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A Two-Level Approach to Characterizing Human Activities from Wearable Sensor Data

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Abstract

The rapid emergence of new technologies in recent decades has opened up a world of opportunities for a better understanding of human mobility and behavior. It is now possible to recognize human movements, physical activity and the environments in which they take place. And this can be done with high precision, thanks to miniature sensors integrated into our everyday devices. In this paper, we explore different methodologies for recognizing and characterizing physical activities performed by people wearing new smart devices. Whether it's smartglasses, smartwatches or smartphones, we show that each of these specialized wearables has a role to play in interpreting and monitoring moments in a user's life. In particular, we propose an approach that splits the concept of physical activity into two sub-categories that we call micro- and macro-activities. Micro- and macro-activities are supposed to have functional relationship with each other and should therefore help to better understand activities on a larger scale. Then, for each of these levels, we show different methods of collecting, interpreting and evaluating data from different sensor sources. Based on a sensing system we have developed using smart devices, we build two data sets before analyzing how to recognize such activities. Finally, we show different interactions and combinations between these scales and demonstrate that they have the potential to lead to new classes of applications, involving authentication or user profiling.

Keywords: Activity Recognition, Wearable & Mobile Computing, Sensing Systems, Data Analytics.

1 Introduction

The industrial revolutions of the past decades have caused our lives to accelerate at a tremendous pace. In recent years, the growing availability and diversity of high-tech connected objects has opened up new opportunities for automatically and opportunistically detecting a range of events in our everyday lives. In particular, new commercially available smart devices such as smartphones, smartglasses and smartwatches, permanently worn by their owners, are packed with precise, responsive sensors that can be always on [1]. These wearables come with processors and memory units that allow them to act not only as collecting nodes but also as real computing units and central decision points. The recent arrival of major players such as Google, Apple and Microsoft has popularized these devices and facilitated the development and widespread adoption of sensing applications. For instance, data from activity sensors and sports watches, usually proprietary to device manufacturers [2], can be accessed via services such as Apple Health and Google Fit.

While motion sensors (i.e. accelerometers, gyroscope and compass) have mostly been used on smartphones or proprietary devices to classify different classes of physical activity, it is now possible to correlate multiple data sources from specific devices to improve the accuracy of the classification process (e.g. using microphone or GPS data, [3]). It is also becoming more common to classify user interaction with

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different IT environments based, for example, on networking sensors (e.g. using Bluetooth or Wi-Fi). However, despite the growing availability of algorithms and methods that detect and recognize movements or what some authors refer to an activity, there is a clear lack of formal and consistent definition across the literature. Most of the time, an activity is considered as a physical activity, which is, according to [4], "*any bodily movement produced by skeletal muscles that requires energy expenditure*". In this paper we use this definition but we split the activity concept into two scales, respectively micro- and macro-activities, in order to investigate different ways of recognizing moments in a user's life. These scales will serve as a basis for understanding how new wearables such as smartglasses or watches can help to interpret different sensor data sources.

This paper reports on experiments where we used smart devices for extracting micro- and macro-activity information. It is an extension of two previous works, published at INFOCOM 2016 [5] and at MOBIWORLD 2015 [6]. This extension comes with a new related work section in addition to new results, figures and details in order to provide a basis that could be useful for future publications and projects related to this research area. After introducing related work in Section 2, we introduce the scales in Section 3 and the methodology used thorough the paper in Section 4. We then show in Section 5 how smartglass devices could be used to determine head gestures along with a long-run visualization of those gestures. A long-run visualization of directional head movement in combination with social ones might be a possible way to understand group interactions in a given environment. In contrast, for the reporting of Section 6 we used smartwatches to classify users in different locomotion and physical activities. Moreover, we used a three sensor approach to propose a 3D visualization of the data, opening the way to enhanced user profiling. To summarize, this work has the following objectives: (1) to present two concepts, i.e. micro- and macro-activities; (2) to characterize and compare those micro- and macro-activities using two smart devices to collect data; (3) to present future ways of using these new devices to improve our understanding of human activities.

2 Related Work

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 [7]. Apart from smartphones, these high-tech connected objects include a wide range of ultra-portable devices that constantly interact with the user and his environment. Devices such as smartwatches and smartglasses have their place in this ecosystem and can open up new perspectives. These wearables have much in common with ubiquitous computing, as they can precisely and continuously detect a range of events [1, 8] (e.g. movement, voice, GPS location update).

2.1 A world of sensors

By combining those devices and building a sensing system, a large amount of data can be obtained from sensors such as GPS, accelerometer, gyroscope or magnetometer. This data is used since several years to interpret physical actions and movements of the arm, hand or head with a great accuracy (e.g. [9]). Social interactions and IT environments can also be considered using Bluetooth, Wi-Fi, NFC or cellular networks [10]. Moreover, the ability of those devices to monitor other bodily metrics, such as heart rate and temperature, leads to new areas of research. For instance, studies in the University of Washington – Intel Mobile Sensing Platform [11] show a real interest in activity detection using new sensors, still little used on the market (e.g. walking on a wet floor using humidity sensors). Activity sensors and sports watches, although they belong to systems whose access is usually restricted by their manufacturers [2], also represent an interesting technology whose data can be accessed via services such as *Apple Health*,

Microsoft Health, or Google Fit.

On the sidelines of the market, the scientific community's focus on the use of miniaturized sensors has resulted in the development of experimental devices, ranging from simple wrist-worn sensors for detecting hand movements, to whole networks of sensors distributed over the subject's body to scrutinize every aspect of its physical activity (e.g. [12, 13]). Technological advances have led to the integration of sensors that can produce results equal to those of these specialized experimental devices. [9] shows for example that movements of the arms, the hands and possibly the fingers, generate energy strong enough to be picked up by the accelerometer and the gyroscope of a smartwatch with 98% precision.

2.2 Creating a Sensing System

Compared to wearables, smartphones have a better battery capacity and can launch several tasks at the same time. By using a smartphone as a local gateway to access the Internet – via WiFi or Cellular – we can turn a local sensing platform into a connected ecosystem registered in the Internet of Things [14] as well as in the emerging paradigm of Big Data [15–17].

The well-know survey of Lane et al. [7] proposes an architecture separated into three parts. First, individual devices collect the sensor data. Next, information is extracted from the sensor data by applying learning methods on one of the devices, in the cloud, or on a partition between the two, depending on the sensitivity of the data, the sampling or the privacy. In most cases, smart devices are connected between them via Bluetooth Low Energy (BLE) [18], a relatively new technology that has been standardized under the Bluetooth 4.0 specification [19]. The last component consists of sharing the data and visualizing it from the cloud. [20] proposes an architecture made up of a wearable, a smartphone and the data hosted in the cloud. In [21], multiple devices can be connected to a cloud platform that allows the control and sharing of data. [10] proposes a smartphone application that sends most of the sensors' data to a set of two servers. The first one is used to control the users' access while the second is used for processing and data visualization.

