# Data Quality Issues in Environmental Sensing with Smartphones

Tiago C. de Araújo[1,2], Lígia T. Silva[2] and Adriano J. C. Moreira[1]
[1]*Centro de Investigação Algoritmi, Universidade do Minho, Azurém, Guimarães, Portugal*
[2]*Centro de Investigação CTAC, Universidade do Minho, Azurém, Guimarães, Portugal*
*tiago.araujo@ifrn.edu.br, lsilva@civil.uminho.pt, adriano.moreira@algoritmi.uminho.pt*

Keywords: Smartphones, Mobile Sensing, Participatory Sensing.

Abstract: This paper presents the results of a study about the performance and, consequently, challenges of using smartphones as data gatherers in mobile sensing campaigns to environmental monitoring.
It is shown that there are currently a very large number of devices technologically enabled for tech-sensing with minimal interference of the users. On other hand, the newest devices seem to broke the sensor diversity trend, therefore making the approach of environmental sensing in the ubiquitous computing scope using smartphones sensors a more difficult task.
This paper also reports on an experiment, emulating different common scenarios, to evaluate if the performance of environmental sensor-rich smartphones readings obtained in daily situations are reliable enough to enable useful collaborative sensing. The results obtained are promising for temperature measurements only when the smartphone is not being handled because the typical use of the device pollutes the measurements due to heat transfer and other hardware aspects. Also, we have found indicators of data quality issues on humidity sensors embedded in smartphones. The reported study can be useful as initial information about the behaviour of smartphones inner sensors for future crowdsensing application developers.

## 1 INTRODUCTION

According to an industry track report from a specialized website (eMarketer Inc. 2015), it is expected that almost 70% of the world population will be using a smartphone in 2017, corresponding to an absolute number of 5.13 billion of people, among which 2.97 billion will be using internet regularly on their smartphones. Also, the potential of the new mobile devices due to its embedded sensors and processing capabilities goes beyond of what most users probably can perceive. The recently announced smartphones from the two market-share leaders (Samsung Galaxy S7 and Apple iPhone 7) have hardware capabilities and performance comparable to high-end computers of few years ago.

Facing these facts, researchers of ubiquitous and pervasive computing have conducted several works to investigate the capabilities of smartphones for collaborative sensing, participatory sensing and correlated topics. For example, D'Hondt et al. (2013) implemented a model for measuring noise levels in urban spaces through a proprietary application using smartphone's microphone, when idle, for estimation of outdoors noise levels. Through the GPS metadata, the authors could compare their results with official levels measured by proper devices, and they found a high correlation between the results leading to the conclusion that participatory sensing can, under appropriate conditions, be an alternative to the conventional monitoring systems.

Investigating the potential of subjective analysis of the environment using the participatory sensing approach, Kotovirta et al. (2012) shared their experiences with the observation of algae presence in lakes through the feedback of non-specialist users. The users, willingly, when near a lake send their evaluation about the presence of algae in it, based only on visual perception. The data were compared to those collected by specific biologic monitoring instruments and, despite the absolute error, they found a strong qualitative correlation between observations provided by users and the results measured by the instruments.

Towards a systemic view of the urban environment, Kanhere (2011) provided an analysis of key challenges and possibilities of crowdsourcing using smartphones. Air quality monitoring, noise pollution and traffic conditions were cited as potential areas of research and development. Yet in efforts



Araújo, T., Silva, L. and Moreira, A.
Data Quality Issues in Environmental Sensing with Smartphones.
In *Proceedings of the 6th International Conference on Sensor Networks (SENSORNETS 2017)*, pages 59-68
ISBN: 421065/17

focused in urban centres, Overeem et al. (2013) proposed an Android application (*Weather Signal*) that uses an algorithm to estimate the air temperature from the battery temperature of smartphones through a heat-transfer model considering some additional parameters. To evaluate the performance of this new proposal, they compared official air temperature data from official entities with the data from their experiment in defined time intervals, and found very positive indicators, but still requiring some adjustments in the heat-transfer model.

In a more recent work with smartphones and urban sensing, the *HazeWatch* project (Hu et al. 2016) used the smartphone as an intermediary between a proprietary data-collection platform and the end-users. The project relies in the mobility of the platform, often carried by taxis, bicycles and voluntaries to identify phenomena that can be unseen by stationary and official platforms. The communication between smartphones and the platforms is through Bluetooth, the smartphone process the data and then upload them to the cloud using mobile Internet access networks. They reached very solid results, but identified the cost of the platform and its weight as a limitation that hinds the spread of this initiative, due to motivations-related issues.

