading a book, playing a (video-)game or driving a car.	**leisure** – is when the participant passively consume information/entertainment or is within a non-goal driven environment such as watching TV or a night out.
inside – a building (at least 4 walls and a rooftop). E.g. a public building, ones home or a public restroom. Open bus stops do not qualify as inside.	**outside** – is not inside a building. Outside is everything where the participant could potentially be hit by wind and rain (also bus stops with a rooftop).
physically active – is every form of prolonged movement. That includes walking to the restroom, but also heading to the bus and exercise.	**not active** – the participant sitting in a chair, sofa or are lying in a bed. Also when he is standing around waiting.
special event – use this label to annotate any special kind of event such as electrodes coming off, changing the batteries of the Mobi or getting excited about something. Whenever there is something you have the feeling that it should be labeled, but it doesn't fit in the categories above, use this label.	

Table 3.2: The coding scheme used for this work

despite the CCTV saturation in public space [Hem04]. Such reservations can be overcome by giving the participants full control over when video is recorded and allowing them to censor the video afterwards.

Some locations have well known link to a specific activity, i.e. the participants movement can be used to infer context. For example, travel can be clearly identified by considering the movement speed (no human being is able to walk 50km/h). We record the participants location using GPS and use it to support post annotation by context inference.

3.3 Technical realization

The technical system used during the study had to integrate and synchronize several datasources (see figure 3.1) – some of them are part of the ground truth, some are the EOG data:

1. **EOG data** is captured using a commercial system called TMSi Mobi8, which integrates instrument amplifiers with 24bit Analog/Digital Converters (ADCs) and uses an undocumented, proprietary protocol to communicate via Bluetooth.
2. **Labels** are applied to by the user (thus performing the self-observation), in order to annotate events and activities, using a mobile application running on a smartphone.
3. **GPS** is recorded using the GPS receiver built-in the smartphone.
4. **Video** is captured as still images using the Microsoft SenseCam [Woo04], as continuous video recording would not only produce too much data, but also be too invasive to the participants privacy.

Using a smartphone as integration platform is a natural choice, as they have a lot of computational power to spare, are highly mobile and are readily available. There are two main smartphone platforms to chose from: Android and the Apple iPhone, where we decided to base this system on Android mostly due to its openness – see table 3.3 for an overview of the criteria involved in the decision.

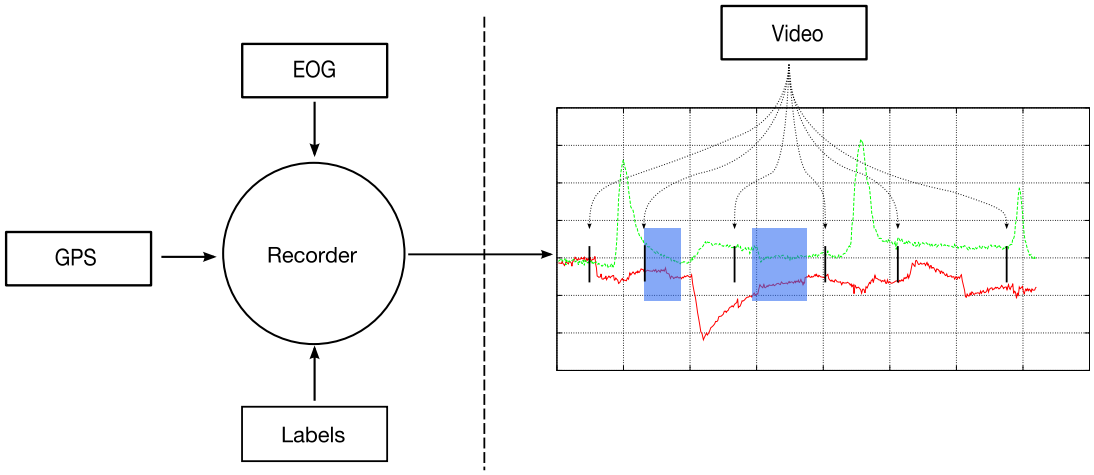


Figure 3.1: Several data streams have to be synchronized

	Android	iPhone
openness	Android is an open source project, is clearly documented and supports modifications down the to operating system.	The iPhone is closed using software mechanisms guarded by license agreements. Opening the system (*jailbreaking*) is possible, but not officially supported.
availability	The development tools are freely available for all major platforms. There are no restrictions in terms of running apps in an emulator or in a phone.	Development tools run only on MacOSX. Although available for free, deploying software to a phone is associated with a fee.
existing experience	The author has gained experience in developing for the Android platform in previous projects and successfully deployed Android Apps using the Android Market.	Some experience in iPhone development exists within the team.

Table 3.3: Criteria for choosing a smartphone platform

3.3.1 TMSi Mobi8 body signal amplifier

Capturing EOG data is a delicate task, as the potentials measured are in a μ-Volt range and are often accompanied by noise and artifacts, still several solutions for recording such data exist. Some attempt to built a very unobtrusive system [Veh05, Bul09] at the expense of signal quality, where others (such as TMSi) focus on quality by reducing noise and motion artifacts[1].

The Mobi had been used in previous projects [Vid11], thus the device itself as well as some experience with that device was available. Reading data from the Mobi is achieved using an undocumented and proprietary protocol over a Bluetooth connection. An open implementation of that protocol exists as part of the Context Recognition Network Toolbox (CRNT) [Ban08] (written in C), which leaves us with several possibilities of integrating the Mobi into the data recording platform (running on Android):

1. port the CRNT TMSi protocol implementation to Java,

1 Motion artifacts are signal errors introduced by moving the electrodes – e.g. when smiling.

2. integrate the protocol implementation into the recording application using the Android Native Development Toolkit (NDK),
3. use the complete CRNT as part of the application, again using the Android NDK.

Approach two and three suffer from the fact, that there is no proper Bluetooth support for the Android NDK, thus we would still use the Java-based Bluetooth stack and pass the received data to the native part. Apart from being inelegant, this solution would most likely result in performance issues as each native call is associated with a performance penalty. So, we choose to port the TMSi protocol implementation to Java and create a clean API for it in the process. An overview of the Java TMSi protocol stack architecture is shown in figure 3.2.

The Java protocol stack implementation is centered around the `TMSiDevice` class, which uses `java.io.InputStream` and `java.io.Outputstreams` to communicate with the device. All Bluetooth related code is kept out of the core protocol implementation, to ensure portability. There are three main methods which constitute the interface of a `TMSiDevice`:

- `initialize`: initializes the Mobi device by following a certain initialization procedure. This method gathers information about the device necessary for interpreting the received data.

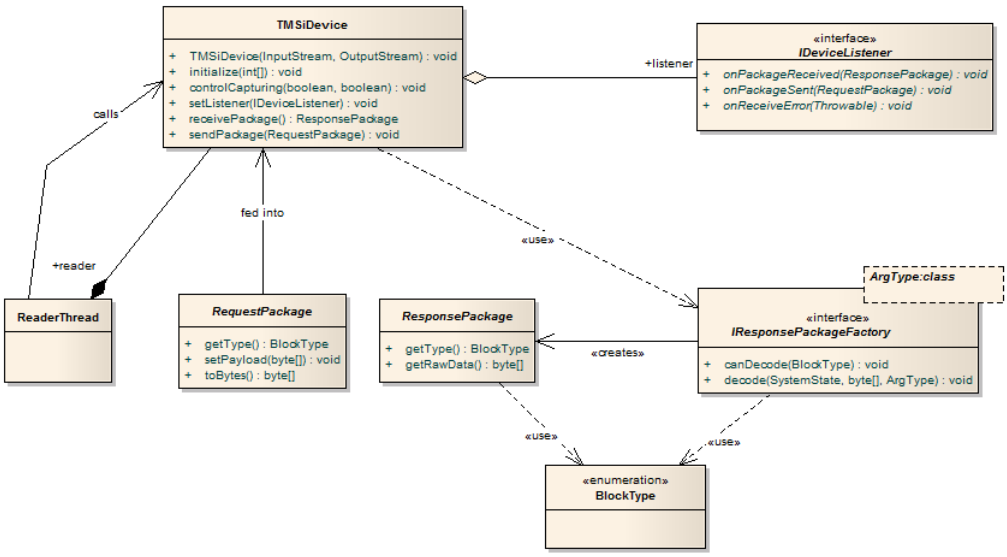


Figure 3.2: TMSi protocol stack architecture

- `setListener`: registers a listener at this device which is notified whenever a package is sent, received or an error occurred. Note that there can only be one listener at a time as supporting multiple listeners would create unnecessary overhead.
- `controlCapturing`: starts or stops the capturing of data. If capturing is to be started, this method will spawn a thread which is constantly trying to read packages from the device and calls a listener accordingly – a behavior described in fig. 3.12.

Constructing the request messages and interpreting the received bytes is the responsibility of `RequestPackage` and `AbstractResponsePackageFactory` subclasses. Each `ResponsePackage` which is merely a data container (a Plain Old Java Object (POJO) bean in Java terms) comes with its own `AbstractResponsePackageFactory` subclass implementing the response interpretation logic. We aimed for a decentralized protocol implementation as monolithic implementations tend to become cluttered and barely maintainable.

While creating the API was straight forward, porting the C code to Java presented a few unexpected challenges, caused mostly by implicit assumptions in the C code and the lack of proper documentation of the protocol.

3.3.1.1 TMSi procotol

The following reference is by no means a complete reference but contains a description of all packets necessary to receive data from the Mobi and (to some extend) reflects to our understanding of the TMSi protocol.

We found this protocol to be based on 16bit little-endian words (see 3.3.1.2). All packets (see figure 3.3) start with the block sync sequence `0xAAAA`, followed by the 1 byte block type and the content length in words encoded as 1 byte. After the variable content, the package ends with a 2-byte checksum computed by adding all previous words, performing bitwise negation and adding + 1. An implementation in `C` of the checksum algorithm is found in listing 3.1.

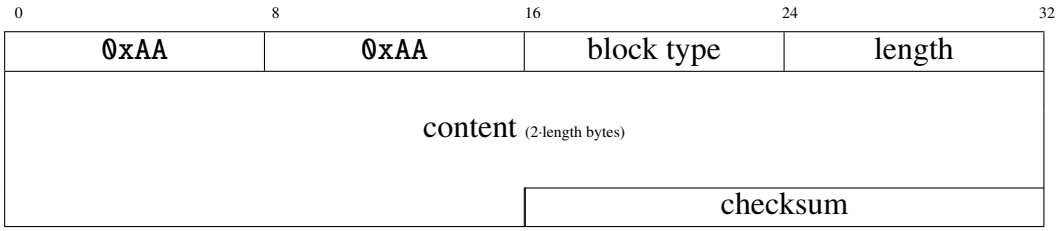


Figure 3.3: The structure of a package in the TMSi protocol. Each package starts with `0xAAAA`, its block type and content length in words. After the package content, the package is completed by a a checksum.

