Usage Pattern Analysis of Smartphones

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***Abstract*—Recently, mobile traffic has increased tremendously due to the deployment of smart devices such as smartphones and smart tablets. These devices use various types of access networks such as 3G, WiFi, and mobile WiMAX. Network service providers also provide these access networks with various types of plans. There is a growing need to manage these smart devices and mobile networks. However, research on mobile network management has focused on the performance of the network itself. Few research has focused on applying the usage patterns of smartphone users to mobile network management. In this paper, we present an analysis of smartphone usage patterns. We define the five possible states of a smartphone based on such a phone's basic operations. We collected *real* usage log data from *real* smartphone users over a two month period. We show that all users have their own usage pattern. We present a case study in order to show how to apply usage pattern information to power management of smartphones. We also discuss how to apply such information to mobile device management and network management.**

***Index Terms*—Usage pattern analysis, Smartphone management, Mobile network management, Personalization**

I. Introduction

As mobile networks and services have grown rapidly in recent days, mobile traffic generated from mobile devices has increased tremendously [1] and mobile devices (e.g., mobile handsets or PDAs) have emerged as important tools in our lives [2]. Mobile devices are used for various applications such as making voice/video calls, browsing the Internet, playing games and so on. Furthermore, mobile devices have multiple network interfaces which can access multiple access networks such as 3G, WiFi, and mobile WiMAX. Network operators are also providing new pricing systems, data plans, and value-added services due to the variety of access networks. Hence, mobile network management is increasingly important to support the growth of mobile networks and spread of mobile devices.

Existing mobile network management methods have focused on the performance of the network itself and on performance requirements from the perspective of network operators. However, there is still a need to address performance requirements from the perspective of customers and to provide personalized services. A number of resent studies have monitored the perceived quality and usage patterns of customers who are using mobile devices in mobile networks and applied them to various areas [3]–[12].

In this paper, we present a usage pattern analysis of smartphones. A usage pattern means how users use their phones. First, we define possible smartphone states based on their basic functions, e.g., voice call and data communication. Second, we define log metrics to measure time and battery spent in each operational state. Third, we develop a mobile application (called a *battery logger*) for collecting log data from real smartphones, deploy this application to our campus and online sites, and observe how it is used by real users. Finally, we analyze the collected data to show that each user has his/her own usage pattern. In this research, we develop a battery logger based on an Android mobile platform [13] and collect log data from Android smartphone users. In all, we collect real smartphone usage logs from 20 users over a two month period. This collection is the first step of the present research. The main goal of our study is to observe high-level usage patterns of real smartphone users, and to understand the implications of these patterns for managing smartphones and their networks.

The remainder of this paper is organized as follows. Section II describes related work that focuses on collecting and analyzing users' activities from smartphones. In Section III, we analyze and apply usage patterns that were collected from smartphones. In Section IV, we present case studies on applying usage patterns to the resource management of smartphones and mobile networks. Finally, we draw conclusions and future work in Section V.

II. Related Work

Recently, many studies have focused on analyzing customer's mobile device usage.

Demumieux and Losquin [3] described a data analysis by gathering used functionalities (directory, calendar, number of SMSs sent and received). They also examined the duration of smartphone activities and the way users navigated OSs (presses on the keypad and history of windows opened) including Windows CE and Symbian 6 and 7). Reades et al. [4] presented real-time and historical visualizations of mobile phone usage levels in central Rome in order to understand urban systems. They analyzed the much larger samples of data generated daily by mobile networks and collected from real telecommunication operators. Rahmati and Zhong [5], [6], [10] analyzed human-battery interaction for energy-efficient design of mobile phones and longer battery lifetime. They evaluated various aspects of human-battery interaction, including charging behavior, battery indicators, user interfaces for power-saving settings, user knowledge, and user reaction which are similar to usage patterns. Our previous work proposed a method of predicting the battery lifetime of mobile devices based on usage patterns [7]. We defined the possible states of mobile devices based on their operating functions and developed a method of predicting battery lifetime based on average battery consumption and the duration of each state. However, one of the limitations of this study was that we did not use real data from real devices. In the present study, we analyze real data in order to overcome the limitation. Oliver [8] presented the preliminary results of a large-scale smartphone user study that examined how users interact and how they consume energy on their personal mobile devices. This study used over one millennium user interaction traces from over 17,300 BlackBerry users. Verkasalo [9] proposed a framework for mobile audience measurements called MobiTrack. These measurements are all about data collection at the point of convergence – mobile devices – rather than network or gateway side measurements, or user surveys. Shye et al. [11] presented a comprehensive analysis of real smartphone usage over a 6-month period, involving 25 users, and one specific smartphone, the Android G1. The goal of this work was to study the high-level characteristics of smartphone usage, and to understand the implications for optimizing smartphones, mobile embedded architecture, and their networks. This work motivated us to start this analysis study of smartphone usage patterns. Their work is very similar to our work, but they focused on applying it to mobile architecture. We focused on how to characterize personalized usage patterns for mobile network management. Shepard et al. [12] proposed LiveLab, a methodology to measure real-world smartphone usage and wireless networks with a reprogrammable in-device logger designed for long-term user studies. They presented an iPhone 3GS based deployment of LiveLab with 25 users intended for one year. They demonstrated the temporal dynamics and trends of application usage. They also showed the difference between individual application and application categories. This work presented a good methodology for measuring data from networks and users, but it only focused on application usage.