There are also efforts towards the user's motivation and engagement in collaborative sensing. When using smartphones, the main issue relates to battery consumption. People avoid to use applications that drain too much energy from batteries and has too few to offer in exchange. Rodrigues et al. (2012) investigated the "engagement of users" in participatory mobile campaigns. As they identified the energy drain as one predominant negative aspect to attract more – and keep the existing – smartphone users, the authors introduced a desktop application to be used in laptops, that are also pervasive, in a study of human mobility. As results, they appointed that the initial attraction of users to get involved, in low and medium quantities, is not difficult, but the main challenge found is how to keep these users active for long-periods, as well as to reach a massive numbers of users even when rewards are considered.

Yet on motivation and engagement studies, the authors in Zaman et al. (2014) demonstrated that collaborative campaigns often emerges from common concerns of a group of people or community, and proposed a conceptual framework for management and orchestration of community campaigns driven by citizens. The most relevant a subject is for a group of people or community, the higher are the chances of more users getting involved. So, keeping these users active through time is also dependent on how the main subject of a campaign is important for each individual, on the role each person can play in it (citizen participation), and also in the quality of data generated by the campaign and made available to its users (closing the loop).

Relying on these efforts, and on the fact that there are a reasonable number of people carrying smartphones with environmental sensors everywhere, the idea of using these embedded sensors for a ubiquitous, collaborative and smart sensor grid emerged inside the smart cities and environmental monitoring contexts. Thus, the motivation used as ground to this investigation is the importance to develop an analysis about the potential role of smartphones for the environmental monitoring, either in urban centres or indoors, using its own hardware in the data-collection stage through some technical considerations about the data quality and other related issues.

## 2 ENVIRONMENTAL ENABLED SMARTPHONES

In recently years we observed an empowerment of smartphones capabilities through the aggregation of several features such as GPS, accelerometers, gyroscopes and lux meters. The presence of these sensors transformed the mobile phones into versatile devices. Thus, the embedding of temperature, pressure and humidity sensors in popular phones, such as the *Samsung Galaxy S4®* (iFixit, 2013), highlighted the possibility of a totally new way of environmental sensing using smartphones.

Table 1 shows the current models of smartphones with environmental sensors embedded, obtained from screening in smartphone-specialized websites databases. The first conclusion is that environmental sensors were hugely deployed in 2013 by Samsung, but they not maintained the trend to the current days (some of these sensors were not included in newer models). The only environmental sensor that stills currently being embedded in a considerable percentage of devices is the barometric sensor, probably due to its function in altitude positioning. This is corroborated by the data extracted from the *Open Signal* crowd sensing campaign for Android devices, where it is possible to see that environmental-enabled smartphones in activity decreased in number from 2014 to 2015 (Open Signal, 2015).

Bearing this information, Table 2 depicts the quantitative of devices listed in Table 1 that was seen by *Open Signal* in its Android fragmentation study. From more than 550 thousand devices seen in 2014, and more than 540 thousand devices seen in 2015, 10% had environmental sensors in 2014, and 7% in 2015. However, as this data was mostly acquired in European countries, it may not be representative of worldwide distributions mainly because of heterogeneity of the worldwide market profiles.

Furthermore, according to GSMA Intelligence (2015), the penetration of smartphones, per unique subscriber, in Europe has reached 78.9% in 2014. In absolute numbers, it is about 585 million people carrying smartphones. Assuming that the crowdsensing campaign led by Open Signal has an acceptable margin of error in Europe resulting in a good sampling of device diversity and fragmentation in that region, and crossing this information (Table 2) with the smartphones penetration given by the GSMA Intelligence report, it is possible to estimate that there were about 60 million smartphones with environmental sensors in Europe in 2014, and about 42 million in 2015. If a linear trend is maintained, it is expected about 25 million actives smartphones with environmental sensors in Europe by 2016.

Despite the decay estimative of active smartphones with environmental-ready sensors, it still is a considerable absolute number of devices. It justifies and reinforces our motivation and investigation objectives. For comparison effect, the Argos consortium for environmental monitoring and oceanography has today about 22 thousand actives transmitters around the world (Argos System, 2016), and the Brazilian Environmental Data Collection System has about 1 thousand active platforms through Brazilian terrestrial and maritime boundaries (Instituto Nacional de Pesquisas Espaciais, 2016).

