Low-Power Ambient Sensing in Smartphones for Continuous Semantic Localization

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Abstract. Extracting semantic meaning of locations enables a large range of applications including automatic daily activity logging, assisted living for elderly, as well as the adaptation of phone user profiles according to user needs. Traditional location recognition approaches often rely on power-hungry sensor modalities such as GPS, network localization or audio to identify semantic locations, e.g., *at home*, or *in a shop*. To enable a continuous observation with minimal impact on power consumption, we propose to use low-power ambient sensors – pressure, temperature, humidity and light – integrated in phones. Ambient fingerprints allow the recognition of routinely visited places without requiring traditional localization sensing modalities. We show the feasibility of our approach on 250 hours of data collected in realistic settings by five users during their daily transition patterns, in the course of 49 days. To this end, we employ a prototype smartphone with integrated humidity and temperature sensor. We achieve up to 80% accuracy for recognition of five location categories in a user-specific setting, while saving up to 85% of the battery power consumed by traditional sensing modalities.

1 Introduction

Location is one of the most common information types humans frequently use in their daily lives, either for navigation to a destination, geo-tagging images with visited spots, or for discovering points of interests on maps. It has been shown that location is a powerful cue for human activities [15] and gained popularity in activity recognition [10] or for learning daily routines automatically [9].

The notion of location has various meanings: it can be expressed in geographic coordinates, e.g., latitude and longitude, as human readable addresses such as street name and number, or as logical labels of the places, e.g., Central Park, the McDonald's around the corner [1]. Our understanding of location refers to routinely visited places in daily life. We refer to these as *semantic locations*, as introduced in [16]. Examples include someone's *home* or *office*, but also non-fixed locations such as commuting by *train*, or *in a shop*, which can map to different physical locations. This information can be fed into location-based services or applications, such as refined searches of places of interest, targeted advertisement, urban planning, analysis of user patterns or triggering user profiles on the handset.

State of the art systems for semantic localization rely on modalities such as GPS [9], WiFi, Bluetooth beacons [4] or audio [5] [11]. While feasible for sporadic localization, their power consumption hinders continuous monitoring [3, 14]. More power efficient approaches use triangulation with cell towers based on signal strength. Apple's iOS region monitoring service, for instance, makes use of this to continuously monitor if a user enters or exits a certain zone. However, localization is coarse in the range of 100s of meters of radius, even with good network coverage, and is designed for fixed geographic locations only.

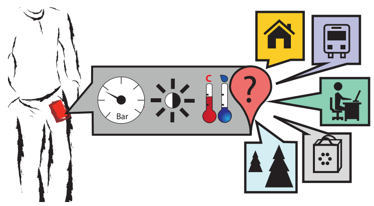


Fig. 1. Recognizing semantic locations (e.g., home, train, office, shop, and outdoors) using low-power sensors from the phone: *atmospheric pressure, light, temperature,* and *humidity.*

In this work, we propose an alternative path to identify routinely visited locations. We investigate ambient characteristics (i.e. barometric pressure, temperature, light, and humidity) for fingerprinting locations. Observation of such characteristics and their variations by a combined set of low-power ambient sensors can indicate whether a user is indoors or outdoors, distinguish between different indoor places or even indicate the means of transportation. For example, *home* or *office* are characterized by a location-specific pressure value ranges. Also, indoor places such as corridors or elevators are characterized by specific and constant light. To capture such characteristics continuously, we employ ambient sensors, i.e., pressure, light sensors, thermometers and hygrometers integrated in a commodity smartphone. With combinations of these sensors we capture a rich set of ambient characteristics that allows to recognize a variety of personalized semantic locations that are routinely visited. The sensor's low power profile allows us to minimize the power consumption. In addition, such sensors become lately embedded in commercially available phones, e.g., Samsung Galaxy S4. This gives the opportunity to assess the semantic location of the phone's user in a realistic and non-intrusive manner.

To study our hypothesis we collected a real-life dataset from five subjects during 49 days. Subjects recorded sensor data using a prototype phone during daily-life activities and they annotated their semantic locations. To study the feasibility of ambient fingerprinting for semantic localization, we formulate the semantic location recognition as a supervised machine learning task.

Our main contributions are as follows: (i) We implement a sensing and recognition platform allowing us to gather, visualize and analyze data from the sensors incorporated in customized smartphone, (ii) we recorded a large and naturalistic dataset from various users for testing the feasibility of our hypothesis, and (iii) we show the effectiveness both in terms of recognition performances and power consumption for ambient sensing for distinguishing typical daily locations visited by a user.