These sensing systems usually address three levels of detection [7]. At individual level, where detection and data processing are targeted at and for the individual (or perhaps some authorized person), as in the case of certain applications connected to sport [22]. At group level, where individual participants with devices share a goal or a common interest, when there is an element of trust within the group [23]. At community level, with many participants [24]. At this level, when people are strangers and don't have the same trust in one another, it is important to define rigorous systems for the protection of personal privacy. Data collection can be as opportunistic [25] as it is participatory [26]. In the case of an opportunistic system, a lot of applications are based on crowd-sensing to aggregate data from sensors [27].

As the applications need to be running on the devices permanently to collect and send data, there is an important compromise to be found between sample rate, rate of transmission and the consumption of energy [28]. Different experiences of deploying detection systems on smartphones show that batteries can be reduced to an interval ranging from 6 to 20 hours, depending on the sensors and defined parameters [29]. The authors of [10] show for example that using all the sensors of a LG Nexus 4 E960 can reduce its battery from 214.3 hours (no sensors) to 10.6 hours (all sensors). Some systems attempt to exceed this energy limit by offloading data processing onto servers [20, 28, 30]. Others propose sharing the data between smartphones in the local area [31]. In this sense, cloud computing is widely used with smartphones and allows the creation of elastic setups [32], where applications are launched on the mobile, and data is processed in the cloud.

2.3 Monitoring Human dynamics

2.3.1 Health

The user's movements and behavior can be analyzed with smart devices to detect symptoms. SPARK [33] is for instance a framework that can detect symptoms associated with Parkinson's disease: analysis of facial tremors, dysfunctional speech, abnormalities in the gait or dyskinesia of the limbs. The authors show dozens of studies using numerous sensors of more or less complexity to obtain results similar to those that can be obtained simply with a smartwatch on the wrist (dyskinesia using motion sensors), and a smartphone in the pocket (gait analysis and sound) or using a camera for face detection. [34] studies patients with mental disorders and uses smartwatches to help quantify the exercise and the amount of sunlight wearers received. This is achieved with the aid of GPS, an accelerometer and a light sensor. The measured data is sent to a server where it can be analyzed and consulted by doctors. UbiFit Garden [22] captures levels of physical activity and links the data to goals of personal health and well being. Further, [35] indicates that wearables have the potential to mitigate the problems of doctors' access to patients as well as allowing specialists from around the world to access a data stream and put an end to rural-urban disparities.

2.3.2 Personality

Personality is a combination of the emotional characteristics, attitudes and general behavior of an individual. In the literature, some authors have focused on the study of personality using smart devices. For instance, EmotionSense [36] is a platform that uses the data collected by smartphones for social psychology studies, detecting activities but also verbal interaction and proximity to others. The Big Five model [37] structures personality into five factors, i.e. extroversion, agreeableness, conscientiousness, emotional and intellect. Using this test, Oliver et al. proposed in [38] a conceptual model that explains the influence of the user's personality on their satisfaction, with actual mobile phone usage and perceived usability of the services. They observed a high correlation between the usage of mobile phone services, and the personality of the users.

2.3.3 Lifestyle

Lifestyle is the way of living, being and thinking of a person or a group of individuals. It is a person's day-to-day behavior, reflected in his activities, sports, mobility, habits, health, and general interests. Common applications of GPS-based location information systems enable to estimate the transportation mode of the user such as walking, riding a bike, driving or using public transport. However, indoor reception is usually bad and connections are often not stable [39]; the accuracy is relative, given that the user does not always have the smartphone or the smart devices with him. By correlating different sources of data, it is now possible to alleviate these problems. [3] uses for example data from the accelerometer, sound, GPS and Wi-Fi signals to classify its activities. By continuously recording sound and networking metrics, it is also possible to identify the contexts and IT environments of a user, whether having a conversation, sitting at the office, walking out on the street, or even making coffee [40,41]. [32] developed an activity recognition application and transferred their data in order to analyze and create an activity timeline. Video sensing also permits to recognize various activities [42]. However, video analysis is both algorithmically and computationally expensive; it prevents a real time implementation especially in a resource constrained environment, and also raises privacy issues.

2.4 Machine-Learning and Activity Recognition

As introduced before, the activities and movements of the user can be reliably deduced by smart devices [9, 43]. Activity detection involves the recognition of spatio-temporal patterns from sensor data that is usually incomplete and noisy. A significant number of models are able to characterize human dynamics from different features (e.g. accelerometer data). The temporal signal shape can be analyzed both in the time and frequency domain. Time-domain features include basic waveform characteristics and signal statistics that can be considered as features of a given signal, i.e. the statistical moments, time between peaks, binned distribution, mean value of local maxima [44]. It is possible to create a condensed feature set that is representative of the signal shapes of a particular user. Data set reduction techniques such as Principal Component Analysis and Linear Discriminant Analysis can be used to extract the most significant discriminating features while reducing the dimensionality of the data representation [45].

Combining the feature extraction techniques above, the activity recognition can be trained using (semi-)supervised methods in a controlled setting. These methods include Decision Trees, Neural Networks and Support Vector Machines, that has been successfully used in human activity recognition [6, 46]. For example, Frame-based Descriptor and multi-class Support Vector Machine [47] is an approach that can classify a large variety of gestures. Unsupervised methods, e.g. k-Means clustering [48], can then be used to find structure in the different activity sequences and durations that were estimated to find common properties or behaviors of user groups.

We can also mention for instance FDSVM [49] (Frame-based Descriptor and multi-class SVM), which is an approach to classify a large variety of gestures using a three-axis accelerometer. [21] presents a pointing device that detects movement with FDSVM and also takes social interaction into account. Other algorithms are also known and are based on the DTW approach [50] (Dynamic Time Warping) or even HMM [51] (Hidden Markov Model).

3 Understanding the Concept of Activity

Detecting and identifying user activity has undergone such extensive research that it is already being integrated into many commercial products. From the fitness tracking market, Google Fit App claims for example to detect basic activities such as walking, running or biking. However, the concept of user activity lacks of a formal and consistent definition across the state of the art or the commercial applications. Approaches presented in Section 2 generally focus on activity understood as physiological and motor activity. While physiological and motor activity can easily be captured by wearable devices through commercial sensors, they point to a limited area of the human activity spectrum. Indeed, human activity is not merely limited to its motor and behavioral expression. Actually, human activity encompass a wide range of behaviors, observable or not, which present different degrees of importance, effort and duration.

