Smartphone-Based Detection of Location Changes Using WiFi Data

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Abstract. Context information, in particular location changes as indicator for motoric activity, are indicators for state changes of patients suffering from affective disorders. Traditionally, such information is assessed via self-report questionnaires. However, this approach is obtrusive and requires direct involvement of the patient. Related work already started to rely on unobtrusively gathered smartphone data. Despite its ubiquitousness, WiFi data was barely considered yet. Due to the increasing availability of public hot spots we want to focus on this data source. We investigate the usefulness of WiFi data in two use cases: detect location changes and estimate the number of nearby persons. In a two-week study we captured MAC addresses, WiFi SSIDs and timestamps to identify current location and location changes of ten subjects in a five minute interval. We achieved a recall of 98% for location changes which proves the usability of WiFi data for this purpose. We confirm a basic feasibility of using WiFi data for unobtrusive, opportune and energy-efficient detection of location changes.

Keywords: Mobile sensing · WiFi · Location changes

1 Introduction

In clinical psychology the assessment of states and state changes of patients suffering from affective disorders – e.g. depression, bipolar or borderline personality disorder – is important to perform an appropriate treatment [1,2]. Location changes are relevant as they can provide insights about motoric activity (lethargically staying at home vs. moving from one place to another) or avoidance of other people (staying at home vs. changing location) which are symptoms of depression [3].

Traditionally, experience sampling questionnaires are used for the assessment. However, they cause a disruption in the patients' daily routines. Smartphones are personal wearables and simultaneously a powerful sensor system. Related work already suggests to rely on automatically gathered smartphone data in psychology [4]. A wide range of contexts and sensors is already covered. Though, until now, WiFi information was barely considered. The increasing number of

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public hot spots and access points suggest to investigate this data. But is it possible to infer location changes only based on smartphone WiFi data? We present results of a first feasibility study to answer this question.

2 Related Work

Smartphones offer different sensors to assess location and location changes. The most common example is GPS (Global Positioning System). However, this is delicate in terms of data protection as it reveals the actual position in fine granularity. In addition, it is fairly expensive in terms of energy consumption. Therefore, we neglect this option. Low-cost alternatives for location detection are GSM, Bluetooth or WiFi [5,6].

GSM (Global System for Mobile Communications) is a standard for mobile communication and digital cellular networks. Via GSM it is possible to identify the cell tower a mobile device is connected to or to create a fingerprint of nearby cell towers. This allows location detection with coarse granularity. It was already used in related work, e.g. [7]. However, location tracking via GSM is too inaccurate for our setting as a person can be connected to two different towers while being at the same location (urban areas) or be connected to the same tower but changing location significantly (rural areas).

An alternative is *Bluetooth* which was used in [8]. Bluetooth is a wireless technology that allows data exchange over short distances. It is possible to create location fingerprints based on nearby devices, even though this is not always accurate. Alternatively, it is possible to equip locations with Bluetooth beacons and identify locations by their unique beacons. However, the process of labeling locations with Beacons is inefficient and not suitable for real-world scenarios in which we do not know where a user will go. In addition, smartphone manufacturers restrict the visibility of devices via Bluetooth: it is only visible while the Bluetooth menu is the foreground app[1].

WiFi is a technology that allows devices to connect to wireless LAN (WLAN). Nowadays, WiFi is often used as a synonym for WLAN as most WLAN rely on this standard. Within the last years, WiFi access became omnipresent[2], especially in urban environments. Some researches already used WiFi for location detection [9,10]. They relied on WiFi fingerprints which were labeled in advance. Again, the pre-labeling is expensive and not suitable for real-world assessment.

In summary, relying on WiFi data is a promising approach. It is suitable for real-world scenarios if no pre-labeling is required. We present an approach to detect location patterns based on unlabeled WiFi fingerprints. This allows identification of location changes or duration of a stay at a location, for example.

[1] https://support.google.com/nexus/answer/2819579?hl=en-GB.

[2] http://www.statista.com/statistics/218596/global-number-of-public%2dhotspots-since-2009/.

3 Detecting Location Changes via Smartphone WiFi Data

We build an Android app to collect WiFi information using the 2.4 GHz and the 5 GHz frequency band. We decided to assess MAC addresses instead of SSIDs, because networks may use the same SSID or broadcast their SSID from multiple access points. We only want to consider long-term stays at locations and location changes between them. This shall avoid counting passing a location as a location change during a transit of the user. We decided to log the currently available WiFi networks every five minutes. This is also a very energy-efficient sampling rate. Location changes can be detected by comparing the available WiFi networks detected by the smartphone at two or three consecutive points in time. In this context a location change occurs when none of the set of access points recorded in measurement M_1 is present in the set of access points recorded in measurement M_2 (five minutes later) or M_3 (ten minutes later).

4 Evaluation

Study Design. The study lasted ten days and was taken by ten subjects (70% male, 30% female), aged between 21 and 68 (mean: 28.8). All subjects were informed about the objective of the study and the data that is captured by the app. Afterwards, we asked them to sign a consent form. In the study, subjects used their own smartphones. We asked them to use the smartphones as usual. As ground truth subjects recorded their location changes in a chart, providing start and end times for stays at every location they visited. We asked them to provide the type of location from which they were coming and going to in the format "P→B". We differentiated between *private* ("P"), *business* ("B"), and *public* ("Ö", in German "öffentlich") locations, analog to location labels in [8].

Results. Location change data of only nine subjects were included in the data analysis. One subjects missed to restart the app after a smartphone restart. During the study 17,406 different access points were detected overall and between 458 and 3426 per subject. We counted 1,065 location changes in total and between 33 and 208 per subject.

The collected data was compared to the manually recorded ground truth to determine the recall (a.k.a. sensitivity) of our detection. This metric specifies how many location changes were detected by our approach. We noticed that when only considering the last two measurements, the recall is rather low, e.g. 0.76 for Subject 1. The high number of errors is caused by fluctuations in the WiFi data, e.g. due to loss of WiFi connection during the measurements or caused by subjects moving to another room within the same but large building. Hence, we decided to take the last three measurements into account, i.e. all measurements within the last 10 min. We achieve an average recall of 98% (95% confidence interval [CI] = 97.1–99.6). The remaining errors are caused by location changes that were logged by the subject but were shorter than the five or ten minute minimum that our app requires.

5 Conclusion

Movement and location changes are interesting measurements in clinical psychology to identify states and state changes in subjects suffering from affective disorders such as depression. However, assessing these metrics requires automatic, privacy-aware and energy-efficient approaches.

We presented results of a study conducted to investigate the feasibility of purely WiFi-based detection of location changes using smartphones. A recall of 98% proves a successful detection of location changes by our approach. We see a high potential of these findings for context recognition in clinical psychology. Apart from the mere number of location changes, WiFi information can reveal regularity, duration, and frequency of location visits. These aspects can give a deeper insight into affective disorder symptoms such as loss of interest to perform usual activities, decreasing motoric activity, or avoidance of other people.

We intend to design and conduct further studies with patients suffering from affective disorders as subjects. Thereby, we want to gain insights about their location change behavior and evaluate the usefulness of our location detection for phase change detection.

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