Participatory Air Pollution Monitoring Using Smartphones

David Hasenfratz, Olga Saukh, Silvan Sturzenegger, and Lothar Thiele
Computer Engineering and Networks Laboratory
ETH Zurich, Switzerland
{hasenfratz, saukh, thiele}@tik.ee.ethz.ch, ssilvan@ee.ethz.ch

ABSTRACT

Air quality monitoring is extremely important as air pollution has a direct impact on human health. In this paper we introduce a low-power and low-cost mobile sensing system for participatory air quality monitoring. In contrast to traditional stationary air pollution monitoring stations, we present the design, implementation, and evaluation of *GasMobile*, a small and portable measurement system based on off-the-shelf components and suited to be used by a large number of people. Vital to the success of participatory sensing applications is a high data quality. We improve measurement accuracy by *(i)* exploiting sensor readings near governmental measurement stations to keep sensor calibration up to date and *(ii)* analyzing the effect of mobility on the accuracy of the sensor readings to give user advice on measurement execution. Finally, we show that it is feasible to use GasMobile to create collective high-resolution air pollution maps.

1. INTRODUCTION

Urban air pollution is a major concern in modern cities and developing countries. Atmospheric pollutants considerably affect human health; they are responsible for a variety of respiratory illnesses (*e.g.*, asthma) and are known to cause cancer if humans are exposed to them for extended periods of time [20]. Additionally, air pollution is responsible for environmental problems, such as acid rain and the depletion of the ozone layer. Hence, air pollution monitoring is of utmost importance.

State-of-the-art air quality monitoring. Nowadays, air pollution is monitored by networks of static measurement stations operated by official authorities. These stations are highly reliable and can accurately measure a wide range of air pollutants using traditional analytical instruments, such as mass spectrometers. However, the extensive cost of acquiring and operating these stations severely limits the number of installations and results in a limited spatial resolution of the published pollution maps [8, 28].

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Participatory air quality monitoring. The concentration of air pollutants is highly location-dependent. Traffic junctions, urban canyons, and industrial installations have considerable impact on the local air pollution [27]. We tackle the challenge of acquiring spatially fine-grained air pollution data with a community-driven sensing infrastructure. Such initiatives that pursue the public gathering of reliable data gained increasing popularity in the last years, *e.g.*, worldwide data collection of local food conditions or nuclear radiation.[1] These examples show that it is possible to collect region-wide measurements by involving the general public. Given the broad availability of personal GPS-equipped smartphones, we aim to use these devices to build a large-scale sensor network of mobile devices for participatory air pollution monitoring [25]. Involving the average citizen in sensing the air she breathes helps to rise public awareness and encourages to move towards sustainable development [1].

Challenges. Getting the general public involved in participatory air quality monitoring to collect useful data posts several challenges. These involve providing the user with:

- Low-cost and low-power measurement hardware suitable for mobile measurements;
- Unobtrusive and user-friendly data acquisition and processing software;
- Support in gathering high quality data;
- Information feedback as reward and incentive.

We tackle these challenges with our prototypical air quality measurement system *GasMobile*. We connect a small-sized, low-cost ozone sensor to an off-the-shelf smartphone running the Android OS. We describe in Sec. 2 the hardware and software system designs in detail and reveal the arising difficulties and constraints in controlling a gas sensor directly with a smartphone. In Sec. 3 we approach the problem of receiving high-quality measurements in a mobile scenario: we *(i)* exploit measurements near static stations to improve sensor calibration, and *(ii)* analyze the effect of mobility on the accuracy of the sensor readings to give advice on measurement execution. In Sec. 4 we use GasMobile measurements to create good quality air pollution maps with a high spatial resolution. We survey related work in Sec. 5, and end the paper in Sec. 6 with brief concluding remarks.

[1] `costofchicken.crowdmap.com`, `radiation.crowdmap.com`

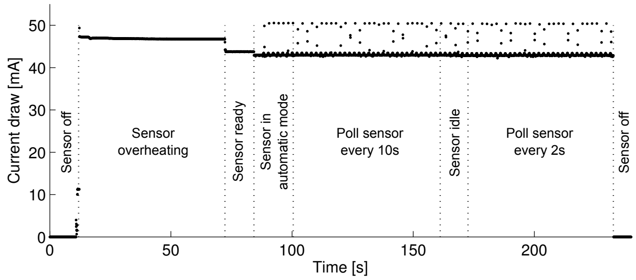


Figure 1: Current draw of the ozone sensor and USB translator over time. *Sensor polling does not noticeably increase the current draw.*

2. SYSTEM DESIGN

This sections describes the hardware and software architecture of GasMobile.

