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Estimation of air temperature using smartphones in different contexts

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ABSTRACT

Measuring air temperature at a high spatial resolution is very important for many applications including detection of urban heat islands. However, air temperature is currently measured by weather stations those are very sparse spatially. In this paper, we propose a new approach to estimate air temperature using smartphones in different contexts. Most of the smartphones are not equipped with air temperature sensors but they are all equipped with battery temperature sensors. When a smartphone is in idle state, its battery temperature is stable and correlated with ambient air temperature. Furthermore, it is often carried close to human body, e.g. in pockets of coats, trousers and in hand. Therefore we developed a new approach of using two linear regression models to estimate air temperature from the idle smartphones battery temperature given their *in-pocket* or *out-of-pocket* positions. Lab test results show that the new approach is better than an existing one in mean absolute error and coefficient of determination metrics. Advantages of the new approach include the simplicity of implementation on smartphones and the ability for creating maps of temperature distribution. However, this approach needs field tests on more smartphone models to achieve its robustness.

1. Introduction

Temperature is a physical quantity that is very important to human health. In urban areas due to different concentration of roads, buildings and population, there exists urban heat islands (UHI) (Rasul et al., 2017). An UHI is an urban area that is significantly warmer than its surroundings. The UHI has bad consequences such as decreasing air quality, water quality and directly influencing human health (Tan et al., 2010). Thus a number of UHI mitigation attempts have been made (Salata et al., 2017). Collection of temperature data of urban areas is an important task in the UHI mitigation.

Currently there are approaches for collection of temperature data: direct measurement, using satellite images, estimating temperature from normalized difference vegetable index (NDVI) and crowdsourcing (Rasul et al., 2017). Direct measurement is often performed by weather stations at very sparse spatial resolution. Satellite data and NDVI approach are limited by temporal resolution that is maximum 2–4 observations per day.

Crowdsourcing for environment data collection is a new approach due to availability of sensor-equipped smartphones. Some models of smartphones, for example Samsung Galaxy S4, Samsung Galaxy Note 3, Motorola Moto X, Huawei Ascend P6 and Xiaomi Mi3, are equipped with environment sensors including temperature ones (de Araújo, Silva, & Moreira, 2017). Tests of de Araújo et al. (2017) show that smartphone environment sensors can collect acceptable temperature readings when idle but the readings are affected by heat from smartphone users. Unfortunately, the number of smartphone models equipped with environment sensors has been decaying (de Araújo et al., 2017).

Since 2013, Overeem et al. (2013), Droste et al. (2017) have been collecting battery temperature from a large number of smartphones and use a heat transfer model to estimate air temperature of urban areas. Data is collected when a smartphone is turned on, turned off, plugged in and unplugged (Overeem et al., 2013). The areas are defined by clusters of smartphones. Experiment results of Overeem et al. are very promising. They published an app on Google Play for data collection since 2014 (Weather Signal app, 2014). However, in an area with a small number of smartphones, the estimated temperature of the app is not very accurate. Furthermore, this approach provides aggregated temperature of an area from a large number of smartphone battery temperature readings rather than its temperature distribution.

In this paper, battery smartphone temperature readings are also used to estimate air temperature. In contrast with Overeem et al., two statistical models those allow each smartphone to predict the temperature *independently* in different contexts (in or out of human clothes pockets) were built. Using the statistical approach, temperature distribution of urban areas can be estimated. In addition, the new approach focuses on single user measurement's accuracy that is considered more important than the number of users participating in crowdsensing (Koukoutsidis, 2017).

This paper is an improved and extended version of the same author in ACIIDS 2018 conference (Chau, 2018). In the new version, all experiments are reimplemented using new smartphones models and independent thermometers to increase data accuracy. Furthermore, two new statistical, context-based models those are not available in the old version are built. In the next sections, experiments and results are presented.

2. Equipments, experiment environments and data processing

When a smartphone is in idle state, its battery temperature is stable and is correlated with ambient air temperature. An idle state of a smartphone is the one that is achieved when the smartphone is unplugged, its screen is off and its battery temperature variance in a temporal window is small enough. When the smartphone is not idle, its battery temperature fluctuates and depends highly on many factors, for example CPU load, screen brightness level, 3G/WiFi and GPS status (Milette & Stroud, 2012). Battery temperature of an idle smartphone is considered data and that of a non-idle one is noise. Air temperature prediction models will be built based on the data only.