Table 1: Smartphones with environmental sensors. (GSM Arena, 2016).

| Brand | Model | Sensors | | |
|---|---|---|---|---|
| | | Temp. | Hum. | Press. |
| Samsung | *Galaxy S4 (i9500/9505)* | y | y | y |
| | *Galaxy Note 3* | y | y | y |
| | *Galaxy J (N075T)* | y | y | y |
| | *Galaxy Round (G910S)* | y | y | y |
| Motorola | *Moto X (2nd Gen.)* | y | n | y |
| Huawei | *Ascend P6* | y | n | n |
| Xiaomi | *Mi3* | y | n | y |

Table 2: Smartphones with environmental sensors seen in the Open Signal crowdsensing.

| | Number of Devices Seen | |
|---|---|---|
| Year: | 2014 | 2015 |
| Total number: | 558770 | 542648 |
| Samsung Galaxy S4 | 36903 | 24456 |
| Samsung Galaxy Note 3 | 16603 | 12409 |
| Motorola Moto X (2nd Gen.) | 3244 | 1448 |
| Huawei Ascend P6 | 897 | 587 |
| Xiaomi Mi 3 | 771 | 652 |
| Devices with environmental sensors: | 58418 | 39552 |

# 3 ACCURACY TESTS

Towards the utilization of sensor-rich smartphones as a centric data-collector element in environmental sensing, we elaborated a sequence of sensibility tests to investigate the behaviour of smartphone's environmental sensors under different situations that are inherent to participatory sensing scenarios. The analysis is done through comparison of datasets generated by a reference and the subjects involved in the experiences. Due to budget constraints, availability reasons and due to the higher popularity among the environmental sensing-enabled smartphones (see Table 1), the chosen subjects was the *Samsung Galaxy S4* that carries the *SHTC1* sensor - from *Sensirion* - for temperature and relative humidity, and one *Motorola Moto X*, which uses an internal sensor to monitor the battery, in a similar approach as the one reported in Overeem et al. (2013). In this way, we will verify both types that the temperature sensors can appear in smartphones.

As reference data, a pair of brand new *AM2302* sensors were used. This sensor model has, nominally, accuracy of ±1°C for temperature and ±2% for relative humidity. The average value between readings of both sensors was used as guide to minimize discrepancies and enhance the accuracy. The logging from smartphones was made through the Android application "*Telemetry*". The data acquisition from the *AM2302* was made using the hardware platform *Arduino*, and for data-logging it was used a computer running a *Python* script to read – through USB – and store the data into a CSV file with the proper timestamps in *HH:mm:ss* format.

The experiment was divided into 4 scenarios: idle (for stability check), handling, dynamic and outdoors. All tests took place in Natal, Brazil, and, all tests were synchronized to the official local time and parameters. Figure 1 depicts the devices involved in this work. The details of each stage, and its respective discussion, are given below.

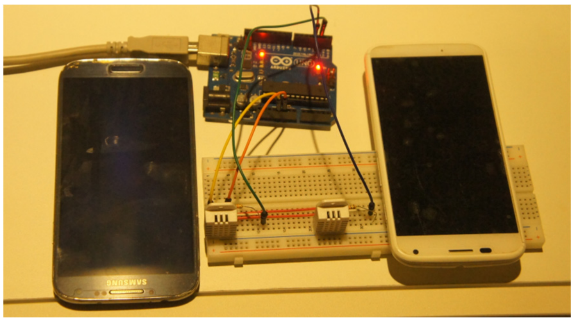


Figure 1: Devices involved in this work.

## 3.1 Idle Scenario

The objective of "idle scenario" was to check the stability of smartphone's readings and its accuracy when they are not being used during a long period. For redundancy, the experiment was performed twice in different days and different hours, obtaining the highest possible number of samples and trying to cover some environmental variation. Based on information obtained from direct contact with the Portuguese Institute of Ocean and Atmosphere (IPMA, 2016), the sampling frequency was set to one sample per minute.

The test was executed near a window in a room with good air circulation, to get the most of temperature and relative humidity from outside air. Also, to ensure that the smartphones would not be artificially warmed, there was no handling of the devices during the experiment. In order to avoid residual heat due to the battery charging process, the measurement procedure started 30 minutes after the complete charge of the smartphones.

