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Design of a light-scattering particle sensor for citizen science air quality monitoring with smartphones: Tradeoffs and experiences

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Abstract

Air quality is an aspect that gains more and more attention in the general public, as knowledge on the harmful effects on human health and the environment increase. Along with this, interest in low-cost instrumentation that enables end-users to measure particulate matter has grown, both for individuals, as well as for the use in distributed sensing scenarios. In this paper, we report on the design of an ultra-low-cost clip-on sensor for light-scattering particle measurements with camera smartphones. We present three design iterations and discuss the lessons learned during the design process and advantages and drawbacks of different design decisions. Aside from the specific hardware design, we discuss general errors that are likely to occur when non-experts carry out the measurement process and countermeasures to deal with them, independent from the sensor technology that is being used. This includessomehints for designing appropriate interaction in smartphone applications.

Keywords: Clip-on sensor;Camera smartphone; Participatory sensing; Air quality monitoring; Ubiquitous computing; PM; Citizen science; Environmental sensing; Mobile computing; Light-Scattering; Low-Cost; Pervasive sensing; Non-Expert users; Particulate matter

1. Introduction & related work

Methods and devices for low-cost particulate matter measurement have received growing attention in the past years as air quality monitoring is currently undergoing a paradigm shift (Snyder, et al., 2013). An underlying reason is that bad air quality is a growing issue, especially in large metropolitan areas. This has lead to citizens developing a

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growing interest and concern for the quality of air in their direct surroundings. As urbanization progresses and so-called megacities increasingly form, these problems will continue to grow. Different scenarios for future air quality monitoring have been conceived, ranging from continuous sensing with vehicular networks to mobile air quality measurements performed by end-users with portable miniaturized samplers (Budde et al., 2014). Among these, especially the latter are challenging. Citizen Science performed by everyday users with personal mobile devices in the public domain, a.k.a. Participatory Sensing (Burke et al., 2006), imposes a number of potential issues. Primarily, there is naturally the design of suitable sensors, which can be embedded into personal handheld devices. Furthermore, and independent from the applied sensing technology, there is the question of adequate measures to ensure the correct measurement process when carried out by non-experts.

This work presents the design of a light-scattering particle sensor for camera smartphones to be used in participatory environmental sensing and discusses design choices, tradeoffs and experiences. The original concept of the sensor has been presented by (Budde et al., 2013). We show subsequent design iterations and discuss non-expert user errors and measures that can be implemented to deal with them. Other efforts to enable particulate matter sensing with smartphones have been made in the past: (Carminati et al., 2014) presented the design of a capacitive particle sensor that has the potential to be micro-fabricated and embedded in to phones. In a different approach, (Doering et al., 2012) enabled direct measurement of the mass concentration of particles with an air-microfluidic MEMS design. Finally, the *iSPEX* system is a passive spectropolarimetric clip-on module for the *iPhone* (Snik et al., 2014), similar to the clip-on concept in this work.

2. Hardware design

This section first presents some theoretical considerations regarding the field of tension between different design parameters of the sensor. Subsequently, three design iterations are presented and the benefits and drawbacks of different design variants are discussed.

2.1 Estimations regarding measurement quality

Particulate matter is a discrete measurement variable, meaning that dust is composed of discrete particles, entering the measuring chamber at discrete events. The pure act of counting these discrete signals within a given volume is a stochastic process. Such processes obey a Poisson probability distribution if the expected mean counting rate $<dn/dt>$ can be assumed to be constant. For such Poisson processes the mean number $<n>$ of measured events is correlated to the standard deviation σ_n of the measured signal:

$$\sigma_n = \sqrt{< n >}$$

This gives constructive limitations to the measurement device if a certain amount of statistical error is not to be exceeded. An indicator for the theoretically achievable precision and repeatability is given by the coefficient of variation (CV):

$$CV = \frac{\sigma_n}{< n >} = \frac{1}{\sqrt{< n >}}$$

For growing numbers $<n>$ the coefficient of variation improves.

Concerning our concrete use case of measuring fine dust with ultra low-cost sensors, we make the following assumptions: a sufficiently small sampling duration T is one in which the mean counting rate does not change significantly. Of course, one can imagine fast intense events perturbing the particle concentration that would technically influence the average counting rate. However, in the majority of scenarios, mean concentrations of fine dust can be assumed to be constant over intervals in the range of minutes. For near-real-time particulate matter sensing this would be an acceptable temporal resolution. We argue that the few cases in which these measurement constraints are not met are more or less negligible since our design aims at distributed sensing scenarios with many dense and possibly redundant individual measurements.

