Poster: Measuring and Optimizing Android Smartwatch Energy Consumption

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ABSTRACT

Smartwatches are operating under tight energy constraints. In this paper, we describe our on-going work on measuring and optimizing Android smartwatch energy consumption. We derived power models for commodity smartwatches, and then applied the power model to an IRB-approved user study involving 30 smartwatch users. We then propose research ideas on improving energy efficiencies for Android smartwatches.

CCS Concepts

•**Human-centered computing** → **Ubiquitous and mobile devices;**

Keywords

Smartwatches; Energy consumption; Android Wear

1. INTRODUCTION

As one of the most popular types of wearable computers, smartwatch brings a wide range of features such as receiving notifications and voice control conveniently to our wrists. However, a smartwatch operates under tight energy constraints. It usually has a battery of only 300 to 500 mAh, much smaller than that of a typical smartphone battery (2–3K mAh) [9]. Also charging a watch requires special charging dock making it difficult for most users to charge the watches during the day. Based on our experience of using commodity smartwatches such as LG Urbane, a fully charged watch often cannot last for a full day. Despite being a great concern about smartwatch, the energy efficiency receives little attention from the research community. Also it is difficult to directly apply existing energy optimizing techniques for smartphones to smartwatches due to many inherent differences between a phone and a watch.

In this extended abstract, we report our on-going work on measuring and optimizing smartwatch energy consumption. We derived power models for commodity smartwatches, and then applied the power models to real smartwatch workload collected from an IRB-approved user study involving 30 smartwatch users at Indiana University. We found that smartwatches exhibit energy consumption characteristics that are very different from those of smartphones. For example, on average, more than 50% of a watch's energy is consumed when the watch is in sleeping mode. And surprisingly, displaying the watch face accounts for more than 30% of the overall watch energy consumption. Based on our measurement findings, we propose concrete solutions for improving the energy efficiency of smartwatches, such as energy-efficient watch face display, smart display dimming, and adding delay-tolerant support to push notification delivery. To our knowledge, this is the most comprehensive and in-depth study of smartwatch energy consumption. We believe our findings will also shed light on improving the energy-efficiency of other wearable devices.

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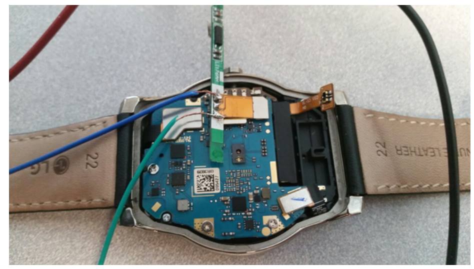

Figure 1: Power measurement of an LG Urbane watch.

2. SMARTWATCH POWER MODELING

A prerequisite for fine-grained energy analysis is a *power model*, which is a function $E(\vec{A})$ that maps $\vec{A}$ to their incurred energy and power consumption where $\vec{A}$ corresponds to system activities and events directly measurable on the device. In the literature, numerous studies have derived energy models for smartphones [12, 10, 3]. Nevertheless, to our knowledge, no comprehensive model is available for smartwatches whose energy consumption profiles are quite different.

To fill the above gap, we are building power models for popular smartwatches. Here we show preliminary results of a coarse-grained power model for an LG Urbane watch. The watch runs Android Wear OS. It is equipped with a Cortex A7 processor, 4GB storage, 512MB memory, 1.3-inch P-OLED display, Wi-Fi, Bluetooth, and various sensors. Our modeling approach follows the high-level methodology for smartphone power modeling [12, 3]. We measure the power consumption of the following components using a Monsoon power monitor [1]: device baseline (in both sleeping and awake mode), CPU, display, Bluetooth, Wi-Fi, and touch screen. As shown in Figure 1, we carved out a compatible

Component	Power Consumption (mW)
Sleep (watch face off)	10.9 for the entire device
Sleep (watch face on)	23.5 for the entire device
Wakeup baseline	43.5
CPU	$184.7u - .6$, $u \in$ (0,1]: CPU util.
Display (default brightness level)	$\sum(.030r + .127g + .233b + 93.7)/K$ Per-pixel $r, g, b \in [0, 255]$, K=320*320
Wi-Fi Tail	Duration: 0.18 sec, Power: 178.3
Wi-Fi Promotion	Duration: 0.30 sec, Power: 299.6
Wi-Fi Data	Tx: 739.9, Rx: 400.1
BT Tail	Duration: 4.8 sec, Power: 97.2
BT Data	Tx: 180.7, Rx: 174.9
Screen touch/swipe	118.9

Table 1: A Preliminary Power model for LG Urbane watch.

