Accurate Prediction of Smartphones' Skin Temperature by Considering Exothermic Components

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***Abstract*—Smartphones' surface temperature, also called skin temperature, can rapidly heat up in certain cases, and this causes a variety of safety problems. Therefore, the thermal management of smartphones should consider the skin temperature, and its accurate prediction is important. However, due to the complicated relationship among the many exothermic components in the device, predicting skin temperature is extremely difficult. In this paper, we develop a thermal prediction model that accurately predicts the skin temperature of a mobile device. In an experiment with smartphones, we show that the proposed model achieves an accuracy of 98%, with a ±0.4 °C margin of error. To the best of our knowledge, our work is the first to reveal the complex relationship between the various components inside of a smartphone and its skin temperature.**

Keywords— thermal management; skin temperature prediction

I. Introduction

Every year, smartphone manufacturers are competitively introducing powerful devices. The accelerated hardware performance generates large amounts of heat inside these smartphones. This leads to various safety problems, such as battery explosion and low-temperature burn injuries. The surface temperature of a smartphone, also called the skin temperature, is important in terms of the user's comfort. Users often report discomfort, anxiety, and inconvenience caused by the devices' high surface temperature [1]. Accidents of devices being scorched and burned are also attributed to high skin temperature [2]. The thermal management of mobile devices typically focuses on solving performance throttling problems in high temperature, but the safety issue related to a device's skin temperature should also be addressed adequately. Acquiring information of skin temperature is therefore critical, and it is necessary to develop an accurate prediction model for skin temperature.

In this paper, we conducted an experiment to explain the relationship between the operating characteristics and heat generation for all active components in a smartphone device. We define a component that directly affects skin temperature as an exothermic component (EC). We experimentally found that as many as eight ECs (Wi-Fi, battery, camera, big core, LITTLE core, GPU, codec, camera, and LCD) operate at any given time, and as a result, the skin temperature changes dynamically. We then observed the relationship between the exothermic reactions of ECs and skin temperature by controlling the operation of each EC that determines the skin temperature. Based on this, we developed skin temperature models for each EC. Finally, we created a concrete model to predict the skin temperature of the device accurately, which was accomplished by combining all the EC models.

This paper makes the following contributions: First, to the best of our knowledge, this work is the first to analyze the effect of various ECs on the skin temperature of a real smartphone. Second, using thorough experiments, we modeled skin temperature while considering the operation of newly discovered ECs. Third, we experimentally validated, not through a simulation, the proposed model on a commercial smartphone.

II. Related Work

Recently, several attempts have been made to study the skin temperature of mobile devices. [3] modeled the relationship between the inside of a smartphone and the surface through a sophisticated RC model; here, the authors considered only three heat sources: the AP, power amplifier chip, and power management chip. [4] drew a temperature map by simulating skin temperature and the temperature of the AP chip. The study also considered the AP as a heat source, which is not adequate when considering recent smartphones. [5] studied user reactions at different skin temperatures and suggested a DVFS policy that considers skin temperature while reflecting personal preference. Most of the previous studies simply predicted the skin temperature based on the predicted AP temperature and on the measured battery temperature. No previous work considered the complex relationship between the various components of a device and its skin temperature.

III. Exothermic Components in Smartphones

To construct a prediction model for device skin temperature, we needed to define the exothermic components of a device. Using the latest smartphones, we measured the skin temperature while controlling for each component. We then analyzed the effect of each component on skin temperature and defined the exothermic components.