2.1. Equipments

To collect data for building the prediction models, two Android smartphones and two thermometers are used (Figure 1). Basic information of the smartphones and
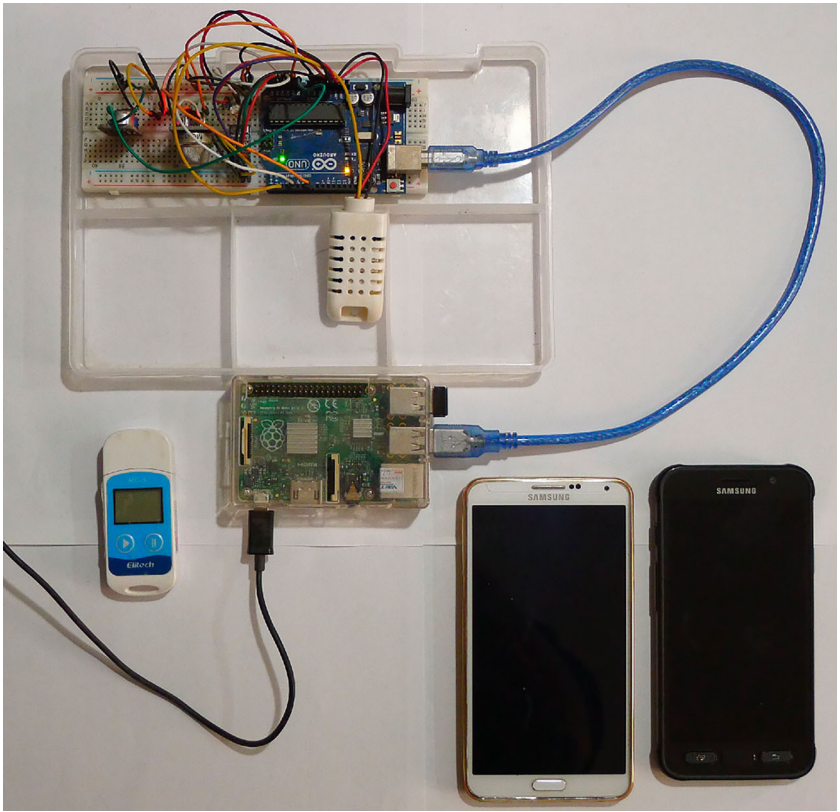
Figure 1. Equipments used in experiments from top to bottom, left to right: an Arduino Uno R3 board with some sensors, a DHT22 thermometer, an Elitech RC5 thermometer, a Raspberry Pi Model B+ V1.2 computer, a Samsung Galaxy Note 3 and a Samsung Galaxy S7 Active smartphone.

thermometers are in Tables 1 and 2. The DHT22 (DHT22 data sheet, 2018) is not able to work independently. It must be wired to an Arduino board and a Raspberry Pi Model B + V1.2 computer to collect temperature data automatically. The RC5 temperature thermometer/data logger (Elitech RC5, 2018) is able to work independently but it requires a dedicated program from its manufacturer to collect the logged data manually.

In all experiments to perform, a reference thermometer must be selected to measure air temperature surrounding the smartphones. It must work independently with smartphones

Table 1. List of smartphones used in experiments.

Smartphone model	Manufacturer	OS version	Air temperature sensor
Galaxy Note 3	Samsung	Android 4.4.2	Available
Galaxy S7 Active	Samsung	Android 7.0	Not available

Table 2. List of thermometers used in experiments.

Device	Work independently	Data retrieval	Max recording frequency
DHT22	No	Automatically	1 Hz or higher
RC5	Yes	Manually	0.1 Hz

and must be pocketable. Among the available equipments, the RC5 is the only one that meets those requirements and will be considered as the reference thermometer. The DHT22 is used to record ambient air temperature. Smartphones battery temperature is recorded using an Android app, namely Sensor Monitor (Sensor Monitor app, 2016). Based on the data collected from the thermometers and smartphones, experiments are performed to build air temperature prediction models.

2.2. Experiment environments

A smartphone is often in idle state and is often kept near its owner. A survey of women aged 15–40 (Redmayne, 2017) shows that participant's smartphones are generally kept on stand by (96% by day, 83% at night). When the smartphones are not used, their positions are off-body (86%), in the hand (58%), in skirt/trousers pockets (57%) or against the breast (15%) (Redmayne, 2017).

Webb shows that human skin temperature at different positions of the body depends on ambient temperature (Webb, 1992). His results are given in Table 3 where the first three columns are human skin temperature of different positions at different air temperature. The last column presents correlation coefficients of skin temperature at given positions and air temperature. All the correlation efficients are high showing strong linear relation of human skin temperature and air temperature.

