ExposureSense: Integrating Daily Activities with Air Quality using Mobile Participatory Sensing

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***Abstract*—With an increasing number of rich embedded sensors, like accelerometer and GPS, smartphone becomes a pervasive people-centric sensing platform for inferring user's daily activities and social contexts. Alternatively, wireless sensor network offers a comprehensive platform for capturing the surrounding environmental information using mobile sensing nodes, e.g., the OpenSense project [2] in Switzerland deploying air quality sensors like CO on public transports like buses and trams. The two sensing platforms are typically isolated from each other. In this paper, we build ExposureSense, a rich mobile participatory sensing infrastructure that integrates the two independent sensing paradigms. ExposureSense is able to monitor people's daily activities as well to compute a reasonable estimation of pollution exposure in their daily life. Besides using external sensor networks, ExposureSense also supports pluggable sensors (e.g., O_3) to further enrich air quality data using mobile participatory sensing with smartphones.**

***Keywords*-participatory sensing, activity recognition, air quality sensing, exposure estimation**

I. Introduction

Modern smartphones have an increasing number of embedded sensor types at each new generation as well as the ever increasing processing and storage capacity. As a result, smartphones are becoming very powerful mobile sensor platforms [8], and accompany users during their professional and private daily life. This includes but is not limited to receiving/sending emails in work hours, reading news during breaks, listening to music while doing recreational activities etc. Researchers start to build many advanced sensor data mining algorithms and services to automatically infer people's daily activities through these rich sensors on the phone. Among them, the accelerometer is one of the dominant sensor type used today for detecting user activities like sitting, standing, walking [11]. These activity information can be used to improve the phone's functionalities. Examples include accepting/rejecting call by specific phone motion, automatically initiating file transfer with NFC etc.

For air quality monitoring, the traditional focuses are on using either fixed [7] or mobile sensing nodes, e.g., the OpenSense project in Switzerland [2]. OpenSense has deployed sensors on top of public transport vehicles such as buses and trams to provide real-time monitoring of the air quality. With the rapid development of mobile end techniques, researchers start to use independent handheld devices to monitor the environment like [4]. More recently, smartphones provide a huge potential for flexibly sensing and monitoring the environment using their continuously increasing embedded sensors, e.g., (1) the mobile phone audio sensors are used to monitor and generate the noise pollution map [9], (2) the accelerometer sensors are applied to establish a community seismic network for detecting Earthquake [5]. Furthermore, the mobile phone sensing is going beyond the embedded sensors. Recently, integrative USB pluggable sensors are built for mobile phones to detect a richer set of air quality information, e.g., the pluggable ozone (O_3) sensor [6].

Nevertheless, activity recognition and air quality monitoring using smartphones (either embedded or pluggable) sensors are fairly independent. To bridge the gap between them and find the correlations, we build this "ExposureSense": on one side, we extract people's daily activities using accelerometer sensor as it is quite suitable for activity recognition with minimal battery consumption; on the other side, we utilize both the external air quality sensing infrastructure like the PM10 monitoring using public vehicles in OpenSense [2] and an internal pluggable O_3 sensor [6]. We provide a quest to build mobile participatory sensing infrastructure to integrate user's daily activities and the surrounding air quality, for sensing people's daily pollution exposure.

II. System Architecture

The principal objective of this paper is to explore possibilities of gaining exhaustive knowledge from various sensors using mobile participatory sensing. To achieve this goal, we build ExposureSense to integrate daily activities from smartphone sensors with air quality data (either third-party service or participatory sensing) to estimate user's daily pollution exposure. Novel idea presented in this demo is gaining additional knowledge from correlation of data acquired from different types of mobile sensors, including