Each measurement run lasted about 6 hours and 370 samples were collected. The readings from the first run are shown in Figure 2 and Figure 3 for temperature and humidity respectively. The readings from the second run are shown in Figure 4 for temperature and Figure 5 for humidity. The analysis of the variation and deviations between the reference sensor and smartphone responses was made using the following statistics parameters: Maximum Absolute Error (MxAE), Mean Absolute Error (MnAE), Root Mean Square Error (RMSE) and Pearson product-moment correlation ($R$). Table 3 and 4 illustrates this analysis for temperature readings from Samsung S4 and Motorola Moto X, respectively, and Table 5 for Samsung's relative humidity readings (the Motorola smartphone does not have a humidity sensor).

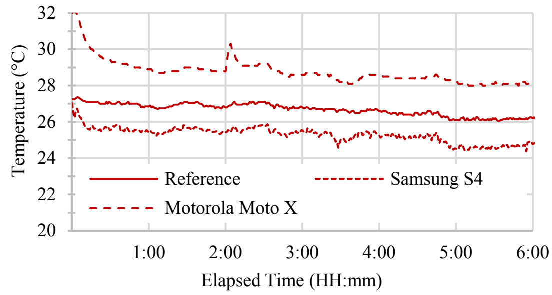


Figure 2: Temperature readings from the first run of Idle Scenario.

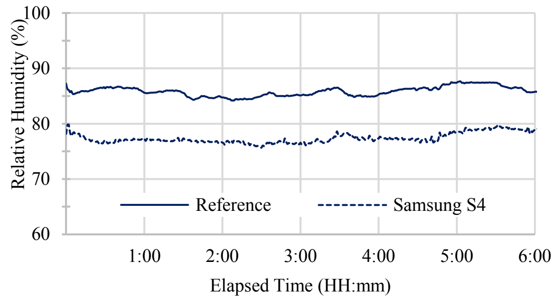


Figure 3: Humidity readings from first the run of Idle Scenario.

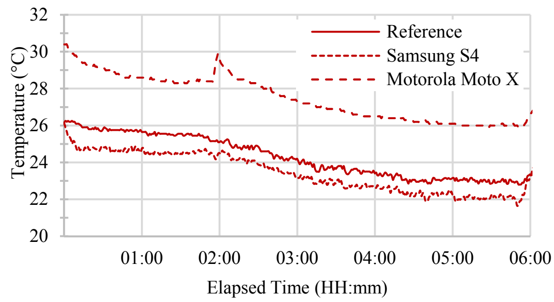


Figure 4: Temperature readings from the second run of Idle Scenario.

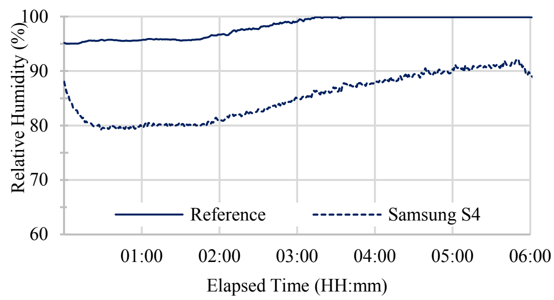


Figure 5: Humidity readings from the second run of Idle Scenario.

Table 3: Statistical parameters obtained from Samsung's temperature sensor compared to reference.

| Parameter | 1st run | 2nd run |
|---|---|---|
| MxAE | 2.0°C | 1,4°C |
| MnAE | 1.39°C | 0.84°C |
| RMSE | 1.40°C | 0.87°C |
| *R* | 0.926 | 0.980 |

Table 4: Statistical parameters obtained from Motorola's inner temperature sensor compared to reference.

| Parameter | 1st run | 2nd run |
|---|---|---|
| MxAE | -5.3°C | -4.8°C |
| MnAE | -2.09°C | -3.21°C |
| RMSE | 2.14°C | 3.23°C |
| *R* | 0.780 | 0.967 |

Table 5: Statistical parameters from Samsung's humidity sensor compared to reference, in percentage points.

| Parameter | 1st run | 2nd run |
|---|---|---|
| MxAE | 10.3 % | 16.5 % |
| MnAE | 8.4 % | 13,0 % |
| RMSE | 8.5 % | 13,3 % |
| *R* | 0.587 | 0,895 |

From both visual and numerical analysis, we observe promising results for temperature readings from the Samsung Galaxy S4, and reasonable readings from the Motorola Moto X. The S4 kept an average error of 1.39°C in the first run, and less than 1°C in the second, always underestimating the true temperature, but with a very high Pearson correlation (0.926 and 0.980 for first and second run, respectively). On the other hand, despite the constant shift of Moto X, with the mean absolute error of about 2 and 3 degrees always overestimating the true temperature, it kept its contour similar to the reference, resulting in a strong positive Pearson correlation of 0.780 and 0.967.