Based on human habits of keeping smartphones (Redmayne, 2017) and the relation of human skin temperature and air temperature (Webb, 1992), *off-body* and *in-trousers-pocket* are chosen as two main environments for experiments. The trousers pocket is selected because of its popularity (57%, similar to 58% *in-hand*) and its convenience during the experiments.

2.3. Data recording and preprocessing

In this section, steps of a data recording session are described. Preprocessing of recorded data is presented subsequently.

Table 3. Human skin temperature in degree Celsius of different positions of the body at different air temperature (Webb, 1992). The last column is added by N. H. Chau.

	Cold (15 °C)	Room (27 °C)	Hot (47 °C)	Correlation
Forehead	31.7	35.2	37.0	0.947
Back of neck	31.2	35.1	36.1	0.890
Chest	30.1	34.4	35.8	0.909
Upper back	30.7	34.4	36.3	0.947
Lower back	29.2	33.7	36.6	0.964
Upper abdomen	29.0	33.8	35.7	0.926
Lower Abdomen	29.2	34.8	36.2	0.888
Tricep	28.0	33.2	36.6	0.965
Forearm	26.9	34.0	37.0	0.931
Hand	23.7	33.8	36.7	0.899
Hip	26.5	32.2	36.8	0.979
Side thigh	27.3	33.0	36.5	0.961
Front thigh	29.4	33.7	36.7	0.970
Back thigh	25.5	32.2	36.0	0.955
Calf	25.1	31.6	35.9	0.966
Foot	23.2	30.4	36.2	0.979

2.3.1. Data recording

In all of data recording sessions, smartphones are in idle states. Each recording session has the following steps:

(1) Put all the smartphones (Galaxy Note 3 and Galaxy S7 Active, hereafter abbreviated as Note 3 and S7, respectively) and thermometers (DHT22, RC5) in the same position as described in Figure 1 in a closed room. Synchronize clocks of all the equipments and set air temperature to a given value using an air conditioner.
(2) Record air temperature using the thermometers and record battery temperature of the smartphones using Sensor Monitor app for 15 minutes. At this step, the thermometers and the smartphones are off-body. Label the recorded data of RC5, Note 3 and S7 as *out-of-pocket*. The DHT22 is always used to record air temperature in the room, consequently its recorded data only has the *out-of-pocket* label.
(3) Put the RC5 thermometer and the smartphones in thigh pockets of worn trousers of a healthy person and continue recording temperature for 30 minutes. Label the recorded data of RC5, Note 3 and S7 as *in-pocket*.

Recording frequency of DHT22, RC5 and the smartphones are 0.1 Hz, 0.1 Hz and 1 Hz, respectively. Note that the RC5's maximum recording frequency is 0.1 Hz (Table 2). When each recording session completes, the following separated, time-stamped data sets are available:

- Out of pocket air temperature recorded by DHT22.
- Out of pocket and in pocket air temperature recorded by RC5.
- Out of pocket and in pocket battery temperature data recorded by Note 3 and S7 smartphones.

2.3.2. Data preprocessing

Because of differences in recording frequencies of equipments and delay at some points of time of smartphones, linear interpolations are applied to the recorded data sets to make recorded temperature as time series at 1 Hz frequency. Purpose of the interpolation is to prevent data loss when applying join operations on the data sets.

When the smartphones and the RC5 are put in pockets, the smartphones battery temperature and RC5 temperature change and need a period of time to achieve stable states. As observed, the smartphones need approximately 20 minutes to achieve stable states. Non-stable part of *in-pocket* data is eliminated, only stable part is kept. Figure 2 illustrates temperature data of the two thermometers and the smartphone batteries collected from a recording session. Other recording sessions are illustrated in Figure A1 and A2, Appendix 1.