Listing 3.1: TMSi protocol checksum computation

```
uint16_t checksum(uint16_t* words, uint8_t length) {
    uint16_t checksum = 0, word = words + length - 1;
    while(word >= words) checksum += *word;
    return ~checksum + 1;
}
```

We subsequently list the packages involved in the device initialization and data recording procedures.

Initializing the Mobi starts with an **FrontEndInfo** package containing the amount of channels to be enabled and two flags denoting whether data is to be sent using bluetooth and if data should be recorded on the internal SD card. The amount of channels seems to be irrelevant and other implementations use a constant value of 14; so do we. A FrontEndInfo package is answered with an **Acknowledge** package. Such a package consists of an error code (which can also indicate ”no error”), a list of error messages and the time of the Acknowledge (ACK).

Sending an empty FrontEndInfo request results in a **FrontEndInfo response** yielding information such as the serial number, the maximum sample rate, hardware and software version, buffer sizes and battery power level. It is worth noting that some of that information is redundant with the **IDData** package.

The **IDData** package contains information about the device at hand. It lists details about the device, such as its serial number, name and a description of all channels. Retrieving the full description usually requires sending several **IDDataRequest** packets, each containing an offset and the restlength of data to be read.

For sampling data above 128Hz, the Mobi uses so called delta packages. They contain the difference to previously received packages and thus reduce the bandwidth requirements for transmitting the recorded samples. In order to interpret those delta packages, some information is required such as the delta length, coding type and mode of operation. Sending a **VLDataInfo** request results in an **VLDataInfo** response which contains all that information.

Once the Mobi was told to send data (using the appropriate flag in a FrontEndInfo request), it will send **ChannelData** packages containing the data. Those packages solely consist of the sampled data, either in 8bit or 24bit wide samples – the configuration has to be previously obtained using the IDData packages. To make sure the Mobi does not go into power save mode, it has to be kept alive using **KeepAlive** packages sent at least every second. We implemented the KeepAlive package as singleton, since it is completely empty and does not contain any specific information.

3.3.1.2 Byte order and unsigned integers issues

Words in the Mobi protocol are 16bit little-endian (least significant byte first), whereas Java integers are stored in a big-endian byte order (most significant byte first). As the CRNT implementation was only tested on x86-based machines, and those machines use the little-endian order as well, that byte-order problem didn't arise earlier. Another Java-specific problem, is that Java does not support unsigned integer arithmetic, as the language omits unsigned integer datatypes. A simple (yet annoying and error-prone) workaround we had to use is to do all unsigned arithmetics in the next bigger datatype and take it modulo $2^{16} + 1$. For example performing the unsigned addition (written in C)

```
uint16_t uadd(uint16_t a, uint16_t b) {
    return a + b;
}
```

has to be performed in Java as follows:

```
int uadd(int a, int b) {
    return ((a & 0xFFFF) + (b & 0xFFFF)) % (0xFFFF + 1);
}
```

Another detail that has to be taken care of in Java is casting bytes unsigned to integers. A regular cast caries over the sign, resulting in a subtle cause of bugs. Converting bytes to

unsigned integers should be done by performing the cast and later masking it to remove the sign:

```
int unsigned_byte_to_int(byte b) {
    return ((int) b) & 0xFF;
}
```

3.3.1.3 Verification and debugging

During development we had to verify the Java implementation against the CRNT, not only to ensure the correctness of our implementation, but also to debug the initialization procedure of the Mobi. We performed those tasks by building a serial device recorder using an open-source prototyping platform, based on the ATMEL ATmega328 microcontroller, called the Arduino[1]. A serial interface to the microcontroller is provided, which we used to simulate a Mobi. We recorded all data written to the serial interface, storing it in the internal EEPROM memory of the ATmega328, thus were able to compare the data sent from the CRNT with the bytes sent from our implementation. That method led to the insight of the wrong endianness and the Mobi using 16bit words.

3.3.1.4 Open issues

Despite best efforts to produce a bug-free TMSi protocol implementation, the code still suffers some known issues as we ran out of time. None of those issues poses a serious problem to the subsequent work, yet we list those issues for the sake of completeness.

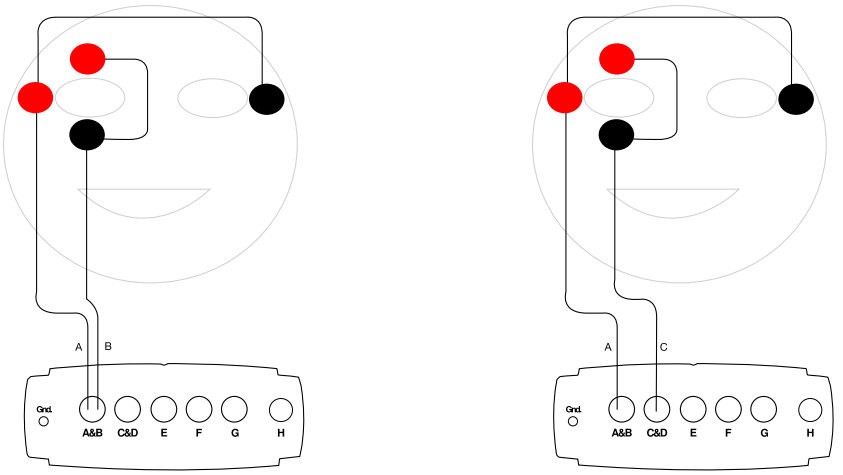
We believe they're linked and caused by the same issue. Our own implementation, as well as the CRNT use blocking IO communicate with the Mobi. Thus communicating with the device should not be time-critical as reads will block until there is something to be read, and writes will block until the bytes can be written. However, trying to read "too early" from the device results in unusable readouts, thus we have to have an empirically determined sleep of 10 milliseconds in the code. Not only is such a sleep inelegant, but also does it limit our effective sample rate to less than 100Hz – as for recording eye-movements a sample rate of 0-60Hz ([Mar11], considering Nyquist-Shannons sampling theorem) is sufficient, that does not present a serious problem is still noteworthy.

1 More information about the Arduino can be found at http://www.arduino.cc

The Mobi variant we have to our disposal connects the electrodes using bipolar connectors, thus providing two channels per connector (as figure 3.4 illustrates) - i.e. the first connector provides channel A& B and the second one serves C& D. With our implementation we have been unable to read meaningful data from the second channel of each bipolar connector (channels B and D), we have yet to find the reason for this behavior. Normally, one would use the two electrode pairs provided by a single connector to record the vertical and horizontal EOG channels. To workaround this second-channel issue, we use the first channels of the two available bipolar connectors, effectively attaching the electrodes as shown in figure 3.5.

A third, yet unsolved problem is that the signal received on the ”working” channels seems to be unscaled and thus does not fit in the 24bit wide integer packets used in the Mobi

Figure 3.4: Top side of the Mobi providing the female electrode ports



regular electrode attachment our electrode attachment

Figure 3.5: Connecting the electrodes to the Mobi

protocol. That causes the signal to overflow (or wrap around) the value range resulting in the block-like appearance shown in figure 3.7. As eye-movements may be rapid but not instant[1], extreme changes in the signal indicate an over-/underflow. We empirically determined the over-/underflow thresholds and identified $\dot{x} < -2^{23}$ as overflow and $\dot{x} > 2^{23}$ as underflow conditions (where $\dot{x}$ denotes the derivate of the signal x in respect to time, unit of measure is one divided by some unit of time). In order to reconstruct the signal, we add 2^{24} for every overflow and subtract the same value for underflows. Feeding an over-/underflown signal to the *fixOverflow* algorithm listed below (figure 3.6), yields the fixed signal plotted in 3.7.

The *fixOverflow* algorithm detects over-/underflows and corrects them by adding/subtracting multiples of 2^{24} (denoted by the variable c), accordingly. Being an offline algorithm, it expects a discrete signal $\mathbf{x}$ with its samples denoted by x_t and a total length of T samples as input. It detects under-/overflow in the t_{t+1} sample after correcting the x_t one. A corrected signal $\mathbf{r}$ (with r_t being the t_{th} sample) is computed as output.

1. (Initialze overflow count) Set $c \leftarrow 0$
2. (Initialize return signal) Set $\mathbf{r} \leftarrow \mathbf{0}$
3. (For each sample) For $t \leftarrow 0$ to $T - 1$
   4. (Correct sample) Set $\mathbf{r}_t \leftarrow \mathbf{x}_t + (c \cdot 2^{24})$
   5. (Compute derivative) Set $\dot{\mathbf{x}}_t \leftarrow \mathbf{x}_{t+1} - \mathbf{x}_t$
   6. (Detect overflow) If $\dot{\mathbf{x}}_t < -2^{23}$ then $c = c + 1$
   7. (Detect underflow) Else If $\dot{\mathbf{x}}_t > 2^{23}$ then $c = c - 1$

Figure 3.6: The *fixOverflow* algorithm

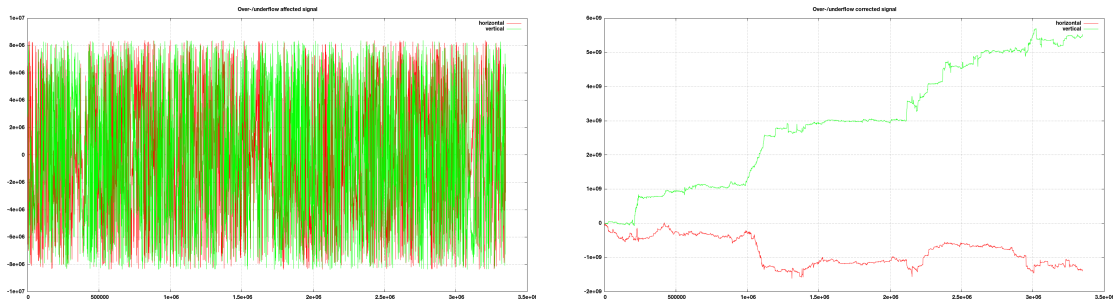


Figure 3.7: Over-/underflow corrected EOG signal

1 As mentioned before, eye-movements can be exhaustively recorded with a sample rate of at least 60Hz.

3.3.2 Microsoft SenseCam

The SenseCam is a digital camera paired with a set of different sensors, designed to passively take pictures triggered by its sensors. Along with a passive infrared (body heat) detector, the list of sensors includes a digital light sensor, accelerometer and a temperature sensor. It's main application is in research and therapy of people with memory-loss related problems [Hod11]. In 2009 the SenseCam became available as a commercial product called the Vicon Revue, which is the model we used (see figure 3.8).