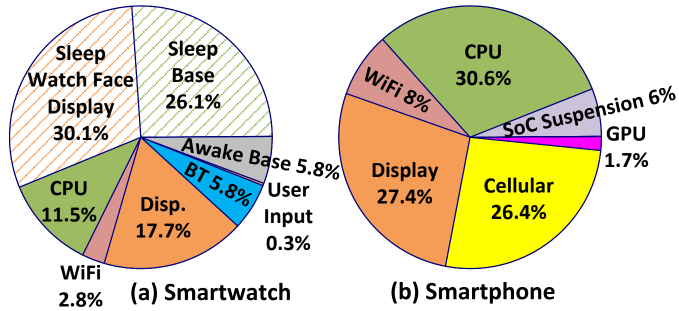

Figure 2: Energy breakdown of (a) smartwatches from our user study, and (b) smartphones from a prior study [2].

battery interface circuit from a smartphone by the same vendor, and then used the interface circuit as an adapter between the watch and the power monitor. When measuring a component, we keep other components offline (*e.g.,* Wi-Fi and BT) or at a steady power state (*e.g.,* display and CPU) whose power consumption is then subtracted from measured power value. For components involving parameters (*e.g.,* CPU utilization), we programmably change them and use regression to derive an empirical model.

Table 1 presents our results. We highlight some key findings below. (1) The CPU power is determined by three factors: the number of cores, the frequency of each core, and the utilization of each core. Our watch is equipped with a quad-core Qualcomm Cortex A7 processor. However, three of the cores are forced to be offline by the OS, and the clock of the only online core is fixed at 768 Mhz. This is a common practice on Android smartwatches [8]. Therefore, the only factor affecting the power is the CPU utilization, and we found both are linearly correlated. (2) The watch has 1.3 inch 320x320 P-OLED display, whose power is determined by the brightness level and the pixel colors [4]. We found blue is the most energy-consuming color, followed by green and then red. (3) The Wi-Fi state machine is similar to that of smartphones [3] except that we observe a non-trivial state promotion delay of 0.3s. (4) The BT state machine consists of an idle and an active state. The state promotion takes negligible time, while the demotion from active to idle state is triggered by an inactivity timer of 4.8s.

On-going Work. We believe power models of other smartwatches can be derived in a similar manner without requiring proprietary information from their vendors. Also we are refining the model by considering more details such as the display brightness, the signal strength, and various sensors' power consumption. We will also perform thorough validation of our models.

3. ENERGY CONSUMPTION OF SMARTWATCHES IN THE WILD

We conducted a user trial to understand the energy consumption of smartwatches in the wild. This IRB-approved user trial involves 30 diverse smartwatch users at Indiana University. Each user was given an LG Urbane watch. We developed a lightweight data collector that collects information needed to derive the power consumption from our preliminary power model. The collected data was uploaded to our server at night when the watch is being charged. The user study was deployed in April 2016 and the data collection is currently in progress.

Compared to controlled in-lab experiments, a key advantage of our user study is it helps understand the energy consumption under realistic usage scenarios. Here we show preliminary data analysis results based on a one-month trace. The methodology is as follows. From our collected data, we compute the total energy consumption of different hardware components (CPU, display, radio, *etc.*) across all 30 users. The energy consumption covers all usage periods except when the watch is being charged. Figure 2a shows the breakdown, which is further compared with the smartphone results shown in Figure 2b. The smartphone results were obtained from a recent crowd-sourced measurement study [2] conducted by Chen *et al.* We describe our key findings below.

- Surprisingly, for smartwatch, more than half of the energy is spent when the watch is in sleeping (idle) mode illustrated by the shaded pies in Figure 2a. This is explained by two reasons. First, the power consumption in sleeping mode is not trivial. In particular, unlike smartphones, the display of the watch remains on in sleeping mode (despite its brightness being reduced) so the user can get the time reading. The watch face display accounts for 30.1% of the overall energy consumption. Second, the active usage periods of watches are much shorter than those of phones due to the very nature of the applications on watches: time checking, push notification, voice control, *etc.* As a result, the sleeping mode becomes an important component in determining the overall energy consumption.

