TherMobile: Measuring Body Temperature Using a Mobile Device

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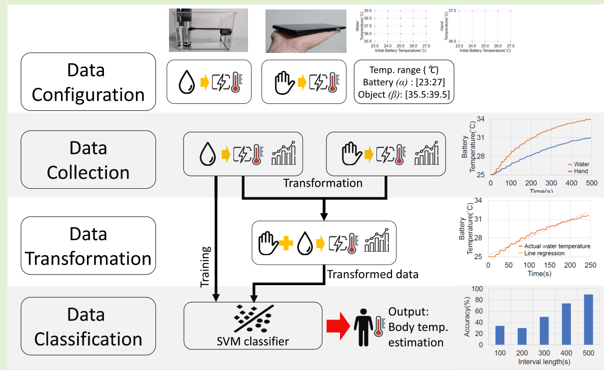
***Abstract*—The spread of COVID-19 issues high demand on measuring body temperature, which necessitates thermometers. To alleviate a burden to equip/carry thermometers, this paper develops a framework "*Ther- Mobile*" that measures body temperature using a commercial-off-the-shelf smartphone that most people carry everywhere. Considering that most (if not all) smartphones have a temperature sensor on its battery, we utilize heat transfer from a body part that makes contact with the smartphone, to the smartphone battery. To this end, we collect a time series of the smartphone battery temperature for different pairs of the initial temperature of the smartphone battery and the temperature of a body part, and then classify them. To enable the data collection and classification to infer the temperature of the body part, we address important practical issues, including how to gather data for different target temperatures of a body part (although human body temperature is not controllable), and how to minimize a burden for individual users to gather all necessary data. Our experiments demonstrate that "*Ther- Mobile*" achieves 90.0% accuracy of measuring body temperature with 1.0°C granularity, enabling a commercial-off-the-shelf smartphone to substitute for a thermometer without any additional hardware.**



***Index Terms*—Measuring body temperature, battery temperature sensor, smartphone, heat transfer, support vector machine.**

I. Introduction

MANY countries are struggling for preventing the spread of COVID-19, and one of simple yet effective ways for the prevention is to separate people with the fever, which necessitates thermometers that are able to check the body temperature over 37.5°C. However, it is a burden to equip a thermometer in all places (e.g., home, the entrance of public buildings); in particular, each individual faces inconvenience of carrying a thermometer when necessary.

To mitigate such inconvenience, this paper proposes TherMobile that can measure the body temperature through a COTS (Commercial-Off-The-Shelf) smartphone, which is carried everywhere by most people. TherMobile exploits the fact that most (if not all) recent COTS smartphones are equipped with the internal battery temperature sensor and the phenomenon that the smartphone battery can transfer/receive the heat to/from an object in contact with the smartphone. Based on them, TherMobile collects data of the battery temperature change behavior according to the different temperatures of a contacting object and trains a classifier based on the collected data. Then, TherMobile is capable of inferring the temperature of the object, by utilizing the classifier and the battery temperature change behavior caused by heat from the contacting object.

To make TherMobile operate for the human body as an object that contacts with the smartphone, we need to address the following challenges.

Q1. Human body temperature is not controllable. How can we gather data for different temperatures of a body part?

Q2. Different people and different smartphones may yield different temperature change behaviors of the smartphone battery. Therefore, individuals may need to gather data for their own, even if Q1 is addressed. How can we minimize a burden for individuals to gather necessary data?

Q3. The posture in contact between the body part and the smartphone affects the temperature change behavior of the smartphone battery. How can we get uniform data in terms of the posture?

Q4. There exist some data parameters that affect the performance of TherMobile, such as the granularity of

Manuscript received May 1, 2022; revised May 30, 2022; accepted May 31, 2022. Date of publication June 8, 2022; date of current version July 1, 2022. This work was supported by 63 Research Fund, Sungkyunkwan University, 2020. The associate editor coordinating the review of this article and approving it for publication was Prof. Meribout Mahmoud. *(Corresponding authors: Kilho Lee; Jinkyu Lee.)*

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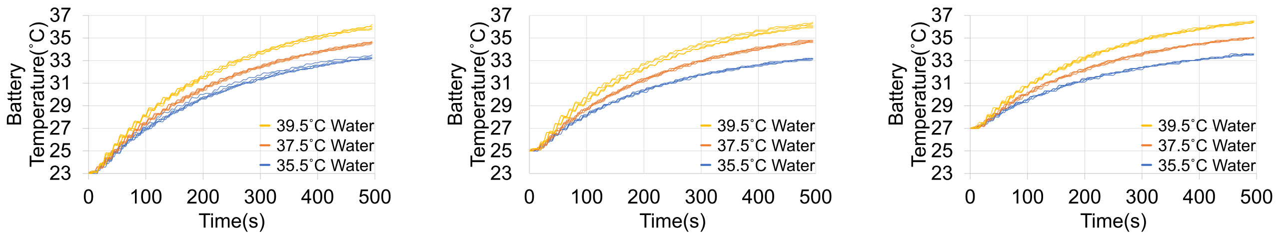
Digital Object Identifier 10.1109/JSEN.2022.3179726