Besides taking pictures using its 640×480 pixels camera module, the SenseCam also records accelerometer, gyroscope, temperature and Passive Infrared Sensor (PIR) sensor data in an ASCII file alongside the JPEG compressed images, stored on a cam internal storage. Once the camera is connected to a computer, recorded sensor data as well as the images are made available as USB drive. Microsoft Research and Vicon both supply software to review the photostream and sensor data. We found both products unsuitable for our purpose, as we needed a synchronized view of the images and the EOG data.

3.3.2.1 Time synchronization

Every entry in the sensor log, as well as every image is labeled with its recording time gathered from a built-in Real-Time Clock (RTC). It is the responsibility of supplied

Figure 3.8: Vicon REVUE, a commercial version of the Microsoft SenseCam

software tools to adjust the RTC by writing the current time to a file called `TIME.CSV`. However, writing any value to that file (either using said software or manually) resulted in the clock being reset to the 01.01.2000, 00:00. For the images to be useful ground truth, they need to have the same time-basis as the EOG data.

As the file-based time synchronization was not feasible, we used the image taking capability of the camera. We developed an App for the Android smartphone, displaying nothing but the phone's clock. Having the SenseCam take pictures of that very clock, which are then automatically timestamped with the SenseCam RTC time. Based on those images we can compute the time difference between the SenseCam and smartphone – a process illustrated in figure 3.9.

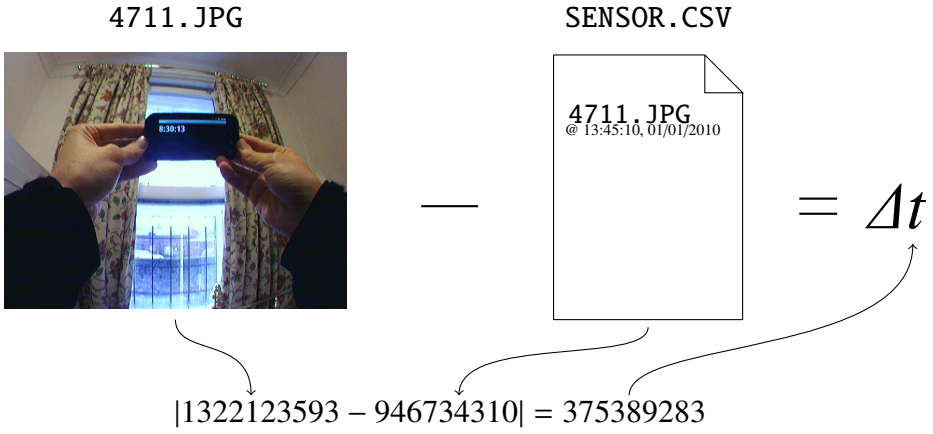


Figure 3.9: Synchronizing the SenseCam and smartphone

3.3.3 Android data recorder

When it comes to structuring Android applications, there are two core components of the Android framework that correspond to the length of a task: an *activity* maps to short-lived tasks (such as initializing the Mobi), whereas *service*s are intended for long-running operations (e.g. recording data for several hours). The sole purpose of activities is to provide user-interaction, hence they always come with an associated Graphical User Interface (GUI) screen (which can also be empty). Services have two purposes: perform long running tasks by explicitly spawning a thread and share functionality across applications.

Our study can also broken down into short and long-running tasks. Initializing the

recording equipment, as well as applying labels are both of short nature. However, recording EOG data is a continuous process running for several hours. That consideration results the recorder application architecture depicted in figure 3.10.

3.3.3.1 Initializing the recorder

When the application is launched, its main activity, called `StartActivity` is started. Once a user chooses to initialize the recording equipment, they will press the ”Initialize” button, causing the `StartActivity` to perform the following setup routine:

1. **Start the `DataLoggerService`** by connecting this activity to it. All further steps aim to initialize the `DataLggerService`.
2. **Initialize Bluetooth connection** by first checking if bluetooth is enabled and if not, asking the user to enable it. With Bluetooth available, the Mobi device is searched using its Media Access Control (MAC) address. Once found, all search effort is quit

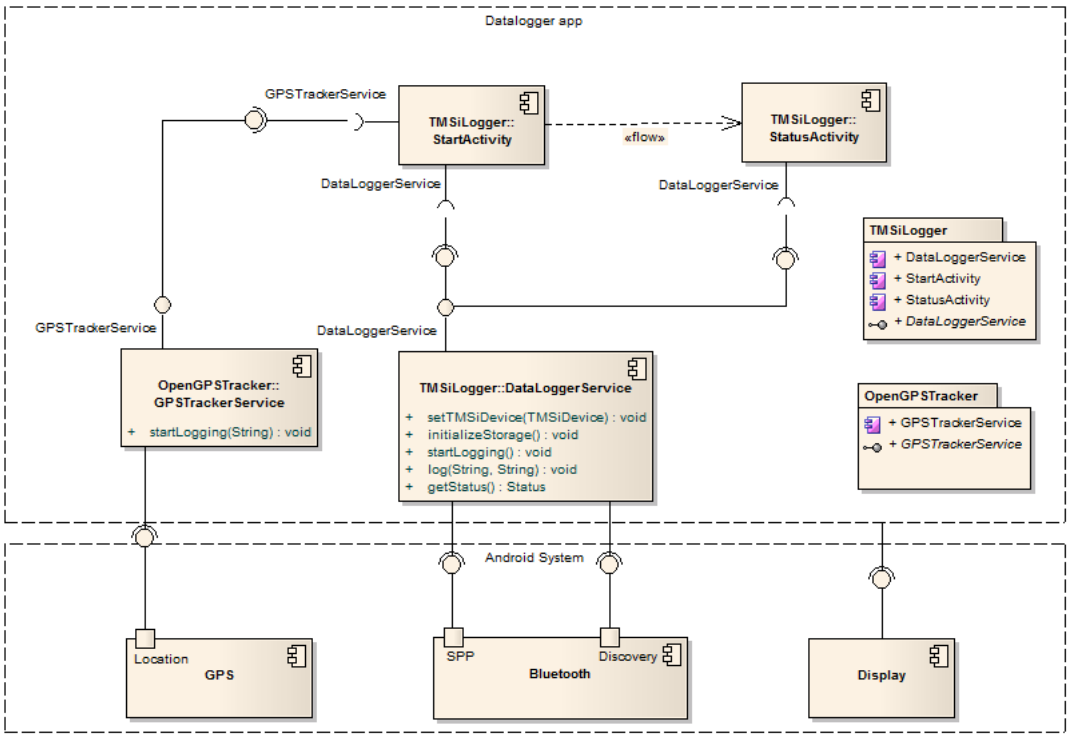


Figure 3.10: The data recorder architecture

and a serial connection to the Mobi is established[1].

3. **Initialize the Mobi** using the initialization procedure implemented by the protocol stack. In this stage we gather information about the Mobi which is then required to decode the measurements coming from it.
4. **Create the log-file file on the sdcard** and prepare it for writing, each log-file is named `/sdcard/datalogger/`*`currentUnixStamp`*`.log`. The information gathered during the Mobi initialization is written to the log-file for debugging purposes.
5. **Setup the `DataLoggerService`** by passing the initialized `TMSiDevice` instance to it and asking the service to start logging.
6. **Start the GPS service**, supply it with a unique track name (which is computed based on the log-file name) and begin logging the position.

3.3.3.2 Applying labels and monitoring the Mobi connection

The `StatusActivity` (GUI shown in figure 3.11, left screenshot) is merely a front-end for the `DataLoggerService`, exposing the status and some functionality of that service to the user. Labels can be applied by pressing the respective button, where the highlighted ones show which labels are active. The number in button text shows how often each label has been applied already. Whenever the user applies a label the amount of money in upper right corner is incremented, thus giving an approximation of the earned amount.

Showing an indicator of logging activity gives confidence in the systems functioning. A regularly updated count of the data points collected so far is shown to the user in the upper left corner. When doubting that the system still works, seeing of that number still continuously increases can be reassuring. In case of a connection failure between the smartphone and the Mobi, an alarm sound would go off asking the participant to reestablish the connection.

1 Establishing a connection using the Serial Port Profile (SPP) on Android is not straight-forward. There is an explicit Application Programmer Interface (API) to open such a socket (as described in the Android API reference [Inc11]), but it does not work reliably across devices. The most reliable way of creating an RFCOMM socket seems to be using Java reflection as explained in an Android bug report: `http://code.google.com/p/android/issues/detail?id=5427`. The Input/Output (I/O) streams of the serial connection are then passed on to the TMSi protocol stack (described in section 3.3.1).

Figure 3.11: GUI of the `StatusActivity`

During the study unforeseeable events may arise, which we want to annotate if they might affect the EOG recording: that's what the special event button is for. Pressing it produces a dialog in which any form of free text can be entered. We tried to anticipate certain "special events" and added them to the dialog using auto-completion assistance (the right screenshot in figure 3.11). Such special activities are not considered for activity classification, but are solely used for signal cleanup and artifact removal.

All labels and special events are passed on the `DataLoggerService` which then logs such events to a file. The service serves as a single point of entry to the logging storage and is the sole governor of the log file, and can thus ensure a proper format and time-logging, as well as log-statement counting used for approximating the earned reward.

3.3.3.3 Recording EOG data

Continuously recording data on an Android phone is a challenging task, as it contradicts the designated usage pattern of a smartphone. Most operations and interactions with a phone are of relatively short nature; but nowhere close to 12 hours. Android supports building such long-running applications, but we had to take special care to make it work. We ensured that Android does not kill the service in low-memory situations by implementing two details: we're starting the service explicitly and make it *sticky*. Starting the `DataLoggerService` as a foreground service, ensures that Android is aware of its importance and marking it as *sticky*, causes special startup handling for long-running services[1].