In this paper, we collect low level data to analyze the usage patterns of smartphone users and show how each user's usage pattern is different from other users' patterns by collecting real data.

III. Usage Pattern Analysis

In this section, we present the hypothesis of this study, a logger application, a collecting method, and analysis results.

A. Overview

In this study, our hypothesis is that we can obtain personalized usage patterns by analyzing users' activity on smartphones. We also assume that each user activity on a smartphone is mutually independent. To validate the hypothesis, we collected the following data from smartphones.

- Voice call status (Ringing, Waiting, Calling)
- Screen status (On/Off)
- 3G data communication status (In/Out/InOut)
- Active network (3G, WiFi)
- WiFi status (On/Off)
- Battery level (0–100 %)
- Battery status (Charing, Discharging, Full)
- Battery plugged status (Battery, AC, USB)

B. Data Collection

First, we developed a mobile application based on the Android mobile platform in order to collect log data. This application monitors the previously defined data and records it to a log file periodically. It transfers the log file to the data analysis server every day at midnight through 3G or WiFi as determined by the user. A smartphone has many operation states, but we considered only five operation states which are a large influence on power consumption: a) voice call, b) data communication via WiFi, c) data communication via 3G, d) waiting, and e) other activity. After collecting those data periodically, we calculated the time and battery spent in each state and compared usage patterns among smartphone users.

First of all, we deployed the application on the project homepage [14] on February 17, 2011. To obtain users for the study, we announced on the online bulletin board for anonymous volunteers in our campus and posted online advertisements to social network services such as Twitter or Facebook to obtain more users outside campus.

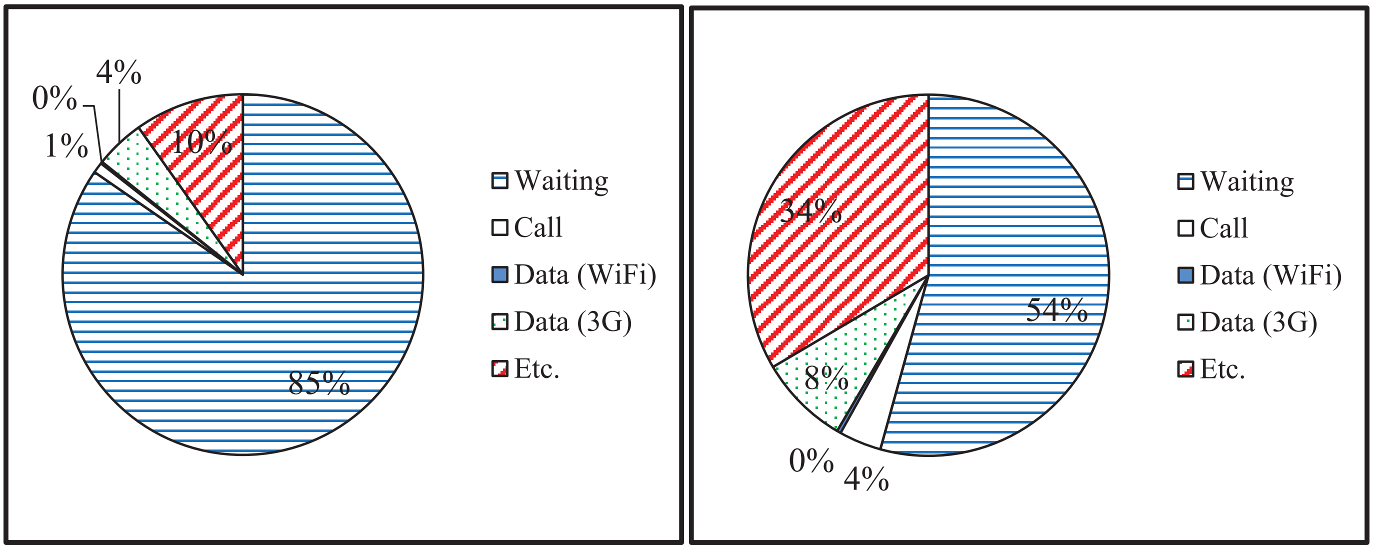
Overall, we collected 40 users from March to April, 2011. For this paper, we used the logs from the 20 users with the longest total recorded time. The data from these 20 users is 1.5 Gbytes and 1.26 Mbytes per log on average.

C. Analysis Results

We present the results of our analysis of smartphone usage data.

1) Average usage: First, we present average usage time and battery spent in each operation states (Fig. 1). As shown in Fig. 1a, most users spent time in a waiting state (85% and 54%). Although this shows an average usage pattern, we need to consider each user's usage pattern which we will mention in Section III-C2. Fig. 1b shows a comparison of battery consumption among all operating states. It shows different rates compared to Fig. 1a because battery consumption rate of each state is different.

2) Usage Pattern: Fig. 2 compares time and battery consumption for five operational states: a) waiting, b) voice calls, c) data communication via WiFi, d) data communication via 3G, and e) Etc. From the spent time comparison (Fig. 2a), each user spent a different amount of time in each state. The state where a user spent more time was used more in the future based on Zipf's law [15] and each user had their own long term usage pattern. Hence, we assume that this usage pattern is one of the user's characteristics and the ultimate goal of our study is to make an analytic model of users' smartphone usage behavior. Fig. 2b shows how much battery individual users



(a) Spent time

(b) Battery consumption

Fig. 1. Average smartphone usage for five operational states in terms of (a) spent time and (b) battery consumption.

spent in each state and the differences from the time pattern shown in Fig. 2a. This figure shows that battery consumption in each state was different. As shown in Fig. 1a, most users spent more time on average in the waiting state, but each user had a different rate for the other states.