2.1 Hardware Architecture

Our measurement system consists of four parts as displayed in Fig. 2(a). We use a MiCS-OZ-47 sensor from e2v [4] to sense the ozone concentration in the atmosphere based on the measured resistance of the sensor's tin dioxide (SnO_2) layer. Digital communication is possible over the board's RS232-TTL interface, which is directly connected to an off-the-shelf HTC Hero smartphone providing a USB Mini-B port. All parts are stock hardware available for low prices (in the range of hundreds of dollars in total). This is essential to obtain widespread acceptance of participatory sensing equipment.

USB host mode. In order to control another USB device with a smartphone, the phone has to support USB host mode. This enables the interaction with various USB devices such as memory sticks, external hard drives, keyboards, or gas sensors in our case. Although many smartphones' hardware theoretically supports USB host mode (*e.g.*, Motorola Milestone, Motorola Droid, Nexus One, and HTC Hero), the manufacturers do not enable this functionality by default.[2]

Power supply in host mode. Usually USB host controllers provide enough power on the 5 V line to at least power a low-power peripheral (*i.e.*, 100 mA at 5 V). Since the HTC Hero is not designed for host mode, its USB controller lacks the ability to provide power over the USB port. Hence, we power the sensor externally with a battery pack. As a side benefit, the sensor's and smartphone's power supplies are entirely independent from each other. However, new smartphones innately supporting USB host mode do not necessarily need an external power source.

Power consumption. Having an extended battery lifetime is crucial for mobile and participatory sensing applications. We analyze the total current draw of the ozone sensor and the USB-RS232 translator, both components being powered by the battery pack. We use an Agilent digital multimeter with a sampling rate of 100 ms; the measured current draws are illustrated in Fig. 1. After each power-on, the tin dioxide layer of the ozone sensor is overheated for 60 s. This overheating decreases the sensor drift over time. The current draw during the overheating phase is 47 mA. After overheating, the sensor is ready for taking measurements. We put the sensor in automatic mode in which it uses its own clock to automatically perform measurements every two seconds. This ensures that an up-to-date measurement reading is always available for the application, which polls the sensor. Each measurement results in a short 50 mA peak of the current draw, as shown in Fig. 1. Applications polling sensor readings do not noticeably increase the current draw.

We operate the gas sensor using four AAA NiMH batteries with a nominal capacity of 2500 mAh at 1.2 V. Considering the highest measured current draw of 50 mA, we roughly estimate a battery lifetime of 50 hours. This lifetime allows us to monitor the ozone concentration for approximately one month, assuming that on average an adult spends 1.7 hours per day outdoors [12].

2.2 Smartphone Client

Next, we detail the software architecture.

Android OS. As described above, the Android kernel supplied by HTC does not support USB host mode. Hence, we choose the popular CyanogenMod custom kernel [3]. At the moment, Android itself does not provide an API for reading and writing to the serial port. Thus, we use android-serial-api [2] for the serial communication between ozone sensor and smartphone. We periodically poll the gas sensor for raw sensor readings, which include the resistance R of the tin dioxide layer and the on-board temperature T. As the resistance is heavily temperature-dependent, we use T to calculate the temperature-compensated resistance $\tilde{R}$

$$\tilde{R} = R \cdot e^{K\cdot(T-T_0)} \tag{1}$$

with the reference temperature $T_0 = 25\,^{\circ}\mathrm{C}$ and the temperature coefficient $K = 0.025$ from [4]. Since the response curve of the ozone sensor is quasi-linear with respect to the ozone concentration c [13], we approximate it with a first-order polynomial

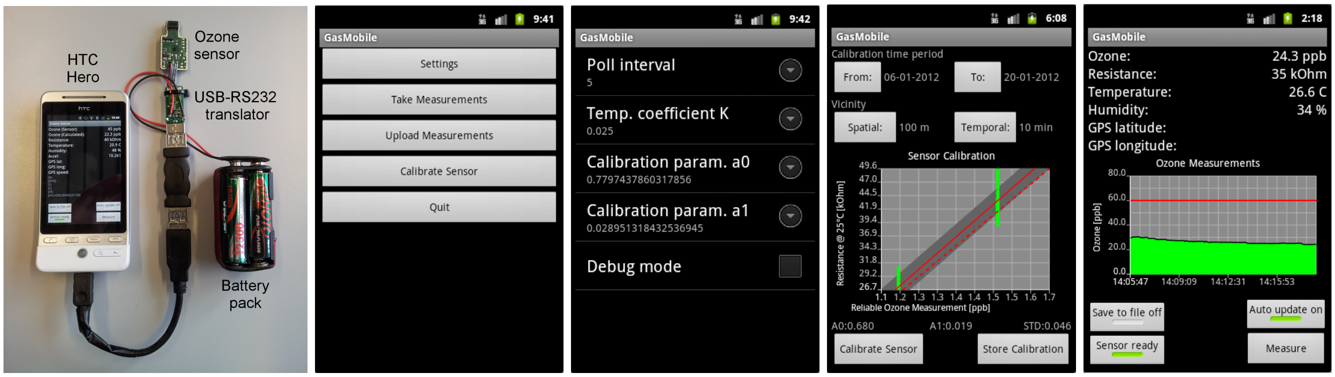
$$c(\tilde{R}, a_0, a_1) = a_0 + a_1 \cdot \tilde{R} \tag{2}$$