In humidity readings, we found indicators suggesting poor data quality in both runs. The average error found was high: 8.4 and 13 percentage points in the first run; in the second run, even with higher maximum absolute and average absolute errors (16.5 and 13 percentage points, respectively) than the first run, it was found a good Pearson correlation indicating that there may exist a systematic error with this type of sensor, as, for example, a non-linear response along the operating range or response time issues.

## 3.2 Handling Scenario

The handling scenario objective was to verify the response time from smartphone’s temperature and humidity sensors. Was assumed that the heat from hands and legs affect the sensor readings, and this test aims to verify how much it occurs.

This test was performed by submitting the smartphone to common situations whilst it sensor stores the measurements each 10 seconds. In addition to the idle situation, three handling cases were considered: simple handling (one-handed; emulating reading or texting), dual handling (two hands on; emulating the usage of hardware capabilities, e.g. running a game), inside leg pocket (simulating the common storage and transportation during daily tasks or walking). The reference sensors were put together in the same place the measurements were performed, as closest as possible.

Each situation lasted approximately 3 minutes, with an idle situation gap of 30 seconds between each case due to handling and positioning process, and also to verify the cooldown time. To double check the behaviour of the devices under these conditions, this scenario was performed twice. The first run time series is depicted in Figure 5 and the second run in Figure 6. The results met the expectations.

In the first run, the ambient temperature was stable around 28°C, and relative humidity around 90%. It was observed that handling the Samsung smartphone can raise its temperature readings up to 4°C from its initial value, whether for utilization with one hand or two (0:01 to 0:04; and 0:05 to 0:08, respectively), and about 1.5°C when kept in the pocket (from about 0:08:30). The Motorola Moto X did not suffer the same amount of interference mainly because the nature of its sensor, but it also raised 4°C from its initial value, but always above the reference, reaching 9°C of difference in dual-hand utilization. The relative humidity measured from the Samsung raised from 69% to 82% after the two hands utilization, suggesting there is also interference on humidity readings.

The second run was deployed with ambient temperature of 27°C and 90% of relative humidity. It was observed a maximum increase of temperature of 5°C for Samsung (at 0:05) and Motorola (at 0:07), suggesting that, regardless of the nature of the embedded sensor (either external or internal), the use of the smartphone causes the same amount of pollution on temperature measurements.

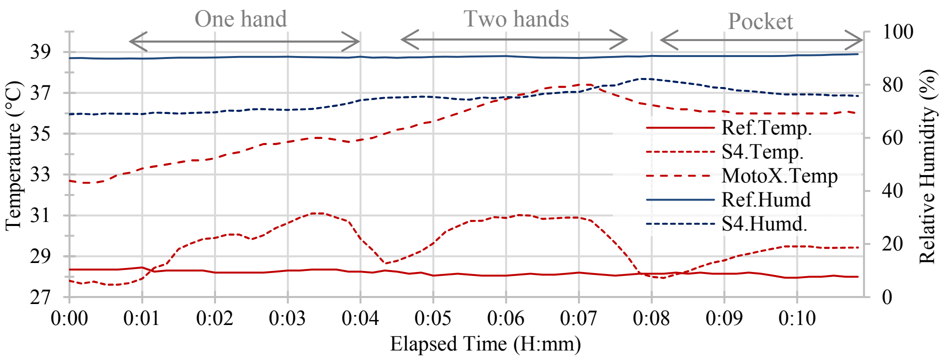


Figure 5: Readings from first run of handling scenario.