In Figure 2, two vertical dotted lines divide the data into three parts. The middle part (*in-pocket*, non-stable) is eliminated because of non-stability of smartphone battery temperature data. The data sets achieved by interpolation and elimination are merged into one using join operators on date-time primary keys. There is a merged data set per recording session. Three recording sessions are conducted at programmed air temperature 26 °C, 29 °C and 34 °C and three merged data sets are generated accordingly. The three data sets are combined by a union operator to form an EX data set that will be used for
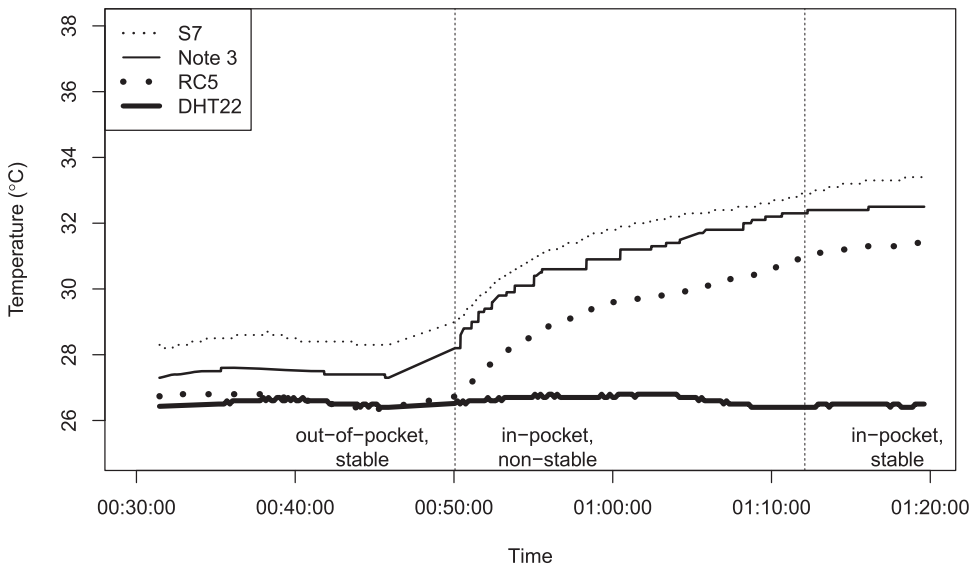
Figure 2. Raw data collected from a recording session at programmed temperature 26 °C.

model building. Observed air temperatures of DHT22 in the three recording sessions are 26.6 ± 0.09 °C, 29.1 ± 0.2 °C and 33.2 ± 0.3 °C, respectively.

3. Data analysis and prediction models building

In this section, bias correction for DHT22 and RC5 thermometers is applied on recorded data. Subsequently, relation of in and out of pocket air temperature is tested and finally, air temperature prediction models are built.

3.1. Thermometer bias correction

Before analysing data recorded by the two thermometers DHT22 and RC5, programmatical bias correction is needed. The *out-of-pocket* data in the EX data set is used to compare difference of temperature readings. Since the temperature data is not normally distributed, a Wilcoxon signed rank test is used. The test shows that measured temperature from DHT22 is 0.18 °C lower than RC5. The two readings correlation is 0.999 and RMSE is 0.19. Since the RC5 is always positioned next to the smartphones, DHT22's temperature data is modified following RC5: each reading of DHT22 is increased by 0.18 °C.

3.2. Relation of in and out of pocket air temperature

In step (3) of each recording session, in and out of pocket air temperature is recorded simultaneously by RC5 and DHT22 thermometers, respectively. Data recorded from this step is used to test correlation of in and out of pocket air temperature. Test results show that the correlation coefficient is 0.976 with [0.974, 0.977] 95% confidence interval (CI95). It shows the compliance of the experiments' recording data with those of Webb (1992) (refer to Front thigh row of Table 3).

3.3. Prediction models building

In this section, two regression models are built based on *out-of-pocket* and *in-pocket* labelled data to predict air temperature. To build the models, EX data set is divided into two subsets. The first one is EXo containing *out-of-pocket* data of the smartphones and RC5. The second one is EXi consisting of *in-pocket* data of the smartphones and RC5. Tables 4 and 5 show samples of EXo and EXi data sets. In Tables 4 and 5, note3, s7 contain values of smartphone battery temperature, rc5 and dht22 contain values recorded by RC5 and DHT22 thermometers, respectively. The context column indicates whether temperature data of the RC5 and the smartphones is recorded in or out of pocket and session is recording session.

Given the data in Tables 4 and 5, two regression models are built using the following steps:

(1) Divide the EXo (or EXi) data set into 10 equal folds. Choose one fold as a test data set, the remaining folds form a train data set.
(2) Build a linear regression model on the train data set where the outcome is dht22 (air temperature) and the predictor is battemp (smartphone battery temperature).
(3) Predict air temperature data on the test set, then calculate the following metrics: mean error (ME), mean absolute error (MAE) and coefficient of determination (R^2).
(4) Repeat steps 1 to 3 for all folds.
(5) Repeat steps 1 to 4 for 5 times.
(6) When steps 1 to 5 completed, a final linear regression model is built and a set of values of ME, MAE and R^2 is obtained. The model's slope and intercept are the mean of slopes and intercepts of models built in step (2), respectively.

The models for prediction of air temperature when the smartphone is out of pocket and in pocket are presented in Tables 6 and 7. The tables show that all coefficients are statistically significant, referring to less than 0.05 values in the last columns.