First of all, activities could also be described as goal-directed behaviors: they are characterized by a hierarchical structure of goals and sub-goals that the subject wants to achieve [52]. In that perspective, goals are hierarchical task structure implying the execution of operations in a particular plan of execution [53]. Goals could be either actively pursued or latent and are executed at different scales of time.

In that respect, Newell [54] described a range of behavioral bands based on their frequency of occurrence in human life: biological, cognitive, rational and social bands (see Table 1 for details). On a specific band of frequency, activities are alternating sequentially, however activities belonging to different bands of frequencies are concurrent by nature.

In that sense, activities are structuring human life, as activities are alternating at different frequencies. In an attempt to reflect this temporal organization, Salvucci et al. [55] proposed a unified theory of multitasking continuum. In this approach, tasks are arranged on a continuum of interruptibility: that

is the frequency at which several tasks could alternate. On the one side of the continuum, at higher frequencies, tasks can alternate rapidly to reach a concurrent mode of execution ; and on the other side, at lower frequencies, tasks are alternating at a slower pace in a sequential execution mode.

	Newell scales	Level	Duration (s)	New scales	Example
Individual	Biological	Cell / cell groups	$10^{-4:-2}$	Micro	Neuron spike
	Cognitive	Physiological response or motor act	$10^{-1:1}$		Jumping, taking a step, heart beat
	Rational	Hierarchy of actions towards a goal	$10^{2:4}$	Macro	Walking or running toward a direction
Group	Social	Coordinated goal	$10^{5:7}$		Sport competition

Table 1: Activity scales

Thus, activities have both a temporal and structural organization and in this paper, we propose that fast alternating (high frequency) activities are subordinate tasks while slow alternating (low frequency) activities are at a higher level of the hierarchy of goals. However, related work about activity recognition focuses on small scale activities and thus, there is no distinction between those scales. For this reason, we propose two new concepts in this work in order to support a better understanding of user activities: on the one side, **micro-activities** are activities detectable from wearable sensors measurements that relate to activities located in the cognitive or even in the upper-bound biological bands; on the other side, **macro-activities** are activities located in the rational or in the lower-bound social bands and which need integration of several source of information in order to be understood.

In our views, users reason in terms of macro-activities (e.g. physical exercise) as those one ones are at the basis of goals selection and organization (i.e. forming plans). Under this perspective, both aspects have to be taken into account to understand an activity as micro-activities give information about plan execution while macro-activity gives information goal and context, which is particularly important in context-sensitive systems [52].

4 Methodology

4.1 Assumptions

In the first study, we used smartglasses in order to detect micro-activities. Indeed, as micro-activities are more sensitive to movements (i.e. we need to collect data at a high rate) and as head movements are generally less important than arm movements, smartglasses are particularly adapted to study this level of activity. Furthermore, the fact that smartglasses are usually less comfortable is not an issue as micro-activities are short duration actions.

In the second study, we used smartwatches and smartphones in order to detect macro-activities. For the reason that macro-activities are longer duration actions, those devices are better suited for studying this level of activity. Indeed, those devices are both more comfortable and have a much higher battery capacity altogether with a good detection of the IT environment using Bluetooth 4.0.

4.2 Architecture

The architecture used as part of our studies is illustrated in Figure 1. It is composed of two main parts. First, the sensing system is based on one or more smart devices with the objective of collecting metrics

when users wear them. This is done in particular through an Android application that we have developed independently for smartglasses and smartwatches, which usually need a smartphone to access the Internet. In addition, an online platform is responsible for data storage and overall processing.

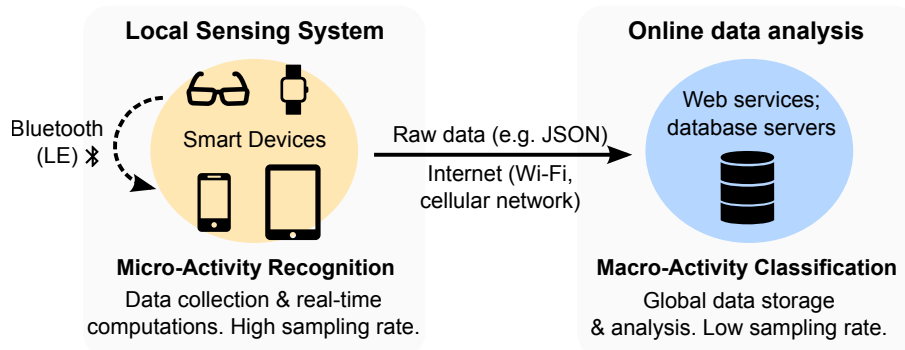


Figure 1: Overview of our architecture

The first application is dedicated to smartglasses and is called *eGlasses Logger*. It is developed as part of the eGlasses project¹. The second application comes from a new initiative at the University of Luxembourg, SnT, and is called *SWIPE*. *SWIPE* is a platform for sensing, recording and processing human dynamics using smartphones and smartwatches. It is freely available online² under a MIT license. Interested readers can refer to [6, 56, 57] for more details.

We assume in the rest of this paper that micro-activity recognition needs reactivity and therefore a high sampling rate, which corresponds to an integration into the local sensing system. On the contrary, macro-activity classification needs historical data and a lower sampling rate, which corresponds to the online analysis depicted in Figure 1.

4.3 Hardware

The devices used as part of our experiments are detailed in Table 2. We used those devices for our experiments because of their advanced and open operating system (Android). However, the methods described in this paper are applicable to any type of device running on Android 4+.

4.4 Metrics Collected by our Sensing Systems

The main metrics that our systems collect are shown in Table 3 (eGlasses Logger) and 4 (SWIPE).

The “recording rate” column indicates the frequency at which a metric is saved in the device, while the “sampling rate” indicates the frequency at which the system acquires raw data from sensors. These values are configured on a millisecond time scale for the eGlasses Logger, in order to have the best possible reactivity when recognizing micro-activities. Regarding *SWIPE*, they are configured on a second time scale to alleviate the data set to be stored on our server. For instance, the average speed of movement of the user’s arm is recorded every 30 seconds, along with the maximum speed in order to detect sudden, unusual gestures.