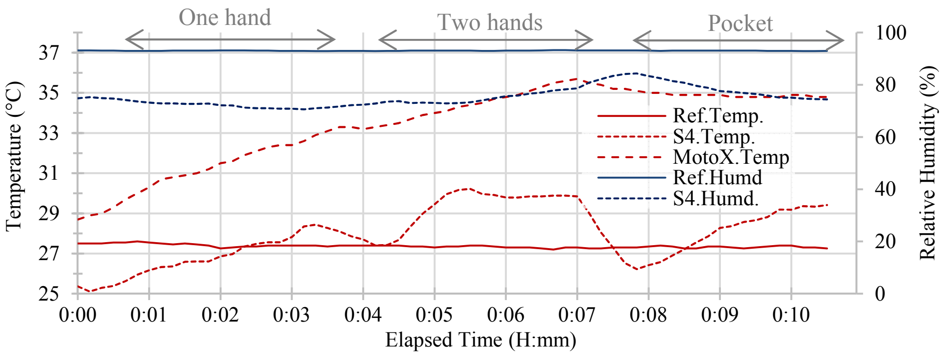


Figure 6: Readings from second run of handling scenario.

### 3.3 Dynamic Scenario

The dynamic scenario objective is to verify, as a complement to the previous experiment, the dynamic of smartphones sensors, and also to obtain a correlation, quantifying the accuracy of a mobile phone as an environmental data collector, and illustrating even more our evaluation protocol.

This test was performed by submitting each smartphone and the reference sensors to artificial variations of temperature. This scenario is divided into three stages: idle at room ambiance (2 minutes); heating by a heat source (hair dryer) at a safe distance (2 minutes); cooldown inside a fridge (4 minutes). The process is repeated three times changing the power of the dryer and the intensity of the fridge trying to distribute the readings equally over the range. As we do not have access to appropriate equipment to change the humidity without heating the sensors, the humidity dynamics will be presented as a time series to be compared to the reference values. The sampling frequency set for this experiment was 10 samples per minute.

The temperature result for the Samsung Galaxy S4 is shown in Figure 7, and for the Motorola Moto X in Figure 8. For a better visual analysis, both scatter graphs contain an upward vertical line in grey indicating where the ideal coefficient of determination ($R^2 = 1.00$) should be, and a dotted line in black indicating the trend line of the coefficient of determination ($R^2$) achieved.

The temperature readings for the Samsung showed acceptable values, considering the smartphone was idle (as explored in 3.1). The maximum amplitude (temperature variation) observed was 40°C by the sensor, and 35°C by the smartphone. From the numerical analysis of this dataset, it was observed very strong positive indicators: Spearman's Correlation ($\rho$) of 0.975 and coefficient of determination ($R^2$) *of* 0.927; corroborating the information observed in section 3.1. On can thus conclude that the external sensor of this smartphone is reliable when the device is not being handled.

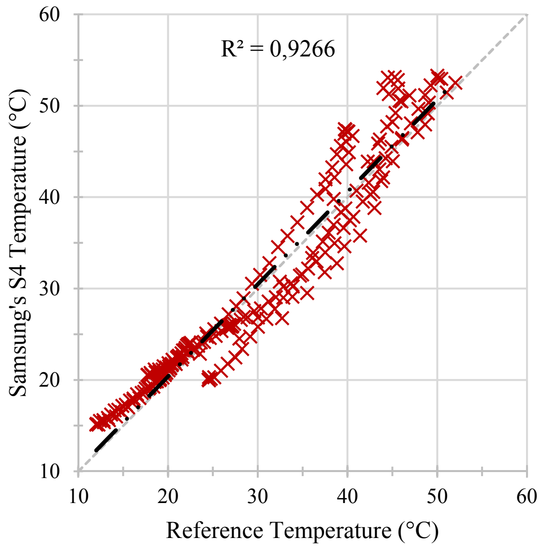


Figure 7: Samsung's S4 scatter plot for readings in dynamic experiment for temperature.

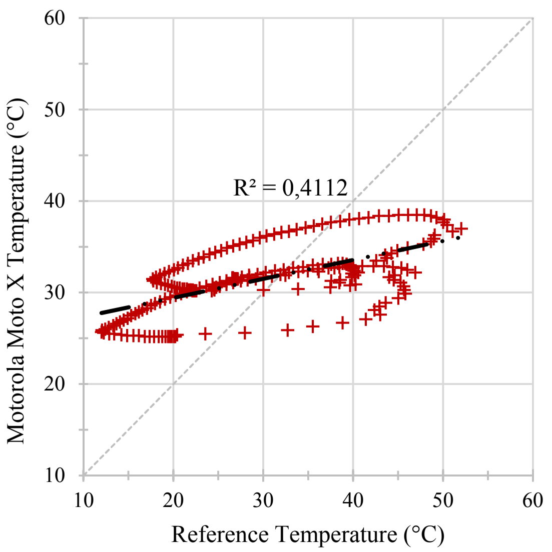


Figure 8: Motorola's Moto X scatter plot for readings in dynamic experiment for temperature.