Fig. 3 shows a comparison of individual user's smartphone usage for the three main operational states for communications: a) voice calls, b) communication via WiFi, and c) communication via 3G. Fig. 3a shows that each user spent a different amount of time in each state. In Korea and on our campus, WiFi networks are deployed widely. However, most users have been using 3G as a major communication method. We present some reasons for this situation. First, although WiFi provides fast speeds and high bandwidth, it is inconvenient because its coverage range is smaller than that of 3G and it is difficult to support seamless horizontal handover. Second, this comparison is based on time spent in each state. When we transfer a data packet, the time spent in WiFi is shorter than that in 3G because the speed of WiFi is faster than that of 3G. We will compare the session duration of WiFi and 3G in Section III-C3. Third, most participants come from our campus. This campus has been completely covered by WiFi networks since March 2011. So, most users have not noticed the WiFi coverage. However, we expect that this network usage pattern will change slightly in the future as developments related to IT services affect smartphone usage patterns. Finally, WiFi is less secure than 3G. Recently, personal information in smartphones and credit card information collection via WiFi have been introduced.

We can see users' characteristics from this chart. For example, User12 is a heavy WiFi user because he or she spends more time in the WiFi state than in other states. User14 is a heavy 3G user because he or she spends more time in the 3G state. Finally, User18 is a heavy voice call user because he or she spends more time in the call state. From this usage pattern comparison, we can guess an individual price plan and recommend a personalized price plan to optimize his or her smartphone usages. From Fig. 3a, we can guess that User12 has a limited data plan and User14 has an unlimited data plan. In fact, User14 is the first author who is using an unlimited data plan. User12 is a friend of the first author who is using a limited data plan.

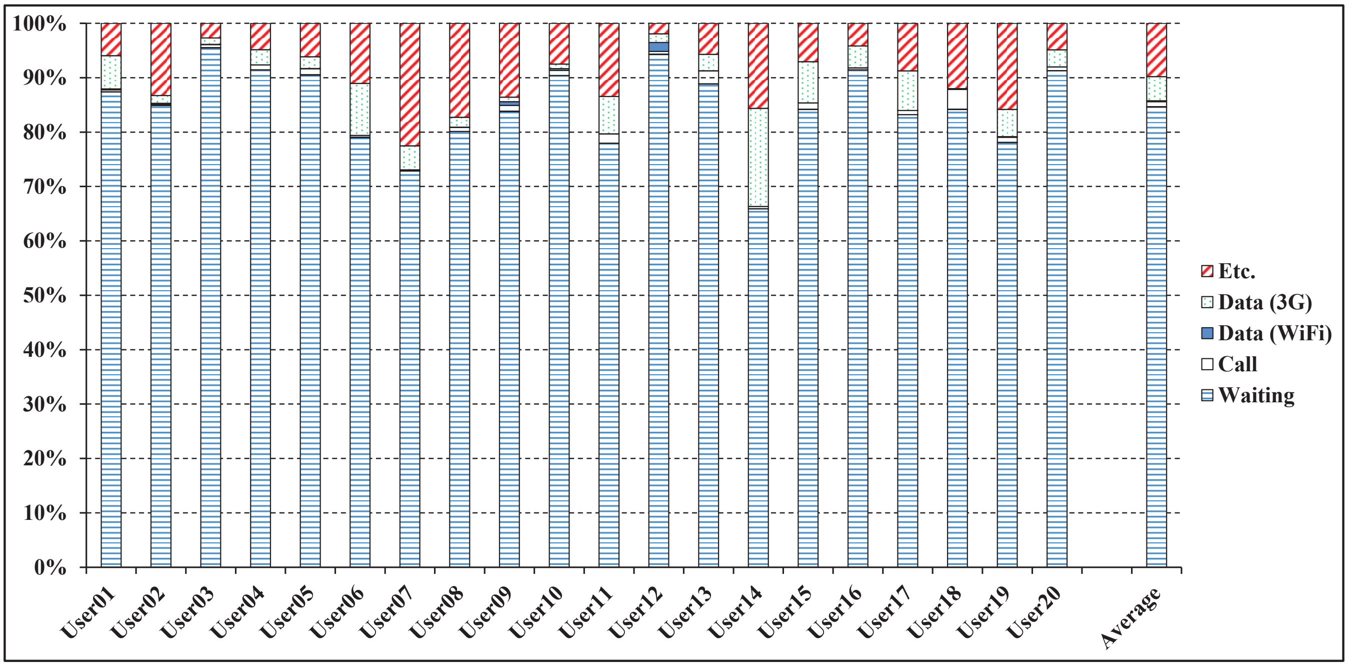
Fig. 3b compares the battery consumption of the three main operational states. This figure shows that the battery consumption varies according to the type of networks.

3) Network Usage: An analysis of network usages is important for modeling the networks that support smartphones. In this section, we study voice call, 3G, and WiFi characteristics for the entire logger session, including both plugged and unplugged time.