The remainder of this paper is structured as follows. In Section 2 we present the rationale for using ambient sensing data to do semantic location recognition. Section 3 reviews the state of the art in semantic localization and power-saving approaches for activity and context recognition. In Section 4 we describe the collected dataset. Further, Sections 5 and 6 present the experimental results on recognition performances and power consumption of the ambient sensors from the smartphone. Finally in Section 7 we discuss and conclude our work.

2 Multimodal Ambient Sensing for Semantic Localization

Our goal is to study whether we can recognize different semantic locations from a user's daily-life pattern using multimodal ambient sensing, such as temperature, humidity, pressure and light of the different locations. We postulate that semantic locations such as the *home*, *office*, *car*, *train*, *restaurant*, or *pub* that are visited by a person are defined by a specific combination of values from these sensors, and these combinations form the *fingerprint* of the location. For example, homes, offices, and even public transportation tend to have constant ranges of temperature and humidity, as they are equipped with air-conditioned systems set to maintain these ambient conditions constant. Restaurants and pubs tend to have higher temperature values than other living places, due to cooking or because they are crowded.

Our research question is: *Is multimodal ambient-based fingerprinting sufficient to discriminate between the locations?* As in [1] we believe that these fingerprints are not necessarily unique and can be shared between different places. Nevertheless, the ambient fingerprints of more general categories, e.g., *train, car, restaurant*, are expected to be sufficiently different, thus allowing to distinguish between them. Also, people have their own set of semantic locations, that are visited during the daily-life pattern. Thus for a user-centric approach, we need only the fingerprints of the places visited by that specific user.

To evaluate the informative power of the multimodal ambient sensing data, we formulate the semantic location recognition approach as a standard supervised machine learning task. To capture the ambient conditions for semantic localization we use light, barometric pressure, humidity, and temperature sensors embedded in a phone. We follow the same steps as in the case of an activity recognition problem solved with supervised machine learning techniques [17], and use data collected from the sensors and the annotated semantic locations to learn how to distinguish between the different locations. For that we follow the next steps: the acquired continuous data is segmented into non-overlapping time windows. We extract mean, standard deviation, min- and max-values for each of the four sensing modalities, and label them with their equivalent semantic location. The resulted feature vectors are then fed into a C4.5 classification tree to learn a discriminative model of the semantic locations. C4.5 was chosen because of its low computational complexity, which makes it appealing for a future deployment directly on the phone.

3 State of the Art

Location and Semantic Location. In [2] GPS data is used for mining semantic locations such as shopping malls and restaurants. However, continuous use of GPS localization is extremely power-hungry [3, 14]. Furthermore, it relies on good GPS perception which can be inhibited when the phone is held in pocket or bag for example or fails completely for indoor locations. WiFi, GSM signatures and Bluetooth-based localization can replace or compensate GPS data [6] to automatically assess the personal semantic locations and daily routines of the user, but the frequency at which the Bluetooth module needs to be used might impact negatively the battery life [3]. Audio is a very rich source of information to capture a location's characteristics [5, 11, 19, 20], but comes at significant battery drainage.

The idea of using small wearable devices with embedded sensors such as light, pressure, acceleration, audio and temperature to detect the context of an individual roots back to the work of Schmidt et al. [21]. Low-power sensing approaches like fingerprinting of room colors and sensing of pressure, light intensity, temperature and humidity have been considered [13], but always in addition to power-hungry modalities [1, 8]. Pressure sensing has been used in isolation but only in a constrained setting of recognizing subway stations [23].

Ravi et al. [18] use the light properties of the indoor places, e.g., offices and corridors of a CS department for fingerprinting and indoor localization. Azyzian et al. [1] propose SurroundSense, a mobile framework to detect the logical indoor locations, e.g., Starbucks, McDonald's, by creating a fingerprint of each indoor location based on the data collected from ambient sound, light, color, or RF layout-induced user movement. Lane et al. [7] use accelerometer, light and temperature data for the so-called *ambient beacon localization* to distinguish different regions of mobile sensors. However, their evaluation relies on simulated data with a limited number of locations.