On the other hand, the results obtained for the Moto X do not show the same accuracy as the Samsung's did. It is important to highlight that this version of Motorola Moto X is using an internal sensor in the battery, and that different behaviours were expected between the two smartphones. The maximum amplitude of temperature observed by the Moto X was 14°C. The numerical analysis of the dataset generated by Motorola's sensor provided a moderate positive correlation ($R^2$) of 0.411 and a "moderate-strong" Spearman Coefficient ($\rho$) of 0.654.

As the humidity experiment was not performed using the proper method, the results for this parameter are presented only for reference, and are a consequence to the temperature sweep. A time series to visual analysis of the behaviour of the Samsung's Humidity module under the dynamic variations is shown in Figure 9.

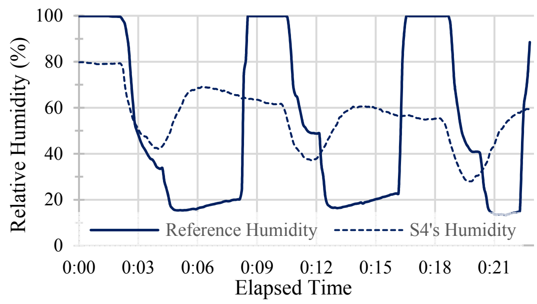


Figure 9: Humidity timeseries from dynamic scenario.

By observing the time series for humidity, the poor data quality indicative observed in section 3.1 becomes more evident, reinforcing that the embedded humidity sensor has some peculiarities. There is both a shifted and inaccurate reading from the smartphone's sensor. While the reference sensor changed from 97% (ambient humidity at the time the experiment was performed) to 18% during the test, the smartphone sensor changed from 80% to 30%. This suggests that this sensor has a higher inertia when compared to the temperature module, and consequently requires much more time to reach the reference value.

## 3.4 Outdoor Test

The outdoor test was designed to simulate a mobile sensing node inserted into a participatory sensing campaign where people are carrying their devices to different places while it collects data samples. Also, it is expected to quantify how much the GPS function can pollute the measurements due to the increase on battery and hardware usage.

This test consists in keeping the smartphones continuous logging the temperature (and humidity, when possible) while also collecting GPS coordinates and time stamps during an outdoor walk. These parameters would be the data used in a sensing campaign with space and time granularity focused on urban sensing or environmental monitoring using smartphones. Thus, trying to cover the different ways people can carry their devices, we made two opposite situations: one measurement run during a 20-minute walk carrying the smartphone in a backpack, exposed to the air, with no user intervention (idle); and a 20-minute walk with the smartphone in the leg pocket (getting some heat from body). This last situation was thought to verify if the heat transfer from the body observed in section 3.2 can be amplified in the walk process and GPS usage. The walk took place along a residential area in Natal, Brazil, during the night of 25 of September. Due to the expected lower variations of the humidity and temperature of this scenario, the sampling frequency was set to 2 samples per minute. As reference, official data provided by a meteorological entity in the moment the test was performed was used, as illustrated in Figure 10.

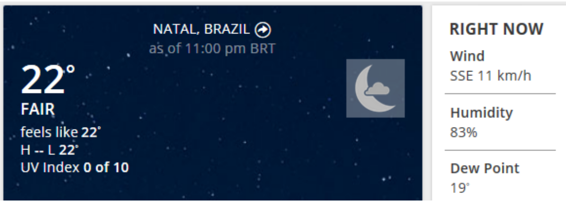


Figure 10: Temperature and Humidity observed for Natal, Brazil, at the time this scenario was performed (The Weather Channel, 2016).

The obtained results are shown in Table 6, where it is possible to see the average temperature and humidity measured in each situation compared with the official air parameters.

Table 6: Obtained results from outdoor scenario.

| **Smartphone** | **Situation** | **Average Measured** | **Official** |
|---|---|---|---|
| *Temperature* (°C) | | | |
| S4 | Backpack | 24.4 | 22 |
| | Leg Pocket | 27.2 | |
| MotoX | Backpack | 30.2 | |
| | Leg Pocket | 32.2 | |
| *Relative Humidity* (%) | | | |
| S4 | Backpack | 82.5 | 83 |
| | Leg pocket | 77.9 | |

Note that there were acceptable results for Samsung S4 readings when in the backpack, both for temperature (+2.4°C error) and humidity (-0.5% error) considering that the official temperature was extracted in a different point of the city, or through the average of multiple observation points, or even with a different sampling rate. The Moto X temperature readings were, again, always above the reference value due to its higher battery consumption, and consequent heating when its GPS function is enabled, and also due to its sensor placement inside the smartphone.