Metrics collected by the phone include contextual data that could be of interest for recognizing macro-activities. This includes accelerometer readings that are complementary to those provided by the watch. Network data also enables us to collect information on both mobility (GPS, Wi-Fi) and

¹<http://www.e-glasses.net>

²<https://github.com/sfaye/SWIPE/>

Devices	RAM / Storage	CPU	Network Interfaces	Main sensors
EPSON Moverio BT-200 (Smartglasses)	1 GB / 8 GB	Dual-core 1.2 GHz	GPS, 802.11 b/g/n, Bluetooth 3.0	Accelerometer, gyroscope, compass, microphone.
Samsung Gear Live (Smartwatch)	512 MB / 4 GB	Quad-core 1.2 GHz	Bluetooth 4.0	Heart rate, pedometer, accelerometer, gyroscope, compass.
LG Nexus 5 (Smartphone)	2 GB / 16 GB	Quad-core 2.3 GHz	4G/LTE, GPS, 802.11 a/b/g/n/ac, NFC, Bluetooth 4.0	Proximity, ambient light, accelerometer, gyroscope, compass, microphone.

Table 2: Specification of the devices

Metrics	Sensors	Description
Motion	Accelerometer, Gyroscope, Compass	Recorded every ~ 250 ms
Recognized Micro-Activities	Gyroscope	Based on DTW as discussed in Section 5.
Ambient sound	Microphone	Ambient sound level, from $[0 : 100]$.
Android Activity	Accelerometer, Android API	Activity recognized by Google Play Services.

Table 3: Key metrics collected by eGlasses Logger (Micro-activity, only on smartglasses).

Devices	Metrics	Sensors	Recording & Sampling rates		Description
Phone & watch	Maximum acceleration	Accelerometer	30 sec.	< 1 sec.	Maximum value of $\alpha = \sqrt{(x^2 + y^2 + z^2)} m.s^{-2}$, where x , y and z are the acceleration along each axis of the device, excluding gravity.
	Average acceleration	Accelerometer	30 sec.	< 1 sec.	Average value of α .
	Pedometer	Accelerometer, Android API	60 sec.	\sim	Number of steps taken by the user, detected by the Android system as a function of the accelerometer.
Watch	Heart rate	Optical heart rate sensor	60 to 300 sec.		Heart rate, in beats per minute, provided by the optical heart rate sensor.
Phone	Ambient sound	Microphone	60 sec.	1 sec.	Ambient sound level, from $[0 : 100]$.
	Bluetooth devices	Network	120 sec.		Number of Bluetooth devices.
	Wi-Fi APs	Network	300 sec.		Number of Wi-Fi Access Points.
	Speed	GPS	60 sec.		Travel speed, in $km.h^{-1}$.

Table 4: Main key metrics collected by SWIPE (Macro-activity, on smartphones and watches).

interaction with other devices (Bluetooth). Finally, in both case, we also store microphone readings to register the level of ambient noise, enabling us to distinguish between noisy and a quiet places.

5 Recognizing Micro-Activities

In this section, we use Dynamic Time Warping (DTW) to detect micro-activities. Using this method on smartglasses and based on a small data set collected over three participants (detailed in Section 5.3), we then study the advantages and disadvantages of using those micro-activities to understand the human behavior and mobility.

5.1 Dynamic Time Warping

DTW is one of the most popular algorithms that measures the similarities between two time sequences of different speed and duration [58]. It aligns two time series in order to minimize the cumulative distance d between each of the data points.

Let $X = (x_1, \dots, x_{|X|})$ and $Y = (y_1, \dots, y_{|Y|})$ be two one-dimensional time series. DTW provides a cost calculated through a two-dimensional cost matrix C ($|X|$ by $|Y|$). Each cell represents the minimum cost accumulated between the time series X and Y to the position of that cell, and is calculated by:

$$C_{(i,j)} = D(x_i, y_j) + \min\{C_{(i,j-1)}, C_{(i-1,j)}, C_{(i-1,j-1)}\}, \quad (1)$$

which represents the distance between point i of series X and point j of series Y , of the minimum accumulated distance from the previous three cells that surround cell i, j (the cell at the top, left and diagonally). D is a distance function, generally Euclidean:

$$D(x_i, y_j) = (x_i - y_j)^2 \quad (2)$$

When the matrix is full, the minimum normalized distance between X and Y is obtained by taking the value of the last cell:

$$DTW(X, Y) = D(|x|, |y|) \quad (3)$$

Figure 2(a) shows two examples of the alignment of multiple time series, taking the three axes of the gyroscope and describing a “Yes”, nodded while wearing smartglasses (Figure 2(a)), and a sudden movement to the left (Figure 2(b)). Note that we used R and the dtw library [59] in order to generate those graphs.

5.2 Considering multiple dimensions

In order to perform motion detection and recognition, the eGlasses Logger application needs a training data set composed of multiple time series identified by a label (i.e. the name of the movement being performed). Using the three axes of the gyroscope as the basis for detecting and registering head movements, those labels are categorized into two groups that contains a total of seven head movements:

- **Social movements:** yes, no, don’t know (which corresponds to a shrug and a slight tilt of the head);
- **Directional movements:** up, bottom, right, left.

After each movement led one or more times, the detection of a movement is done simply by comparison with the training data set by using DTW. In order to treat the three dimensions represented by the three axes of the gyroscope, we use a Euclidean normalization (L2 norm) to reduce each movement to a one-dimensional series $\sqrt{\alpha^2 + \beta^2 + \gamma^2}$, with α , β and γ axes of the gyroscope.