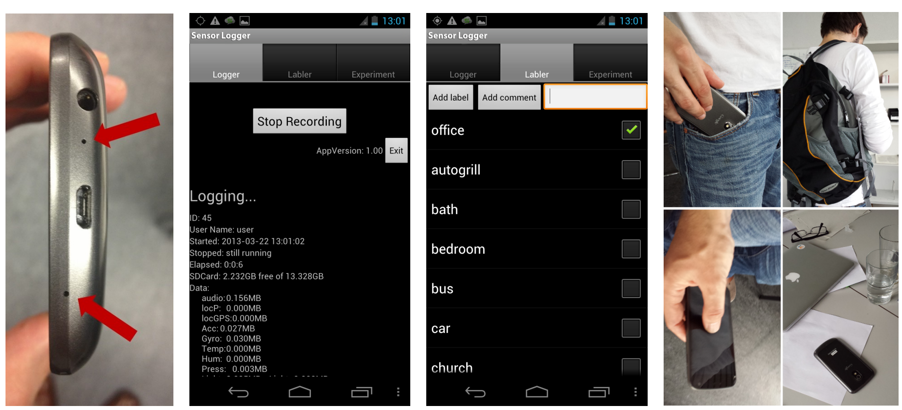
Power Saving. Wang et al. [22] propose a framework for energy efficient mobile sensing by using a hierarchical sensor management strategy to recognize the user states and detect state transitions. A minimum set of sensors are turned on to monitor the current state of the user, and a new set of sensors is triggered only when it is necessary to detect a state transition. The evaluation done on ten users over one week shows that their approach can increase the battery life up to 75%, while identifying the end-user activities. Yan et al. [24] seek to reduce the energy consumption on the mobile phones for continuously detecting locomotive activities by adapting the accelerometer sampling frequency manually creating groups of activities for each sampling rate. Lu et al. [12] propose Jigsaw, an engine for continuous sensing for mobile phones which are dynamically turning on/off the acceleration, GPS and audio sensors.

4 Dataset Collection

We gathered data from five subjects (S1 to S5): two graduate students and three employees working in different companies, two females and three males, with ages varying between 26 and 51 years. Except for two employees, all subjects exhibit a regular daily life, consisting of working, leisure time at home, commuting, or shopping.

4.1 Sensing platform

We used a modified Samsung Galaxy Nexus phone, courtesy of Sensirion AG[1], with four ambient sensors integrated. Pressure and light sensors are incorporated off the shelf. In addition, temperature and relative humidity sensors have been integrated (see Fig 2(a)). For comparison to state of the art localization, we obtained location from Android location services and we gathered data from the microphone to compare to localization approaches based on audio. The data was recorded in the background by an Android application and stored locally, with each user visiting between 4 and 11 semantic locations.



(a) (b) (c) (d)

Fig. 2. (a) The modified Samsung Galaxy Nexus with added temperature and humidity sensors, (b, c) screenshots of the Android application for data gathering, and (d) an illustration of different phone wearing-contexts for a user during its daily-pattern (pocket, backpack, hand, table).

[1] http://www.sensirion.com

4.2 Data recording

Subjects were asked to use the prototype phone for the data collection as if it was their own. This naturalistic usage resulted in different placements of the phone, e.g., different pockets, in the backpack, purse, on the table, on the couch. Variations of the placement occurred between different users as well as for single users, e.g., wearing the phone in the purse while commuting or wearing it in the trouser's pocket during work or putting it on the office desk. Users recorded data for at least five consecutive days. Additionally, arbitrary days within a month have been recorded. In total, we gathered 250 hours of data, during 49 days of sensor data from five users in realistic settings.

High level category	**Semantic Location**
Outdoors	general outdoors
Indoor public places	Opera, Theater, Cinema, Church, Shop, Department store, Mall, Pub, Restaurant, Cafeteria, Seminar room
Indoor personal places	Home (living room, office home, bedroom, bathroom, kitchen), Office (office room, meetings room, conference room), Friends home, Indoor (other)
Transportation	Tram, Train, Car, Bus, Funicular

Table 1. User-annotated semantic locations.

4.3 Data annotation

The Android application used for data recording offers user interfaces to label semantic locations. It contains a list of predefined categories, e.g. *home, tram, train, car*, but gives the option to add individual categories (Fig 2(c)). This allows to capture a personalized set of the semantic locations in which individual subjects reside. Table 1 contains the sum of all semantic locations grouped in categories that were labeled by all subjects during data collection. Subjects did not visit all the locations enumerated, but only a subset of locations visited on a week-pattern basis for each of them. In total we obtained labeled data for 26 categories of semantic locations. Users provided annotations in real-time when changing their location, resulting a total of about 1000 location changes. Annotations were not always provided at the exact time of location change. However, the users remained in the locations for a sufficient time and annotated data correctly, allowing to neglect this label noise.

5 Location Recognition Experiments

Each subject experienced an individual lifestyle with specific activities and semantic locations during the recording days. Also, the same semantic location category, e.g. *home, office*, had different ambient signatures for each subject, i.e., *home* category for S1 does not have the same ambient fingerprint as *home* category of S5. Therefore, we consider for the semantic-location recognition model a subject-dependent learning and classification scheme, as semantic categories are specific for each individual user.