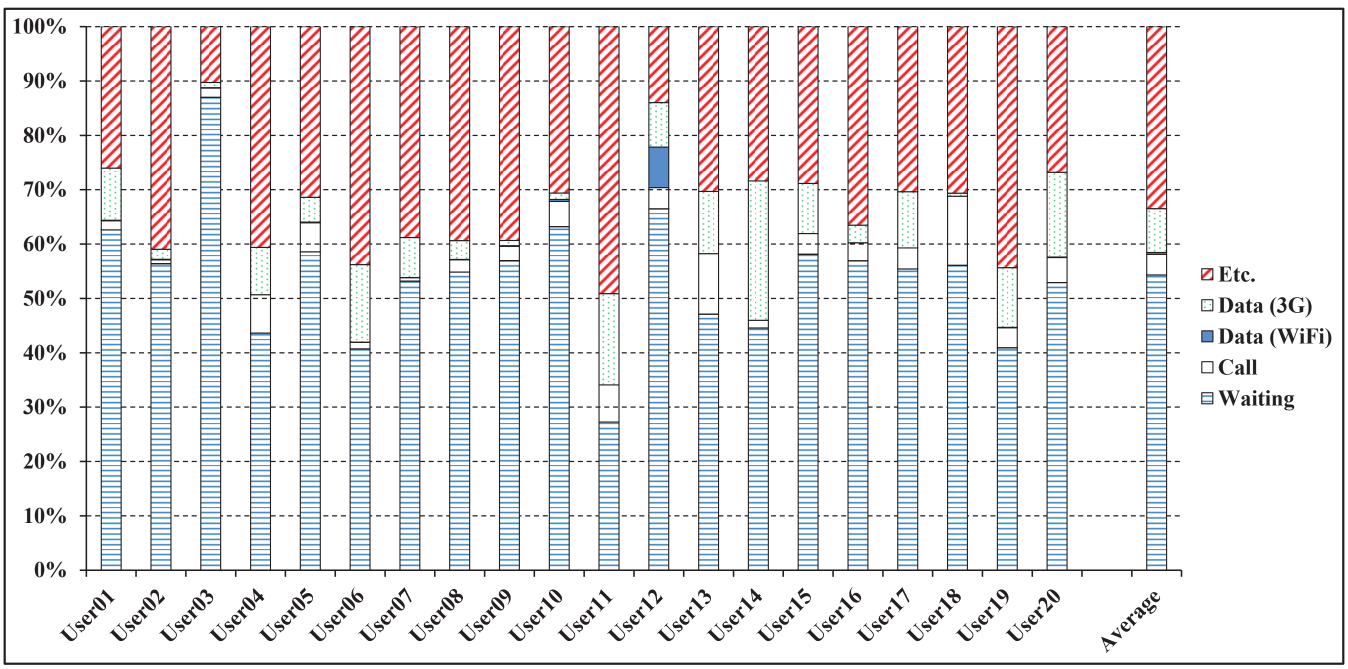
Fig. 4 shows the cumulative distribution functions (CDFs) of voice call, 3G, and WiFi network session durations for all users, User12, User14, and User18. As we mentioned in the previous section, we selected three users because their usage patterns shows clear characteristics in terms of 3G, WiFi, and voice call. We present session durations on a log scale in order to improve readability. From the figure, we can see how much time a user has spent in a session.

Fig. 4a shows a CDF for the session durations across all users. As shown in the figure, the 3G network has many short session durations that dominate the samples, whereas the voice call state has many long session durations. Because data communication via the 3G network is expensive, it has a short duration. The WiFi network has longer session durations than the 3G network.

However, the session durations for each user are different. Fig. 4b shows a CDF for the session durations of User12. When this user uses the WiFi network, the session duration is



(a) Spent time

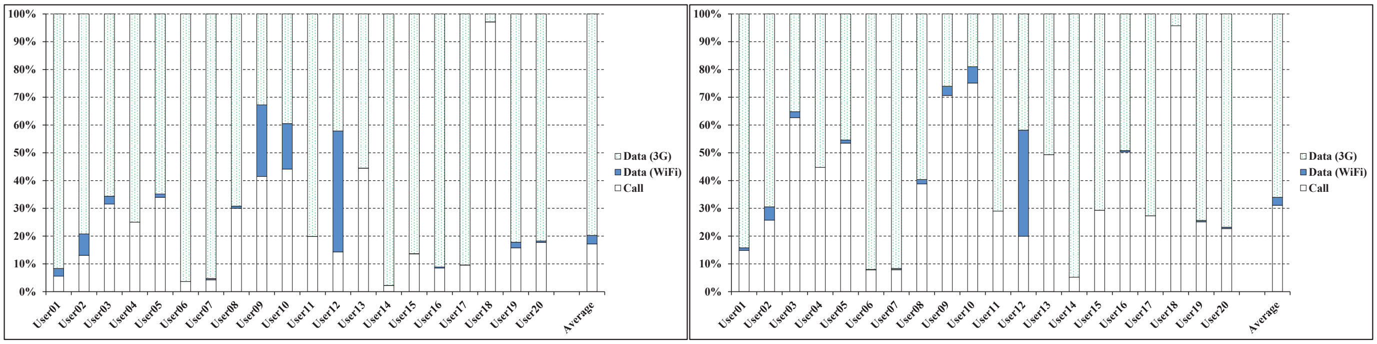


(b) Battery consumption

Fig. 2. A comparison of individual users' smartphone usage for five operational states in terms of (a) spent time and (b) battery consumption.