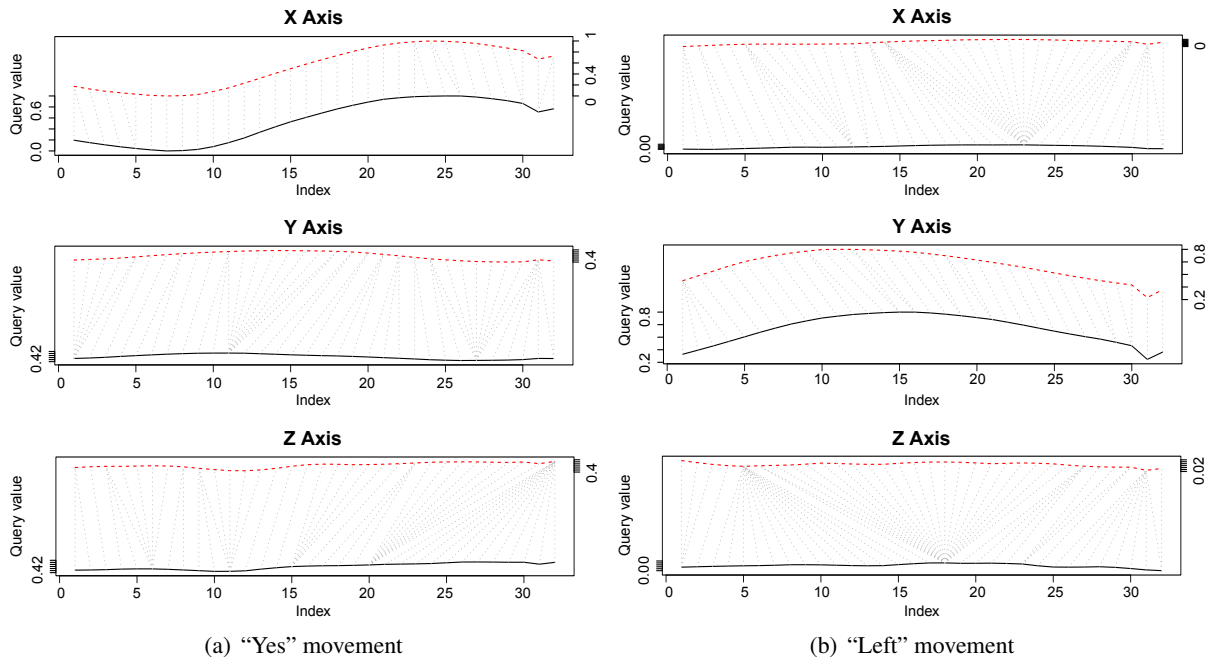


Figure 2: Alignment of multiple time series. The red lines represent the references (i.e. training data set – historical time series) while the black lines are the queries (i.e. current pattern).

5.3 Experiments

We have implemented our method through the eGlasses Logger application and on smartglasses whose choice was justified in the previous section. The interface of this Android application allows (1) to record a training data set consisting of several movements defined by the user, and (2) to return the movement and the distance determined using DTW that match a current movement.

To record the user’s movements, the application automatically detects sudden changes of the gyroscope, and stores (i.e. training data set) or classifies (i.e. current pattern) the corresponding time series. Two other methods were also implemented, one based on a time slot (e.g. registration or classification every 5 seconds) and the other based on a button that the user must push to start or stop recording.

Figure 3 shows the number of occurrences of each movement in our data set. Our experiments were based on three different participants. The first recorded the movements described in Sec. 5.2 for a training data set. The second wore glasses for 2.8 h at different places (work, public transport, city center, etc.), which caused the detection of 1,863 movements (i.e. one every 5.4 seconds). The third wore them for 3.6 h and was most of the time in the same room (office), which caused the detection of 1,689 movements (i.e. one every 7.65 seconds). It seems logical that an inactive person does less movements that a person who is moving.

5.4 Results

Figure 4(a) shows the number of movements (described in Sec. 5.2) detected in both groups for the second participant. The red dots show the difference between group A (direction) and group B (social). After consulting a diary activity³ provided by the participant, we can draw some conclusions. Around 2,000 and 8,000 seconds, the participant was sitting in a bar, which caused more social movements. Be-

³Available online: <http://swipe.sfaye.com/jowua16/diary-activity.pdf>

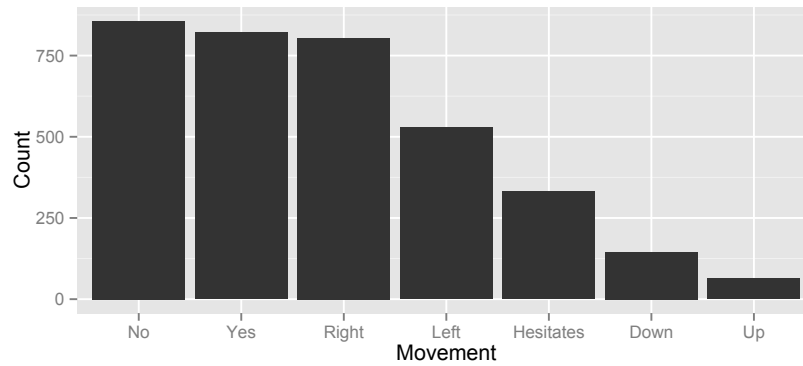


Figure 3: Overview of the data set (eGlasses Logger).

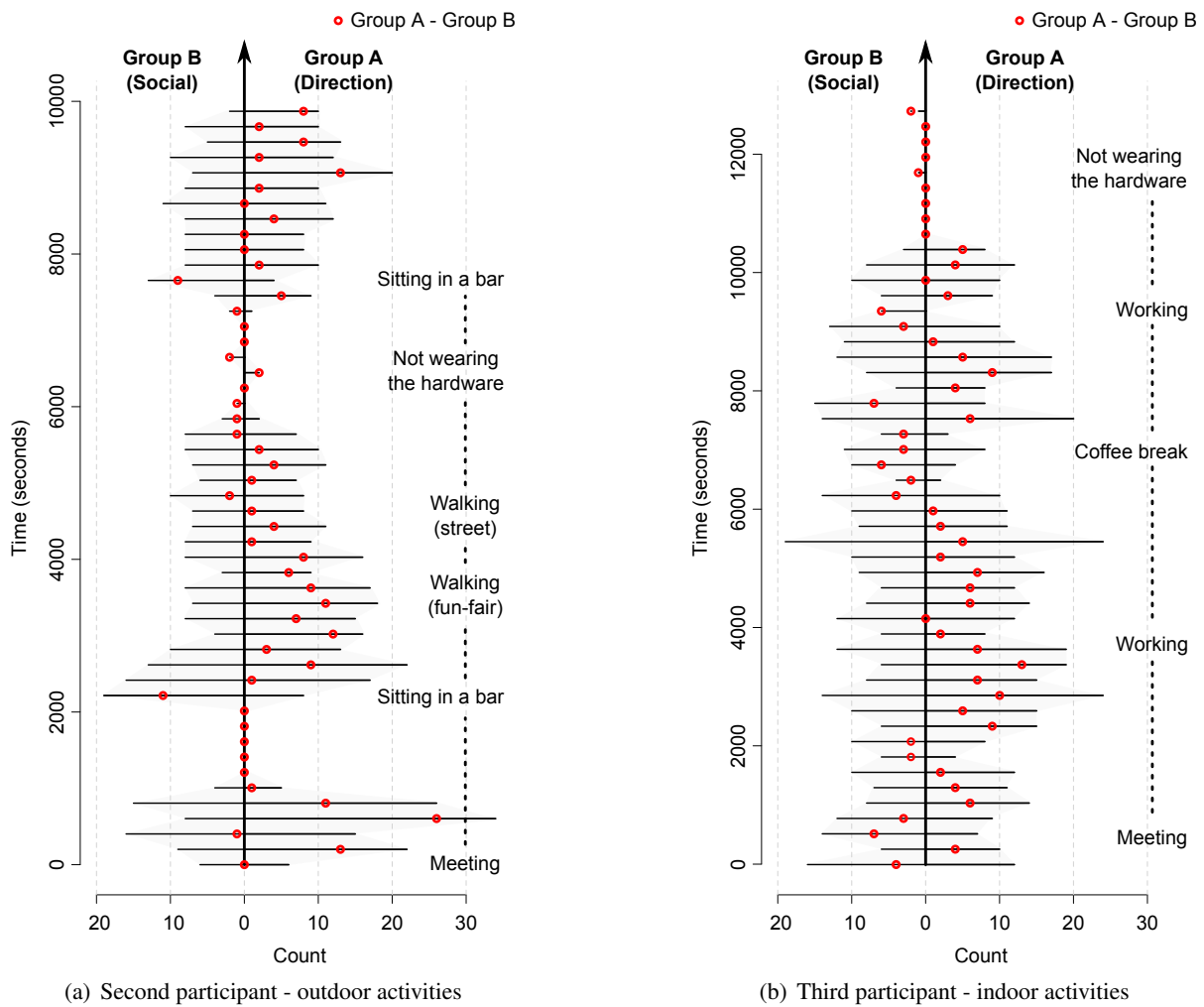


Figure 4: Micro-activity detection timeline. The labels at the right are extracted from the activity diaries.