Table 4. Samples of *out-of-pocket* data set.

datetime	context	session	rc5	dht22	note3	s7
2018-06-24 21:51:24	out-of-pocket	1	29.60	29.15	31.90	31.80
2018-06-24 21:51:25	out-of-pocket	1	29.60	29.15	31.90	31.80
2018-06-24 21:51:26	out-of-pocket	1	29.60	29.15	31.90	31.80
2018-06-24 21:51:27	out-of-pocket	1	29.60	29.15	31.90	31.80
2018-06-24 21:51:28	out-of-pocket	1	29.60	29.15	31.90	31.80
2018-06-24 21:51:29	out-of-pocket	1	29.60	29.15	31.90	31.80
2018-06-24 21:51:30	out-of-pocket	1	29.60	29.15	31.90	31.80
2018-06-24 21:51:31	out-of-pocket	1	29.60	29.15	31.90	31.80

Table 5. Samples of *in-pocket* data set.

datetime	context	session	rc5	dht22	note3	s7
2018-06-24 22:33:45	in-pocket	1	32.40	28.35	34.40	33.50
2018-06-24 22:33:46	in-pocket	1	32.40	28.35	34.40	33.50
2018-06-24 22:33:47	in-pocket	1	32.40	28.35	34.40	33.50
2018-06-24 22:33:48	in-pocket	1	32.40	28.35	34.40	33.50
2018-06-24 22:33:49	in-pocket	1	32.40	28.35	34.40	33.50
2018-06-24 22:33:50	in-pocket	1	32.40	28.35	34.40	33.50
2018-06-24 22:33:51	in-pocket	1	32.40	28.35	34.40	33.50
2018-06-24 22:33:52	in-pocket	1	32.40	28.35	34.40	33.50

The formulae of models given in Tables 6 and 7 are:

$$T_{air} = T_{battery-out-of-pocket} \times 0.903 + 1.074 \tag{1}$$

and

$$T_{air} = T_{battery-in-pocket} \times 1.877 - 35.1, \tag{2}$$

where T_{air} is the estimated air temperature, $T_{battery-out-of-pocket}$ and $T_{battery-in-pocket}$ are smartphone battery temperature given smartphone context is out of pocket or in pocket, respectively. Scatterplots those describe relationship of smartphone battery temperature and air temperature in two contexts are in Figure 3.

4. Models validation

In this section, validation of statistical models in Equation (1) and (2), hereafter denoted as SMo and SMi, is presented. A field study is a robust way to validate the models. However, such a field study is not yet implemented in this paper due to limitations of human resource and equipments. Thus a preliminary validation is performed alternatively by comparison of SMo and SMi with the heat transfer model of Overeem et al., abbreviated as HM (Droste et al., 2017; Overeem et al., 2013). Due to many differences of experiment details of

Table 6. Prediction model for out of pocket smartphones, $R^2 = 0.95$.

	Estimate	Std. error	*t*-value	Pr $(> |t|)$
(Intercept)	1.0740	0.0847	12.69	0.0000
battemp	0.9032	0.0027	336.20	0.0000

Table 7. Prediction model for in pocket smartphones, $R^2 = 0.87$.

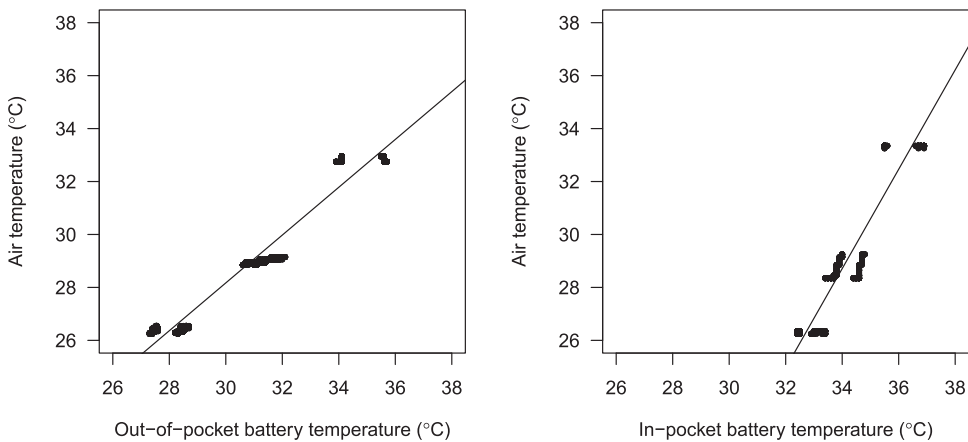|	Estimate	Std. error	*t*-value	Pr $(> |t|)$
(Intercept)	−35.1003	0.4686	−74.91	0.0000
battemp	1.8767	0.0136	137.78	0.0000