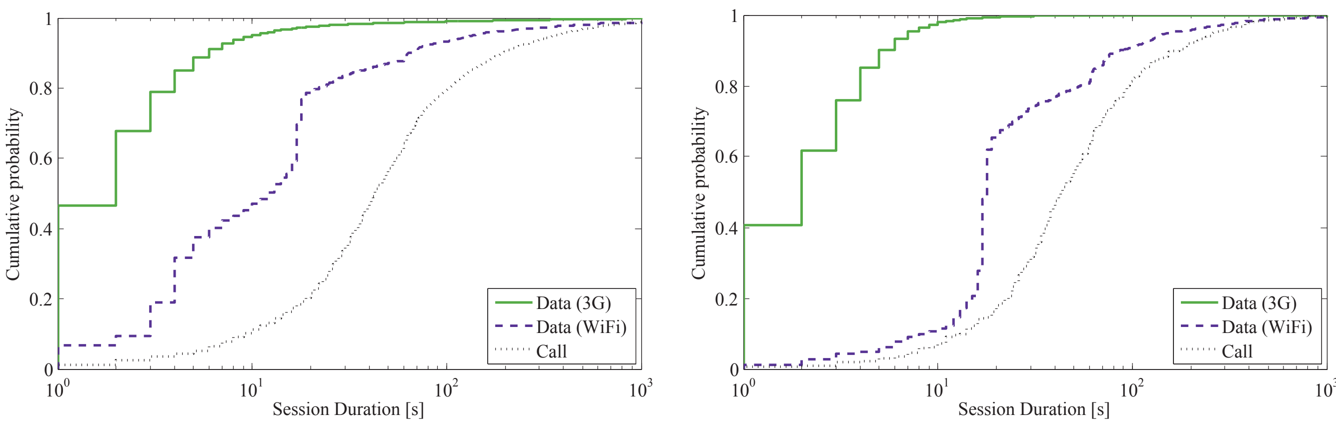
longer than that of other users. That is, we can see that this user is a heavy WiFi user. Fig. 4c shows a CDF of the session durations for the User14. When this user uses the 3G network, the session duration is longer than that of the WiFi network. That is, we can see that this user is a heavy 3G user. Fig. 4d shows a CDF of the session durations for User18. When this user uses the voice call function, the session duration is longer than that of 3G and WiFi network. That is, we can see that this user is a heavy voice call user. From the differences in session durations, we can see that each user has his or her own characteristics and we can use these to optimize smartphone communications and to create new services.

4) Battery Usage: Understanding of human-battery interaction in smartphones is important to support efficient battery usage [6]. To study the battery usage of our users, we extracted battery intervals from each of the logger sessions. A battery

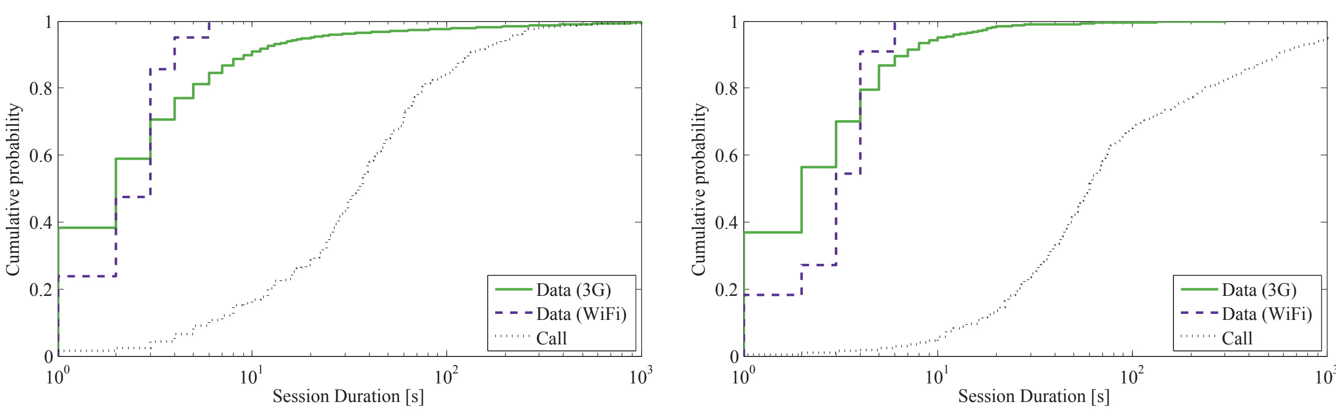


(a) Spent time (b) Battery consumption

Fig. 3. A comparison of individual user's smartphone usage for three main operational states (calls, WiFi, and 3G) in terms of (a) spent time and (b) battery consumption.



(a) All users (b) User 12 (WiFi biased user)



(c) User 14 (3G biased user) (d) User 18 (call biased user)

Fig. 4. CDFs of call, WiFi, and 3G session duration

interval represents a time interval where the battery is plugged in via AC and or a USB cable.