Our TMSi protocol stack (described in section 3.3.1) supports an event driven programming model, which allows us to simplify the `DataLoggerService`. As the protocol stack spawns a reader thread when necessary, we only have to wait for data to arrive and don't have to deal with multi-threading in the service implementation. Whenever a new `ChannelDataPacket` arrives, we write its content to the logfile using the `DataLoggerService`s functions (see figure 3.12) which are thread-safe, thus it's possible to call them from the reader thread.

All data recorded on the phone during a recording instance – let that be EOG data, labels or debugging information – goes into a single file. Such a recording instance is started by initializing the app (as described above) and ends when the app is quit, crashes or is killed otherwise. Each file is named `/sdcard/datalogger/`*`currentUnixStamp`*`.log` where *`currentUnixStamp`* denotes the file creation time, formated as Unix timestamp[2]. In each file are of the form

```
<timestamp> <tag> <content>
```

and are separated by line breaks. Timestamps are formated as milliseconds since 01/01/1970 and the tags denote the type of an entry, thus describe the content format. For an overview of tags and their content see table 3.4.

1 More information about the lifecycle of Android services can be found in the Android documentation: http://developer.android.com/reference/android/app/Service.html#ProcessLifecycle

2 A Unix timestamp (also called Unix time) is the amount of seconds passed since the 01/01/1970

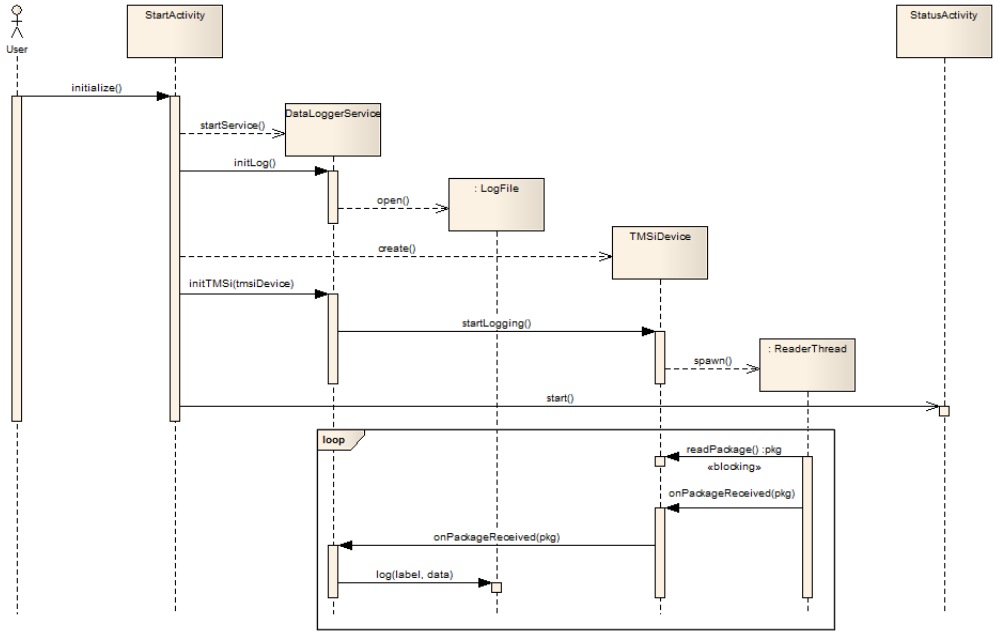


Figure 3.12: EOG logging initialization

tag	content
TMSi	eog_x *noise* eog_y *noise*
TMSiRAW	raw bytes as received from the Mobi as base64 encoded string
TMSiChannelDesc	channel description as received during the Mobi initialization
label	a single label, e.g. interacting, not interacting, inside, outside, concentrated, leisure or free text
phoneInteraction	start or stop, denoting when interaction with the phone began and ended

Table 3.4: Datalogger file structure

Listing 3.2: Example of a datalogger file

```
1321950051430 TMSiChannelDesc Channel [unit=VOLT, exponent=-6, type=
   BIP, subType=UNKNOWN, size=24, chnumber=0, sign=true, process=true,
    portnumber=0, a=1.0113601E9, b=0.0, name=A, refsample=0, overflow=
   false, vld_samplefs=0, vld_deltas=0, vld_samplediv=0, vld_divcnt=0]
1321950051446 TMSi 7953920 622592 0 -8355840 0 0 0 0 0 0 0 0 0 0
1321950051446 TMSiRAW eV4ACYAAAAAAgIAAAAAAgIAAAAAAgIAAZH8A/
   yYAU0sWNc1AHiWNoA/cC1AeknMQsDtUdwHpL80AAxzK
1321950051461 label 1e not interacting
1321950051468 TMSi 7915520 622592 0 -8355840 0 0 0 0 0 0 0 0 0 0
```

3.3.3.4 Recording the GPS track

Recording a precise track provides several challenges, none of which are to be solved in this work. Such issues may be the GPS signal quality, the receiver drift (remaining stationary results in a ”moving” signal) and power consumption.

Others have tackled those problems before us, so we integrated their implementation. The *OpenGPSTracker* project[1] produces a versatile GPS recording Android app, under an open source license. That GPS logging app consists of a `GPSLoggerService` and several activities controlling this service using the `GPSLoggerServiceManager`. We made the `GPSLoggerServiceManager` part of our codebase (within its original namespace and including the comment header clarifying its origin) and use it to connect and control the `GPSLoggerService` without having to include the complete OpenGPSTracker in our application. As the service itself remains part of the OpenGPSTracker application, it runs in a different process than our recording app. Android provides its own mechanism for implementing such Inter-Process Communication (IPC) capable services, called Android Interface Definition Language (AIDL). The `GPSLoggerServiceManager` requires that AIDL definition, so we copied the `IGPSLoggerServiceRemote.aidl` into our source tree, causing the Android development tools to generate the interface appropriately.

Although the original `GPSLoggerServiceManager` had a way of providing a track name at the beginning of a new recording, we found that doing so remained without effect. But to be able to clearly identify the recorded track with out measurements, we had to properly name the GPS logging session. Calling the `GPSLoggerService.startLogging()` method yields a numeric track ID which is valid within the OpenGPS tracker. That ID is used to set the track name using the OpenGPS tracker *content provider*. However, that integration path uses unofficial API and we expect it to break in future versions.

3.3.3.5 Battery runtime optimizations

One of our biggest concerns was the power consumption of the system which is the limiting factor to the systems runtime. That concern had great influence on the development of the Android recorder app. On some occasions we favored performance over ”beauty”, on others did we disable features because of their power consumption.

1 http://code.google.com/p/open-gpstracker/

The Android development guide [Inc11] advices developers to avoid unnecessary object creation. The clean object-oriented way for implementing unsigned 16bit integer arithmetic would be using an immutable `uint16` class. That class would provide all required basic arithmetic functions, such as `plus`, `subtract`, `multiply` and `divide`. Although the implementation of such a class would still use regular Java integers (thus produce no overhead for the operations themselves), we'd end up creating a lot of object instances just to have them garbage collected a second later. Receiving a single package of n bytes size, requires $\frac{1}{2} \cdot n + 3$ uint16 operations – e.g. receiving a 76 byte long ChannelData package would create 41 new objects. With a sampling frequency of 75Hz, that would be at least 3075 new unnecessary objects per second.

We use the smartphone solely to receive data and store it, but do not make it accessible to any other entity on the phone. Android has a special mechanism for storing structured data using SQLite[1]. Typically such an SQLite database is further encapsulated using so called `ContentProvider`. Both mechanisms improve the separation of concerns and code re-usability as they define clear interfaces and responsibilities, especially when sharing data across multiple Android applications or services. We do not need to share data or store it in a database, thus we circumvent the overhead induced by such measures and write all data to a single file. Doing so makes further processing slightly harder as all different kinds of data end up in the same file, but we cope with that during pre-processing (see section 4.3).

Android has a method profiler built in which shows the amount of time spent in each method. We used that profiler to bring down the CPU load caused by recorder app from a total of 80% to 60%. The first thing we realized was that, with every arriving measurement, we'd create a new integer array holding that data. That was according to our design, as we followed the rule of making objects immutable if possible. By ridding the `ChannelData` class of its immutability and reusing the integer array instead of creating a new one every single time, we decreased the time spent for allocation and garbage collection. We thought about using the sensors built into the smartphone for complementary sensing (see table 3.1 for more details). The profiling showed that each additional sensor makes up for roughly 5% of total CPU load due to the reading and logging overhead they produce. Disabling all sensors yielded a total CPU load reduction by roughly 16%.

1 The Android SQLite API is explained in the Android Dev Guide [Inc11]: `http://developer.android.com/guide/topics/data/data-storage.html#db`

CHAPTER 4

Data acquisition

With the experimental system being available, we have to *prepare* for the study. Besides checking the equipment, we especially focused on training the participants. Once prepared we set out to *collect* data using the system and with the help of the participants - a process described in section 4.2. We have to *preprocess* the recorded data to condition it for analysis. This preprocessing involves data cleanup, merging and format transformation, more details can be found in section 4.3.

4.1 Preparation

We had to prepare each recording session by preparing the equipment and training the participant where both tasks are equally important. Improperly prepared equipment leads to bad data quality or even the loss of a complete recording session. Insufficient training results in incomparable results, bad data quality or again, the potential loss of data. We found it harder to provide sufficient training than properly preparing the equipment, i.e. we lost a complete dataset due to improper participant training. To ensure proper preparation, we designed a preparation checklist (found in appendix B) and verified its feasibility in a test run.

4.1.1 Preparing the equipment

The EOG data and labels are stored on the phone (described in section 3.3.3), while the images and sensor data recorded by the SenseCam are stored on the cams internal memory (see section 3.3.2). Before starting a new recording session, both devices need to be cleaned from previous recordings.

Recording over 12h comes with power consumption challenges, which we tackled by designing our system to last for that amount of time, once fully charged. Both, smartphone and SenseCam can be charged using a standard Universal Serial Bus (USB) connection. The Mobi runs on Nickel-Metal-Hybrid (NiMH) AA batteries which have to be charged using a specialized device. We found the time for a full recharge of all devices to be eight hours, thus charging the system over night was feasible.

