An Open Dataset for Human Activity Analysis using Smart Devices

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Abstract

The study of human mobility and activities has opened up to an incredible number of studies in the past, most of which included the use of sensors distributed on the body of the subject. More recently, the use of smart devices has been particularly relevant because they are already everywhere and they come with accurate miniaturized sensors. Whether it is smartphones, smartwatches or smartglasses, each device can be used to describe complementary information such as emotions, precise movements, or environmental conditions. In this short paper, we release the applications we have developed and an example of a collected dataset. We propose that opening multi-sensors data from daily activities may enable new approaches to studying human behavior.

Keywords: Human Mobility, Smart Devices, Sensing Systems, Opendata

1 Overview

Our sensing system relies on the parallel use of three complementary devices, as described in Table 1 and Figure 1.

Device	Type	Main metrics	Battery during data collection	Network Interfaces
Google Nexus 5X	Phone	Contextual data	Up to 20h	LTE, Wi-Fi, Bluetooth
LG Watch Urbane 2	Watch	Physiological data	Up to 20h	LTE, Wi-Fi, Bluetooth
Jins MEME ES_R	Glasses	User activity	Up to 16h	Bluetooth

Table 1: Specification of the devices used in our studies.

First of all, a smartphone is used to capture mainly contextual data. Two applications are used: a simple data collection application based on the SWIPE open-source sensing system[1] [FLGE16], and a logbook application for obtaining real data on user activity (aTimeLogger[2]). SWIPE is a platform for sensing, recording and processing human dynamics using smartwatches and smartphones.

Then, a smartwatch is used primarily to capture the user's heart rate. Motion data is also collected, without being at the heart of the dataset due to its need to be configured with a low

[1] `https://github.com/sfaye/SWIPE`
[2] `http://www.atimelogger.com/`

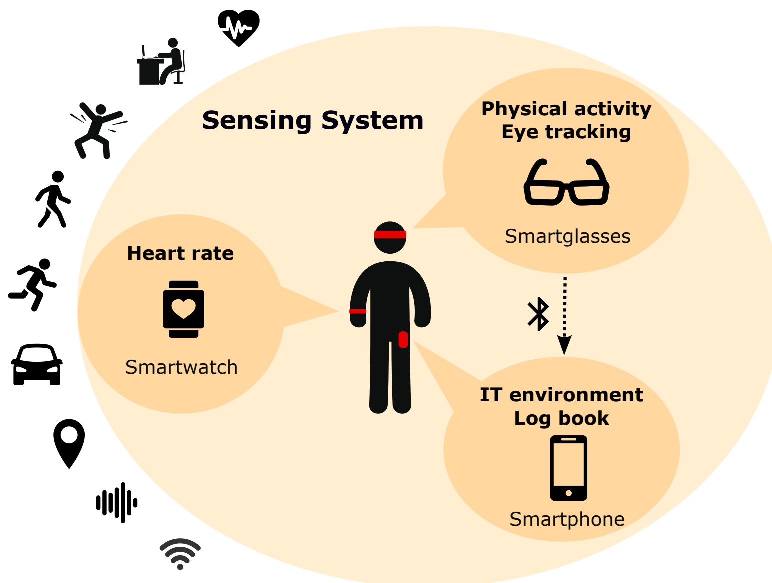

Figure 1: Overview

sampling frequency, which would drastically increase the dataset and drain the battery as well. An application based on SWIPE is used.

Finally, JINS MEME smartglasses are used. This model has the advantage of being compact and simple to carry. It does not have a camera or a screen; it simply has three types of sensors: an accelerometer (for detecting steps or activities), a gyroscope (for head movements) and an occulographic sensor (eye blinking, eye orientation). The official DataLogger application from JINS MEME is used[3].

As stated in [FBTE17], the use of smart devices as key elements in an activity monitoring platform has been discussed for many years, in both industrial and research communities. By combining multiple smart devices and building a sensing system, it is possible to interpret physical actions, social interactions, IT environments and so on (e.g. [LL13, HLL^{+}12]). Interested readers can refer to [FLGE16] to get an overview of existing sensing system architectures and solutions.

2 Dataset

In July 2017, a dataset has been collected from one of the co-authors from morning until evening for 15 consecutive days. During the data collection, the smartphone has been carried in the pocket for a considerable amount of time. The smartglasses have been used a few hours everyday.

This dataset is provided completely free of charge online[4]. The metrics collected by the different applications and their main parameters are described in Table 2.

[3] https://github.com/jins-meme/ES_R-DataLogger-for-Android
[4] https://goo.gl/RNx1SX

Device	Metric	Source	Recording rate	Comments
Watch	Heart rate	Optical heart rate sensor	Event-based	Heart rate, in beats per minute, provided by the optical heart rate sensor. Each value comes with an accuracy representing the status of the monitor during the reading.
	Step Detector	Accelerometer	Event-based	Indicates whether the user is taking a step or not.
	Step Counter	Accelerometer	Event-based	Number of steps taken by the user, detected by the Android system as a function of the accelerometer.
	Battery	Android	5,000 ms	Battery level.
Phone	Ambient sound	Microphone	1,000 ms	Maximum absolute sound amplitude returned by the microphone.
	Ambient light	Light sensor	~5,000 ms	Ambient light level.
	Bluetooth devices	Network	5,000 ms	List and number of Bluetooth devices.
	Wi-Fi APs	Network	5,000 ms	List and number of Wi-Fi Access Points.
	Speed	GPS	~30,000 ms	Travel speed, in $m.s^{-1}$.
	Activity	Activity Recognition API	Event-based	List of activities performed by the user, sorted by the most probable activity first. A confidence is associated with each activity.
	Step Detector	Accelerometer	Event-based	Same as above.
	Step Counter	Accelerometer	Event-based	Same as above.
	Battery	Android	5,000 ms	Same as above.
	Real activity	aTimeLogger app.	–	Activity tags manually selected by the user.
Glasses	Acceleration	Three-axis accelerometer sensor	10 ms	Three values describing the current acceleration.
	Angular velocity	Three-axis gyroscope sensor		Three values describing the current angular velocity.
	Corneo-retinal standing potential	Three-point Electrooculography Sensor		Four values extracted from the electrodes. See the official documentation for more information[5].

Table 2: Key metrics collected by the sensing systems.

3 Research Perspectives

While activity detection from smart-things sensors has largely been understood as quantification of physical activity, a greater intelligence of how humans are managing their time and their personal engagement in their various activities is both possible and desirable. Indeed, our daily lives are incorporating a continuously growing number of interactive systems. Obviously, these systems are bringing a good deal of disruption and distraction [Rod11], or might be disappointing in terms of usefulness and engagement. Solving these issues will make interactive services more context-relevant for users.

Such issues have been pointed out recently by [MLK], but scientific work in this field is still far from being consolidated. Conceptualization efforts have been made to better understand organization of time (e.g. [New94, STB09]). Work is also being undertaken to understand how an activity could be resolved as a combination of smaller chunks (e.g. [CIT16, CTIB15]). Finally, in [FLGE16, FBTE17], we recently proposed that wearable devices along with machine learning techniques might help classifying micro- and macro-activities, thus leading to new ways of understanding human activities and mobility.

The value of releasing the dataset and the data collection system presented in this paper is to allow the scientific community to grow beyond small-scale studies and to get a greater insight into what make a person engaged in an activity. We believe that wearable sensors are opening the way to new perspectives by bridging phenomenological description and quantification of daily and multi-scale behaviors.

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