Figure 3. Scatterplots of out-of-pocket (left) and in-pocket (right) linear regression models.

the three models as presented in Table 8; R^2, ME and MAE are chosen as metrics of comparison. The metrics have the following properties: $R^2 \in [0, 1]$ and $MAE \geq 0$. R^2 is the proportion of the outcome (air temperature) variation that is explained by a linear regression model. ME measures mean difference of real and predicted air temperature while MAE measures mean absolute difference. A high value of R^2 and low values of ME, MAE indicate a good prediction model.

Overeem et al. tested their approach for eight cities in 2012 and re-tested for Sao Paolo in 2017. Their test results are in Table 9.

To compare three different groups (SMi, SMo and HM) in R^2 metric, an analysis of variance (ANOVA) (Faraway, 2015) and a subsequent Tukey honest significant difference (Tukey HSD) post-hoc test are required. The former tests a null hypothesis (refers as AnovaNull) that means of R^2 of the three groups are identical, the latter subsequently tests multiple null hypotheses that the means are identical pairwisely, if the AnovaNull is rejected.

ANOVA test result in Table 10 shows that AnovaNull is rejected because p-value at approach row, $Pr(> F)$ column is 0<0.05 and $F - value = 113.48 \gg 1$. It implies that means of R^2 of the three groups are not identical and a subsequent Tukey HSD test is needed.

Table 11 lists the Tukey HSD test results. There are three null hypotheses named as SMo-HM, SMi-HM and SMi-SMo. SMo-HM is expressed as

$$\text{mean of } R^2 \text{ of SMo} - \text{mean of } R^2 \text{ of HM} = 0 \tag{3}$$

Table 8. Comparison of experiment details of statistical and heat transfer models.

Criteria	SMo and SMi	HM
Experiment type	Lab experiment	Field experiment
Reference temperature	Thermometers in lab	Weather stations at a distance
Data collection type	Periodic based	Event based
Tested smartphone models	2	Many
Metrics of assessment	R^2, ME, MAE	R^2, ME, MAE

Table 9. Overeem et al. test results on eight cities (Droste et al., 2017; Overeem et al., 2013).

City	Time period	ME	MAE	R^2
Buenos Aires	Jun–Sep	−0.25	1.76	0.65
Buenos Aires	Sep–Nov	−0.28	1.30	0.86
London	Jun–Sep	−0.28	1.45	0.65
London	Sep–Nov	0.10	1.59	0.72
Los Angeles	Jun–Sep	−0.13	1.57	0.39
Los Angeles	Sep–Nov	0.15	1.16	0.79
Mexico City	Jun–Sep	0.25	1.69	0.36
Mexico City	Sep–Nov	−0.14	1.49	0.33
Moscow	Jun–Sep	−0.27	1.55	0.75
Moscow	Sep–Nov	−0.04	4.00	0.51
Paris	Jun–Sep	−0.38	1.63	0.62
Paris	Sep–Nov	−0.23	1.96	0.70
Rome	Jun–Sep	0.21	1.30	0.86
Rome	Sep–Nov	0.20	1.25	0.83
Sao Paolo	Jun–Sep	−0.31	1.21	0.65
Sao Paolo	Sep–Nov	0.08	1.23	0.85
Sao Paolo	Year 2017	−0.53	1.09	0.87

Table 10. ANOVA test result for comparison of means of R^2 of SMo, SMi and HM approaches.

	Df	Sum Sq	Mean Sq	F value	Pr ($>$ F)
Approach	2	1.03	0.51	113.48	0.0000
Residuals	114	0.52	0.00		

and is rejected because adjusted p-value at SMo-HM row, p adj column is 0<0.05. Moreover, the mean difference in Equation (3) is 0.28 with [0.24, 0.33] CI95. The numbers are in diff, lwr and upr columns, respectively. In other words, mean of R^2 of SMo is 0.28 higher than that of HM with [0.24, 0.33] CI95. Similarly, mean of R^2 of SMi is 0.2 higher than that of HM with [0.16, 0.25] CI95. Graphical representation of Table 11 is in Figure 4. Means of R^2 of SMo, SMi are 0.95 and 0.87, respectively (Tables 6, 7); mean of R^2 of HM is 0.67 as calculated from Table 9.