We enabled the participants to start recording as early in the day as they wanted to, by packing the equipment in a ruggedized and compact case, which they would take home (see figure 4.1). This package contained

- the smartphone, turned off and without any previous recordings,
- the SenseCam, turned off and without any previous images stored on it,
- at least four fully charged NiMH AA batteries for the Mobi,
- the TMSi Mobi without any batteries in it (so that they could not drain over time),
- both electrode connector cables and at least 10 electrodes; five for the initial setup and five spare ones,
- and a participants manual providing instructions for attaching the electrodes and explaining the labels in detail.

4.1.2 Training the participant

Before a participant started a recording session, we introduced them to the system and their duties during participation. At no point did we mention the purpose of the recording, however six of the seven participants were team-members and knew about our goal. During the participant training we emphasized how vital precise labeling is for the data quality and later analysis.

Figure 4.1: Packed recording equipment

While explaining the system, we assumed that the participants knew how to use an Android smartphone, but had no prior knowledge of the system as a whole. In the training session, the participants were given detailed instructions how to install and setup, as well as operate the recording system. Every component involved was shown and its usage was demonstrated.

Proper electrode attachment is crucial to the study. Placing the electrodes in an unconventional configuration, e.g. too far away from the eyes might render the recorded data useless. We put special emphasis on demonstrating the electrode attachment and Mobi setup procedure. All participants were also given a diagram of the electrode configuration, so that they could ensure proper attachment when setting up the recording equipment themselves.

The smartphone is used for storing the data as well as collecting the ground-truth; its latter function turning it into the component participants interact the most with. After briefly

showing how to turn the smartphone on and off, as well as unlocking the screen, we went on to demonstrate how to connect the TMSi Mobi to it. Once connected, the labeling interface appears (figure 3.11). Participants were introduced to the labels and how to apply them. Again we emphasized the importance of proper labeling.

Using a SenseCam is easy, but its privacy implications need to be dealt with. To operate it one only has to press and hold the button on top of it until the LEDs light up and wear it like a necklace. Its green LED indicates its powered on, the orange one lights up whenever a picture is taken. Participants were given full control over when they wanted to wear the camera and when they did not want to. There are special occasions requiring privacy (e.g. the restrooms) and in such participants were encouraged to turn around the camera, so that it would only record black frames. We also informed the participants that after the study, they would be given the set of images to censor any images they deemed necessary.

4.1.3 Consent form and survey

Participants engaged on a voluntary basis only. Before they would start their training and recording, every user signed a consent form (see appendix C). By doing so, they acknowledged their voluntariness and that there were no foreseeable risks involved by participating.

After their participation we asked the participants to fill out a short survey. Completing it was voluntary and no question was mandatory, however we had a 100% return rate, with all questions (except for those marked optional) answered. In the survey we asked for basic data such as gender, age and if they required visual aids. One question was whether the participant smoked or not; the motivation being less the potential influence of the Nicotine, but more the motion artifacts introduced by the suction movement when smoking.

4.2 Data collection

We collected 86.7 hours of data during one month, with 7 participants aged between 23 to 30 (mean: 26.29, std.: 3.55). All participants were non-smokers and right handed. Four of the participants wore prescription glasses during the data collection. All participants

recorded their dataset the day after their training and set up the recording equipment themselves.

The participants were told to go for their regular every-day life. In personal discussions we identified a common structure of all participants days (table 4.1). The mean recording start time was 09:42 (std.: 50min.) and as most participants (except for one) were members of our team, they share a similar day. None of them engaged in physically demanding tasks despite their commute, which in one case was done by bike. All participants recorded their data in the area of Lancaster, one commuted to Manchester.

Once a recording session was done, we extracted the data from the SenseCam and smartphone. All EOG data and labels were fed into the preprocessing pipeline (section 4.3), the SenseCam images were directly given to the participants on a USB thumb drive for blackening. We made sure that no one would see the pictures before them by handling them only on the command line. Once they returned the (possibly censored) set of images, we'd store the images along with the collected data and delete the originals on the SenseCam.

4.2.1 System performance and problems encountered

The recording system performed as expected. Three recording sessions - including the longest one with 14 hours - were recorded without a single system restart. We did recharge the smartphone battery during the recording sessions to extend the runtime beyond the 12 hours we had originally designed the system for.

08:00	wake up and perform morning tasks such as taking a shower
10:00	set up the recording equipment and begin collecting data
10:30	arrive at the workplace, engage in interaction and concentrated work
13:00	have lunch
18:00	leave the office and commute home
21:00	engage in social activities such as meeting friends
22:00	end of the recording session

Table 4.1: The structure of a typical day shared by all participants (although the times might vary).

After each recording session we performed a manual inspection of the data to ensure proper quality. During one of those inspections we realized that, in one dataset the measurements for vertical eye-movements were missing. That missing data essentially rendered one dataset of 13 hours useless. In retrospect we came to the conclusion that the second EOG electrode cable (channel C) was not properly attached, hence that channel was not correctly recorded.

We also encountered minor problems which did not destroy datasets, but still were unexpected. For example, users would forget to take the smartphone with them (up to ten times during a single recording session). Forgetting the smartphone resulted in an annoying alarm tone as the connection to the TMSi Mobi is dropped once the bluetooth range is exceeded. Restarting the system brings everything back to order and has no direct effect on the data quality.

Performing the required self-annotation is a hard task, participants had to change the label configuration every 8 minutes (mean, std.: 15min.). To ease their task, they would constantly keep the display awake causing the battery to drain much faster than anticipated. We solved this problem by bringing the participants attention to the issue and providing enough chances to recharge the smartphone.

4.3 Preprocessing

All data recorded on the smartphone is stored in the same location – channel information, EOG data, labels, other sensor data is all written to the same file. While such an implementation allows for performance and battery efficiency, it is unsuited for analysis in Matlab.

1. The data needs to have several operations applied to it before we use it for analysis (see figure 4.2). We found that the channel information (which is also stored in the log files for debugging purposes) may contain encoding errors which cause the subsequent operations to fail. Thus, our first step is to perform a *cleanup* the file by opening it in a text-editor and correcting those few errors manually.
2. Those multiple files exist mainly because of the technical implementation of the recording application, but serve no practical purpose; even worse, they make further

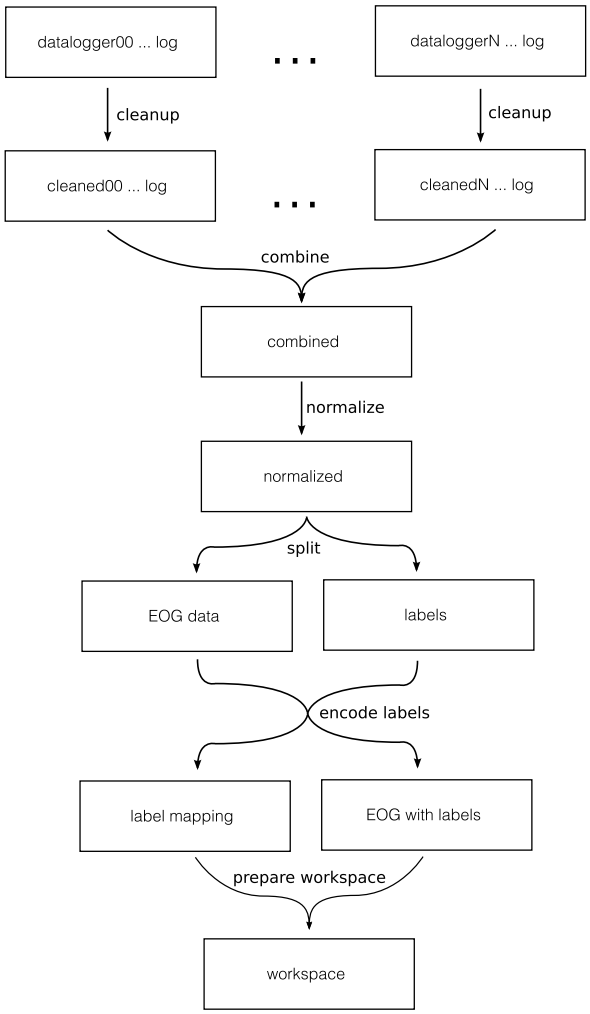


Figure 4.2: The preprocessing pipeline

processing more complicated. We *combine* all datalogger files of a single recording session into one file and make sure that we maintain the datas timely order.

3. Each datalog entry is associated with a Unix timestamp (in milliseconds). Those numbers tend be very large (roughly $x \geq 10^{13}$) which is likely to cause problems when processing the data – e.g. *gnuplot*[1] cannot handle such large indexes. Comparing the datasets with each other is also hindered by the different offsets in the data, depending on when they were recorded. We're interested in the time relative to the recordings beginning and not in absolute terms. Subtracting the first timestamp from

1 Gnuplot is a versatile and widely used plotting program. See http://www.gnuplot.org for more details.

all subsequent ones, yields such relative time. We call that process *normalization*.

4. Until that stage, all types of data are stored in a single file (see section 3.3.3.3). It's easier to process the data separately, simply because that reduces the amount of data that has be read in a processing step. Hence, we *split* the data into several files, depending on their tags and create a file for each tag.

5. We store labels as point labels, yet interpret them as continuous events by letting the labels denote the start and end of a event – figure 4.3 illustrates this concept. For the subsequent processing scripts to work, we need to interpolate the point labels, so that each sample is associated with its respective label configuration. That label configuration is a number denoting which label in which group is currently active. As we have mutually exclusive, binary label groups (refer to table 3.2 for more detail), we can *encode* the labels using a binary encoding of the following form:

$$L_0 \times \ldots \times L_n \quad \rightarrow \quad k_0 + \ldots + k_n \cdot 2^n, \tag{4.1}$$

where the L_i are the label groups and the k_i denote the which label in the label group is currently active – either the label 0 (e.g. inside) or the label 1 (e.g. outside). That mapping associates each label group with a bit and sets that bit to one or zero depending on the active label. Considering only our labels, we can write down the label configuration encoding – see table 4.2.

6. In the last stage we *prepare the workspace* by loading the data from the previous step into Matlab, applying the fixOverflow algorithm to the EOG data (as described in section 3.3.1.4, specifically in figure 3.6) and save the result in a Matlab file, which serves as input for the subsequent feature extraction.