5.1 Evaluation

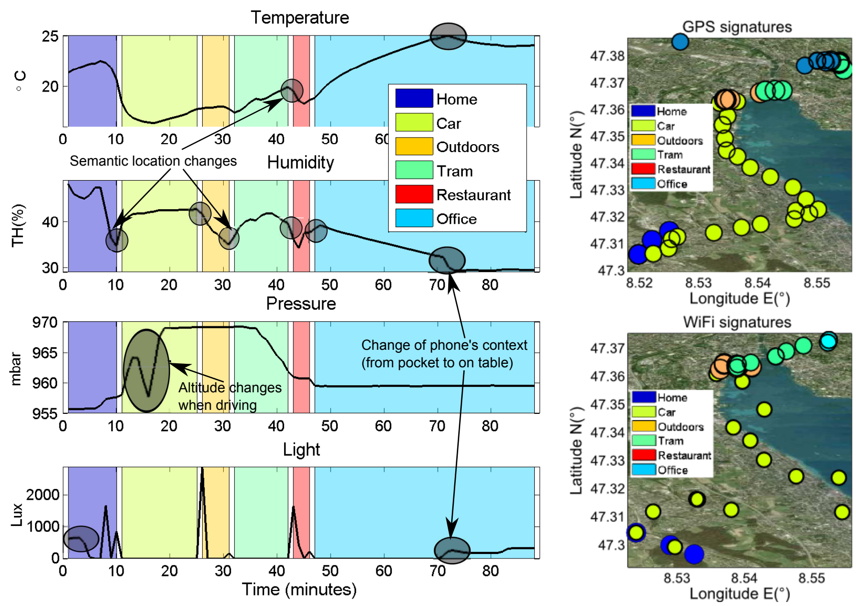
We compare our approach based on low power sensors – temperature (T), humidity (H), pressure (P), light (L) – to two baseline approaches: (1) standard Android localization using GPS and WiFi/GSM fingerprinting, and (2) localization using audio data collected with the smartphone microphone. The time-series collected from the sensors are divided into non-overlapping segments of W seconds. For each window we consider latitude and longitude data obtained from Android's location manager, as standard localization data. For audio localization, we extract from the time-window 13 *Mel-frequency cepstral coefficients* (MFCC) channels, and for each MFCC channel we compute *mean* and *standard deviation* as features. An experimental evaluation of multiple window lengths $W \in \{5s, 10s, 15s, ...30s\}$, showed similar performance results for semantic location recognition. Therefore, we fixed the window size to $W = 10s$. For both baselines we use the same machine learning technique, i.e, C4.5 trees, as for our approach with low-power sensors. This paper does *not* aim to find the best performing algorithm for semantic localization for each type of sensor. Our objective is to investigate the feasibility of using ambient low-power sensors data from a smartphone for semantic location of the smartphone's user. Thus, we fixed the classifier to C4.5 trees throughout the remainder of the paper.

To evaluate the semantic location recognition performance, we conduct for each of the five subjects a *leave-one-recording-out* cross-validation. We report the accuracies averaged per category, so the semantic location in which the users reside in.

5.2 Visual Inspection of Ambient Sensor Data

Fig. 3 illustrates how data from ambient sensors in the phone characterizes several daily locations. It shows 90 minutes of continuous sensor data and the corresponding localization tracks collected from a phone. The subject wore the phone in the trousers pocket, used different transportation modes (*car, tram*) and visited typical locations during her daily life (*home, office, restaurant*). The variations of the sensor readings can be clearly seen during the location changes. The pressure is constant at the *home, office* and *restaurant* locations, since they lie at a certain altitude. Furthermore, temperature and humidity have different ranges across locations. The light intensity is informative at the beginning and at the end of this recording, since the phone was put on the table at home and in the office, yielding a characteristic light intensity, i.e., in the office there were neon tubes, whereas at home there were traditional, warmer light bulbs.