Fig. 5 shows a comparison of smartphone power sources of all users: a) battery, b) USB, and c) AC. Each user has a different pattern in this case. For example, User1 connected his or her smartphone to an AC power source 30% of the time. We can see that User1 works inside where an AC power source is available or kept to connect his or her smartphone to an AC power source during sleeping. User13 connected his or her smartphone to a USB power source 12% of the time and almost never used an AC power source. We can see that User13 is near a computer or a device which has a USB power sources. User14 connected his or her smartphone to AC and USB power sources 28% and 22% of the time, respectively. We can see that User13 also works inside. User20 used his or her smartphone's battery power. We can see that this user

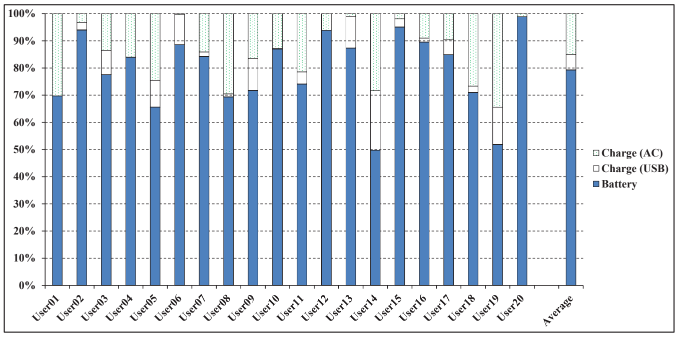


Fig. 5. A comparison of smartphone power source (battery, USB, and AC) percentage in terms of spent time.

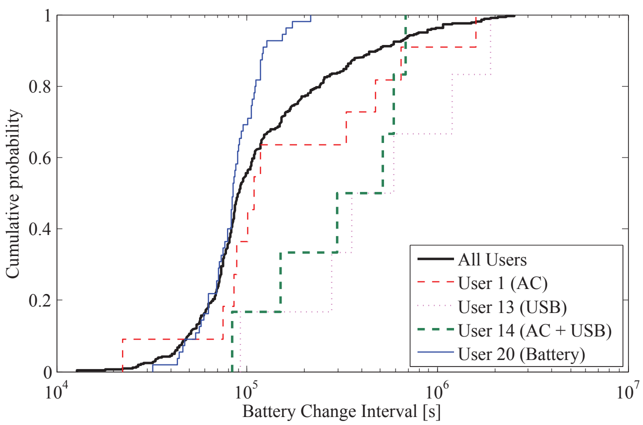


Fig. 6. CDFs of battery change interval; User1: AC biased, User13: USB biased, User14: both AC and USB biased, and User20: battery biased.

always changed the battery when it ran out. We will provide details related to the battery change interval, start battery level, and end battery level. A start battery level is an indicated level when a user starts to change a battery or charge with an AC or USB power source. An end battery level is an indicated level when a user finishes to change a battery or charge with an AC or USB power source.

Fig. 6 shows the CDFs of the battery change interval of all users, User1, User13, User14, and User20, who uses his or her smartphone without connecting to an AC or USB power sources, changes the battery periodically and after a shorter time than average users. On the other hand, User1, User13, and User14, who connected their phones to an AC and/or USB power source, took longer to changes their a batteries than the average users.

Fig. 7 shows the CDFs of battery level when smartphone users charge or their change batteries at a session on a start and end point. As shown in Fig. 7a, User20 changed his or her battery when the battery level was lower then 40%, whereas User1, User13, and User14 changed or charged their batteries frequently regardless of the battery level. We can see that User20 charged his or her phone based on charge level feedback from the battery interface and the other users often charge their batteries, regardless of the charge level. As shown in Fig. 7b, when User20 finished changing or charging his or her smartphone, his or her battery level was higher than 90%. In the analysis of battery usage, we showed that users have their own characteristics. These analysis results can help improve mobile phone design for users to effectively deal with battery life issues and to apply personalization to battery management [6].

D. Discussion

In this section, we have shown that smartphone users have their own usage patterns and that the amount of time they spend and the amount of battery power that they use in different operating states varies. If we can make an analytic model for usage patterns, we can use it to optimize energy efficiency of mobile networks and to design smartphones that consume less power. In fact, the WiFi network is inexpensive and has fast transfer speeds, and high bandwidth, but our users did not use WiFi as a major communication method with their smartphones. In particular, the introduction of an unlimited data plan has resulted in more users utilizing 3G as their major communication method.

IV. Case Study

In this section, we provide case studies related to various applications of smartphone usage pattern analysis.

A. Usage pattern based battery lifetime prediction

A mobile device's short battery lifetime can cause much inconvenience or reduce the device's usefulness ([16], [17]). Mechanisms to provide long and stable battery life are required. One of the methods to guarantee long battery life is to minimize battery consumption by reducing unnecessary battery usage.

The key to successfully minimizing battery consumption is accurately predicting the battery consumption of mobile devices' various operating states. In our previous work [7], we proposed a method for predicting available battery lifetime in mobile devices based on the usage patterns of individual users. However, we did not validate it with a real usage pattern data from smartphone users. In this section, we present a battery lifetime prediction based on usage patterns as a case study.