- When the watch is in active use (the solid pies in Figure 2a), despite its small screen size, the display is still the biggest energy consumer, accounting for 40.4% (17.7%) of the active-mode (overall) energy consumption. Also the CPU contributes less (but still non-trivially) to the overall energy consumption, likely because the LG Urbane watch always runs on a single core with fixed frequency. Note this is a common practice on many Android watches [8].

- Compared to a smartphone, a watch's radios (Bluetooth and Wi-Fi) play a less important role in draining the battery. This is attributed to two reasons. First, the vast majority of smartwatches (including ours) do not have a cellular interface that is much more power-hungry than short-range radios such as Wi-Fi and Bluetooth. Second, traffic generated by watches has much lower volume compared to its smartphone counterpart.

On-going Work. The preliminary analysis of our pilot user study data indicates that smartwatches' energy consumption profile differs considerably from that of smartphones. Leveraging our on-going user study, we are conducting more in-depth analysis such as the following. (1) How diverse is the smartwatch energy efficiency across users/applications? (2) How does a user's usage behavior affect the watch's energy consumption? (3) How predictable is the energy consumption from historical usage data? (4) What is the energy overhead incurred on the phone when it is paired with a smartwatch? Note that to answer the last question, we also need to do instrumentation on users' phones using energy profiling apps such as eStar [2].

4. IMPROVING ENERGY EFFICIENCY FOR SMARTWATCHES

The crowd-sourced measurement in §3 provides us with deep insights for our ultimate goal of improving the energy efficiency for smartwatches. We next describe several promising directions we are currently investigating.

- **Energy-efficient Watch Face Display.** Figure 2 indicates that the watch face display accounts for more than 30% of the overall energy consumption. A natural idea is thus to take energy efficiency into consideration when designing watch faces, and to make users aware of the energy costs. The watch face selector can provide energy efficiency ratings for different watch faces. For example, for OLED display, a watch face with black background is much more energy-efficient than one with white background. Also a watch can switch to "greener" faces when the battery level is low.

- **Smart Display Dimming.** The brightness level is an important factor determining the display power. By default, Android Wear displays the watch face in low brightness level when the watch is in sleeping mode, and increases the brightness when the watch wakes up. We note that a key use case of a watch is to check the time. It is handled by Android Wear as follows. When the user turns the watch toward herself to look at it, the sensors (accelerometer and gyroscope) will detect this action and wake up the watch automatically. However, Android Wear uses a simple inactivity timer (5 seconds) to dim the watch. In other words, even if the user just takes a glimpse at the watch, the watch face will still light up for 5 seconds. It may seem this is not a big issue, but given a user may have tens of even hundreds of short interactions with the watch every day, such a static timer may cause considerable energy overhead. We thus propose to dynamically and intelligently set this timeout to save energy. One possible way is to also use sensors to detect when the user moves her wrist away so that the display can be immediately dimmed.

- **Delay-tolerance Support for Push Notification.** Besides functioning as a timer, a smartwatch's most important application is receiving push notifications of phone calls, instant messages, weather updates, news, *etc.* The Android Wear OS treats all notifications equally important, and immediately wakes up the watch as long as a notification is received. This causes high energy overhead when notifications appear frequently. Our key observation is that many notifications are delay-tolerant. Therefore, multiple notifications can be delivered to the watch (from its paired phone) and presented to the user in a single batch to reduce the energy footprint. Doing so also helps make the watch less distractive when there are a large number of notifications. We plan to design and implement a new OS service allowing app developers to specify urgent levels or delivery deadlines of notifications. We will also develop an algorithm that strategically schedules the notification delivery to minimize the energy consumption while meeting the delivery deadlines.

On-going Work. We are designing and implementing the above solutions. We will first evaluate them using controlled experiments before deploying them to our user study. We are also actively exploring other directions at various layers that can make smartwatches more energy-efficient.

5. RELATED WORK

Compared to a plethora of work in improving smartphones' battery life, little effort has been made toward measuring and optimizing energy consumption of smartwatches (and wearables in general). LiKamWa *et al.* characterized the energy consumption of Google Glass [7]. Recently, Min *et al.* studied the practices for smartwatch battery use and management, using a combination of online survey and a user study involving 17 Android smartwatch users [9]. Compared to our on-going work, they collected a much smaller set of data (battery level, charging status, *etc.*) in their user study, and only examined the overall device-level energy consumption. Also their work did not propose concrete solutions for improvement. There are other studies of wearables on OS performance [8], user engagement [5], storage [6], and networking [11]. None of them focuses specifically on energy.

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