tween 3,000 and 5,000 seconds, the participant was in the street walking with a variable speed. The peak of attention seems longer between 3,000 and 4,000 seconds, when the participant was in the middle of a fun-fair. Finally, before 2,000 and around 6,500 seconds, the participant was not wearing the hardware, which explains the lack of movements. This allows to understand more precisely the type of interaction performed by a user, without having to use expensive methods (e.g. image processing).

Figure 4(b) shows the number of movements detected in both groups for the third participant, who was most of the time in the same room. This case is probably less rich than the last one because of the context, which was quite limited. The user was working on his/her computer most of the time, except at the beginning of the session and between 6,000 and 8,000 seconds, where the user indicated that he/she had a coffee break with colleagues.

As just described, the combined recognition of several micro-activities can describe moments in the user's life and forms macro-activities. This approach can be useful to understand how small physical actions can compose into complex and goal-directed actions.

5.5 Limitations

Figure 5(a) and 5(b) show the distribution of distances computed for each micro-activity and for the two participants. As described in Section 5.1, the distance is computed according to the formula 2. It is a similarity measure between a current pattern and a registered micro-activity.

The graphs show three categories of micro-activities that are detected each with different distances. This means that the training data set does not provide the same accuracy for each micro-activity. Moreover, we can see clear differences between the two participants. For instance, the movements of the third participant (Figure 5(b)) seem to be performed with smaller distances than those of the second participant (Figure 5(a)).

These results suggest that this training data set is not generalizable to any individual, who has his/her own way of behaving. The micro-activity scale is probably too precise and sensitive to identify goal-oriented actions.

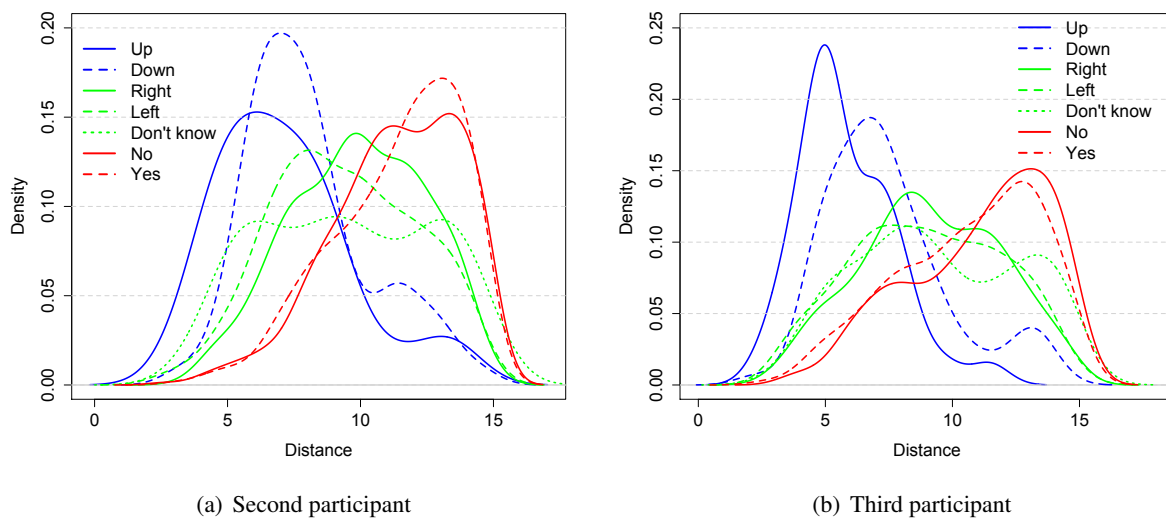


Figure 5: Micro-activity detection distribution.

6 Classifying Macro-Activities

In this section, we rely on a data set obtained from 13 participants we have collected using a smartwatch, a smartphone and the SWIPE open-source application. This data set will form a basis to apply machine-learning methods and see if it is possible to recognize activities using one or multiple sensors. Interested readers can refer to [6], where we proved that it is possible to use a combination of different sensors from a smartphone and a smartwatch to describe physical and social behaviors of different users.

6.1 Data collection

The first step was to collect a data set using the SWIPE application described in Section 4.2. These studies involved 13 participants working in the same building at the University of Luxembourg. They were selected as a representative sample of both genders and of different ages, and were systematically subjected to the same requirements:

- wear the watch and smartphone for one day, from 10:00 to 23:59;
- complete a questionnaire⁴ asking for an exact description of activities carried out (work, commute and leisure activities);
- sign an informed consent form to accept the privacy policy of the study.

Figure 6 shows the macro-activities indicated by the participants and their total durations in our data set, which consists of 157.2 h of recordings.

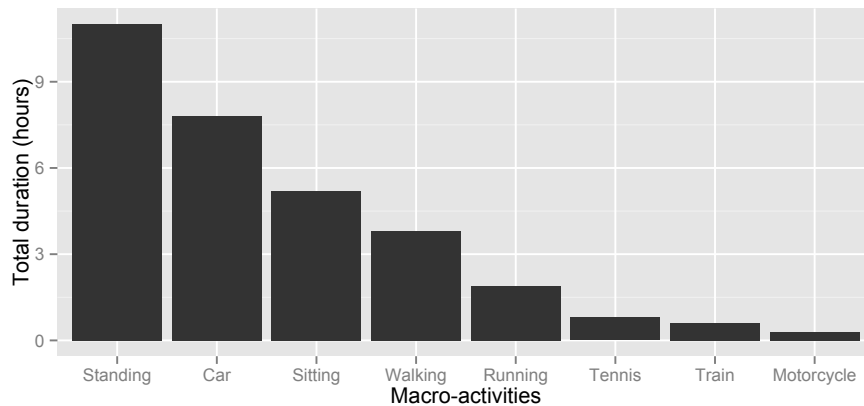


Figure 6: Overview of the data set (SWIPE).