First of all, we assume that a mobile device has n possible states and r users are using the mobile device. We define a number of symbol descriptions and formulations as follows for describing our problems:

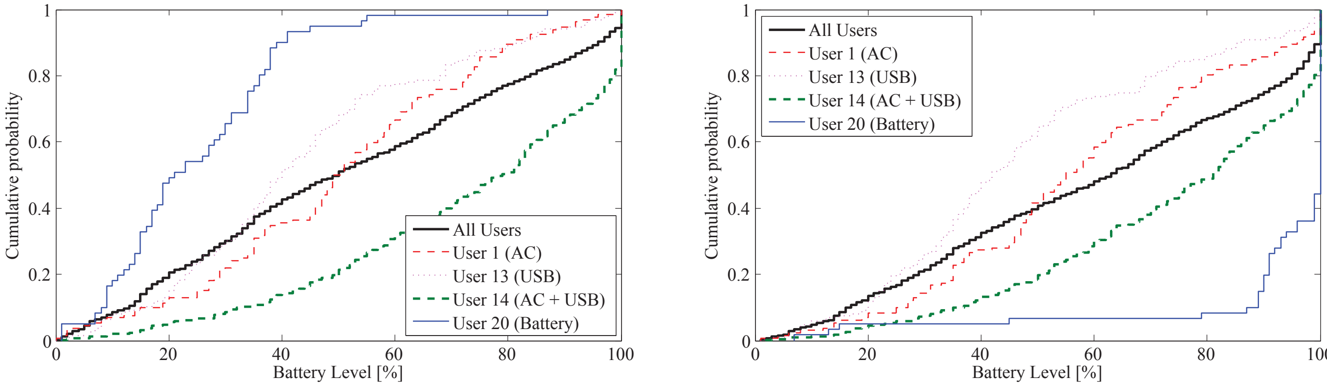
$$\vec{B} = (B_1, \ldots, B_n), \quad (1)$$

$$\vec{p} = (p_1, \ldots, p_n), \quad (2)$$

$$\vec{R} = (R_1, \ldots, R_n), \quad (3)$$

$$R_i = p_i \cdot B_i, \quad (4)$$

where B_i is the average battery consumption rate of the ith state, and p_i is time consumption rate of the ith state, which is determined to satisfy $\sum_{i=1}^{n} p_i = 1$. Because each user has a different vector $\vec{p}$ according to the usage pattern, this



(a) Start battery level

(b) End battery level

Fig. 7. CDFs of battery level when smartphone users charge or change battery at a session (a) start and (b) end point of time; User1: AC biased, User13: USB biased, User14: both AC and USB biased, and User20: battery biased.

vector represents the usage pattern. R_i is the ratio of battery consumption of the ith state.

We can formulate the given problem as follows.

Problem formulation: Determine the average battery consumption rate vector $\vec{B}$ and the usage pattern vector $\vec{p}$ to minimize the mean square error (MSE) of an predictor

$$MSE(\hat{\theta}) = E\left[(\hat{\theta} - \theta)^2\right] \tag{5}$$

where $\hat{\theta}$ is an estimator, our prediction method, and θ is the true values measured from users. We predict the available battery lifetime based on usage patterns using the following formulation.

$$T = \frac{V}{\sum_{i=1}^{n} R_i} = \frac{V}{\sum_{i=1}^{n} p_i \cdot B_i}, \tag{6}$$

where T is the available time predicted by usage patterns, and V is the total battery capacity. Because each user has a different $\vec{p}$, every user's battery has a different remaining lifetime. Previous approaches cannot represent the user's personal characteristics, because they do not consider usage patterns.

We define two symbols that represent the usage patterns of each user.

$$\vec{p_k} = (p_k^1, \ldots, p_k^n), \tag{7}$$

$$\vec{U} = (U_1, \ldots, U_r), \tag{8}$$

where $\vec{p_k}$ is the usage pattern of the kth user, p_k^i is the ratio of operating time that the kth user spent in the ith state, and U_k is the average battery consumption rate of the kth user considering the usage pattern—That is, p_k^i represents the probability that the kth user will spend time in the ith state because we assume that the usage pattern will be consistent with the user's history. In this paper, we have defined five possible states: a) waiting, b) voice call, c) data communication via WiFi, d) data communication via 3G, and e) other activity. Based on these states, we present a way of predicting the battery lifetime if the average battery consumption rate and usage patterns are known. The average battery consumption rates ($\vec{B}$) of each state based on the collected time-series data are as follows:

$$\vec{B} = (0.048, 0.252, 0.300, 0.132, 0.271), \tag{9}$$

If the usage pattern is given as Fig. 2a, we can define $\vec{p}$ for User12, User14, and User18 as follows:

$$\vec{p} = \begin{pmatrix} 0.94504 & 0.00527 & 0.01345 & 0.01622 & 0.02003 \\ 0.63739 & 0.00788 & 0 & 0.22672 & 0.12801 \\ 0.81914 & 0.04231 & 0.00001 & 0.00146 & 0.13708 \end{pmatrix},$$

where the row value represents each user's usage pattern and the column value represents each state: column 1 is $Waiting$, column 2 $VoiceCall$, column 3 $WiFi$, column 4 $3G$, and column 5 $Other$. For example, User12 spent more time in the WiFi state than other users. User14 in the 3G state, and User18 spent more time in the voice call state. To predict the battery lifetime of users with different usage patterns, we compare our proposed method with a method based on the static value which is an arithmetic mean of all battery consumption rates.

The average battery consumption rate based on an arithmetic mean is about 0.2006. However, the average battery consumption rate for each user using the proposed method are as follows:

$$\vec{U} = \vec{p} \cdot \vec{B}^T = \begin{pmatrix} 0.058294 \\ 0.097198 \\ 0.087325 \end{pmatrix}, \tag{10}$$

where the average battery consumption rate of User1 is 0.058294, that of User2 is 0.097198, and that of User3 is 0.087325. From this case study, we can present different battery consumption rates for each user, based on his or her usage patterns. Furthermore, we can adaptively predict the battery lifetime of a mobile device using dynamic usage patterns.