In general, one wants to capture and detect as many particles as possible within a single measurement. For a certain mean concentration c, a detector volume V, a mean particle diameter pm, and a mean density ρ, the theoretical coefficient of variation (respectively the amount of error) is:

$$CV = \frac{1}{\sqrt{<n>}} = \sqrt{\frac{\rho \cdot 4/3 \cdot \pi \cdot (pm/2)^3}{c \cdot V}}$$

As an example, for a mean concentration of $c = 10.0\ \mu g/m^3$(typical background concentration in industrialized countries), a measurement volume of $V = 1000\ mm^3$ (10 mm edge length), a mean particle diameter of $pm = 10\mu m$ and a density of $\rho = 2.5\ g/cm^3$ (which is in the range of common particulate matter solids), the relative statistical error would be A ≈ 1140%. Thus a single detector of such characteristic length scale cannot measure such concentrations reliably. However, by performing several *independent* measurements within the time interval I, in which the counting rate $<dn/dt>$ is assumed to be constant, one can effectively improve the CV rating if the individual readings are treated as a single big measurement. E.g. for a measurement rate f and a sampling duration T, we reach an effective CV as

$$CV_e = \frac{1}{\sqrt{f \cdot T \cdot <n>}} = \frac{1}{\sqrt{f \cdot T}} \cdot CV$$

If we consider the calculation for the example above again, a number of $k \approx f, \cdot T = 52349$ independent measurements which e.g. correspond to a time period of $T \approx 8.72\ min$ and a measurement rate of $f = 100Hz$ have to be performed to lower the CV rating to 5%. Table 1 shows different combinations of these parameters for various sampling frequencies (current smartphone cameras easily reach 30 – 60 Hz) and measurement durations.

Table 1. Theoretical estimations for different sampling times and frequencies for the measurement of particles of 10µm diameter in a 1000 mm³ detector volume. CV_e denotes the relative statistical error that can be achieved

Coefficient of Variation (CV_e)	**Sampling frequency (f)**	**Sampling duration (T)**
5%	30 Hz	~ 29.0 min
5%	60 Hz	~ 14.5 min
10 %	30 Hz	~ 7.3 min
10 %	60 Hz	~ 3.6 min
20 %	30 Hz	~1.8 min
20 %	60 Hz	~ 50 sec

This shows that theoretically meaningful readings with a small sensor of 1 cm edge length can be carried out, given sufficiently high sampling frequencies and measurement intervals. As sampling frequencies are very likely to increase further in future smartphone generations, smaller sampling durations that can still guarantee high data quality will become possible. Still, even with current technology, the constraints of our scenario can be met.

2.2 Design iterations and lessons learned

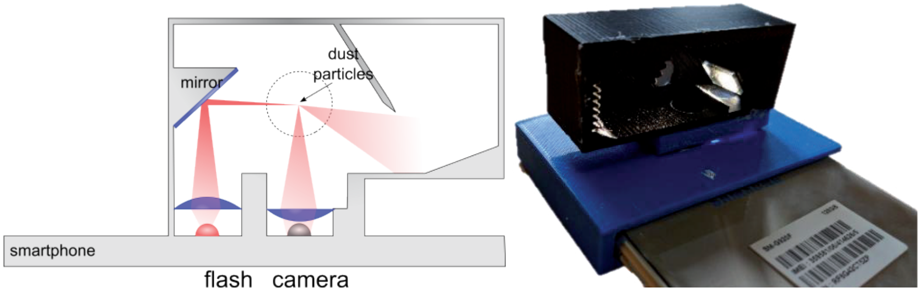
The original proof-of-concept version of the clip-on light-scattering sensor as presented by (Budde et al., 2013), is shown in Fig. 1(a). That version basically consisted of an original *Sharp GP2Y1010* dust sensor that was attached to the back of a smartphone so that the phone's camera replaced the original photodiode receptor. The light of the phone's LED flash was rerouted to the position of the LED in the original sensor using an optical fiber. This prototype demonstrated the general feasibility of the clip-on light-scattering approach, but did not yet achieve a sensitivity suitable for realistic applications.

(a) (b) (c)

Fig. 1. Design iterations: the first generation design used a Sharp GP12P1010 dust sensor casing and an optical fiber to re-route the light from the camera flash (a). In the second generation, a custom sensor casing was prototyped in 3D-printing (b). Active versions using external LEDs (c) were tested for comparison in both generations

When comparing the passive version to an active one that – instead of the optical fiber – featured an externally powered white LED, we observed that the principle was sound, but the passive version failed to produce a sufficient light intensity within the measurement chamber. The reason for this likely was that camera phones' LED flashes are designed to emit diffuse light which made the coupling to the optical fiber very ineffective. In the second generation (Fig. 1(a) and (b)), we therefore introduced semi-spherical lenses to improve this. Still, also in this generation, the active version clearly outperformed the passive one. Therefore, we switched to a mirror-based layout in the third and current generation (see Fig. 2).