(a) Initial battery temperature of 23.0°C (b) Initial battery temperature of 25.0°C (c) Initial battery temperature of 27.0°C

Fig. 1. Battery temperature change behavior for different initial battery temperature and target object temperature.

measuring body temperature, and the duration of measuring the battery temperature. How can we determine those data parameters?

To address Q1 and Q2, we utilize two types of data of the battery temperature change behavior: data with water as a contacting object, and data with a hand as a contacting object. For the former, we thoroughly collect data for a *complete* set of different temperatures of the contacting object (i.e., water), which is conducted by a Sous Vide machine that can precisely control the water temperature. The data can be shared by all users. Therefore, once we provide the data (although it takes time), each user does not need to gather the data. For the latter, each user gathers data for a *partial* set of different temperatures of his/her hand, because body temperature is not controllable. Using the partial data for the latter and the corresponding data for the former, we derive a mapping function to transform the data for the latter into the data for the former. Then, we can transform any data with a hand into that with water, which enables to infer the temperature of a hand using a classifier trained by the data with water.

This approach is adopted by TherMobile that consists of the following four stages: data configuration, data collection, data transformation, and data classification. Section IV details each stage, including how to address Q3 and Q4. By addressing Q1–Q4 by the four stages, TherMobile is capable of measuring body temperature, which is demonstrated by experiments with a COTS smartphone. In particular, TherMobile is proven to achieve 90.0% accuracy of measuring body temperature with 1.0°C granularity, enabling a smartphone to substitute for a thermometer if not available.

A. Related Work

There have been a bunch of attempts to measure body temperature by utilizing a mobile device with additional hardware, such as wearable sensors [12], [19], [20], body temperature sensors [24], and bluetooth-based wireless sensors [5], [6]. However, no work is capable of measuring body temperature without any additional hardware. On the other hand, a group of studies have achieved measuring ambient temperature using COTS smartphone(s) only. They have applied the crowd-sourcing method [13], [22], the context-aware method [10], [11] or the location-based method [27], or utilized the different sound speeds in air at different temperatures [8], [9]. In particular, some studies have utilized the smartphone battery sensor to measure air temperature [3], [7], [15], but their method cannot be directly applied to measuring body temperature.

B. Contribution

While our preliminary conference poster paper (which is 3-page-long) [16] presented a brief idea of body temperature measurement, this paper completes a framework that is capable of measuring body temperature by addressing the critical issues. The contributions of this paper can be summarized as follows.

- Developing a novel framework that measures human body temperature using a COTS smartphone,
- Identifying practical issues that should be address to enable TherMobile to measure body temperature,
- Addressing the practical issues with novel solutions, and
- Verifying the proposed framework in correctly measuring body temperature through experiments.

This paper is organized as follows. Section II explains background of smartphone battery. Section III conducts a pilot study. Section IV develops TherMobile. Section V presents experiment results, and finally, Section VI concludes the paper with discussions.

II. Background of Smartphone Battery

A. Nature of the Battery Temperature of Smartphones

Depending on smartphone usage and ambient environment, the temperature of a smartphone battery contiguously varies. As a smartphone battery is a major heat radiation component in smartphones [14], [23], [28], the battery temperature may increase when the smartphone drains the battery. In addition to the heat radiation, the battery temperature may vary according to the ambient temperature, because a battery transfers or receives heat to/from ambient environment. For instance, an idle smartphone (that does not execute any foreground application) in the higher temperature environment gets higher battery temperature, compared to that in the lower temperature environment. We verify this property through an experiment that the battery temperature increases over time when an idle smartphone makes contact with an object with high temperature (see Fig. 1). Therefore, the battery temperature changes could be a hint to estimate the temperature of the object that makes contact with the smartphone.

B. Heat Transfer to Smartphone Battery

The heat transfer from a contacting object to the smartphone battery can be explained as *heat conduction*. A recent work [17] has revealed that the heat transfer within a smartphone is caused by two major factors: *conduction* and *convection*. A smartphone consists of multiple layers of printed circuit boards, which have wide and thin layout. Due to this layout, the vertical heat transfer between *thin* layers (i.e., conduction) is stronger than the horizontal heat transfer within a *wide* single layer area (i.e., convection). According to this property, when a user puts a smartphone on his/her hand, the human hand effectively conducts its heat to the smartphone battery.