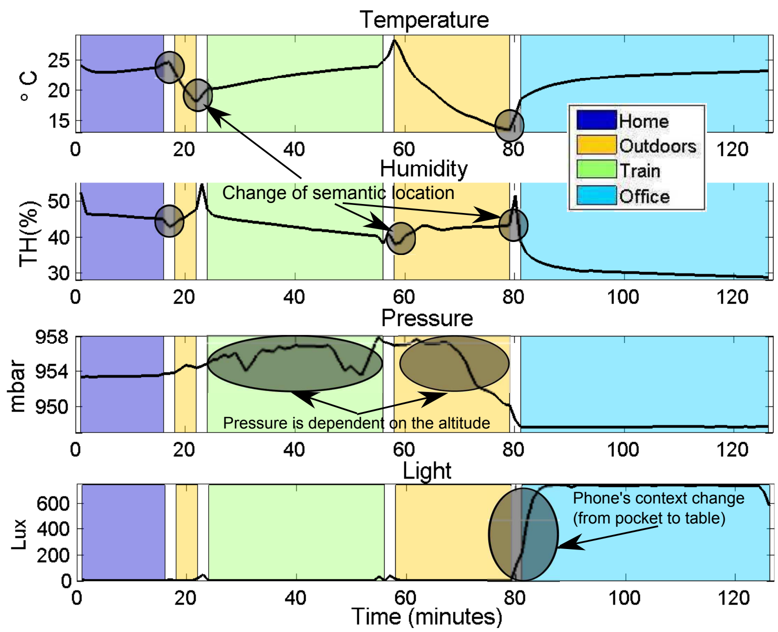
We observe that for each semantic location, the data variations contain discriminative information, that form a signature of various activities, e.g., when the phone's context changed from *in the pocket* to *on the table*, in the *office* location. Temperature and humidity data gives the same clues, and furthermore we can easily see the moment when the location changes. When in the *car* or *tram*, the pressure is varying, being dependent on the altitude and weather conditions, thus giving a clue on the moving semantic location of the user. Fig. 3(b) shows



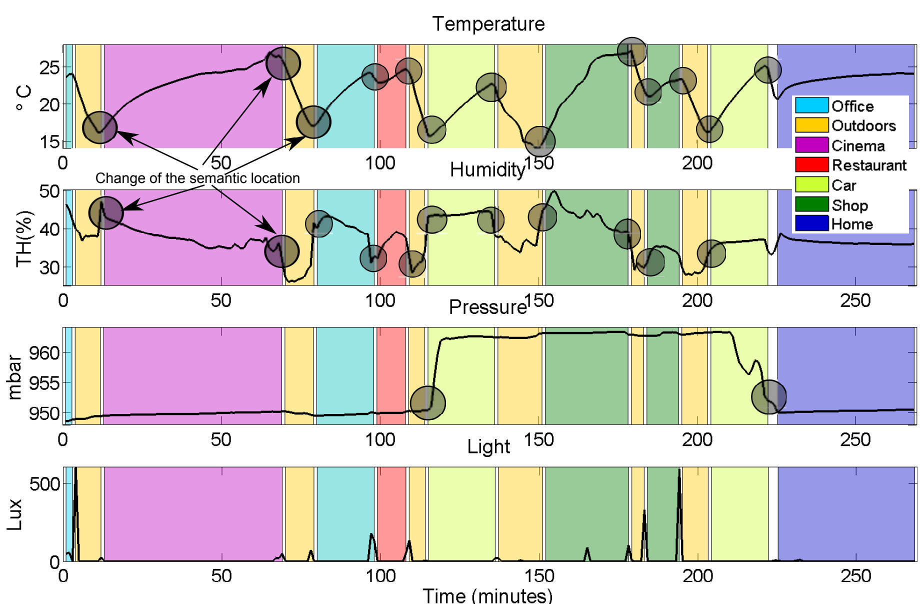
(a) Ambient Sensors (b) GPS/WiFi/GSM

Fig. 3. An example of 90 minutes of multimodal data from (a) low-power ambient sensors from the phone (temperature, humidity, pressure, light), and (b) Android Location Service (GPS, WiFi/GSM). Semantic locations can be inferred from the data patterns (for ambient sensors) as well as directly from the physical coordinates.

the physical coordinates, which were obtained by Android Location service – GPS, WiFi and GSM data. These location signatures are sufficient to provide information about the locations and the moving pattern of the user. However, GPS failed to acquire the satellites when indoors or even when the phone was placed in the pocket. Locations obtained from WiFi and GSM triangulation are partially imprecise, e.g., some coordinates are in the middle of the lake, while some others describe multiple semantic locations such as *home*, *outdoors*, and *car*. This can be only remediated by large temporal smoothing windows. Fig. 4 shows additional examples of multimodal ambient sensing data from two other subjects. In Fig. 4(a) data is collected from a user with a regular daily pattern



(a) Subject 1



(b) Subject 3

Fig. 4. Example of ambient sensing data from two different subjects: (a) from a subject with a fixed daily-pattern in the morning, and (b) from a subject with complex transitions over the day.