We kept true to the strategy of designing an active and a passive version in parallel, as there are certain advantages and drawbacks to both designs: The biggest advantage of the passive version is simply that: it is passive. It is ultra-low-cost and the control of the whole measurement can be implemented in software on the phone. A drawback is that the layout of the camera and the flash is model dependent, so the physical sensor design has to be adopted for different phone types. Proper ventilation of the measurement chamber to ensure that individual measurements are actually independent may also be an issue. The active version on the other hand need some sort of power supply for the LED and possibly an additional interaction (turn on/off) by the user. This could also cause secondary effects, such as possible limitations of the runtime, or negative effects (especially for environmentally conscious users) if consumables, e.g. external batteries, are frequently required. Possible solutions to circumvent this are discussed in the next section. On the other hand, the active version can potentially be attached to a wider range of phones without individualized design.



(a) (b)

Fig. 2. The third generation concept (a) features a mirror instead of optical fibres and a changed light trap layout. A prototype was designed for a *Galaxy S6* (b, side opened for inside view). Initial results are promising, but the real-world performance of different versions regarding the theoretical assumption in Sec. 2.1 is currently being evaluated

2.3 Powering external electronics and other issues

As described in the previous section, the active version of the sensor requires some sort of energy source to power the LED and possibly a micro fan. In order to supply the LED we used in our prototype, we require *20 mA @ 3.2 V* that we need in rated operation, which corresponds to a power of $P = U * I = 64\ mW$. Adding a micro fan for ventilation would additionally add upwards of *35 mA @ 2V =70mW*.

If we were to use standard batteries, options are either tubular batteries or some sort of coin cell(s). With a standard *CR2032*coin cell (*230 mAh @ 3V*), we could operate our setup for *~1.7h*, two would bring up to a maximum of *~3.5h*. AAA batteries, which would notably increase the size of the setup, come at up to *1100 mAh @ 1.2V*, which would mean two batteries would be needed to power the setup for up to *~8.5h*.StandardLiPorechargeable batteries with a higher energy density and suitable dimensions (e.g. from *Adafruit*[1],*34 x 62 x 5mm*) can provide up *to1200 mAh@3.7 V*, providing energy for up to *~9 h* of operation.

Among energy harvesting approaches (e.g. converting solar, thermal, kinetic energy, etc.), solar panels are currently the only option that can potentially deliver the amount of energy needed for operation of our setup (or, in combination with batteries, to recharge them) while also fitting our size constraints. Small cells[2] (*35 x 22mm*) with an efficiency of *22%* can deliver up to *~100mW* at maximum power point. Integrating two or three onto the surface of the sensor could be a realistic option that could potentially remove the requirement to charge the sensor (at the cost of additional parts and engineering complexity).

A different approach would be to power the external components through the phone. One option to do this is would be to pull power from the mobile phone's audio interface (i.e. microphone jack), as proposed by (Kuo et al., 2010). Relevant to the question whether this is feasible or not is primarily the power that can be drawn. In their work, they describe that under optimum laboratory conditions (a perfectly adapted load), they were able to reach a current of *66mA @ 250mV*, i.e. *15.8 mW*. Even without the loss that converting this voltage to suitable levels, the approach of powering the LED directly through the headphone jack, let alone an additional fan, is not feasible.

[1] https://www.adafruit.com/product/258
[2] http://www.digikey.com/short/39vczc

Another option to draw power from the smartphone would be USB On-The-Go (OTG). This has the benefit of being in principle able to supply sufficient power, theoretically up to *500mA @ 5V*.However, according to the USB 2.0 OTG specification (USB Implementers Forum Inc., 2001), devices acting as OTG power source must only provide a minimum current of *8mA@ between 4.4 V and 5.25V*, anything beyond is allowed based on negotiation, but not guaranteed. Realistically, this means that for handheld portable devices*100mA @ 5V* are a commonly accepted maximum for external loads (Texas Instruments, 2010). A drawback is that this approach could possibly require introducing additional electronics on the sensor side in order to authenticate to the phone and negotiate the power supply. However, as added bonus, this would also allow communication over the same connection, which would eliminate the need for the user to actively switch on the sensor module. The communication could also be realized in a different manner, e.g. by controlling the sensor via Bluetooth. However, this would mean adding a suitable communication module and by that further increasing the complexity of the module.

In summary, the active design of the sensor is more flexible, but also much more intricate than the passive one. Of the options for powering an external sensor module, the microphone jack approach can be discarded as infeasible and using non-rechargeable batteries could lead to an acceptance problem(producing too much waste). The other approaches have their pros and cons, ranging from simple solutions requiring more user interaction and maintenance (rechargeable batteries) to more sophisticated solutions that involve external electronics, making them more expensive in terms of design and unit costs. We propose that the passive solution, provided it can properly be ventilated, is the most elegant one. When designing the active sensor, the approaches using USB OTG or rechargeable LiPo batteries (possibly recharged via small solar panels) are options we intend to explore further.

