# Demo Abstract: Human Mobility Profiling Using Privacy-Friendly Wi-Fi and Activity Traces

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## ABSTRACT

Human mobility is one of the key topics to be considered in the networks of the future, both by industrial and research communities that are already focused on multidisciplinary applications and user-centric systems. If the rapid proliferation of networks and high-tech miniature sensors makes this reality possible, the ever-growing complexity of the metrics and parameters governing such systems raises serious issues in terms of privacy, security and computing capability. In this demonstration, we show a new system, able to estimate a user's mobility profile based on anonymized and lightweight smartphone data. In particular, this system is composed of (1) a web analytics platform, able to analyze multimodal sensing traces and improve our understanding of complex mobility patterns, and (2) a smartphone application, able to show a user's profile generated locally in the form of a spider graph. In particular, this application uses anonymized and privacy-friendly data and methods, obtained thanks to the combination of Wi-Fi traces, activity detection and graph theory, made available independent of any personal information. A video showing the different interfaces to be presented is available online[1].

## 1. METHODOLOGY

Our methodology is illustrated in Figure 1. As described, we first conducted data collection using the SWIPE open-source sensing system[2] [3]. The experiment, which involved 13 participants wearing a smartwatch and a smartphone, has allowed the collection of several metrics from smart device sensors, including GPS location, speed, linear acceleration, Wi-Fi and Bluetooth traces, ambient noise, and motion data. In addition, we recorded aggregated metrics such as activity performed by the user (e.g. walking, running, being in a vehicle or at rest), which can be computed using raw data (e.g. from accelerometers and gyroscopes) or dedicated APIs (e.g. Android `ActivityRecognitionApi`, iOS `CMMotionActivity`). More information can be found in existing surveys (e.g. [4]). Aggregating all the collected data into a proper database has allowed the development of an analytics system, a limited example of which is publicly available online[3]. This platform was a key enabler to visualize, analyze and process data from every user in order to discover the importance as well as the privacy-efficiency of each metric. Thus, it allowed us to understand the relationships between activities, mobility and metrics recorded by different devices.

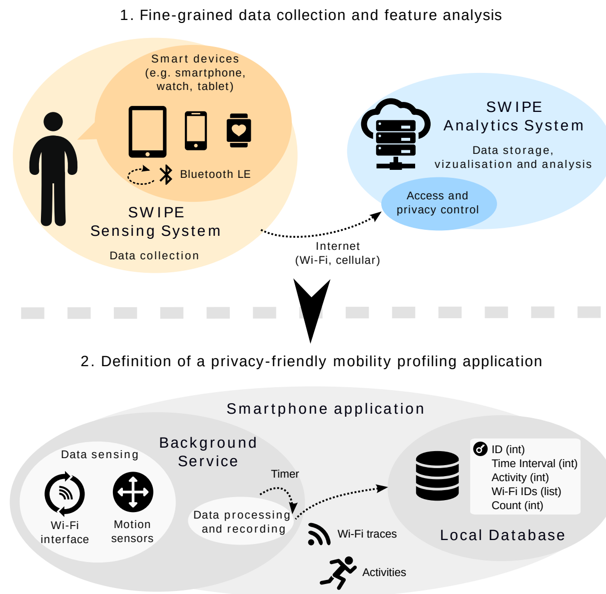


**Figure 1: Overall methodology**

### 1.1 Metrics and Features

After studying different categories of sensors, we decided to use Wi-Fi and detected activity traces as a basis to generate a mobility profile. In particular, Wi-Fi traces have the potential to be used as a substitute for GPS data, to identify locations and their characteristics (e.g. [5]). While several theories can be considered to explore those traces, we decided to use graph theory as it is a good, convenient way to represent a large amount of data. It also offers a solid collection of methods, algorithms and concepts [1]. Each Wi-Fi access point BSSID encountered by the user's device

[1] `http://swipe.sfaye.com/sensys16/`
[2] `http://github.com/sfaye/SWIPE/`
[3] `http://swipe-e1.sfaye.com/`