6.2 Analysis

Based on the data set collected, the problem to be solved is how to identify a specific class (i.e. a macro-activity) based on a set of sensor data. As described in section 2, we chose to use Support Vector Machines (SVMs) to classify data into separate categories and to decide which class a sample is in (i.e. discrimination). SVMs are a set of supervised machine-learning techniques that have the ability to deal with large amount of data while providing effective results [60].

⁴Available online: <http://swipe.sfaye.com/jowua16/questionnaire.pdf>

We used the SVM classifier provided by the e1071 package for R [61], configured with the default optimization method (C-classification) and the classic radial kernel. Grid-search with 10-fold cross validation [62] was used to adjust the cost parameter C (within a range of 1 to 100), as well as γ (within a range of 0.00001 to 0.1).

Note that, as shown in Table 4, the numerous measurements that we have in our data set were not all recorded at the same frequency. For instance, acceleration was recorded twice as often as GPS speed. To simplify operations, we chose to refine the data for each metric by sampling the same number of values from each. For each of the known macro-physical activities, we used a sliding window of ten minutes, moving over the data stream every five minutes. With each movement of the window, two representative values of metrics are included in the window: their average, which gives an overall view of the data over the interval; and their standard deviation, which is fundamental to understanding the variations around the average. This representation is simple and has the advantage of abstracting from the excessive precision of the data. The number of features is therefore twice the number of metrics considered.

6.3 Results

In this subsection, we are first interested in finding a combination that minimizes the error rate. To do this, we generate all possible combinations of metrics and create a data set for each combination (e.g. watch acceleration and pedometer; Wi-Fi access points, microphone and Bluetooth devices, etc.). For all possible combinations, each data set is randomly divided into a test set (30% of instances) and a training set (70%) in order to calculate the average error rate provided by the combination, over 100 iterations. The combination retained is the one with the minimum average error rate.

Macro-Activity	Best combination										Best accuracy				
	Watch				Phone						Phone & Watch	Phone only	Watch only		
	Max. Acceleration	Acceleration	Pedometer	Heart rate	Max. Acceleration	Acceleration	Pedometer	Microphone	Bluetooth devices	Wi-Fi APs				Mobile network data state	GPS speed
Sitting													99.5	99.0	85.6
Standing													95.3	81.4	68.8
Walking													95.8	87.0	73.2
Running													100	97.4	100
Tennis													100	-	100
Bus													88.9	69.5	73.1
Train													100	96.6	83.9
Motorcycle													100	97.8	100
Car													93.2	90.4	77.0
Average													93.2	88.1	81.5

Table 5: Best combinations of metrics for each macro-activity. The “Best accuracy” columns (at the right) denote the best possible percentage of the test data set which is correctly identified in the training data set.

Table 5 represents the best combination of metrics obtained for each macro-activity and for three cases: combined watch and phone metrics, watch metrics, and phone metrics. For each line, the best combination presented is the one that has the best accuracy. For example, the best combination for recognizing the “walking” class is a combination of metrics on the watch and on the smartphone, giving us a 95.8% average recognition accuracy. We can also see that, for the “running”, “motorcycle” and

”tennis” classes, using the watch alone provides better accuracy than a combination of the watch and phone sensors. However, in most cases, the combined use of both devices offers better results than a phone or a watch alone. Finally, the “average” line indicate a common combination in all classes that minimizes the average error rate.

To illustrate these combinations, we have taken as an example a new participant. Each activity class is identified using the ”average” combination. The recognition method is applied by progressively comparing the individual user’s data with the data in our full data set using SVM. As we can see in Figure 7 and by consulting the participant’s questionnaire (gray bars), we obtain a very realistic result, which is made possible by the collaboration of all participants and the pooling of their data. For example, we see that at around 18:00 the participant was driving, and at between about 19:00 and 20:00 he was walking and running.

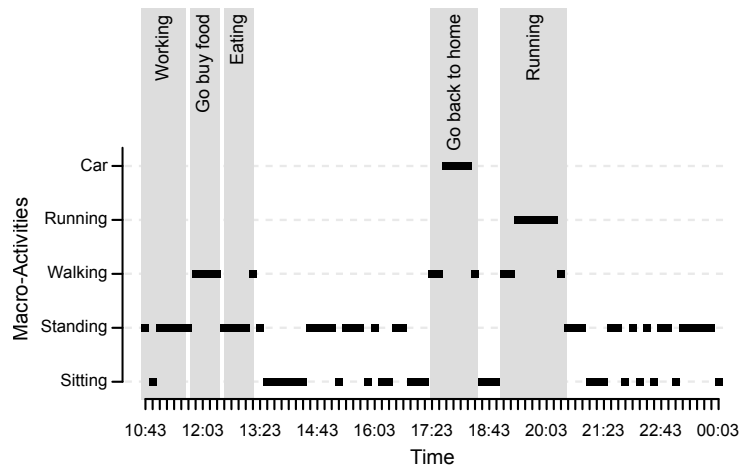


Figure 7: Recognized Macro-Activities (SVM parameters: γ : 0.1, cost: 10).

6.4 Combining micro- and macro-activities

In order to go further in trying to compare and classify users doing similar activities, our idea is to combine different macro-activities (e.g. walking) with micro-activity metrics (e.g. amplitude of sudden movement). To this extent, we introduce a novel 3D visual representation, allowing the comparison of different users with similar activities.

First of all, we choose three macro-activities to represent a user’s everyday life, namely ”in vehicle” (transportation), ”walking” (activity) and ”sitting” (inactivity). Then, we choose one representative micro-activity as a basis to compare the participants. We avoid using metrics such as GPS or environmental data because we want to focus on the behavior of the user, i.e. his movements or physiological data. For this reason, we choose to use the maximum linear acceleration recorded by the smartwatch to detect sudden movements of the users (recorded every 30 seconds). The linear acceleration can be described as the rate of change of velocity of an object. It is computed over the three axes of the accelerometer: $\sqrt{x^2 + y^2 + z^2}$. Combining this metric with different macro-activities has the potential to provide different behavioral profiles.

Figure 8 is a 3D representation of the three normalized maximum linear accelerations computed on average when the users was in different situations. We can see that there is a good distribution of all users. This means that each user has his own way of moving, and it is visible easily using this kind of graph. This figure gives an idea of how we can compute a profile for each user. We can see for example than the profile of P12 seems to be close to the one of P8. P9 seems to have more important movements

than the other participants when he/she is in a vehicle, which may be interpreted as a form of aggressive driving.