3. Application design

Independent from the hardware sensor technology, smartphone-based fine dust sensing needs suitable signal processing techniques and appropriate user interfaces. This is especially vital since non-expert users perform the sampling to an increasing degree. This can be problematic in terms of data quality, as typical requirements for correct measurement procedures typically cannot be ensured. Non-expert users could handle the clip-on equipment wrong or perform process steps incorrectly (e.g. because they are *untrained, overwhelmed*, or *inattentive*). Designing the application software appropriately can help to mitigate these problems. This can be done on different levels.

3.1 Designing for non-expert participants

When designing for non-expert participants, *Training* users is the most obvious way of making sure that non-experts perform a task correctly. However, at a large scale, training individual participants is simply not feasible. A closely related measure is that of providing a set of instructions (e.g. manuals or *tutorials*) in order to help users understand the measurement process. A possible drawback of this approach is that people might fail to understand or recall new material if it is sufficiently complex. If possible, in shorter form and closely to the task, e.g. as an in-app tutorial, instructions can be a good approach. Providing *feedback* to the user is also a helpful measure. When collecting data, feedback can be either given live, e.g. by displaying pollution levels while measuring, or directly after completing a measurement, or as a visualization in a greater context, e.g. data overview on a map. Especially live feedback provides the possibility to help the users better understand the effects of their actions on the sensing process. Simple *repetition* of measurements leads to multiple instances of the same data which can then in turn be processed, e.g. to remove outliers. This approach only works if the overall error is non-systematic, i.e. people will on average perform the task correctly. A more sophisticated way of computationally addressing procedural errors is *recognition*. This ranges from checking whether the GPS receiver is enabled or the accelerometers of the phone pick up movement when there should be none, to full-fledged activity recognition. All the aforementioned mechanisms can possibly also be used in games that beyond incentivizing participation, use game mechanics to support correct sensing, as proposed in (Budde et al., 2016).

3.2 Addressing errors on a signal processing level

A very robust way to deal with different types of erroneous data of phenomena that can be modelled as particles was originally presented in (Budde et al., 2015): robust signal *reconstruction* from Poisson noise. Errors may stem from low-cost equipment (e.g. systematic cross-sensitivity), sensor aging (e.g. dirt residue, LED degradation), limited control (e.g. automatic adjustment of camera settings) and, again, users (e.g. device handling, assembly). In camera-based sensing, if a user instance were to inadvertently put a smudge on the lens, this would create an offset in readings afterwards.

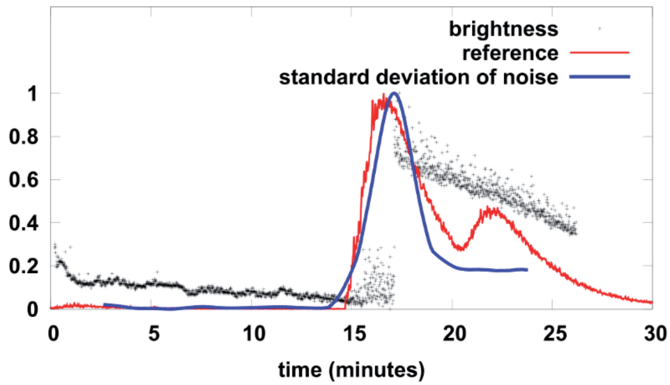


Fig. 3. An approach for reconstruction of a signal from its Poisson noise for phenomena that can be modelled as particles was shown in (Budde et al., 2015). It is robust against changing offsets and/or systematic drift

The idea behind the reconstruction approach is to exploit the fact that particle measurements are afflicted with sensor-dependent noise. Thus, it is possible to reconstruct the true signal from the noisy one. As discussed above, in Poisson processes the mean number $<n>$ of measured particles is correlated to the standard deviation σ_n of the measured signal:

$$\sigma_n = \sqrt{< n >}$$

As a result, knowledge of the standard deviation of the measured signal is sufficient to reconstruct the signal as a whole. This can be a great advantage, since the standard deviation is calculated against the mean value and thus has a relative property which neglects constant shifts due to e.g. decalibration in the signal.

4. Conclusion

In this paper, we reported on advances in smartphone-based particulate matter sensing. The progress in the design of low-cost clip-on instrumentation to enable light scattering fine dust measurements using camera smartphones was presented. General issues that arise when air quality sensing technology ultimately starts to disappear into end-user devices in the future were discussed. Central to this – next to the actual sensing hardware of course – are approaches to deal with untrained, non-expert users performing the sampling, and the effects this can have on data quality. Aside from presenting techniques that target user handling, we discussed a signal processing approach to directly stabilize sensor readings.

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