Getting Closer: An Empirical Investigation of the Proximity of User to Their Smart Phones

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ABSTRACT
Much research in ubiquitous computing assumes that a user's phone will be always on and at-hand, for collecting user context and for communicating with a user. Previous work with the previous generation of mobile phones has shown that such an assumption is false. Here, we investigate whether this assumption about users' proximity to their mobile phones holds for a new generation of mobile phones, smart phones. We conduct a data collection field study of 28 smart phone owners over a period of 4 weeks. We show that in fact this assumption is still false, with the within arm's reach proximity being true close to 50% of the time, similar to the earlier work. However, we also show that smart phone proximity within the same room (arm+room) as the user is true almost 90% of the time. We discuss the reasons for these phone proximities and the implications of this on the development of mobile phone applications, particularly those that collect user and environmental context, and delivering notification to users. We also show that we can accurately predict the proximity at the arm level and arm+room level with 75 and 83% accuracy, respectively, with features simple to collect and model on a mobile phone. Further we show that for several individuals who are almost always within the arm+room level, we can predict this level with over 90% accuracy.

Author Keywords
Proximity, mobile devices, mobility, smart phone.

ACM Classification Keywords
H.m. Information systems: Miscellaneous.

General Terms
Experimentation, Human Factors

INTRODUCTION
It is without question that we are living in a world where emerging mobile personal devices and high-capacity wireless networks are enabling new and innovative applications that compliment many different aspects of daily life. Over the past decade, mobile computing has become ever more present in our society, particularly as smart phones become more prevalent. By December 2010, 31% of U.S. mobile phone users had smart phones [14] and this figure is expected to cross 50% by the end of 2011 [7]. This trend holds worldwide, with almost 300 million smart phones being sold in 2010 [5] and another 500 million predicted for 2012 [4].

In keeping with this trend, there has been an underlying assumption in much of the work in ubiquitous computing that a phone is always with its owner. This assumption, if true, means that ubiquitous computing systems can use the phone as a medium for collecting data from users and communicating information to users, at any time. Further, this means that the mobile phone is an accurate proxy to collect contextual information on users' location and activity. This assumption was investigated in 2006 [20] when mobile devices were not as robust and feature-filled as they are today. At that time Patel *et al*. found that when participants had their phones on (81% of the time), they kept their phone within arm's reach 58% of that time, which was less than the participants perceived themselves as doing, and the phone was within the same room as participants an extra 20% of the time.

Since this study, five years ago, we have seen the introduction and mass adoption of Apple's iPhone and the Android platform that have redefined the mobile computing experience, and the operating systems and capabilities of mobile devices that are available to the average user. We now live in an era of so-called "smart" phones. These mobile devices have progressed far beyond a means of making and receiving phone calls, and for many, have become an almost indispensable tool to access information, complete tasks, be entertained and communicate in a wide variety of ways (*e.g.*, Skype, instant messenger, email). As a whole, it seems reasonable then to presume that people rely on their mobile phones far more than they used to and are thus likely to keep it more accessible as well. Based on the widespread availability of smart phones, it is important to re-investigate the assumption (and Patel *et al*.'s findings) about users' proximity to their phones, to determine if the smart phone is as ubiquitous a device as we believe.

Using a series of surveys and interviews, as well as by employing an application on Android mobile devices, we have gathered both quantitative and qualitative data from 28 participants over 4 weeks of real-world behaviors with their own smart phones. For this study we looked at participants'

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proximity to their smart phone via Bluetooth monitoring. In addition we automatically collected a wide range of sensor data from their phones. Supplementing this objective field data are interviews, surveys and day reconstruction exercises with users that help to give a sense of context. Beyond these 28 participants, we also surveyed 367 smart phone users about their perceived proximity to their smart phones and their habits surrounding smart phone use.

The contribution of this paper is three-fold. The first is to present empirical evidence to understand the degree to which current smart phones are an accurate proxy for their owners' location and context. Second, we identify themes that help explain these results, providing implications for future application development. Finally, we demonstrate that we can build accurate predictive models of proximity using readily available features about user activity. We begin with a discussion of related work.