where a_0 and a_1 represent the calibration parameters of the sensor. We will detail in Sec. 3.1 how our Android application helps the user determine these calibration parameters.

Android application. The application starts with the main menu depicted in Fig. 2(b). The user can access the settings, take measurements, calibrate the sensor, or upload the measurements to a server. Using the settings screen, shown in Fig. 2(c), the user can change several configuration parameters. Both the temperature coefficient K and the calibration parameters a_0 and a_1 are usually predefined by the manufacturer. However, to get the best possible accuracy, it is recommended to calibrate the sensor with real pollution measurements [16], as described in Sec. 3.1.

In the measurements screen (see Fig. 2(e)) the user can put the sensor in automatic mode and choose whether to poll the sensor once or continuously with a pre-configured poll interval. The application polls the latest raw data from the ozone sensor (resistance, temperature, and humidity), and position and speed information from the GPS module. The ozone concentration is calculated using (2) and displayed in the plot on the screen. The geo-localized and time-stamped measurements can be permanently stored on the smartphone's memory card and uploaded to a server for further processing and visualization, *e.g.*, to refine sensor calibration and to produce ozone concentration maps as described in Sec. 4.

[2]Lately some smartphones appeared on the market that innately support USB host mode (*e.g.*, Samsung Galaxy S II).



(a) Hardware architecture (b) Main menu (c) Settings (d) Calibration (e) Measurements

Figure 2: GasMobile hardware architecture (a) and Android application (b)-(d). *The user can set the poll interval, adjust calibration parameters, poll sensor measurements, and upload the measurements to a server for further processing.*

Memory and CPU footprint. A resource-sparing application is essential to achieve a long battery lifetime and thus gain consumer acceptance. The GasMobile application uses just 41.5 kB from the 166 MB of internal storage on the HTC Hero. When the application is running, it uniquely uses 5.5 MB of system memory and shares 25 MB with other running processes. The CPU usage is increased by 5 % while polling the sensors and calculating the ozone concentration. In summary, the resource requirements are very low.

2.3 Extensibility to Other Gas Sensors

Extending GasMobile to support other sensors is straightforward and only requires minor modifications in two software components, as long as the sensor provides serial communication over USB. First, the serial communication protocol has to be tailored to the software and hardware requirements of the intended sensor. Second, the Android application must be implemented to facilitate the interaction between user and sensor.

3. INCREASING SENSING ACCURACY

Usually data users must assume a certain data quality. Thus, a high data quality is vital to the success of participatory sensing applications. This section examines the possibilities to optimize data quality gathered by mobile sensors. We keep sensor calibration up to date by exploiting sensor readings near a static reference station, and analyze the influence of mobility on the measurement accuracy to give advice on measurement execution.

3.1 Sensor Calibration with Quality Feedback

Sensor calibration is a difficult and time-consuming task. Low-cost gas sensors must be frequently re-calibrated [26] as they are unstable and responsive to the influence of interfering gases [16]. GasMobile provides assistance in keeping the calibration parameters up to date by using publicly available high-quality measurements from static reference stations maintained by official authorities [13].

We exploit GasMobile sensor readings that are measured in the vicinity of a static reference station. The temporal and spatial vicinity requirements largely depend on the measured pollutant. The spatial dispersion of ozone in a street canyon is in general constant [27] and the ozone concentration is typically slowly changing over time (in the order of minutes). Hence, we specify in the settings (see Fig. 2(d)), that sensor readings and reference measurements are considered to be exposed to very similar ozone concentrations if their measurement time and location do not differ more than 10 min and 400 m, respectively.