A. Target Device

We conducted experiments using four Samsung Galaxy S8+ smartphones. The smartphone employs Qualcomm's Snapdragon 835 [6] as the mobile AP, a 6.2 inch AMOLED display with a 1440 × 2960 resolution, and 802.11 a/b/g/n/ac Wi-Fi interfaces. The device has a 12 MP rear camera and a

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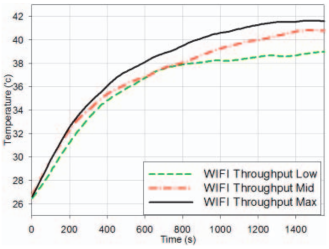

Fig. 1 Wi-Fi throughput

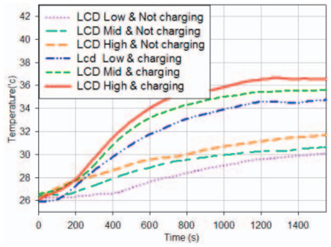

Fig. 2. Battery charging and LCD

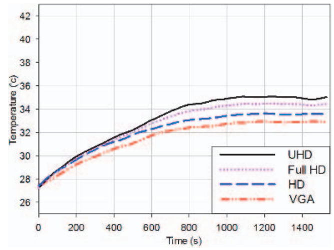

Fig. 3. Camera recording

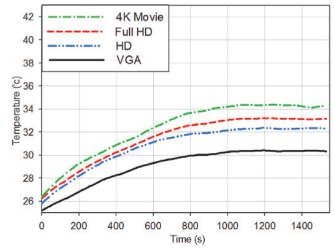

Fig. 4. Video decoding

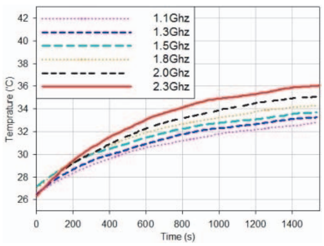

Fig. 5. big core

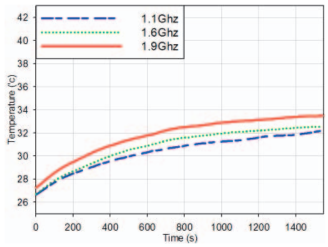

Fig. 6. LITTLE core

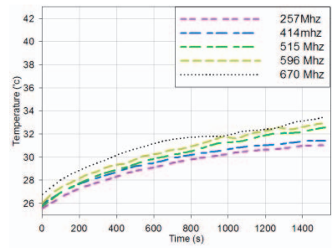

Fig. 7. GPU

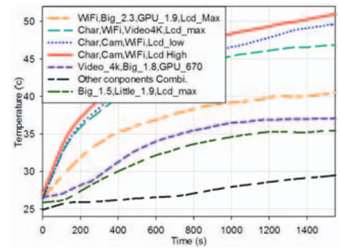

Fig. 8. Combined cases

3500 mAh battery. The Qualcomm Snapdragon 835 chip has a big/LITTLE architecture-based Octa-core (4 × 2.35 GHz Kryo and 4 × 1.9 GHz Kryo) CPU, Adreno 540 GPU, and various peripheral components.

B. *Exothermic Components*

By predicting the operating characteristics and power consumption of each component in the device, we selected 12 EC candidates. For the experiment, we created a kernel module that could read and store the temperature of each candidate. Among the 30 *thermal_zones* set under /sys/class/thermal, we selected 16 thermistors that covered the temperature of the internal component in AP and also six external thermistors. The external thermistors were placed on the PCB next to each candidate component. The COX CX1000 thermal imaging camera [7] was used to measure skin temperature. We selected eight ECs out of the 12 candidates that directly affect skin temperature. The components and their control factors are summarized in Table 1.

TABLE 1 COMPONENTS AND CONTROL FACTORS

Name	Control Factor
big core	Clock frequency step
Little core	Clock frequency step
GPU	Clock frequency step
Codec	Resolution(4K, FHD, etc.)
Wi-Fi	Throughput (50M/25M/1M)
Charging	Charging rate (quick/normal)
Camera	Recording resolution (UHD, HD, etc.)
LCD	Brightness (high, mid, low)

The CPU load generator [8] was used to produce a 100% load for the big/LITTLE cores at each frequency. For the GPU load generation, the hard-intensive GPU benchmark [9] was used. We used the Qualcomm Trepn Power Profiler [10] to verify the CPU and GPU settings and check the operating clock and its utilization. Iperf [11] was used for the Wi-Fi throughput test, and the battery charging-related experiment was conducted by using a Quick-charge compatible charger. For video decoding, we used 30-minute movie clips at each resolution. The camera test was performed while recording video for 30 minutes at various resolutions.