The heat conduction rate is explained as follows [17].

$$\text{The amount of heat transferred: } \frac{kA}{d} \times \Delta T, \tag{1}$$

where k is the thermal conductivity, A is the area, and d is the thickness of an object. Also, ΔT is the temperature difference between two objects (e.g., hand and battery). In this work, the object is the smartphone case which is the heat transfer path between the human hand and the smartphone battery. In this case, k, A, and d are constants as we target a single smartphone. ΔT is the only variable that may vary depending on temperature changes.

C. Temperature Sensor of Smartphone Battery

Some past COTS smartphones (e.g., Samsung Galaxy S4) had internal ambient temperature and humidity sensors, and thereby, a number of studies proposed solutions to accurately measure the ambient temperature through the internal sensors of smartphones [21], [29]. However, those approaches are not applicable as of now, since recent smartphones typically have no internal temperature and humidity sensors. Fortunately, most (if not all) smartphones are equipped with the battery temperature sensor, because a smartphone requires to continuously check the battery temperature and properly operates based on the measured temperature. For instance, if the battery temperature increases to the limit, the smartphone should slow down or shut down internal components (e.g., throttling the CPU frequency) to secure safety and performance. Some studies [18], [25], [26] have addressed smartphone's shut-off related to the battery temperature. As most smartphones have internal battery temperature sensors, the Android operating system provides a well-defined interface, which is Android Battery Manager [1], to monitor and collect the battery temperature. Therefore, users can easily make an application that can keep track of battery temperature changes.

III. Pilot Study and Observation

Utilizing the properties of a smartphone battery explained in Section II, we investigate the temperature change behavior of a smartphone battery, when a target object touches a smartphone for a fixed period. To control and maintain the temperature of a target object, we employ water as a target object and use a Sous Vide machine as shown in Fig. 2. The Sous Vide machine can maintain the water temperature with 0.1°C precision, which can be easily checked by the water thermometer in the figure. We put the smartphone into a thin plastic pack to prevent it from soaking, and the smartphone's backside makes contact with the water with the plastic pack.

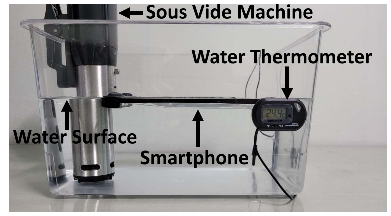


Fig. 2. A Sous Vide machine that controls a target water temperature.

We first focus on the initial battery temperature of 23.0°C with different water temperatures of 35.5°C, 37.5°C and 39.5°C. For each setting, we observe the battery temperature change behavior during 500 seconds, which can be plotted as a line as shown in Fig. 1(a). As expected, the temperature change behavior of a smartphone battery enables to distinguish the water temperature; for example, a line for 35.5°C is easily separated from that for 37.5°C and that for 39.5°C in the figure. Next, to investigate the effect of the initial temperature on the battery temperature change behavior, we conduct the same experiments for different initial battery temperatures of 25.0°C and 27.0°C, which are illustrated in Fig. 1(b) and (c), respectively. We confirm that the battery's temperature change behavior still enables to distinguish the water temperature even with the different initial battery temperatures. In addition, the temperature change behavior of a smartphone battery for given water temperature is different, according to the initial battery temperature. For example, the temperature change behavior of a smartphone battery with the water temperature of 35.5°C varies with initial battery temperatures of 23.0°C, 25.0°C and 27.0°C as shown in Fig. 1(a), (b) and (c), respectively. From this pilot study, we record our observation as follows.

Observation 1: The temperature change behavior of a smartphone battery depends on (α, β), where α denotes the initial battery temperature and β denotes the target object temperature.

Then, for each of nine pairs of (α, β) where α =23.0°C, 25.0°C and 27.0°C and β =35.5°C, 37.5°C and 39.5°C, we repeat five times to measure the battery temperature during 500 seconds and record it every five seconds. Therefore, each data instance consists of a series of 100 points of battery temperature where the battery temperature is collected every five seconds, and we have five data instances of each pair of (α, β). We apply four data instances to train the classifier and one data instance to validate the classifier; here we employ SVM (support Vector Machine) as a classifier. The test result shows 100% accuracy on inferring a right answer for all nine pairs of (α, β); in other words, different pairs of (α, β) can be distinguished by the clustering.