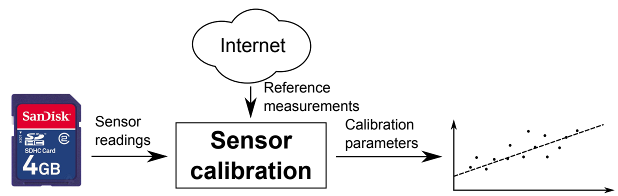


Figure 3: Calibration procedure. *Measurements near a reference station are used to update calibration parameters.*

Fig. 3 depicts an overview of the calibration procedure. The application fetches all sensor readings from the memory card that satisfy the time period set by the user. Additionally, the available reference measurements for this time period are retrieved from the web. Both data sets are streamed through a data filter in order to construct calibration tuples of those sensor readings and reference measurements that satisfy the given vicinity requirements. Consider that set $\mathcal{S}$ contains these calibration tuples $(\tilde{R}, M)$ with sensor reading $\tilde{R}$ and reference measurement M. We use the method of least squares [6] to choose the calibration parameters a_0 and a_1 such that the sum of squared differences between $c(\tilde{R}, a_0, a_1)$ and M are minimized $\forall\,(\tilde{R}, M) \in \mathcal{S}$

$$\arg\min_{a_0,a_1} \sum_{(\tilde{R},M)\in\mathcal{S}} \Big(c(\tilde{R}, a_0, a_1) - M\Big)^2 \tag{3}$$

The application provides a visual feedback on the calibration as shown in the plot in Fig. 2(d). The green dots display the calibration tuples, the red dashed line denotes the current calibration, and the red straight line represents the new calculated calibration parameters a_0 and a_1. The gray area visualizes the standard deviation σ of the new calculated

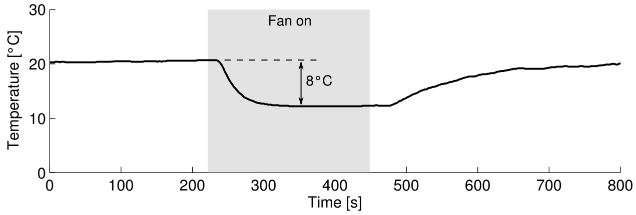


Figure 4: Air flow generated by a fan (shaded area) influences the readings of the on-board temperature sensor. *We measure a maximum drop of 8 °C.*

calibration parameters given by

$$\sigma^2 = \frac{1}{|\mathcal{S}|} \cdot \sum_{(\tilde{R},M)\in\mathcal{S}} \left(c(\tilde{R}, a_0, a_1) - M \right)^2 \qquad (4)$$

In general, the adjustment of the calibration parameters is not advisable if the calibration curve currently in use lies inside the gray area, which denotes the uncertainty of the new calculated calibration curve (as shown in Fig. 2(d)).

3.2 Effect of Mobility on Sensor Readings

In the following, we analyze the effect of sensor mobility on the accuracy of the sensor readings, mostly due to the varying air flow around the sensor head.

We carry out several experiments in a closed room with a constant ozone concentration. We use a table fan that generates a maximum wind speed of 6.6 m/s to analyze the influence of the air flow on the raw sensor readings. We observed that the air flow mainly impacts the on-board temperature T used in (1) to calculate resistance $\tilde{R}$. The air flow around the sensor head influences the heat dissipation on the sensor board and results in a lower temperature reading of at most $T_a = 8\,^\circ$C as shown in Fig. 4. The temperature drop induces a maximum relative error of 14 % in the calculation of the temperature-compensated resistance:

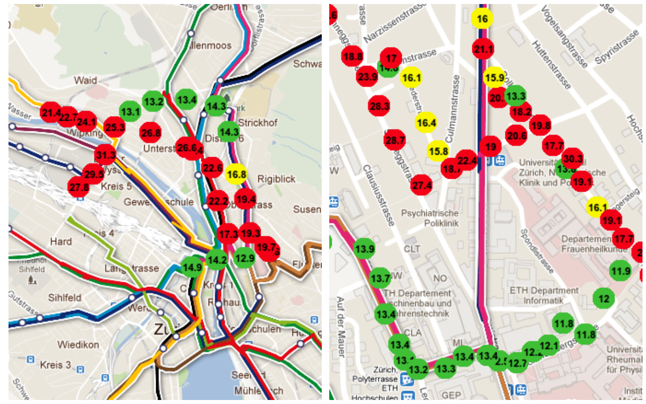
$$1 - \tilde{R}_a/\tilde{R} = 1 - e^{-K\cdot T_a} = 0.14 \qquad (5)$$

This maximum relative difference is negligible for low ozone concentrations, but results in a high offset under high pollution levels. No precaution is required for measurement campaigns with pedestrians, which are usually moving at a slow speed. However, we recommend to protect the sensor head from a direct exposure to air flow under rapid motion speeds of the sensor head, *e.g.*, while riding a bicycle. Alternatively, accelerometer data can be used to measure motion speeds in order to compensate the temperature drop due to mobility.