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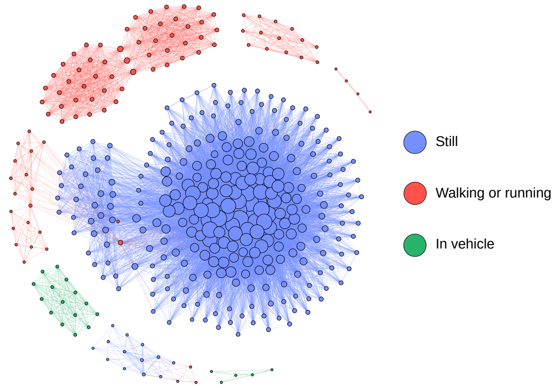


**Figure 2: Using graph theory to study mobility**

is defined as a node in the non-directed graph we intend to build. Each time the device scans two (or more) access points at the same time, an edge is created between these nodes. This graph is created for a certain time period (e.g. one day) in order to enable mobility to be analyzed over different time scales. Finally, each node is created with an "activity" attribute, indicating whether or not the user was mostly still, physically moving, or traveling in a vehicle when he/she encountered the node.

An example of a graph representing one participant is depicted in Figure 2, which is generated using Gephi 0.9.1[4]. This graph shows a large group of nodes, indicating the place where the user spent most of the time during the data collection period: at work. Different interactions between nodes and groups of nodes can help us to understand user mobility patterns. For instance, the number of disconnected groups of nodes (i.e. connected components) has a direct relationship with the number of locations visited. The number of nodes registered when the user is moving (i.e. red and green on the figure) reveals the environment in which the user is evolving when moving (i.e. the higher the number, the more urban the environment). The interested reader can refer to [2], where we perform an evaluation of the relationship between this graph theory approach and mobility metrics (i.e. by comparing the current results to those obtained using the motion sensor data alone).

## 1.2 Mobility Profiling Application

As shown in Figure 1 and based on conclusions made thanks to the analytics system, we implemented a mobility profiling application for Android. This application includes data sensing and recording modules which run in a background service. The data sensing module is responsible for collecting time-independent Wi-Fi and user activity traces. The data recording module regularly processes and records these traces to a local SQLite database, to alleviate the privacy concerns of the user personal information.

The proposed data collection algorithm is decomposed into three steps. **Step 1** (probable activity detector). During a predetermined time window, a list of activities detected thanks to regular calls to the Android `ActivityRecognitionApi` is maintained. At the end of the time window, the most repeated activity in the list is considered as the most probable activity performed. **Step 2** (Wi-Fi signature detector). In a parallel thread, a list of existing Wi-Fi access point BSSIDs is maintained, thanks to regular scans. **Step 3** (filtering and storage). A time interval identifier is allocated to the couple *best activity* (*step 1*) and *Wi-Fi list* (*step 2*). It represents a given period (e.g. a day). Finally, a counter keeps track of similar situations (same time interval, activity, Wi-Fi list).

This algorithm feeds a mobility database, which is stored locally on the smartphone. It forms a basis for building non-directed graphs and analyzing mobility features. In particular, the application has two main parts. The first retraces the user's activity through a spider graph containing five activity proportions: still, walking, running, riding a bicycle and traveling in a vehicle. The second interface also works using a spider graph, but uses mobility characteristics extracted from graph theory. In addition, the application allows the user to choose between different time intervals.

[4] `https://gephi.org/`

# 2. DEMONSTRATION

This demonstration includes the presentation of the analytics system, showing different cases we have constituted in a dataset. We will use the platform to show the pertinence of using graph theory and Wi-Fi traces to analyze different mobility behaviors.

We will then demonstrate the smartphone application, which is constantly evolving, and show the profile of the presenter, based on traces collected during the conference.

Finally, we will introduce different applications we are developing as part of the MAMBA project, with the goal of using our mobility profile generator as a key enabler of enhanced user experience. We plan to integrate this service to a trip planning software, in order to automatically consider user preferences (e.g. mode of transportation, types of roads to use), in addition to help him/her understand his/her daily mobility. Other application areas include transportation activity surveys and social networks.

# 3. ACKNOWLEDGMENTS

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