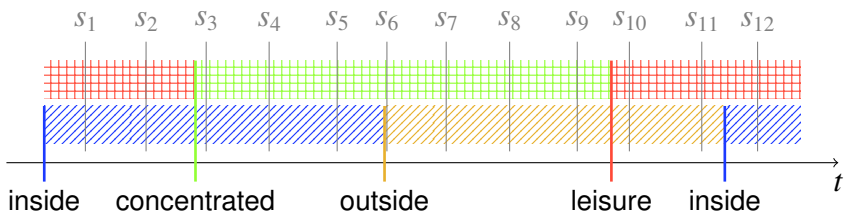


Figure 4.3: Interpolating point labels to continuous events

code	value	labels			
	0	not active	not interacting	outside	leisure
	1	active	interacting	inside	concentrated
0x00		not active	not interacting	inside	leisure
0x01		not active	not interacting	inside	concentrated
0x02		not active	not interacting	outside	leisure
0x03		not active	not interacting	outside	concentrated
0x04		not active	interacting	inside	leisure
0x05		not active	interacting	inside	concentrated
0x06		not active	interacting	outside	leisure
0x07		not active	interacting	outside	concentrated
0x08		active	not interacting	inside	leisure
0x09		active	not interacting	inside	concentrated
0x0A		active	not interacting	outside	leisure
0x0B		active	not interacting	outside	concentrated
0x0C		active	interacting	inside	leisure
0x0D		active	interacting	inside	concentrated
0x0E		active	interacting	outside	leisure
0x0F		active	interacting	outside	concentrated

Table 4.2: The encoded label configurations

CHAPTER 5

System verification and data analysis

We analyzed the data to verify the its validity, thus verifying the experimental system developed in this thesis is sound. For analysis we partially relied on existing methodology and algorithms, notably developed by *Bulling et al.* An overview of first results that we found, is given to demonstrate the viability and soundness of the experimental system and recorded data.

5.1 Methodology

The dataset recorded during this study is a novelty. As no such dataset existed before, there is no experience or even proven methodology on how to analyze an eye-movement dataset of such length. We find, however, the methodology and algorithms developed in previous eye-movement based activity recognition work (namely Bulling's work [Bul11]), could be applicable for our purpose.

When designing the study, we identified four high-level activities. All of those activities are typically typically sustained over a period of at least several minutes, e.g. it is unlikely that someone is concentrated only for 30 seconds. Hence it is legit to segment the data into windows of several minutes length. As there is no proven methodology we arbitrarily choose a set of three different window lengths: 15 minutes, 10 minutes and 5 minutes.

Subsequent algorithms rely on equal window length in terms of samples. Although there is variance in the sampling frequency (mean: 76.6Hz, std.: 10Hz), we consider it fixed to 75Hz and create windows containing $minutes \cdot 60^2 \cdot 75$ samples length. The error

introduced by the fixed sampling frequency assumption is negligible as we are interested in high-level activities, and thus a few samples too much or too less in a window do not matter.

Bullings work in eye-tracking based activity recognition has shown that there are eye-movement characteristics which can be used to discriminate certain activities. Also, neurological mechanisms discovered in behavioral and biological research, motivate certain eye-movement features. E.g. the duration of spontaneous blinks is influenced by cognitive effort [Caf03], or the fixation duration has been found linked to certain activities such as talking, reading and counting [Can09]. So we extract a set of features from the segmented EOG data – figure 5.1 illustrates the process, table 5.1 gives an overview of the feature set.

In addition to the feature extraction, every window is assigned an encoded label by performing a majority vote on all labels within the window. The majority vote simply selects the most often occurring label out all labels within the window, more formally it selects the label $k \in L_W$ out of all labels L_W in the window W, so that $\forall k' : \text{count}_W(k) \geq \text{count}_W(k')$, where $\text{count}_W(x)$ counts all occurrences of the label x in L_W.

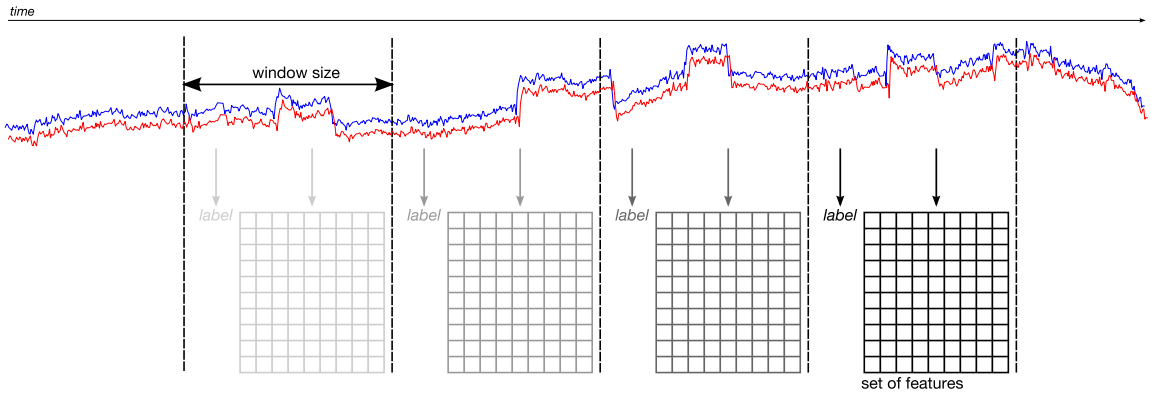


Figure 5.1: The data is segmented into windows of 15,10 and 5 minutes. For each window a set of features is computed. Those features include mean blink length and rate, mean fixation length and rate and saccade amplitudes. In addition to the features, each window is assigned a label using majority vote.

Group	Features
blink	mean and variance of the • blink duration (in samples) and • blink rate (in events per second).
saccade	mean and variance of the • EOG signal amplitudes • saccade rates (in events per second) for all small, large, positive, negative, horizontal and vertical saccades
fixation	mean (and variance for the first item) of the • fixation length (in seconds) • fixation rate (in events per second) • vertical and horizontal signal amplitudes during fixations

Table 5.1: An overview of the set of features extracted from each data segment, adapted from Bulling et al.

5.2 Feature extraction

We extracted the exact same set of features Bulling et al. describe in their work [Bul09, Bul11], as it is properly motivated and has been shown to have great discriminative power for different activities. Those features were computed on the *Cambridge Computer Laboratory Processor Bank*[1]; a cluster of 25 dual-Opteron computers. The feature extraction process was started at the beginning of December 2011, stopped over Christmas, resumed beginning of January 2012 and as of January 2012, it has yet to finish for all window sizes less than 15 minutes.

We detect saccades using the *continuous wavelet-transform saccade detection* (CWT-SD) algorithm described in Bullings' work. This algorithm computes the continuous 1D wavelet coefficients using a Haar mother wavelet and applies a threshold th_{sd} to these coefficients. All wavelet coefficients $C_i(s)$ (with s being an EOG signal component) satisfying $-th_{sd} \leq C_i(s) \leq th_{sd}$ mark a non-saccadic segment (i.e. fixations), whereas all

1 http://www.cl.cam.ac.uk/local/sys/processor_bank/

others mark saccades. The threshold th_{sd} is person specific and we determined it for each recording by manually inspecting EOG data during reading periods.

All segments marked as non-saccadic are considered to contain a fixation. During a fixation gaze remains stable, i.e. the points at which gaze is directed cluster over time [Sal00]. Bullings dispersion based fixation detection algorithm exploits this behavior by thresholding the gaze point dispersion. For a segment S composed of the vertical EOG signal component S_v, as well as the horizontal one S_h, the dispersion is defined as

$$\mathrm{Disp}(S) = (\max(S_h) - \min(S_h)) + (\max(S_v) - \min(S_v)).$$

All segments satisfying $th_{fl} \leq \mathrm{Disp}(S) \leq th_{fh}$ are assumed to contain a fixation, where the lower threshold $th_{fl} = 200$ms and upper threshold $th_{fh} = 10^3$ have been determined during the CWT-SD evaluation.

Blinks are only seen in the vertical EOG signal component and are extracted using an algorithm similar to saccade detection algorithm (CWT-SD). The *continuous wavelet-transform blink detection* algorithm (CWT-BD) focuses on the vertical EOG signal component only, and uses a person independent threshold th_{bd} that has been identified by the algorithms author [Bul11].

5.3 First results

All subsequent analysis is performed using the features and majority voted labels, so in the following whenever we speak about data, we refer to those feature/label pairs. This higher-level view of the recorded data allows for better comparability with existing results as they refer to features such as blink time and not to raw eye-movement data, too. It remains an open question if there is interesting information to be found in the raw EOG signal.

Analyzing this feature data can be done relative to time or relative to the labels. The procedure is the same for both choices: segment the data by some criteria and apply statistical methods to the classes, such as hypothesis testing or Exploratory Data Analysis (EDA) [Nat10] methods. Time segmentation lends itself to exploratory methods as one would expect to find trends over time. Label segmentation is especially suited for

hypothesis testing, as one can answer questions like: ”do we blink more often during periods of concentration?”.

To segment data by time, we choose an arbitrary number of segments $|S|$ and assigned all features f to their corresponding segment $S_i, i = \left\lfloor \frac{24 \cdot 60^2}{|S|} \cdot f_{td} \right\rfloor$ where f_{td} is the time of the day in seconds the feature window falls into. We treat label segmentation as binary segmentation problem: there are two classes L_x, L_y where all features with the label x fall into L_x and all features labeled y fall into L_y. The label of a feature data point is determined using majority vote during feature extraction (described in section 5.1).

5.3.1 Leisure vs. concentrated

The purpose of this particular analysis is to verify the soundness of the data and hence of the experimental system. It is well established that the blink rate is influenced by cognitive load and thus serves as an indicator for the level of concentration [Caf03, Sch08]: the more we blink, the less concentrated we are. We shall consider our data and system sound, if those results can be verified using our data.

We segmented the features extracted from all participants using the *concentrated* and *leisure* labels and choose to evaluate the blink rate. So let $S_{br,concentrated}$ be all blink rate feature samples labeled as concentrated and $S_{br,leisure}$ be all blink rate feature samples labeled as leisure, figure 5.2 shows a boxplot and normplots of those two classes. Consider the null hypothesis H_0 to be that the blink rate is independent of the level of concentration:

$$\overline{S_{br,concentrated}} = \overline{S_{br,leisure}}.$$

A two sample t-test rejects the null hypothesis at a significance level of 1% ($p < 0.001$), thus the means of both classes are significantly different. As $\overline{S_{br,concentrated}} < \overline{S_{br,leisure}}$ we conclude that the blink rate is significantly higher during leisure, which is en par with the findings of Caffier and Schleicher.