IV. Development of TherMobile

After the pilot study in Section III, one may think that measuring body temperature can be achieved by simply applying the process in the pilot study to a body part. This is not true, as we need to address the important practical challenges Q1–Q4 explained in Section I. In this section, we develop TherMobile that measures body temperature using a COTS smartphone. To address Q1–Q4, TherMobile is designed as

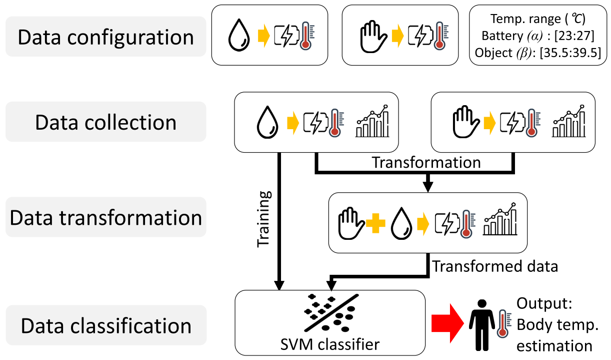


Fig. 3. Overview of TherMobile.

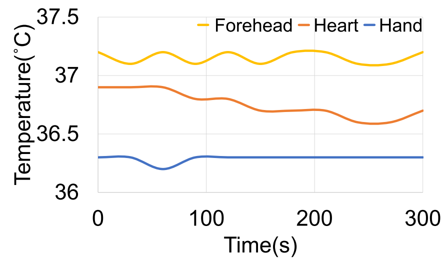


Fig. 4. Temperature in different body parts.

four stages as shown in Fig. 3: data configuration, data collection, data transformation and data classification.

A. Data Configuration

As a first step to address Q1-Q4 by clustering data, we need to define the format and range of the data to be gathered and used. The major parameter in heat transfer is the conduction rate, which is linear in term of the temperature difference between the two objects as we explained in Eq. (1). Therefore, we focus on two target objects' temperatures that correlate each other by the heat transfer, and use a pair of them as an input variable to be classified. That is, we let (α, β) denote the input variable, where α is the initial temperature of the smartphone battery and β is the temperature of the object making contact with the smartphone.

We set the range of β (i.e., the target object's temperature) to [35.5°C, 39.5°C] with 1.0°C granularity. Since 36.5°C is the normal body temperature, 37.5°C, 38.5°C and 39.5°C can be interpreted as a mild, high and extremely high fever, respectively; note that although rare, 35.5°C implies a sign of hypothermia. By the five representations of temperature, we can classify each person's status in terms of whether and how much s/he is sick, and therefore 1.0°C granularity is reasonable. On the other hand, a finer-granularity of representations than 1.0°C is a burden for gathering data and applying classification. For example, if we choose 0.1°C granularity of representations, we would have to conduct 10 times more experiments to gather data than 1.0°C granularity. Also, as shown in Fig. 4, the temperature of body parts slightly varies over time; therefore, with 0.1°C granularity, it is difficult to classify the data due to minor fluctuation of body temperature and noise of measuring it. Therefore, 1.0°C granularity is a good choice in making it feasible to gather data and infer the body temperature through clustering.

To determine the range of α (i.e., the initial battery temperature), we simply observe the battery temperature of an idle smartphone (that does not execute any foreground application). According to the observation, we set the range of the initial battery temperature to [23.0°C, 27.0°C]. For the same reason as the target object's temperature, we apply 1.0°C granularity, meaning that we consider 23.0°C, 24.0°C, 25.0°C, 26.0°C and 27.0°C to represent the initial battery temperature.

B. Data Collection

As we explained in Section III, we need to collect two types of data: data with an object whose temperature is easily controllable, and data with a body part. The former is shared by all users, while the latter is valid only for each individual user. We will explain how to transform the data for the latter into that for the former in Section IV-C. From now on, we first detail how to collect the data for the former.

For the former, we choose water as a target object and use a Sous Vide machine that is capable of controlling the water temperature with 0.1°C precision. The smartphone is put inside the waterproof plastic bag and makes contact with the water surface as shown in Fig. 2. This setting allows the smartphone battery to get heat from the water. We set the target water temperature to given β on the Sous Vide machine and wait until the water reaches β. Then, we put the smartphone in a plastic bag on the water with the target initial battery temperature α (which is set by cooling), and start our smartphone application that records the temperature of the smartphone battery every 5 seconds during 500 seconds; the recorded data can be represented by a single line in Fig. 1. We empirically set the duration and frequency of recording to 500 seconds and 5 seconds, respectively, by considering a trade-off between the accuracy of measuring body temperature and the convenience for users in using TherMobile, to be discussed in Section V. Note that we implemented such an application by continuously reading the values of the smartphone battery temperature sensor through the API provided by Android Battery Manager.