that commutes in the morning. Again one can observe clear differences in temperature, humidity and pressure signatures between the fixed semantic locations, e.g., *home* and *office* and transportation, thus making it possible to distinguish between them and *outdoors* category. Light sensor data gives discriminative information only in case of *office* location. Fig. 4(b) shows data from a user with a more complex daily-pattern, containing many transitions between the seven semantic locations. Still, we observe specific combinations for locations such as *cinema, office, restaurant* and *home*. For the *shop* category, respectively location, the data exhibits variation, as there are two distinct shops that are visited by the user. Furthermore, in temperature and humidity data are signatures of transition from one semantic location to another, e.g., from *car* to *outdoors*, *outdoors* to *shop*, *office* to *restaurant*. As in the previous figure, the light sensor data changes give information when the context of the phone changes, e.g., on the table, in the pocket.

Further, Fig. 5 presents a visualization example of the average temperature vs. the average humidity values for the dataset S1 with four semantic locations (*office, home, train* and *outdoors*) to which the *null category* is added. Same as before, the original time series was cut into windows of 10 seconds. We observe the data has a fibrous appearance, being clustered in threadlike series, corresponding to different recordings. Even if overlapping, data tends to form stable clusters corresponding to the different labeled locations. For example, *home* and *office* data formed two distinct, non-overlapping clusters. Although spread on a larger area, the *train*-category data is also grouped in a distinct cluster.

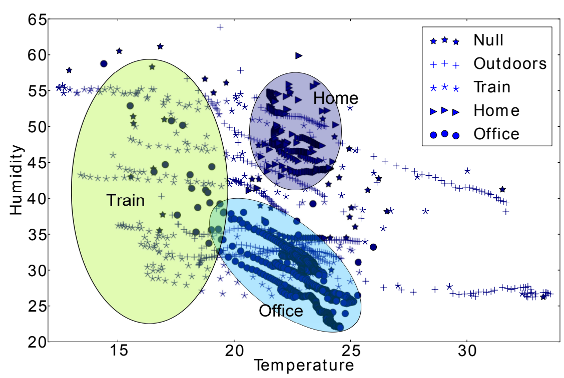


Fig. 5. A scatter plot with temperature vs. humidity for S1 dataset, with 5 semantic location categories.

5.3 Overall Recognition Performances

Table 2 contains the overall semantic location recognition results for ambient sensors, audio, and physical location data gathered for each of the five subjects, with the locations specific for each user's weekly pattern.

Subject	S1	S2	S3	S4	S5
TH	70	48.6	32.5	71.9	47.1
THP	69.5	**61.6**	**41.9**	**73.3**	**55.3**
THL	76.3	45	35.6	63.4	40.4
THPL	**80.3**	59.6	41.3	66.3	43.9
Audio	51	26.6	39.5	46.9	33.1
Location	55.5	40.7	38.7	61.4	38.6
Number of Semantic Locations	**5**	**7**	**12**	**5**	**9**

Table 2. Average accuracies (%) over all categories for each subject dataset, for semantic-location detection, in case of using low-power sensing data (different subsets), audio data, and location data (GPS and WiFi/GSM coordinates), for $W = 10s$ windows.

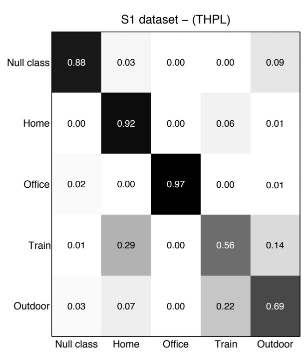
For the multimodal ambient sensing we evaluate different subsets of data: TH (temperature and humidity data), THP (temperature, humidity and pressure), THL (temperature, humidity and light) and THPL (temperature, humidity, pressure and light). In case of low-power sensing models, the best results are obtained when using THP (for S2, S3, S4, S5) and THPL (for S1). For all subjects the ambient-sensors-based recognition methods outperform the recognition methods based on physical coordinates location and audio data, with up to 25% improvement, for the S1 dataset. The recognition performances are strongly linked to the number of semantic locations and also to the subject's daily pattern: S1 dataset has only 4 semantic locations, data being gathered from a corporate employee with a regular daily pattern. The other extreme is dataset S3, from a graduate student with a more complex and not often repetitive daily pattern – after the working hours, the subject was having different recreational activities, consisting of *cinema, theater, opera, shops* semantic locations. This subject visited 11 semantic locations and some of them were complex in terms of data variations - e.g., the *shop* includes data from different smaller clothing shops, department stores and grocery stores.