4. APPLICATION SCENARIO

We provide a full system for mobile participatory sensing [7], ranging from the sensing hardware and client software with calibration support as described in the previous sections to a powerful web-based data visualization tool to create collective air pollution maps. In the following, we present results from a measurement campaign using GasMobile and provide an estimation of its measurement accuracy.

Measurement campaign. We used GasMobile over a period of two months for pollution measurements in an urban area. For this, we mounted the sensor on a bicycle (protected from wind) and took measurements from several bicycle rides all around the city. Throughout the measurement campaign we used a sampling interval of five seconds and collected in total 2,815 spatially distributed data points. All sensor readings were directly uploaded to our server running GSN (Global Sensor Network) [5]. The measurements are publicly available[3] and it is possible to browse through the full data set. We use location- and time-based data aggregation and caching for efficient data retrieval [18]. This allows the user to easily revisit past measurements and combine different data sets from multiple participants to produce collective air pollution maps with different spatial resolutions as shown in Fig. 5. Using these maps, we can clearly spot differences between streets of high and low pollution concentrations, which is impossible with currently published pollution maps.



(a) Overview (b) Close-up view

Figure 5: Two ozone pollution maps with distinct spatial resolutions based on GasMobile measurements. *Data are from several bicycle rides with a poll interval of five seconds.*

Total number of measurements	Measurements near a reference station	Mean error [ppb]	Std. error [ppb]
2,815	34	2.74	4.19

Table 1: Measurements in the vicinity of reference stations are used to calculate the measurement error. *On average the error is within 2.74 ppb.*

Generation of air pollution maps. To produce the air pollution maps, we divide the area excerpt selected by the user into rectangular regions of 35 x 35 pixels. For each region we calculate the average ozone concentration based on the measurements performed in that region. We classify the regions into three zones (green, yellow, and red) corresponding to the average ozone concentration level as illustrated in Fig. 5 with two distinct spatial resolutions.

Measurement accuracy. We estimate the measurement accuracy by extracting sensor readings that were measured in the spatial and temporal vicinity (≤ 400 m and ≤ 10 min) of one of the four reference stations. The errors are on average 2.74 ±4.19 ppb compared to high-quality measurement instruments as summarized in Table 1, this is only slightly higher than in a static setting [13]. This is sufficient to create accurate air pollution maps considering that the daily ozone concentration typically ranges between 0 and 70 ppb.

[3] `http://data.opensense.ethz.ch`

5. RELATED WORK

Mobile phones are used in a wide range of application scenarios to facilitate data collection, such as visibility monitoring [22], traffic conditions surveillance [23], sensing individual emotions [24], and bicycle localization [19]. Many of these smartphone-based sensing applications use bluetooth for data transfer between sensor and smartphone [10, 11, 14, 15]. Bluetooth gives the user great freedom in sensor placement, but leads to higher battery drain due to bluetooth communication on the device and sensor side. We instead exploit USB host mode and directly connect the sensor to the smartphone. With this we reduce the power draw by a factor two.

Monitoring air pollution using low-cost gas sensors has gained high interest in recent years [26]. Low-cost gas sensors are often embedded in custom-build sensor nodes that are part of mobile sensor networks [9, 10, 14]. Instead, we control the gas sensor with minimal additional hardware using an off-the-shelf smartphone. This keeps material costs low and thus makes our measurement system attractive to a large number of people as a large-scale sensor network of mobile phones [17].

Compared to previously proposed participatory sensing applications [10, 14], we tackle the challenge of improving data quality of mobile sensors. To this end, we provide support to continuously keep sensor calibration up to date.

Only few publications are dealing with sensor calibration in mobile sensor networks. Most similar to our calibration approach is CaliBree [21], a distributed self-calibration protocol for mobile wireless sensor networks.

6. CONCLUSIONS

We show with our GasMobile prototype system, that participatory air pollution monitoring is feasible. We use small, low-cost, and off-the-shelf hardware to monitor the ozone concentration. GasMobile provides a high data accuracy by exploiting sensor readings near static measurement stations to regularly keep sensor calibration up to date. Finally, we show, that it is feasible to use GasMobile in participatory sensing applications to increase public awareness and to create spatially fine-grained air pollution maps.

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