Applying the same procedure, comparisons SMo, SMi and HM by ME and MAE metrics are performed. Graphical results of the comparisons are in Figure 5 and 6; corresponding details are in Tables A1–A5, Appendix 2. The results show that ME of SMo and SMi are higher than that of HM; MAE of SMo and SMi are lower than that of HM. In summary, SMo and SMi are better than HM in R^2 and MAE metrics but HM is better than SMo and SMi in ME metric.

5. Discussion and future development

In this paper, a new approach of using statistical models to estimate air temperature from smartphone battery temperature in different contexts is presented. Using models in Equations (1) and (2), one can estimate air temperature when smartphones are out of pockets and in pockets, respectively. Since each smartphone is able to estimate air temperature independently, users can have temperature distributions rather than aggregated

Table 11. Pairwise comparison of means of R^2 of SMo, SMi and HM approaches using Tukey HSD test.

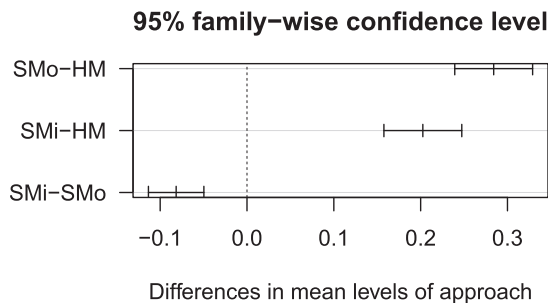|	diff	lwr	upr	p adj
SMo-HM	0.28	0.24	0.33	0.00
SMi-HM	0.20	0.16	0.25	0.00
SMi-SMo	−0.08	−0.11	−0.05	0.00

Figure 4. Tukey HSD graph showing pairwise differences in means of R^2 of SMo, SMi and HM approaches.
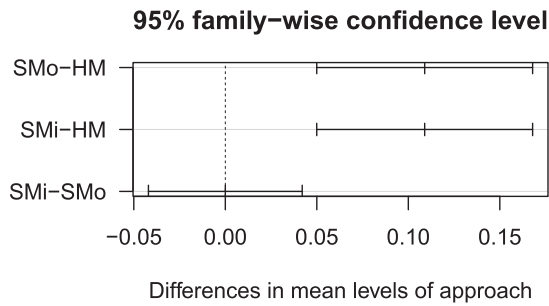
Figure 5. Tukey HSD graph showing pairwise differences in means of ME of SMo, SMi and HM approaches.
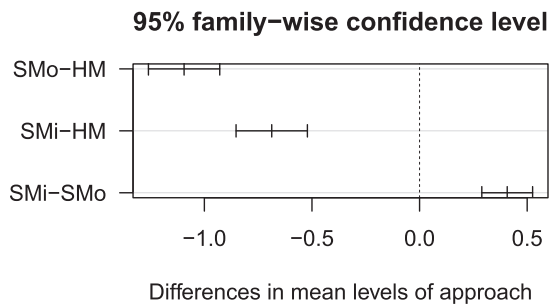

Figure 6. Tukey HSD graph showing pairwise differences in means of MAE of SMo, SMi and HM approaches.

temperature of areas. This is an advantage of the new approach to that of Overeem et al. Statistical tests show that in comparison with Overeem's approach, the new one is better in R^2 and MAE metrics and is worse in ME metric. In addition, the statistical approach uses simple linear regression models those are energy economy and very easy to implement on smartphones.

However, as stated in Table 8 this paper only performed tests in lab with a limited number of smartphone copies and models while Overeem et al. already had quantitative tests in the field with a large number ones. To obtain robust statistical models, the new approach needs field tests with more equipments in the future.

An Android app using the SMo model in Equation (1) is developed. The app's main function is to report estimated air temperature to its users. It is released on Google Play in March 2016 (Smart Thermometer app, 2016). To June 2019, the app has approximately 70,000 downloads and its user rating is 3.2/5.0.

Smartphone context recognition (in pocket/out of pocket, indoor/outdoor) is vital to implement the SMi model in Equation (2) and will be an important successive research topic.

Disclosure statement

No potential conflict of interest was reported by the author.

Notes on contributor

Nguyen Hai Chau received the PhD degree in computer science in 1999 from Vietnam National University (VNU). His research interests include smartphone sensor data analysis, geographical information systems (GIS) and parallel computing. He is currently an associate professor of VNU University of Engineering and Technology, Hanoi, Vietnam.