For the latter, we choose a hand as a body part whose temperature is measured, due to two reasons. First, a hand is one of the body parts whose temperature is stable as shown in Fig. 4. Second, it can address Q3 as we can easily control the posture and the pressure of hands. To figure out whether the pressure between the smartphone and a body part affects the smartphone battery temperature, we consider two situations where a user pushes the backside of the smartphone on the desk by his/her hand with two different pressures. As shown in Fig. 5, the situations yield different temperature change behaviors of the smartphone battery according to different push pressures. This indicates that we need to find a way to impose a uniform pressure between the smartphone and a body part whenever we try to measure body temperature using the smartphone. Therefore, we choose a posture where a user puts smartphone on the hand as shown in Fig. 6. This posture enables the smartphone to make contact with a hand in uniform pressure, yielding similar temperature change behaviors of

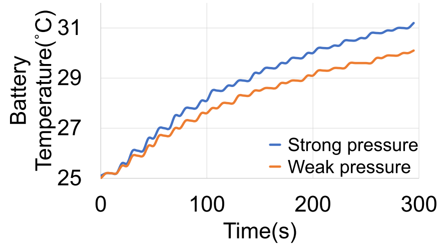


Fig. 5. Different pressures resulting in different temperature change behaviors of the smartphone battery.

Fig. 6. A posture for the smartphone that makes contact with a hand.

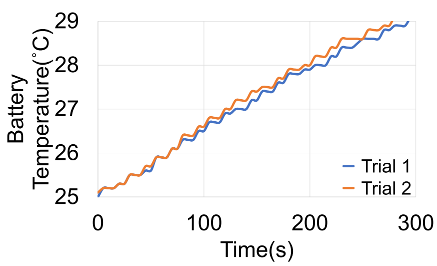


Fig. 7. Different trials resulting in similar temperature change behaviors of the smartphone battery.

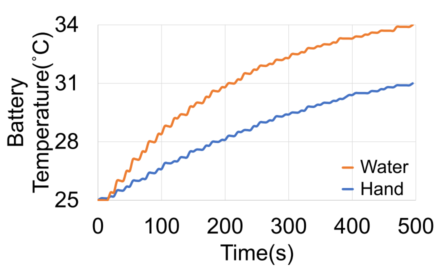


Fig. 8. Different temperature change behaviors of the smartphone battery contacting with water and a hand.

the smartphone battery even with different trials as shown in Fig. 7.

C. Data Transformation

Once we perform the data collection stage in Section IV-B for water and a hand, we have two types of data. However, as shown in Fig. 8, even with the same pair of (α = 25.0, β = 36.5), the two types of data exhibit totally different behaviors due to different heat conduction rates. As mentioned in Section III, we can easily collect data for any pair of (α, β) from the water; however, the same cannot hold that from a hand, because we cannot control the temperature of a body part. Therefore, we derive a function that transforms the data with a hand into that from the water. If the function is sufficiently accurate, we can measure the temperature of a hand by transforming the data with a hand into that from the water and then classifying the transformed data. This requires *all* necessary data with water, but does not require that from a body part.

By observing the temperature change behavior in Fig. 8, we may apply the linear regression to each data. However, the linear regression, once applied to the data with water between 0 and 250 seconds, yields non-negligible errors as shown in Fig. 9(a). On the other hand, the data with water between 250 and 500 seconds fits to a linear function as shown in Fig. 9(b); the same also holds for the data with a hand between 250 and 500 seconds as shown in Fig. 9(c). Therefore, we focus on [250, 500) seconds for the data with water and find a linear function $a^{water}_{(\alpha,\beta)} \cdot t + b^{water}_{(\alpha,\beta)}$, where t denotes time and $a^{water}_{(\alpha,\beta)}$ and $b^{water}_{(\alpha,\beta)}$ are linear coefficients for given pair of (α,β). To find the coefficients, we apply the linear regression for multiple instances of data with water for given (α,β), which is repeated for different pairs of (α,β). Similarly, we also focus on [250, 500) seconds for the data with a hand, and find a linear function $a^{hand}_{(\alpha,\beta)} \cdot t + b^{hand}_{(\alpha,\beta)}$ through linear regression.[1]

Now, we have $(a^{water}_{(\alpha,\beta)}, a^{hand}_{(\alpha,\beta)})$ and $(b^{water}_{(\alpha,\beta)}, b^{hand}_{(\alpha,\beta)})$ pairs for some (α, β) pairs. By utilizing such coefficient pairs, we can derive a linear function that transforms $a^{hand}_{(\alpha,\beta)}$ and $b^{hand}_{(\alpha,\beta)}$ into $a^{water}_{(\alpha,\beta)}$ and $b^{water}_{(\alpha,\beta)}$, respectively, for any given (α, β) pair. The function is derived as follows.