Using the same approach as for blink rate, we found that the saccade amplitude is lower during concentration compared to leisure ($p < 0.001$, figure 5.3). Those results indicate the eyes move slower during times of concentration, a behavior that could be exploited to detect concentrated activities.

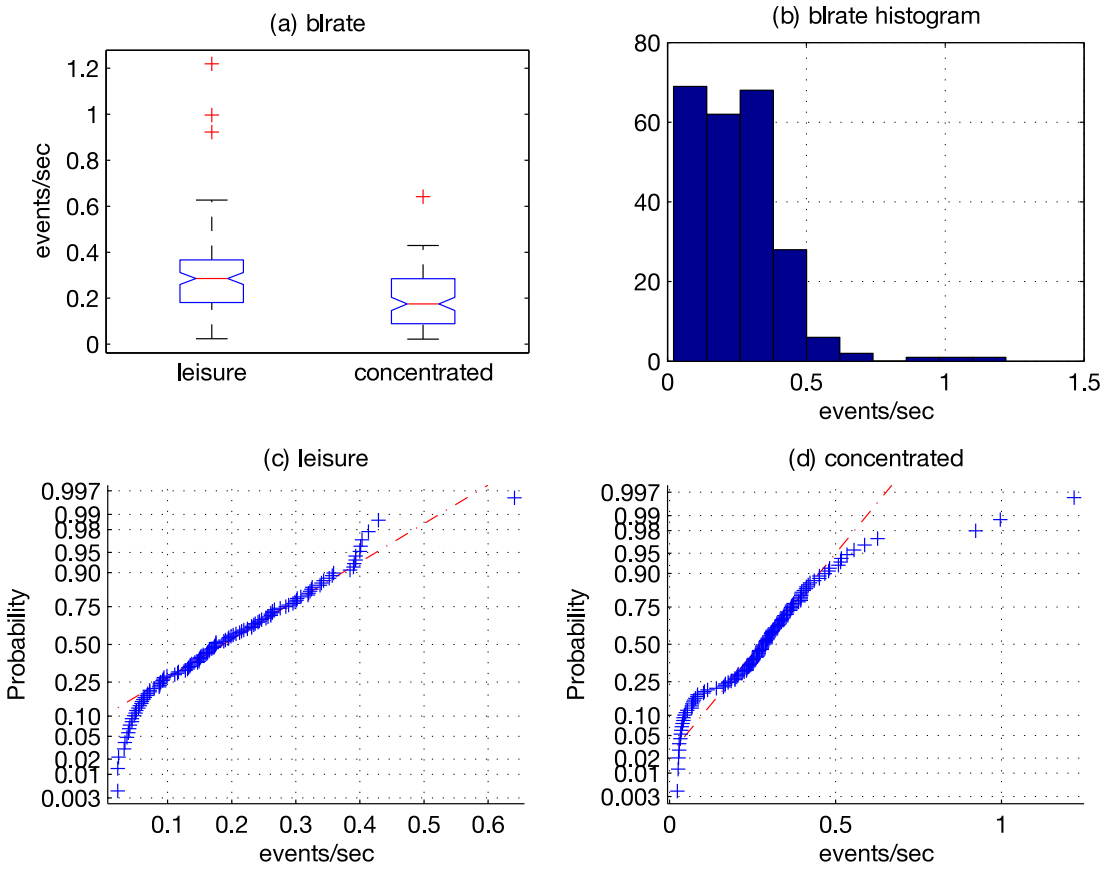


Figure 5.2: The blink rate of all datasets partitioned by the *concentrated* and *leisure* labels. Subfigure (a) shows the boxplot of both classes, subfigure (b) shows a histogram to give an impression of the data. Subfigures (c) and (d) are normplots and visualize how normally distributed both classes are (the more resemblance the datapoints have with the line, the closer the data is to a normal distribution).

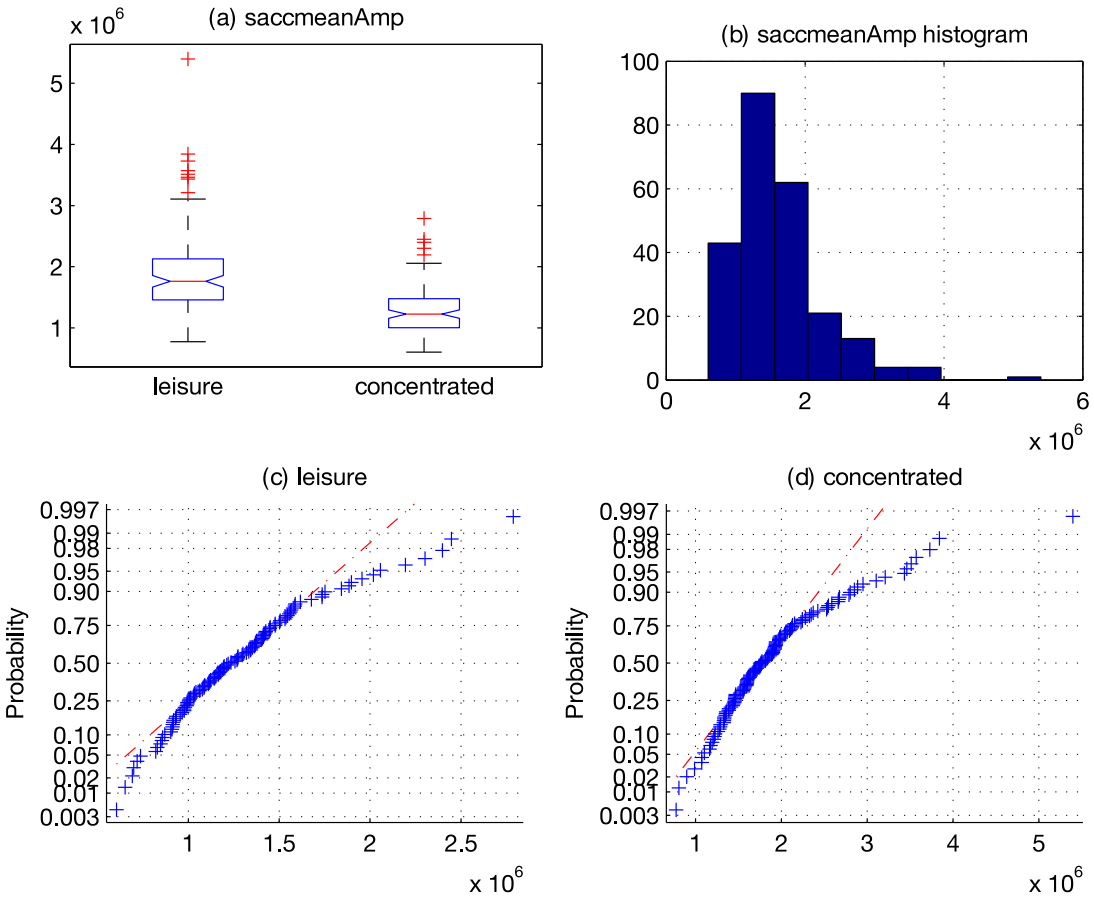


Figure 5.3: The mean saccade amplitude of all datasets partitioned by the *concentrated* and *leisure* labels. Subfigure (a) shows the boxplot of both classes, subfigure (b) shows a histogram to give an impression of the data. Subfigures (c) and (d) are normplots and visualize how normally distributed both classes are (the more resemblance the datapoints have with the line, the closer the data is to a normal distribution).

CHAPTER 6

Conclusion

The experimental system developed in this work will be the platform for future mobile eye-movement based applications. In this thesis we showed that recording eye-movement in daily live is feasible and that such a system can be implemented using available technology. The system performed extremely well during the data collection in terms of stability as well as battery runtime. We presented ideas for analyzing such massive datasets and showed that the methodology is resilient against data recording flaws by confirming existing results with the data recorded during this work.

Several open questions remain. Increasing the systems recording speed so that no data is dropped during data collection remains an open problem. Also do we expect that further analysis will show that the four high-level activities on which we focused on in this work can be discriminated using the features we used for our system verification. Future work should focus on showing such discriminative power using statistical methods.

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Ich bin mir bewusst, dass eine falsche Erklärung rechtliche Folgen haben kann.

Ich versichere, dass die beiliegende CD-ROM und alle darauf enthaltenen Bestandteile auf Viren überprüft und kein schädlicher, ausführbarer Code enthalten ist.

Furtwangen, den 31. Januar, 2012 Christian Weichel

APPENDIX A

Data loss and signal corruption

Three days before the deadline of this work, we set out to build new applications based on the recording system. During the evaluation of one of these applications, we realized that at the end of each recording, 6-9 seconds seemed to be missing. Something we had never noticed before as all previous recordings were performed over a at least five minutes.

To investigate the issue, we recorded a predefined sequence of blinks: one blink every three seconds and five blinks at every full minute. When comparing the recorded data with the expected pattern, we found several blinks missing. During the time marked by the five blinks, we would expect to see 20 blinks as the participant blinks once every three seconds ($60\text{sec.} \cdot \frac{1\text{blink}}{3\text{sec}} = 20\text{blinks}$). In the recorded data, however, we counted 11 blinks between start and end, hence 9 blinks were dropped (figure A.1). We repeated that experiment several times, leading us the conclusion that roughly every 10 seconds, 7-8 seconds of data is dropped.

This phenomenon can be explained by considering the inner workings of the TMSi Mobi. It always samples the data at 1kHz and broadcasts the data over Bluetooth at the same rate. If one wants a lower sampling frequency, one has to receive all packages and drop those which are unnecessary; that's how the CRNT does it. Our implementation drops packages on the wireless interface by only receiving packages at a certain rate (roughly 75Hz). As opposed to a traditional RS232 serial connection, the Bluetooth SPP is reliable, so an ACK is expected for every byte. But as we only read the data coming on the SPP connection too slow, the Mobis send-buffer runs full and is discarded at some point - figure A.2 illustrates that process. It is that buffer-clearing that we experience as data loss.