C. *Results*

The measured temperature was logged while changing the behavior of the ECs.

Wi-Fi upload: The most noticeable EC was the Wi-Fi module. Fig. 1 shows the results for the Wi-Fi upload. We observed that the Wi-Fi module can raise the skin temperature very quickly. According to a previous study [5], the hot spot of a smartphone's surface is the area around the AP, but we noticed that the hot spot is also around the Wi-Fi chipset area. This is illustrated in Fig. 9.

Battery charging: One unexpected observation was that battery Quick-charging leads to a high skin temperature. Fig. 2 shows the results for each of the six cases with charging and without charging while adjusting for LCD brightness.

LCD brightness: Fig. 2 shows the skin temperature while changing the brightness of the LCD. When the device is Quick-charged in conjunction with high brightness settings, the temperature difference between the charging and without charging scenario is over 5 °C. This synergistic effect occurs because the battery is not hot enough to affect skin temperature directly. The display occupies a large physical space, as shown in Fig. 10, hence preventing the heat from dissipating to the outside of the device.

Camera recording: The camera test was conducted by recording a 30-minute video at various resolutions. Fig. 3 confirms that camera recording indeed raises the skin temperature. It is interesting that the effect of a UHD camera recording on skin temperature is similar to that of the 2.3 GHz big core in Fig. 5. Also, when UHD recording starts in a combined scenario, as in Fig. 8, the skin temperature also increases sharply.

Video decoding: Fig. 4 shows that the operation of the video codec has a significant influence on the skin temperature for the selected resolution. Also, Fig. 8 shows that the skin temperature increased more than 6 °C in a short time period when video decoding is processing in the combined scenario.

Fig.9. Wi-Fi activated

Fig.10. LCD (max brightness)

Fig.11. AP core (max frequency)

big/LITTLE core: As reported in a previous study [3], when the big core operates at a high frequency, heat is generated inside the AP chip, as shown in Fig. 11. Fig. 5 shows the effect of the big core on skin temperature. Similarly, the LITTLE core in Fig. 6, with an operating clock frequency of 1.9Hz, also contributes to skin temperature.

GPU: Fig. 7 shows the skin temperature when the GPU is operating. We observed that the effect on skin temperature is similar to that of the LITTLE core. We measured the skin temperature at each frequency step of the GPU. Because the big core's clock was fixed to a minimum, the GPU utilization was not always at a stable 100%. For this reason, the GPU was measured at a relatively with low temperature.

Other components: In addition to the ECs discussed above, we observed the effect of other components on skin temperature, such as the speaker/amplifier for playing music, Bluetooth (BT) for file transferring, and even Power Management Integrated Circuit (PMIC) for charge-related operation. Fig. 8 shows the temperature when these components are combined. We noticed that the influence of each component on skin temperature is rather trivial, so we do not consider these components to be ECs.

D. Summary

We analyzed the operational characteristics of the ECs and their direct effects on skin temperature. Based on the experimental results, we classified the ECs into two types: *stand-alone* and *synergetic*. Stand-alone indicates that even when the EC is operating alone, it directly affects the skin temperature due to high heat generation; stand-alone types included Wi-Fi, big/LITTLE core, GPU, camera, and codec. Synergetic means that although the heat generation of either component alone is negligible, when two or more synergetic ECs operate together, they affect skin temperature significantly. The LCD and battery are categorized as synergetic ECs. Fig. 8 shows the combined cases, and we use more experimental data include these for the regression.

IV. Skin Temperature Prediction

A. Modeling

Our model directly correlates the operating characteristics of each EC to skin temperature. This is similar to the thermal model using gray-box identification [12]. Static power-thermal dissipation and dynamic power-thermal dissipation determine a smartphone's skin temperature. Static power-thermal dissipation can be expressed as a dynamic power-thermal component with the appropriate coefficients and a constant term [13]. Thus, we developed a basic model for the behavior of each EC, as shown below.