$$\begin{aligned} a^{hand}_{(\alpha,\beta)} \cdot c + d &= a^{water}_{(\alpha,\beta)} \\ b^{hand}_{(\alpha,\beta)} \cdot e + f &= b^{water}_{(\alpha,\beta)} \end{aligned} \tag{2}$$

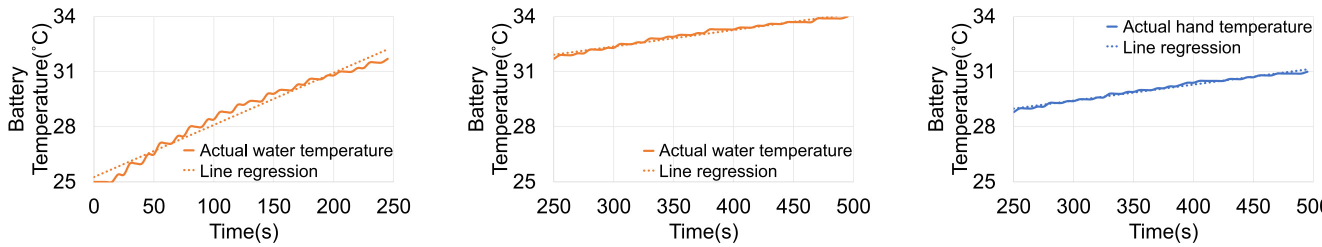
To determine the coefficients c and d as well as e and f, we apply the linear regression to all available $(a^{water}_{(\alpha,\beta)}, a^{hand}_{(\alpha,\beta)})$ as well as $(b^{water}_{(\alpha,\beta)}, b^{hand}_{(\alpha,\beta)})$ for all pairs of (α, β).

D. Data Classification

With the collected data, TherMobile performs the data classification stage. For this, TherMobile employs SVM (support vector machine), a widely-used supervised machine learning technique, that can effectively classify the input data into proper classes. For better accuracy, TherMobile employs the multi-level SVM that applies a separate SVM classifier for different initial battery temperature (i.e., α) values. As input, the SVM classifier takes i) the α value and ii) the temperature change of the smartphone battery over time in the form of a 100 dimensional vector (i.e., measured temperature every 5 seconds for 500 seconds). With them, the SVM classifies the input into the estimated body temperature (e.g., 36.5°C or 37.5°C).

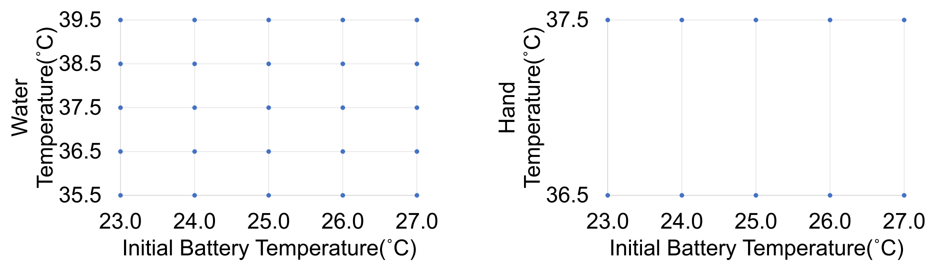
The SVM classifier is trained by the data with water, as we can get a wide-range and well-controlled data set when collecting them with water. We first categorize the data based on the

[1] Note that we applied different types of formulas with different ranges (e.g., 0–250, 0–500, 250–500 seconds) in order to represent the actual temperature change of the smartphone. However, it is difficult to distinguish different (α, β), if we utilize data from 0–250 seconds without data from 250–500 seconds.



(a) Data with water in $[0, 250)$ seconds (b) Data with water in $[250, 500)$ seconds (c) Data with a hand in $[250, 500)$ seconds

Fig. 9. Applying linear regression for ($\alpha = 25.0, \beta = 36.5$).



(a) Data with water (b) Data with a hand

Fig. 10. Pairs of (α, β) for data to be collected.

α value and train each individual SVM classifier corresponding to each α value. It is worth noting that the classifier utilizes the β value of the data as the ground-truth of the output class (i.e., the estimated temperature). To utilize the classifier, TherMobile first transforms the input (i.e., the temperature change data with a hand) into the proper data through Eq. (2), as the SVM classifier is trained by the data with water (not with a hand). After the transformation, TherMobile checks the α value of the input and feeds the transformed data into a proper SVM classifier. Then, the classifier properly estimates the body temperature.