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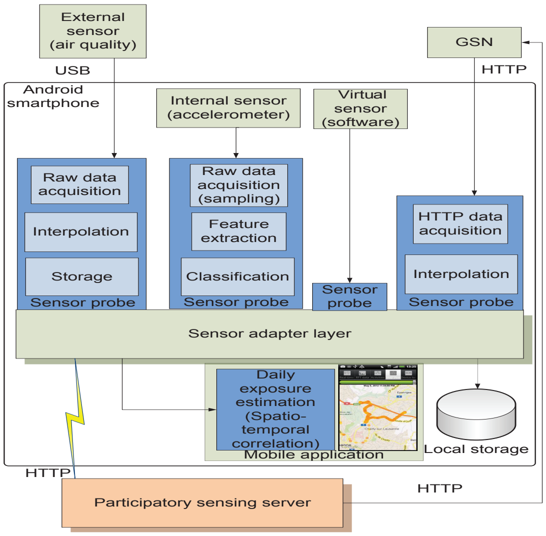


Figure 1: The ExposureSense system architecture

smartphone embedded sensors, smartphone USB-pluggable sensors, and external mobile sensor network. For this particular demo we focus on combining user activities detected from accelerometer with air quality data acquired from both OpenSense sensor network and the pluggable O_3 sensor.

The main technical challenge in this approach of integrating heterogeneous sensor types is developing uniform sensor access interface. This is especially important if we introduce "virtual" sensors capturing additional phone states. For this purpose we opt for a sensor adapter/wrapper middle layer. Such sensor abstraction is inspired by and implemented using sensor probe software components based on the Funf - an open sensing framework [1].

The general architecture of our ExposureSense approach is shown in Fig. 1, and its five main technical components are described in the following paragraphs in more detail.

A. *Inferring Daily Activities*

The first main component is inferring user daily activities by designing an extended accelerometer probe which extends simple accelerometer probe and encapsulate inference engine for activity recognition. Like many studies on classifying accelerometer data [11], the extended probe encapsulates the whole accelerometer data analysis in four main steps: (1) sampling accelerometer data based on the initial Funf accelerometer probe, (2) extracting statistical features, (3) building inference models based on training data with manual labels, and (4) classifying unknown accelerometer streams. In our experiment, the Weka tool [3] was used to implement a J48 classification decision tree in the probe.

B. *Gathering Air Quality from External Sensor Network*

Participatory air quality sensing does not eliminate the need for external sensor networks, no matter static or mobile. For example, the OpenSense project has deployed a rich set of sensors on public transports to measure air quality, like CO, PM10, O_3. Another important component of this demo is a novel concept in participatory sensing that a mobile user (node) might have roles of not only an air quality data consumer but also data contributor. For this purpose we develop a sensor probe that represents an interface with Global Sensor Network (GSN) - the middleware server for third party sensor - and provides modeling and capturing the pollution data [12]. In this case, a smartphone acts as a consumer of external air quality data. Different types of air quality data are stored in GSN and are ready to be interpolated when calculating exposure.

C. *Gathering Air Quality from Pluggable Sensors*

Different from the previous subsection, the smartphone can also be used as a mobile sensor node for capturing air quality data. In modern phones, smartphone is still in the lack of environmental sensors - except the temperature and radiation sensors developed in certain brands. An alternative probe module is devoted to interfacing with external (pluggable) sensors. The initial motivation for this pluggable sensor can be found in [6] for easy deployment of measuring public heath. Research in the field of participatory air quality sensing illustrates that more air quality sensors will be available in future smartphones. With standard UBS alike interface, additional third party sensors can be easily plugged into modern phones for personalized measuring purpose.