Eq. (1) explains the model of the temperature change when using the big core. In Eq. (1), we assume that the heat of the EC is accumulated without loss; the rising value of the skin temperature from the big core during time window k is expressed as Eq. (2).

$$\mathrm{T_{big}} = \alpha_{\mathrm{big}} * (\mathrm{F_{big}})^3 + \delta_{\mathrm{big}} \tag{1}$$

$$\mathrm{T_{big}^{k}} = \alpha_{\mathrm{big}} * \sum_{\mathrm{i=t-k}}^{\mathrm{t}} \left(\mathrm{F_{big}^{i}}\right)^3 + \delta'_{\mathrm{big}} \tag{2}$$

The relation between the power consumption and the operating clock $\mathrm{F_{big}}$ is the cubic-frequency relation [14]. Thus, we define the clock and temperature model as in Eq. (1). The Wi-Fi throughput model and other ECs' thermal models are derived from a previous study [15]. In the same way, the contribution of each EC to skin temperature during time k can be modeled as Eq. (3).

$$\mathrm{T_{EC}^{k}} = \alpha_{\mathrm{EC}} * \sum_{\mathrm{i=t-k}}^{\mathrm{t}} Coff_{EC}^{i} + \delta'_{\mathrm{EC}} \tag{3}$$

Here, $\mathrm{T_{EC}}$ is one of $\mathrm{T_{Big}}$, $\mathrm{T_{Little}}$, $\mathrm{T_{gpu}}$, $\mathrm{T_{lcd}}$, $\mathrm{T_{charg}}$, and $\mathrm{T_{codec}}$ and represents the temperature increase during one sample time of the big/LITTLE core, GPU, LCD, battery, and camera, respectively. $Coff_{EC}$ is one of $\mathrm{F_{big}}$, $\mathrm{F_{Little}}$, and $\mathrm{F_{gpu}}$ and represents the values for the clock frequency of the CPU and GPU, while $\mathrm{Br_{lcd}}$ the LCD brightness, $\mathrm{C_{charg}}$ the charging rate of the battery, $\mathrm{R_{size}}$ the camera recording resolution, and Re_{size} the resolution when playing a movie. δ'_{EC} is one of δ_{big}, δ_{Little}, δ_{gpu}, δ_{lcd}, δ_{charg}, δ_{cam}, and δ_{codec}, and α_{EC} is one of α_{LITTLE}, α_{GPU}, α_{lcd}, α_{charge}, α_{cam} and α_{codec}. β_{big}, β_{Little}, β_{lcd}, β_{charg}, β_{cam}, and β_{codec} are the constants specific to each smartphone. We finally obtain $\mathrm{T_{Skin}^{t}}$ and $\mathrm{T'_{Skin}}^{t}$, as follows:

$$\begin{aligned}\mathrm{T_{Skin}^{t}} = {} & \beta_{\mathrm{big}} * \mathrm{T_{big}^{t}} + \beta_{\mathrm{LITTLE}} * \mathrm{T_{LITTLE}^{t}} \\ & + \beta_{\mathrm{codec}} * \mathrm{T_{codec}^{t}} + \beta_{\mathrm{cam}} * \mathrm{T_{cam}^{t}} \\ & + \beta_{\mathrm{gpu}} * \mathrm{T_{gpu}^{t}} + \beta_{\mathrm{wifi}} * \mathrm{T_{wifi}^{t}} \\ & + \beta_{\mathrm{charg}} * \mathrm{T_{charg}^{t}} - \mu * \mathrm{T_{Skin}^{t-1}}\end{aligned} \tag{4}$$

$$\begin{aligned}\mathrm{T'_{Skin}}^{t} = {} & \mathrm{T_{Skin}^{t}} \\ & + \gamma_{\mathrm{synergy}}(\beta_{\mathrm{lcd}} * \mathrm{T_{lcd}^{t}} + \beta_{\mathrm{charg}} * \mathrm{T_{charg}^{t}})\end{aligned} \tag{5}$$