When inside the pocket, as expected, the heat from legs was transferred to the smartphones and polluted the measurements. In numbers, the average temperature increased by 2.8°C for the Samsung S4, and 2°C degrees for the Moto X, when compared to the backpack situation. When compared to the reference given, the temperature was increased by 5.2°C for Samsung S4, and 10.2°C for Motorola Moto X.

# 4 DISCUSSION AND CONCLUSIONS

In this work we evaluated the potential of using smartphones in environmental monitoring through participatory sensing given that the *Samsung* and other manufacturers started to embed these sensors in their products a few years ago. From our analysis, two essential aspects that affect the implementation of useful environmental sensing campaigns using smartphones could be highlighted: quantity of devices to cover urban spaces entirely (high space and time granularity); and data quality to properly and accurately monitor the environment. Each one deserves the proper efforts to elucidate, enumerate and overcome the challenges and difficulties.

Regarding the quantitative of devices, we analysed the available data from market specialized websites and the crowdsourcing project led by Open Signal, and we found that there is a soft downward trend on the utilization of smartphones with built-in environmental sensors, and a lack of new models carrying these sensors. Thus, there is an industry dependence that hinders the geographic spread of these devices, and consequently, makes the engagement of users a more challenging task due to the reduction of the target people, and to the reduction of active devices with environmental sensors in urban spaces. In addition, we have not found any information that justifies the reason why manufacturers have stopped putting such sensors in their newest models.

Regarding the quality of collected data, we have found that smartphones can collect acceptable readings for temperature when idle, but the utilization of the device pollutes the measurements by virtue of heat transfer from hands and by the hardware natural warm up from battery, CPU and GPU activity. A context-aware application to identify if the smartphone is being handled could potentially overcome some of these limitations. For example, by monitoring the CPU usage, lux meter, accelerometer and gyroscope data, it would be possible to detect if the smartphone is idle or not and then trigger the sensor logging. On the other hand, smartphones equipped with temperature sensors inside batteries requires a much more sophisticated context-aware detection and temperature estimation process because there is a constant power transfer causing a natural warming.

Yet on quality aspects, we also concluded that humidity sensors provides inaccurate measurements even when the device was idle. The position of the sensor in smartphone's hardware probably creates a shield effect, making it difficult to detect the outside air and quick changes in it, and in the environmental monitoring a fast time response is essential.

Therefore, to date we concluded that the existing smartphones are not ready yet to act as discrete, autonomous, complete and user-centric data-collectors in participatory sensing campaigns using embedded environmental sensors, or battery sensors, without any "data-treatment", mainly due to the observed issues in data quality when the devices are being handled or used. There is a need to a complementary application to estimate the context the smartphone is inserted into, and that is not guaranteed to work equally for all models. Nevertheless, there are other roles in environmental sensing that smartphones can play reliably, acting as supporting devices. There are satisfactory results from studies using smartphones as data mules or as data transmitters from peripheral sensors, for example the work reported by Tong & Ngai (2012) and by Park & Heidemann (2011).

Considering that the proven ubiquity of smartphones makes them a great instrument for crowdsensing; that micro sensors are neither expensive nor drain too much battery; that the evolution of MEMS technologies behind these sensors are enabling the development of more accurate devices; and considering the results we obtained from our experiments, it would be positive to see manufacturers integrating these sensors again in their future smartphones. It would enable a totally pervasive and friendly perspective for environmental monitoring through participatory and collaborative sensing.

With this work we hope to have contributed with "first step" information for future developers who plan to develop participatory sensing applications – and campaigns – focused on environmental monitoring or on observation of urban climate phenomena using smartphones, despite the budget constraints that limited the subject smartphones utilized in the experiments. As a work in progress, and as a consequence of this report, we are evaluating the performance and data quality issues of low-cost sensors often used in urban environment monitoring systems by "*DIY*" initiatives.

## ACKNOWLEDGMENTS

This work has been supported by COMPETE: POCI-01-0145-FEDER-007043 and FCT – Fundação para a Ciência e Tecnologia within the Project Scope: UID/CEC/00319/2013.

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