B. Other Useful Cases

We can apply usage pattern analysis to personalized access network selection in heterogeneous wireless networks [18] and the extensive research on energy-efficient design for a longer battery lifetime [10]. It can be also used to promote effective battery usage by reducing useless battery consumption, and it can detect abnormal battery usage by comparing operating time between normal and abnormal states. We utilize it for user identification as a security aspect.

V. Concluding Remarks

Smartphones are one of the fastest growing types of devices in the current mobile networks. Hence, we need to manage smartphones for mobile network management. In this paper, we have presented a usage pattern analysis using log data collected from smartphones. A usage pattern shows the length of time each user spends on voice calls, data communication, and waiting. Our study is the first step in monitoring smartphone usage and constructing usage patterns. We have presented our analysis results using *real usage log data* from *real smartphones* users. Our results can help network providers install mobile networks that take into account usage patterns that vary by location and users. The results will also help them optimize network infrastructure and create new services by analyzing usage patterns. Finally, the results can also be used to access network selection and energy efficient communication [10], [18]. the results also contribute to optimize battery usage on smartphones, predict personalized battery lifetime, detect abnormal processes and intrusion, and identify users.

We are continuously collecting usage log data from smartphone users for showing large-scale analysis results. In the future, we will collect new types of data such as the amount of network traffic and signal strength as well as running applications. We will also analyze users' characteristics to support usage patterns. Finally, we will apply our usage pattern analysis to managing mobile networks.

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References

[1] "Cisco virtual networking index: Global mobile data traffic forecast update, 2010-2015," http://www.cisco.com/en/US/solutions/collateral/ns341/ns525/ns537/ns705/ns827/white_paper_c11-520862.html, [Online; accessed 21-March-2011].

[2] S. Rollins and C. Chang-Yit, "A Battery-Aware Algorithm for Supporting Collaborative Applications," *Collaborative Computing: Networking, Applications and Worksharing*, pp. 594–608, 2009.

[3] R. Demumieux and P. Losquin, "Gather customer's real usage on mobile phones," in *Proceedings of the 7th international conference on Human computer interaction with mobile devices & services*. ACM, 2005, pp. 267–270.

[4] J. Reades, F. Calabrese, A. Sevtsuk, and C. Ratti, "Cellular census: Explorations in urban data collection," *IEEE Pervasive Computing*, pp. 30–38, 2007.

[5] A. Rahmati, A. Qian, and L. Zhong, "Understanding human-battery interaction on mobile phones," in *Proceedings of the 9th international conference on Human computer interaction with mobile devices and services*. ACM, 2007, pp. 265–272.

[6] A. Rahmati and L. Zhong, "Human-battery interaction on mobile phones," *Pervasive and Mobile Computing*, vol. 5, no. 5, pp. 465–477, 2009.

[7] J.-M. Kang, C.-K. Park, S.-S. Seo, M.-J. Choi, and J. W.-K. Hong, "User-centric prediction for battery lifetime of mobile devices," *Challenges for Next Generation Network Operations and Service Management*, pp. 531–534, 2008.

[8] E. Oliver, "The challenges in large-scale smartphone user studies," in *Proceedings of the 2nd ACM International Workshop on Hot Topics in Planet-scale Measurement*. ACM, 2010, pp. 1–5.

[9] H. Verkasalo, "Analysis of Smartphone User Behavior," in *Mobile Business and 2010 Ninth Global Mobility Roundtable (ICMB-GMR), 2010 Ninth International Conference on*. IEEE, 2010, pp. 258–263.

[10] A. Rahmati and L. Zhong, "Context-based network estimation for energy-efficient ubiquitous wireless connectivity," *IEEE Transactions on Mobile Computing*, pp. 54–66, 2010.

[11] A. Shye, B. Scholbrock, G. Memik, and P. Dinda, "Characterizing and modeling user activity on smartphones: summary," in *ACM SIGMETRICS Performance Evaluation Review*, vol. 38, no. 1. ACM, 2010, pp. 375–376.

[12] C. Shepard, A. Rahmati, C. Tossell, L. Zhong, and P. Kortum, "LiveLab: measuring wireless networks and smartphone users in the field," *ACM SIGMETRICS Performance Evaluation Review*, vol. 38, no. 3, pp. 15–20, 2011.

[13] "Google, Inc. Android – An Open Handset Alliance Project," http://developer.android.com, [Online; accessed 1-May-2011].

[14] "Battery Logger Project, DPNM Lab., POSTECH," http://dpnm.postech.ac.kr/battery/, [Online; accessed 1-May-2011].

[15] G. Zipf, "Human behavior and the principle of least effort." 1949.

[16] L. Benini, A. Bogliolo, and G. De Micheli, "Dynamic power management of electronic systems," in *Proceedings of the 1998 IEEE/ACM international conference on Computer-aided design*. ACM, 1998, p. 702.

[17] C. Krintz, Y. Wen, and R. Wolski, "Application-level prediction of battery dissipation," in *Low Power Electronics and Design, 2004. ISLPED'04. Proceedings of the 2004 International Symposium on*. IEEE, 2005, pp. 224–229.

[18] J.-M. Kang, J. Strassner, S.-s. Seo, and J. W.-K. Hong, "Autonomic personalized handover decisions for mobile services in heterogeneous wireless networks," *Computer Networks*, vol. 55, no. 7, pp. 1520–1532, 5 2011.