$\mathrm{T_{Skin}^{t}}$ is the skin temperature when the device is not charging. The skin temperature is obtained by multiplying the temperature of each EC with the β coefficient. Then, we subtract the temperature at which heat radiates to the outside. If we multiply the skin temperature before one sample time by the heat release rate μ, we can calculate the decreased value by heat dissipation going outside the smartphone. This is because the amount of heat emitted to the outside increases in proportion to the temperature. $\mathrm{T'_{Skin}}^{t}$ is the skin temperature

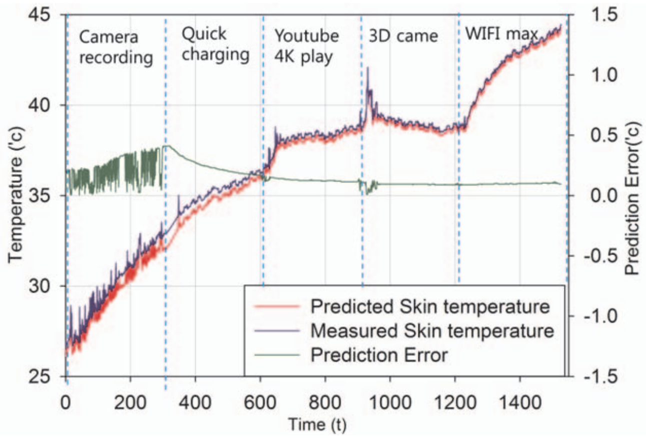

Fig. 12. Combination of short term use case

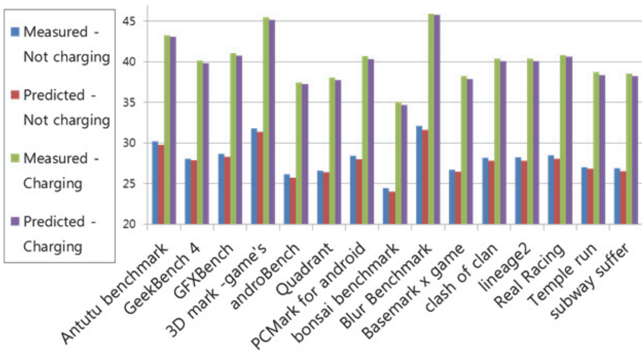

Fig. 13. APP/Benchmark result

when charging the smartphone. At this time, due to the synergy between LCD and charging, the temperature increases further by the product of $\gamma_{synergy}$ and the sum of the LCD and charging values.

The model coefficients from Eq. (1) through Eq. (5) were obtained using the curve-fitting tool provided in MATLAB with the experimental results of Section III.C. To improve the accuracy of the predictions, we measured the temperature of the ECs at all operable steps. These data were used to determine the most appropriate coefficient.

B. Model Validation

We compared the skin temperature measured using an infrared camera and the predicted temperature using the proposed model for actual use cases. The results of the short-term use case scenario are shown in Fig. 12. We conducted the following tasks for five minutes: UHD camera recording, Quick-charging, playing YouTube at 4K, playing a 3D game, and Wi-Fi uploading, in this order. Fig. 13 shows the highest temperature measured in 10 benchmarks and 10 popular games and the highest temperature calculated by using the prediction model at each case with and without charging. The difference between the predicted temperatures and measured temperatures was calculated with a maximum error of ±0.4 °C. In Fig. 12 and Fig. 13, by comparing the predicted skin temperature with the measured temperature, we notice that the prediction error is smaller at higher temperatures but is larger at lower temperatures. This is because we measured the temperature obtained from the experiments when each EC was operating at almost 100% utilization.

V. CONCLUSION

In this study, we conducted an experiment on all the controllable components of AP and found the ECs that affect skin temperature. We developed a better understanding of the relation of each EC and skin temperature and subsequently developed a sophisticated model for skin temperature prediction. We experimentally confirmed that the proposed model accurately predicts a smartphone's skin temperature. As part of our future work, we plan to build a skin-temperature-aware thermal manager for smartphones based on the proposed prediction model.

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