As a general observation from all the performance results on the five datasets, data from light sensor seems to not be as informative as expected. A reason is that light data is strongly related to the context of the phone, i.e., where the phone is placed, and not to the location visited by the user. For example, light information can be the same when the user visits *home, outdoors, train, car, office* personal locations, because the phone is located in the pocket, so light data obtained will have similar values, which will not help discriminate between the locations. So the best combination of ambient sensors to create a fingerprint range of visited locations are temperature, humidity and barometric pressure.

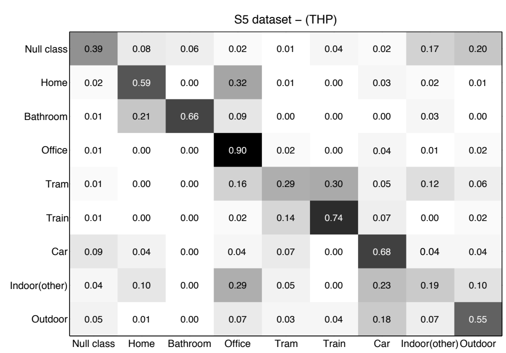
Low-power, audio and location-based recognition are equally affected by the label noise. Previous studies [9] showed that GPS is sufficient to provide information about outdoors locations. However, in these studies the GPS unit was attached to the user's hat or backpack for better accuracy. In our study we found that in a realistic setup, i.e. phone placed in the pocket or in bag, indoors, or even in the trains, the GPS did not produce any location data in 39% of the time, as only 45 out of 113 recordings were containing GPS data. When no data from GPS were available, we took into account the information from network localization. However, the coarse location estimation leads to the confusions and low recognition rate of semantic locations. In contrast our proposed set of ambient sensors does not suffer from signal loss and continuously acquires ambient parameters.

5.4 How Informative is the Multimodal Ambient Sensing Data?

Fig. 6 contains the confusion matrices for the combinations of low-power ambient sensing data that performed best in detecting the semantic locations, for datasets S1 and S5. For S1 dataset, while *home* and *office* are well recognized, there are confusions for *train* and *outdoors*. The ambient sensing data converges in describing the fixed semantic locations, e.g., *home*, *office*, while transportation is strongly connected to the outdoors conditions. In case of dataset S5, most of the confusions appear between the indoor locations, e.g., *bathroom* is detected sometimes as *home* or *office*, *home* is mislabeled as *office*. Even if the ambient data describing the *home* and *office* locations is different, for this particular dataset the *home* category was under-represented compared with the *office*, thus resulting in these confusions. Similar to dataset S1, there are confusions between modes of transportation, i.e., *tram* and *train*.



(a) Dataset S1, THLP



(b) Dataset S5, THP

Fig. 6. The confusion matrices for location recognition for datasets S1 and S5.

The *indoor* category contains all the indoor data that was not included in the other semantic locations. Being a general category, indoor is often mislabeled as *outdoors, car*, or *office*. The ambient sensors measurements are different for each indoor location, therefore this category cannot be reliably detected.

6 Power Consumption Experiments

In this section we perform an analysis of the power consumption of the smartphone sensors. We begin with a rough estimation of consumption based on sensor datasheet figures. Then, we empirically study the battery drainage during data collection with different combinations of sensors.

6.1 Datasheet-based Consumption Estimation

In Fig. 7 we plot the distributions of semantic localization accuracies reported to the power consumption of the sensing modalities. The horizontal axis shows a coarse estimation of the power consumption. We used the values provided in the datasheets by the sensor manufacturers for the prototype used in recordings. Surprisingly, using ultra-low-power sensors does not come at an expense of the performance detection, but it rather introduces more variance in the results. The THP combination appears to be the most stable one, having higher median and more compact distribution compared to all others. In theory this combination is up 180x less power-hungry than audio and location based recognition. However, the measurements do not include the computational effort for semantic location detection.