Here is the detailed information of the data used for the classifier. By the data collection stage in Section IV-B, we utilize two types of data: i) the data with water for all pairs of (α,β) where $\alpha \in$ {23.0°C, 24.0°C, 25.0°C, 26.0°C, 27.0°C} and $\beta \in$ {35.5°C, 36.5°C, 37.5°C, 38.5°C, 39.5°C}, and ii) the data with a hand for all α with some β where $\alpha \in$ {23.0°C, 24.0°C, 25.0°C, 26.0°C, 27.0°C} and $\beta \in$ {36.5°C, 37.5°C}. With them, TherMobile trains the classifier and derives the data transformation function. And, TherMobile can classify the input into five different estimations identical to the collected β values: {35.5°C, 36.5°C, 37.5°C, 38.5°C, 39.5°C}.

V. Experiments

In this section, we explain the experiment setup and present the evaluation results for TherMobile in various aspects.

A. Experiment Setup

We employ Pixel4a [2] as a target smartphone, which operates with Android OS and is equipped with a battery temperature sensor whose update period is sufficiently short [4]. As explained in Sections IV-B, we evaluate TherMobile based on the experiment setup shown in Figs. 2 and 6, for gathering data with water and that with a hand, respectively. To measure the ground-truth temperature of water and a hand (i.e., β), we use a water thermometer and a medical infrared thermometer, respectively.

B. Evaluation of TherMobile

1) Collected Data: Fig. 10 shows pairs of (α, β) for data with water and that with a hand, to be collected by experiments. For each pair of (α, β), we collect five instances of data with water and those with a hand. For data with water, we can simply achieve a target temperature of water as a Sous Vide machine is capable of controlling water temperature with 0.1°C granularity. On the other hand, it is very difficult to gather data with a hand for other than (α, β = 36.5°C), because the human's normal temperature of 36.5°C is not controllable. To get data with a hand for different β from 36.5°C, we can increase the temperature of a hand up to 37.5°C by soaking an arm and wrist in warm water; however, we cannot increase the temperature more than 37.5°C using this method. Therefore, we collect data with a hand for β = 36.5°C and 37.5°C only.

2) Validation of Classification by SVM: Before evaluating TherMobile in terms of measuring body temperature, we need to assure that SVM accurately classify the data with water. We train SVM with 100 different instances of data with water, which consists of 4 different instances of data with water for given (α, β) as shown in Fig. 10(a). We then test 25 different instances of data with water, each of which is for different (α, β). Out of 25 tests, only one test yields wrong results (i.e., (25.0°C, 38.5°C) is classified as (25.0°C, 39.5°C)), which yields 96% accuracy. As a result, we confirm that applying SVM yields sufficiently accurate results.

TABLE I
TRANSFORMATION COEFFICIENTS

Coefficients	c	d	e	f
Value	0.7780	0.0120	0.4517	18.9000

TABLE II
REGRESSION COEFFICIENTS OF THE DATA WITH WATER AND A HAND, WHERE THE DATA WITH A HAND IS TRANSFORMED BY EQ. (2)

(α, β)	$a^{water}_{(\alpha,\beta)}$	$a^{hand}_{(\alpha,\beta)}$	$b^{water}_{(\alpha,\beta)}$	$b^{hand}_{(\alpha,\beta)}$
(23.0, 36.5)	0.0592	0.0521	31.50	31.33
(24.0, 36.5)	0.0504	0.0482	31.54	31.61
(25.0, 36.5)	0.0469	0.0449	31.88	31.89
(26.0, 36.5)	0.0426	0.0425	32.27	32.13
(27.0, 36.5)	0.0377	0.0397	32.60	32.33
(23.0, 37.5)	0.0596	0.0536	31.80	32.17
(24.0, 37.5)	0.0562	0.0612	32.07	32.25
(25.0, 37.5)	0.0507	0.0527	32.40	32.51
(26.0, 37.5)	0.0461	0.0503	32.76	32.70
(27.0, 37.5)	0.0411	0.0454	33.12	33.02

Before we evaluate the accuracy of measuring body temperature using data transformation, we show the same without data transformation, which justifies why data transformation is needed. We also apply the same SVM trained with 100 different instances of data with water. We test 50 instances of data with a hand, which consist of 5 distinct instances for each (α, β) pair presented in Fig. 10(b). Out of 50 tests, no test yields correct results. This is because the temperature change behavior with water is different from that with a hand as shown in Fig. 8.