RELATED WORK

As mobile phones become smaller and more powerful computing devices, they have also become more prevalent in the world at large [5,14]. The evolution of the mobile phone has led it to move far beyond a simple communication device and now is a versatile tool for connecting people to their digital lives on various social networks and e-mail, providing them with access to the Internet, and even for entertaining them by supporting the playing of games, music, and video. This evolution has even lent itself to referring to these robust devices as *smart phones*. The potential for the use of smart phones in ubiquitous computing has not gone unexplored over the past decade.

Leveraging the capabilities of smart phones, data can now be captured that would have previously required carrying customized hardware or a large number of specialized devices [22]. Examples of new applications enabled by the convergence of functionality in smart phones include healthcare [9,12,21], support for the elderly [18], augmenting advertising [16], understanding social networks and behavior [6,17], among many others.

Knowing that a user has her smart phone on and nearby (or tends to) is useful for ubiquitous computing and mobile application development, as the smart phone offers the unique ability to communicate information to a user and collect information from a user, regardless of location or time. However, it is not just knowing that the phone is nearby that can offer a meaningful contribution. There is a whole field of research and design that has arisen from being able to leverage the mobile phone as a means to gather contextual information and build an understanding of human behavior and the environment at large. Related work in this area includes activity sensing endeavors such as UbiFit [1], SenSay [15], and MotionBand [9] that leverage context-sensing to support people's day-to-day actions.

In 2006 Patel *et al*. studied people's proximity to their mobile phone as well as their perceived proximity to their phone and found that people had higher expectations of their availability to their phone then was found to be the case in actuality [20]. On average they found that the phone was on 81% of the time. When it was on, it was within arm's reach 58% of the time, and within the same room as their owners an additional 20% of the *on* time, leaving 23% when the phone was on and considered "unavailable" to the user. In actuality, the true unavailable time should include the time when the phone was off, equaling 38% of the day, on average. Trends that were noted upon by Patel include a small, not statistically significant variance on cell phone proximity between weekday (59%) and weekends (53%), waking versus sleep (61% awake, 52% asleep, and home and away (est. 50% to 71%). Furthermore they explored whether a proximity relationship between users and their mobile phones could be *predicted* by applying classifiers to context data that could be easily acquired from the phones themselves. With one week of training data, their classifiers determined whether the phone was within arm's reach with 86% accuracy.

The findings of this research, and its implications for how the data gathered on a mobile phone can be leveraged to give insights into the user's context, have been cited in numerous subsequent articles. While some have referenced it as evidence that mobile phones *can* serve as a reasonably accurate proxy for a user's location and context [8,19,23], others interpret the paper's findings as the opposite: the phone is *not* a good proxy for a user's location [1,12,16]. Not surprisingly, the true interpretation depends on the application, users, and context of use being designed for.

The question we want to explore in this paper is whether with the evolution of the smart phone (and all the services and apps now available) over the past five years since the Patel *et al*. paper was published, users' proximity to their phone has changed. Smart phones have become not only more commonplace, but more powerful computing devices used to connect people to their e-mail, social networks, and entertainment, through a wide variety of available apps. In investigating user behavior at this stage of mobile technology, we explore implications for mobile applications that can inform developers, researchers, and technologists as they innovate and envision new uses and applications for mobile phones.

EXPERIMENTAL DESIGN

We now describe the design of our experiment in which we sought to understand how users' proximity to their phones has changed with the availability of smart phones.

Overview

In order to accurately replicate the proximity study from Patel *et al*. [20], we contacted the authors of this paper and requested the experimental instruments they used and asked for additional details on their experimental setup. By doing so, we were able to closely replicate the original study. We briefly describe that study and the instruments used, and highlight differences in our study.

In keeping with the original experimental setup, we used mixed methods: surveys to collect information about subjects' perceptions about their phone use and phone proximity, and a 4-week long deployment of data collection software on subjects' *own* Android phones to collect both proximity information and a wide variety of contextual information. We also conducted weekly interviews to provide additional context to this data. Our study differs from the original study, which provided mobile phones to subjects, and included 16 participants for 3 weeks.