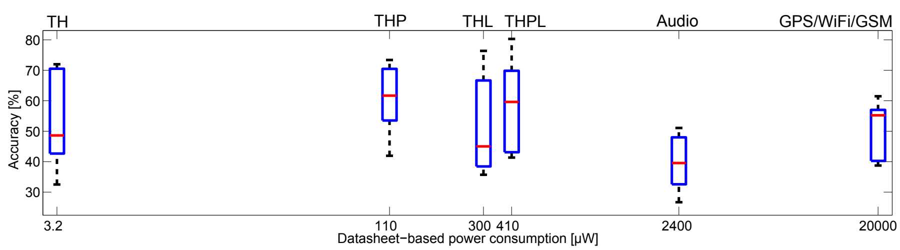
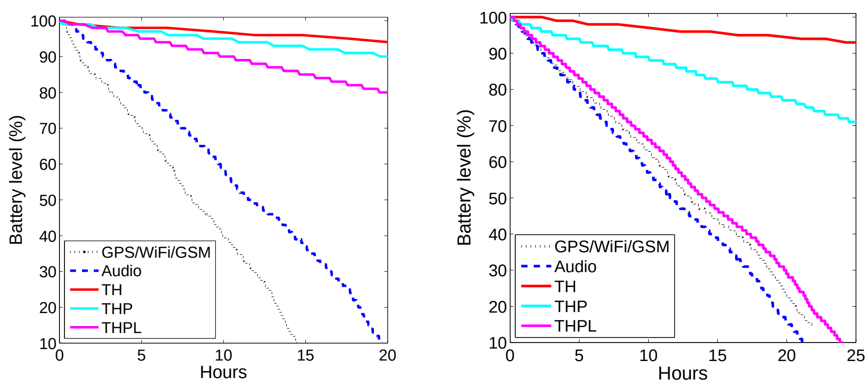


Fig. 7. Distribution of the accuracies for different sensor combinations versus power consumption. The boxes represent the 75th percentile. The consumption is given for a sampling frequency of 1Hz, apart from audio, where the sampling frequency is $16kHz$.

6.2 Empirical Consumption Study

The total power consumed during data gathering is $P_{total} = P_{sensor} + P_{gathering}$. P_{sensor} is the power consumed to run the sensor and its associated analog to digital converters. $P_{processing}$ is the power consumed while moving, storing and processing the data from the sensor. It includes the consumption of the processor, system memory, system storage and various system buses. In the previous section we took into account only P_{sensor}. For a more realistic evaluation, we have to include the second component. To this end, we monitor the battery level while running the data gathering application for the different combination of sensors used in the performance evaluation section.

The results are plotted in Fig. 8 for (a) the prototype phone with temperature and humidity sensor integrated, used during the recordings, and (b) the recently released Samsung Galaxy S4, which has the same humidity-temperature sensor integrated. For both phones, temperature-humidity, pressure and light sensors were set at the highest sampling rate from Android API, as they were used during the data gathering experiments. The audio data was gathered at $16kHz$. All the empirical battery consumption experiments were performed in similar settings as the data gathering for dataset S3. As expected, the most power hungry data were from GPS/WiFi/GSM and audio. Surprisingly for the THPL combination of sensors the battery consumption was similar as in case of audio and location data, but only for the Samsung Galaxy S4 phone.



(a) Prototype phone   (b) Samsung Galaxy S4

Fig. 8. The measured battery level in case of collecting different sensor data combinations from (a) the prototype phone with temperature-humidity sensor integrated, and (b) a Samsung Galaxy S4 phone.

However, in the previous performance analysis experiments for semantic location detection we concluded that light data is not informative enough to help to discriminate between different locations. So our target for power consumption analysis was the temperature, humidity and pressure (THP) combination. Still, with the other combinations that do not imply light sensor, we can save from 65% (THP) up to 85% (TH) of battery in case of Samsung Galaxy S4. We expect to increase the power savings when setting the ambient sensors to lower sampling rates in Android API.

In case of the phone prototype, for gathering all the ambient sensing combinations, we can save from 70% of battery (THPL) to around 85% (TH), when compared to gathering audio and standard location data.

7 Conclusion

Many mobile computing applications benefit from knowing the user's semantic location. In this work we study the feasibility of recognizing semantic locations from low-power ambient sensors embedded in phones. We gathered 250 hours of data from five subjects in a naturalistic setting during typical phone usage. In total 26 labeled semantic locations, e.g., *office, shop, church* have been annotated. Experimental results show that semantic location recognition with low-power ambient sensors can be an alternative to standard localization methods, i.e., GPS/WiFi/GSM and audio, while significantly reducing the power consumption and saving up to 65% of battery power for the THP sensor combination, and up to 85% for the TH combination.

Experiments show that the best combination of low-power ambient sensors to create discriminative fingerprints of locations visited by an user during a week-pattern are temperature, humidity and pressure. Allowing for continuous monitoring of the user's location it can serve as trigger for location changes, e.g., entering/exiting train, leaving/entering shop, for applications. Furthermore such triggers can be released for locations that are not attached to fixed world coordinates, e.g., in the train, in the car.

The clear visibility of location changes in the data is promising and we plan on investigating location changes as triggers. For example, more power-consuming modalities can be triggered only when a change in the low-power sensor data was observed. The limitation, however with our current supervised classification approach, is to require the user to annotate the data. In future research we will explore transfer learning techniques and make use of third party sources.

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