3) Accuracy of TherMobile: We then evaluate the body temperature estimation accuracy of TherMobile. For given α, we train the SVM classifier with 25 instances of the temperature change data with water, which consist of 5 distinct instances for given (α, β) pairs in Fig. 10(a). As input of TherMobile, for given α, we test 10 instances of temperature change data with a hand, which also consists of 5 different instances for given (α, β) pairs in Fig. 10(b). For accuracy, we apply the data transformation to the input data. As a result, TherMobile shows the accuracy of 90%, as TherMobile accurately estimates the body temperature of 45 out of 50 test instances.

It is worth noting that the five error cases consist of two under-estimations when β (i.e., the ground truth) is 36.5°C and three over-estimations when β is 37.5°C. Despite the estimation error, TherMobile accurately classifies the normal (36.5°C) and the fever (37.5°C) cases. This implies that TherMobile is sufficiently accurate for our purpose, checking a fever conveniently.

4) Effect of Data Transformation: To validate the effectiveness of the data transformation, we compare $(a^{water}_{(\alpha,\beta)}, b^{water}_{(\alpha,\beta)})$ and $(a^{hand}_{(\alpha,\beta)}, b^{hand}_{(\alpha,\beta)})$ coefficient pairs for different (α, β) values, after applying the transformation. We first derive the coefficients for the transformation (i.e., c, d, e, and f in Eq. (2)) as presented in Table I. We then apply Eq. (2) to the data with a hand and derive the transformed $(a^{hand}_{(\alpha,\beta)}, b^{hand}_{(\alpha,\beta)})$ coefficient pairs. Table II shows the data regression coefficient pairs of the water data $(a^{water}_{(\alpha,\beta)}, b^{water}_{(\alpha,\beta)})$ and those of the transformed hand data $(a^{hand}_{(\alpha,\beta)}, b^{hand}_{(\alpha,\beta)})$, for given (α, β) pairs. The table shows that the regression coefficients of the transformed hand data are very close to those of the data with water. This implies that the data transformation is effective in achieving the accurate temperature estimation performance.

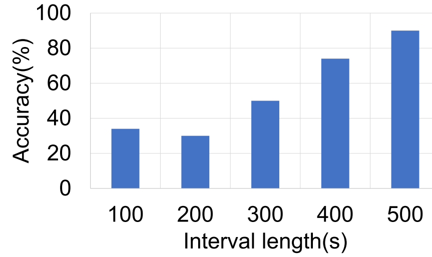


Fig. 11. The temperature estimation accuracy with different lengths of the data collection interval.

5) Effect of Data Collection: Considering the trade-off between the accuracy of measuring body temperature and the convenience for users, TherMobile collects the temperature data with the interval of 500 seconds. To identify the trade-off and justify our design, we test TherMobile with varying data collection intervals. Fig. 11 shows the estimation accuracy with different data collection intervals. It shows that TherMobile results in better accuracy as the data collection interval increases. One exception is that the accuracy with the interval of 100 seconds is higher than that of 200 seconds; while the result exhibits a non-monotonic trend, it has no significant meaning due to the low accuracy with the interval of 100 and 200 seconds. In addition, we confirm that the temperature estimation is sufficiently accurate (i.e., 90%), when TherMobile applies 500 seconds as the data collection interval.

VI. CONCLUSION AND DISCUSSION

In this paper, we developed a novel framework TherMobile, which measures body temperature using a COTS smartphone. By utilizing the heat transfer from an object contacting with a smartphone to the smartphone battery, TherMobile collects and classifies a time series of the smartphone battery temperature data under different temperatures of the contacting object, which allows to infer the target object's temperature. The experiment results demonstrate that TherMobile achieves 90.0% accuracy of measuring body temperature with 1.0°C granularity.

Although we successfully demonstrated the feasibility of measuring body temperature using a smartphone, there exist some remaining issues to improve the performance of TherMobile. First, TherMobile needs to measure a body temperature for 500 seconds. To make TherMobile more convenient to users, it would be a good direction of future work to shorten the duration for measurement, without compromising the accuracy of measuring body temperature. Second, TherMobile utilizes a limited temperature range of data with a hand due to the difficulty in controlling the temperature of a human body part. If we secure a wider temperature range of data with a hand, we can improve the accuracy of measuring body temperature, which is another direction of future work.

Third, it is difficult for TherMobile to achieve a finer granularity than 1.0° due to variation of body temperature (as shown in Fig. 4) and measurement errors of gathering samples with target body temperature. Finally, while the principles of TherMobile can be applied to most (if not all) smartphones that are equipped with battery temperature sensors, it varies with smartphones how to extract the information of battery temperature (e.g., frequency of reading sensor values). We leave it as future to apply TherMobile to different smartphones.

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