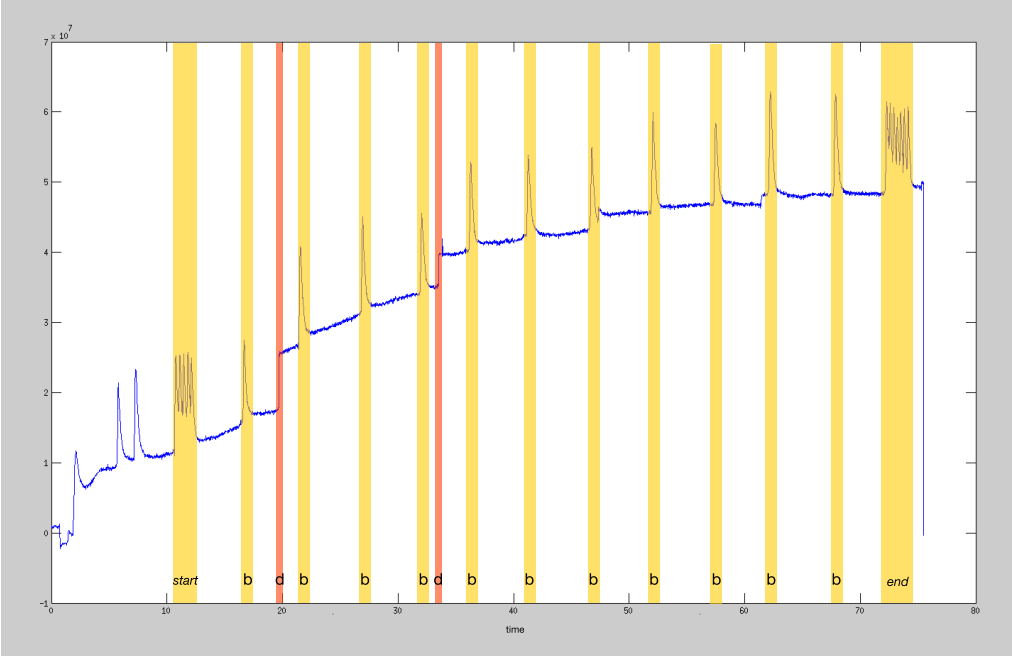

Figure A.1: Testing the recorded signal against a predefined blink pattern. All events (start, blink, end) are marked in yellow, clearly identifiable points of signal corruption are marked red. The blink count between *start* and *end* should be 20, but is 11: 9 blinks have been dropped.

This issue was not realized before, as the data coming from the Mobi does not contain timestamps, but it is the logging program which timestamps the data upon reception (see section 3.3.3.3). Due to the 1kHz sampling frequency of the Mobi, we do receive enough samples which are then incorrectly scaled in time by having their timestamp assigned to them at reception; a concept illustrated in figure A.2.

All parameters influencing the data dropping are fixed. The rate and length of the discarded segments are influenced by the parameters listed in table A.1. As all of those parameters are fixed, the dropping is fairly regular and applied to the whole dataset.

parameter	**value**
Mobi sampling rate	1kHz
send buffer size	*unknown*
data reception speed	75Hz

Table A.1: All known parameters influencing the data dropping rate.

Next steps (outside the scope of this thesis) are to analyze those data gaps by feeding a controlled signal into the Mobi and comparing the measured signal with the original. We could then perform a statistical analysis of the dropping rate and length. Such a test could be performed using a signal generator to generate a sine wave with an amplitude of 5-6μV. We expect the coupling between the Mobi and the signal generator to be a non-trivial task, as one has to take the active shielding and external noise into account.

With the data dropping being regular and occurring during throughout the whole dataset, we argue that we can still draw valid conclusions from the features we extract, as they're all affected to the same degree. However, we can not give absolute numbers, such as "the blink rate during times of concentration is x blinks per second". Trends and other insights identified by any subsequent analysis of this dataset have to be subject to further validation.

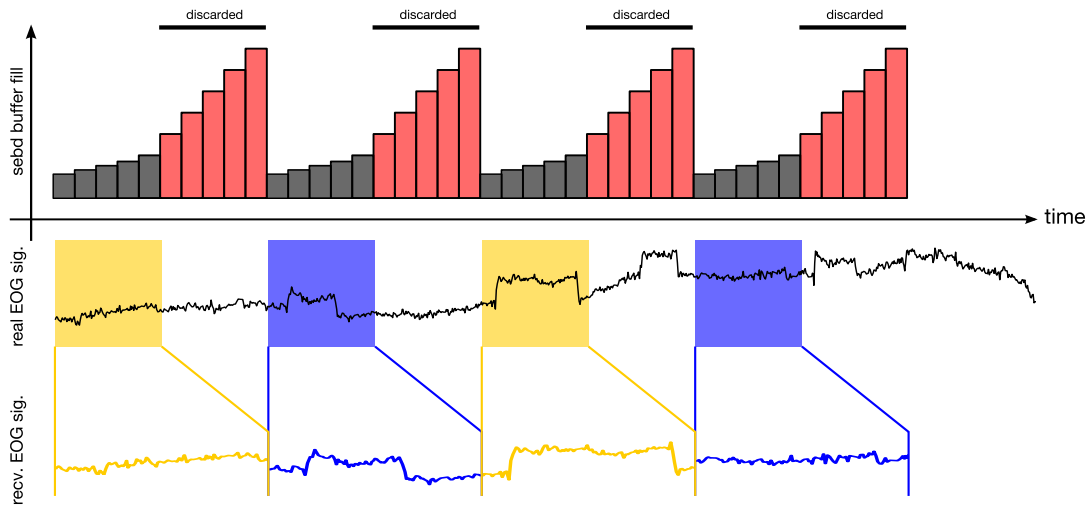

Figure A.2: Signal corruption due to too low packet reception speed. The EOG signal is only partially received and scaled to fill the gaps.

APPENDIX B

Study preparation checklist

Experiment ID:
Date of preparation:
Date of study:
Observer:

1 Prepare equipment

☐ **Prepare recording equipment**
☐ On the phone `/mnt/sdcard/datalogger` is empty
☐ The phone is fully charged
☐ The SenseCam has no previous data stored on it
☐ The SenseCams clock is synchronized to the phone
☐ The SenseCam is fully charged
☐ Four AA batteries charged

☐ **Pack the case**
☐ Four AA batteries charged, wrapped and placed in the case
☐ Phone is turned off and placed in the case
☐ At least 10 electrodes are packaged with the user manual, which is placed in the case
☐ Both electrode cables, as well as the ground electrode cable, are placed in the case
☐ The Mobi carrying case is placed in the case
☐ Mobi is placed in the case
☐ SenseCam is turned off and placed in the case

2 Train participant

All following items have to be shown to the participant.

☐ **Mobi specifica**
☐ How to connect the electrode cables
☐ How to attach the electrodes properly (special focus on the electrode order). Referred to the diagram in the user manual
☐ Inserting/replacing the batteries
☐ Turning the Mobi on and off
☐ Placing the Mobi in its carrying case and extracting it from said case

☐ **Recording application**
☐ Connecting to the Mobi
☐ Told that the user *must never hit the back button as it will end the recording*
☐ Told that a warning sound will ring if the connection to the Mobi is lost
☐ Shown the labeling functionality (incl. special event - e.g. reattached electrodes)
☐ Pointed out that the running number is an indicator for the logging activity (number is data points logged so far)
☐ Pointed out that accurate labeling is key to the study *(can't emphasize this enough)*

☐ **SenseCam**
☐ How to turn the SenseCam on and off
☐ Informed that the participant may choose to cover or not wear the cam in any situation deemed too private (e.g. in the restroom)
☐ Informed that before we use the pictures, the participant gets to see those pictures and can blacken them when deemed necessary

☐ **Ethics approval**
☐ Participant has signed the participation waiver

3 Review video stream

☐ Ask if the participant wants to review the images

☐ **Image censorship process**
☐ Give the images to the participant
☐ Request the images back from the participant
☐ Delete the original images

4 Data recovery and post processing

☐ Create a directory named as the experiment ID (`experiment_dir`)
☐ Download the *datalogger* (TMSi) data to the `experiment_dir`
☐ Download the *GPX track* to the `experiment_dir`
☐ Copy the (revised) SenseCam images to the `experiment_dir`/images

APPENDIX C

Study consent form

Consent Form

Participant	
Date	
Title of Study	A day in the life of our eyes
Researcher	

Before agreeing to participate in this research study, we kindly ask you to read and understand the following explanation of the purpose and how it will be conducted.

Purpose of the study

The purpose of this study is to explore if one can identify high-level activities within eye-movement data. Further do we seek to explore other markers and information contained in day-long eye-movement data.

Procedures

During the study, the participants eye movement data along with other modalities is recorded. Those modalities include images being taken, accelerometer and gyroscope sensor data as well as the users position using GPS. During the day of recording, the user is obliged to label his/her activities using a predefined set of labels. The total experiment duration is roughly 12 hours per subject.

Confidentiality

All information collected in the study is confidential, and the participants name will not be identified any time. Before using the recorded images, the user is given those images and is allowed to withhold or censor those images he/she deems necessary.

Risks

There are no risks to participants with this experiment.

Consent

I have had the opportunity to discuss this study and my questions have been answered to my satisfaction. I consent to take part in the study with the understanding I may withdraw at any time. I voluntarily consent to participate in this study.

Participant signature	Date
Researcher signature	Date

APPENDIX D

Participant survey

Questionnaire

This questionnaire is voluntary. By providing this data you agree that we use it for statistical purpose. Once you have completed the survey, please scan it and mail it back. **Most PDF viewers are not able to save the form data, thus printing this questionnaire is required.**

Experiment ID: _____

General

How old are you? ..... _____

Are you male or female? ..... male female

Are you left or right handed? ..... left right

Do you smoke? ..... yes no

Visual aids

If you do not require visual aids, only the first question of this subsection is relevant. Leave the others unanswered.

Do you require visual aids? ..... yes no

Are you short or far sighted? ..... short sighted far sighted

Did you wear [...] while recording? glasses contact lenses

Daily life

Did you behave differently because of the recording equipment? yes no

How long is your commute (h)? ... _____

By what do you commute? ..... bus bike train car

Please tick the items which apply to your everyday life

- mainly performing physically demanding tasks
- mainly performing tasks which require high concentration
- mainly working on a computer

Optional questions

This section is optional not directly related to the study. Feel free to answer it or leave it blank.

Est. your amount of interactions per day:

Other comments:

APPENDIX E

CD-ROM

A CD-ROM, containing the following files is attached to this work:

/thesis.pdf
: bachelor thesis as PDF file

/thesis-latex/
: bachelor thesis as LaTeXsource code

/prasentation.pdf
: thesis seminar presentation as PDF file

/monthly_reports/
: monthly reports of the thesis seminar

APPENDIX F

Acknowledgements

I would like to thank Prof. Dr. Gellersen for giving me the chance to write this thesis in such a vivid and productive environment, as well as for his supervision and advice during the entire time.

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