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Appendix

Appendix 1. Data recording sessions at programmed temperature 29°C and 33°C
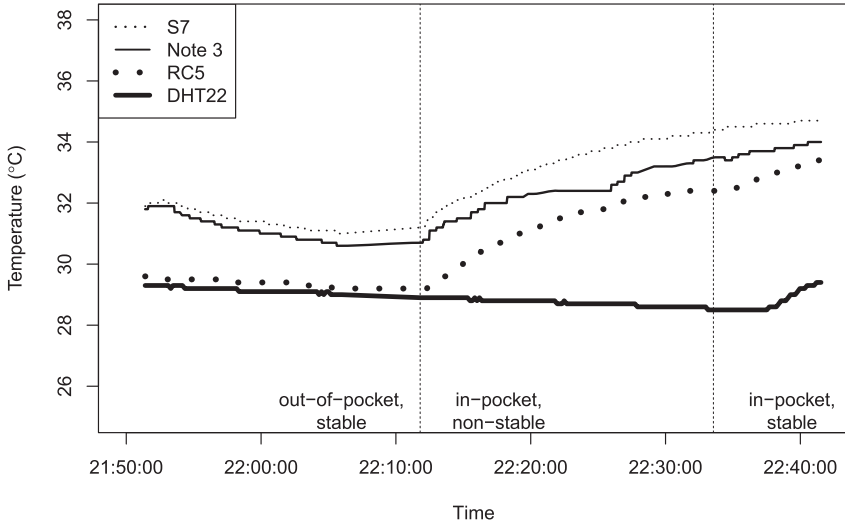

Figure A.1. Raw data collected from a recording session at programmed temperature 29°C.
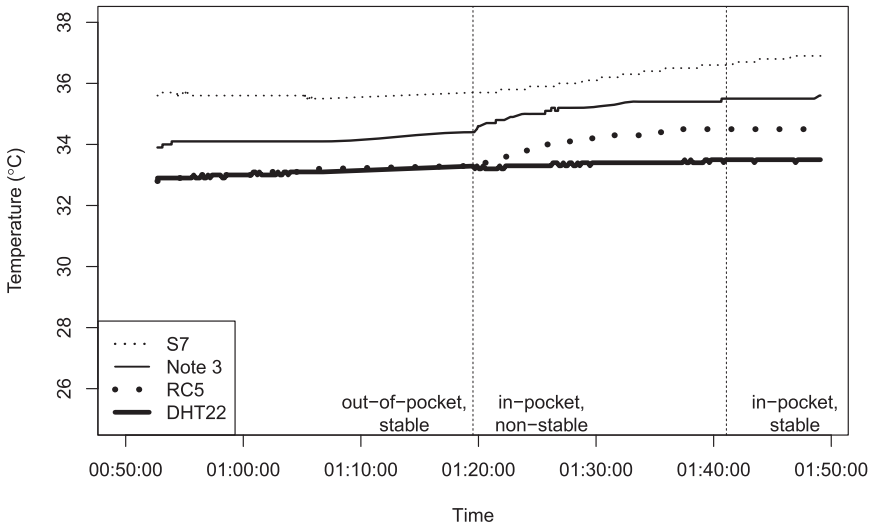

Figure A.2. Raw data collected from a recording session at programmed temperature 33°C.

Appendix 2. Results of ANOVA and Tukey HSD tests to compare SMo, SMi and HM using MAE and ME metrics

Table A1. ANOVA test result for comparison of means of ME of SMo, SMi and HM approaches.

	Df	Sum Sq	Mean Sq	*F*-value	Pr($>$ *F*)
Approach	2	0.17	0.09	11.02	0.0000
Residuals	114	0.89	0.01		

Table A2. Pairwise comparison of means of ME of SMo, SMi and HM approaches using Tukey HSD test.

	diff	lwr	upr	*p* adj
SMo-HM	0.11	0.05	0.17	0.00
SMi-HM	0.11	0.05	0.17	0.00
SMi-SMo	0.00	−0.04	0.04	1.00

Table A3. ANOVA test result for comparison of means of MAE of SMo, SMi and HM approaches.

	Df	Sum Sq	Mean Sq	*F*-value	Pr($>$ *F*)
Approach	2	15.67	7.84	126.84	0.0000
Residuals	114	7.04	0.06		

Table A4. Pairwise comparison of means of MAE of SMo, SMi and HM approaches using Tukey HSD test.

	diff	lwr	upr	*p* adj
SMo-HM	−1.09	−1.26	−0.93	0.00
SMi-HM	−0.69	−0.85	−0.52	0.00
SMi-SMo	0.41	0.29	0.53	0.00

Table A5. Means of MAE and ME of SMo, SMi and HM approaches (small numbers are rounded to 0).

	ME	MAE
HM	−0.11	1.60
SMo	0.00	0.51
SMi	0.00	0.91