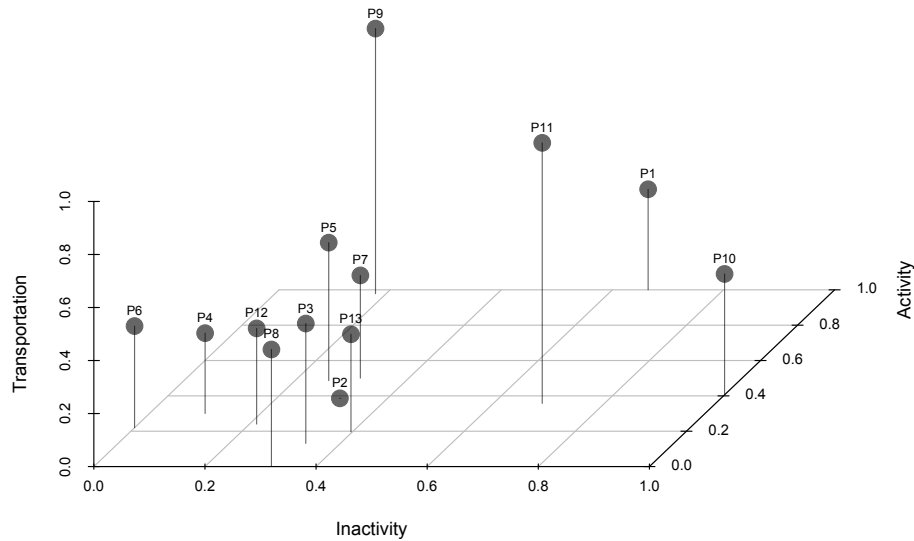


Figure 8: Combining three macro-activities (i.e. in vehicle, sitting and walking) with one micro-activity metric (i.e. sudden movements).

6.5 Perspectives

This example is just an introduction to the possibilities we have using such aggregated graphical methods and can lead to user profiling and enhanced personalized services. In our point of view, the originality of combining micro- and macro-activity levels of behaviors will lead to two types of innovative applications and services. First, if a gesture is the unit of user’s daily routine as a word is the unit of a sentence, combining different levels of activity will allow for a better understanding of the user’s goals which in turn will improve tailoring applications and services to his/her needs. Then, having a complete scope of a user’s daily routine will make it easier to match user content or service recommendations by using preferences of users who share the same routine. Such an approach can rise challenges in terms of the trade-off between privacy constraints and profiling accuracy.

Beyond detection and classification, sensing activities and environments may open possibilities of long-term life-logging and memory augmentation. More specifically, long-term memory mostly works based on contextual cues and priming that actually activate more abstract, verbal memories about facts and self. A good illustration of this is Proust’s “episode of the madeleine”. What if a wearable device could sense, store and (re-)activate context automatically and on a large scale? Applications are ranging from personal information management, social sharing of stories and activities, and even medical applications related to supporting memory or detecting disease early-on. Finally, it is important to note that those applications rise important issues in terms of privacy: how to improve user awareness of what is currently being logged, how it is processed or shared, and how the user may tune the sensitiveness of context sensing.

7 Conclusion

In this paper, we presented a two-level approach to characterizing and understanding human activities computed from wearable sensor data. Using different methods and algorithms, we show that new commercially-available smart devices – considered by many as gadgets – can recognize those micro- and macro-activities with a good accuracy. Whether smartglasses, smartwatches or smartphones, those connected objects have an important role to play in understanding the lives and behaviors of individuals.

On the one hand, micro-activities can easily be deduced based on time series analysis algorithms such as Dynamic Time Warping. This first category of activities is detectable directly from wearable sensors measurements and is represented in this paper as head movements whose clustering allow the understanding of bigger chunks of behaviors we call macro-activities.

On the other hand, these macro-activities can be recognized based on supervised machine-learning algorithms such as Support Vector Machines. In particular, the use of multimodal metrics from smartwatches and smartphones allows the recognition of nine user-defined activities, with an average accuracy greater than 90%. Furthermore, we show that using a smartwatch in addition to traditional smartphones leads to a better detection accuracy, and that smartwatches can detect specific activities without the help of any smartphone.

Finally, as presented in this paper, studying interactions between micro- and macro-activities has the potential to address new categories of problems such as user profiling and authentication as discussed in Section 6.5.

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Sébastien Faye obtained his Ph.D. degree from Télécom ParisTech (Paris, France) in 2014. After completing his Master’s, Sébastien carried out a number of studies on wireless sensor networks and the security mechanisms they offer. During his Ph.D., he studied ways in which such distributed systems can manage intelligent transportation systems, investigating their deployment and performance in the area of traffic signal management. Since 2014, he has been a Research Associate at the University of Luxembourg (SnT). His research interests are wireless sensor networks, mobile & wearable computing and intelligent transportation systems.



Nicolas Louveton is a research associate at the Interdisciplinary Centre for Security, Reliability and Trust (SnT) at the University of Luxembourg. He is holding a PhD in human perceptual-motor control and learning. He participated to the development of innovative prototypes for assistive technologies, augmented reality, gamification and in-vehicle applications. He is leading the HCI team at SnT, and participated to the acquisition of several successful research projects both at National and European commission (CHIST-ERA and H2020) levels. His research have been published in international peer-reviewed journals and conferences.



Gabriela Gheorghe is currently a researcher at the University of Luxembourg, working in the usability and security of wearable devices. She received her Ph.D. from the University of Trento in Italy, on the topic of security policy enforcement for service-oriented middleware. She was an academic visitor at the University of Leuven and a research intern at British Telecom, and has been working on the security and privacy of connected mobile devices.



Thomas Engel is Professor for Computer Networks at the University of Luxembourg. From 1987 to 1995 he studied Physics and Computer Science at the University of Saarbruecken, Germany, where he graduated in 1992 and received the title Dr. rer. nat. in 1996. Between 1996 and 2003, as joint founder, he was a member of the board of directors and vice-director of the Fraunhofer-guided Institute for Telematics e.V. in Trier, Germany, co-responsible for the scientific orientation and development of the institute, definition, acquisition and realization of all research projects, which were 70% industry-financed. Since 2002, he has taught and conducted research as a professor at the IST/University of Luxembourg. His SECAN-Lab team deals with performance, privacy and identity handling in Next Generation Networks. As a member of the European Security Research Advisory Board (ESRAB) of the European Commission in Brussels, he advised the Commission on the structure, content and implementation of the FP7 Security Research Programme. He was coordinator of three European projects, including the Integrated Project u-2010 with 16 partners, about Next Generation Networks using IPv6. Prof. Dr. Thomas Engel was Vice-Director of the newly created Interdisciplinary Center for Security, Reliability and Trust (SnT) at the University of Luxembourg between 2009 and 2016.