D. *Daily Exposure Estimation*

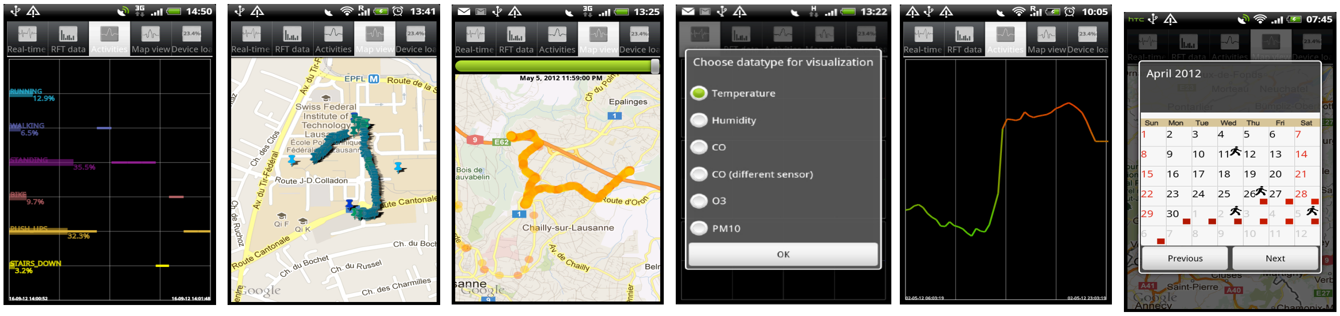
When all heterogenous sensor data is in place interpolation is performed and data is spatio-temporally correlated in order to estimate people's daily pollutant exposure. Exposure intensity is scaled based on activity type, burned calories and movement speed [10]. This process is based on the MET research - metabolic equivalents of various activities tables. CO and O_3 concentration data is acquired either from external sensor network service or local pluggable sensor. User's location with classified activity is matched against air quality interpolated values and exposure is calculated with multiplication factor taken into account.

E. *Mobile Front-End Interface*

Finally, the mobile client side is developed for personalized data visualization, linking to the backend data collection, logging, analysis and integration. The detailed front-end UI for representing the ExposureSense outputs will be discussed in the next section. It is worth noting that our experiment is based on Android devices.

III. Mobile Client Demostration

This sections demonstrates key mobile interfaces of ExposureSense, in terms of the smartphone client side. These demonstrations will show our initial work in developing flexible mobile participatory sensing framework for integration of everyday user's activities and air quality data.



(a) (b) (c) (d) (e) (f)

Figure 2: ExposureSense mobile client screenshots - (a) realtime and history activities detected, (b) geo-visualization of activity data, (c) geo-visualization of air quality data, (d) choice of air pollutant exposure, (e) timeline view of exposure details, and (f) calendar widget.

Output of the activity classification module is a system broadcast that contains currently detected user's activity. This is based on classification of calculated accelerometer feature set and finally, user's physical activity is detected and stored in the local storage. Two widgets have been developed for visualization of the detected activities: (1) a time-line with activity percentage statistics and (2) a geospatial visualization representing types of activities as color-coded push-pins. The time-line and geospatial visualization are shown in Fig. 3-(a) and Fig. 3-(b), respectively.

In ExposureSense, interesting observations arise when user activity data is correlated with external sensor data such as air quality data. In our demo, we have OpenSense external sensor network data: mobile sensors mounted on public transport vehicles collect data on air temperature, humidity and concentrations of CO, PM10 and O_3 and submit data periodically to the GSN service. In addition, we also have O_3 data collected from locally USB pluggable sensor hardware. Geospatial visualization widget for air quality data is shown in Fig. 3-(c). The visualization for all these air quality parameters on both timeline and geospatial widgets are color coded according to typical parameter values.

Among these various air quality sensors, mobile users can adaptively choose an exposure parameter as their preference. Both geospatial and timeline widgets have an integrated view of the air quality data with the activity data. The selection of air quality exposure parameters and their visualizations are shown in Fig. 3-(d).

Timeline view for calculated air pollutants exposure is shown in Fig. 3-(e). As stated in previous section, exposure is estimated based on user's detected type of activity, movement speed and the matched air quality data by the location. The air quality data can be either from the sensor network or by locally pluggable sensor hardware.

Finally, ExposureSense provides a top-level overview of user's daily activity cross-correlated with acquired air quality data in a customized calendar widget, as shown in Fig. 3-(f). In the widget, the people icon indicates that day has enough calories burn by daily activities, while the red-color rectangle indicates the pollution exposure level at that day.

IV. Conclusion

In this paper, we demonstrated ExposureSense, the initial research results on developing a personalized daily diary that integrates activity data with the air quality data. Towards this goal, ExposureSense builds a mobile participatory sensing infrastructure that utilizes various sensors, like smartphone accelerometer for activity detection, external air quality data from OpenSense, and USB pluggable sensors like O_3. ExposureSense offers a rich insight about fusing people's daily activities and their pollution exposure – a high potential to next generation healthcare applications using smartphones.

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