Surveys

The original survey instrument asked questions about the respondents' age and occupation, how they thought they used their phones and how close they thought they kept their phones in different situations. We adapted this survey to collect additional information on mobile applications they use and their frequency of use, what applications they would be interested in using, as well as their general experience with the phone and expectations being met (or not) with respect to mobile communications. We also collected detailed socio-economic status information of respondents, including education level, experience with mobile technologies (year started using).

We used the responses to the survey to select subjects for our study of smart phone proximity. Subjects were randomly selected from those respondents having an Android phone with an unlimited data plan and being willing to participate in the 4-week long study.

Mobile Users Data Collection Study

Interview

Participants selected for our study came to our lab, where we explained our study and what we expected of them in detail. We also deployed our proximity monitoring and context data capturing framework on their Android phone, provided them with a Bluetooth device to collect proximity information, and collected some proximity calibration data. We describe our automated data collection process below.

Android AWARE Data Collection Framework

Sensors and Internet connectivity in mobile devices provide researchers an opportunity to capture real-life context information from the owners of the mobile devices and to collect information on the proximity of the phones to their owners. We developed the AWARE Android framework, to help gather this information. The framework was developed using Android SDK 2.1, was tested and then deployed on a variety of Android devices throughout our user study. In consideration of space, we only present the sensing modules in the framework that are relevant to our exploration of phone proximity. While some of these modules may not seem relevant to proximity, we erred on the side of sensing completeness in order to identify as many factors as possible that impact proximity.

Activity Manager: Every 3 seconds, this module collects information about the active, inactive and background processes, current active activity on the screen, CPU and memory usage by application and system by querying the Android API Activity Manager.

Battery Manager: This module logs battery-related events with information such as percentage, temperature, health, voltage, technology and uptime (amount of time without charging), when the phone was plugged in and unplugged to the power supply (USB and AC).

Bluetooth Manager: The framework scans each minute for Bluetooth devices in the vicinity, keeping a record of their MAC address, friendly name and Received Signal Strength Indication (RSSI) value.

Call Manager: This module keeps track of incoming, missed and outgoing calls, including call duration, time of call and phone number.

Phone Manager: This module captures the phone's carrier information on the device, such as tower location, whether the phone has an active data plan, IP address, the device ID (IMEI for GSM devices and MEID for CDMA devices), the device's phone number, neighbor cell towers, network country, network operator, network type (CDMA, GSM, UMTS, *etc*.) and roaming status. It also provides information about the software running on the device, including version, manufacturer and device model.

Location Manager: This module collects the device's location (latitude, longitude, bearing, altitude, speed and accuracy), using network triangulation and GPS coordinates. As per the Android's developer recommendation, a one-minute interval is used for polling for GPS and Network-provided coordinates. The *Location Manager* first acquires a network-provided location, as it requires less battery power to quickly get the mobile device's location. Once a preliminary location is acquired, a GPS location is requested, as network location is less accurate. If the acquisition of GPS location fails for some reason (*e.g.*, user is indoors, phone failed to acquire satellite GPS signal, GPS turned off), the network location is logged. If the user is moving, a new location is requested for every ten meters of motion on GPS or for every 100 meters through the network location.

Network Manager: This module logs network traffic (received and sent) on available network interfaces (Wi-Fi, Carrier network) and assigned IP address for each network interface, along with network connections/disconnections.

Screen Manager: This module detects when the user turns On/Off the screen and unlocks/locks the screen.

Sensor Manager: This module logs sensor events from all the available sensors on the device, such as the accelerometer, ambient light sensor, magnetometer, pressure sensor, gyroscope, orientation sensor and temperature sensor. It also captures the vendor, precision, power consumption and sensor range values for each.

Messaging Manager: This module logs SMS and MMS messages received/sent (including time and phone number).

Weather Manager: Each time the device's location changes, the weather forecast for the current day and location is gathered from Weather.com.

Wi-Fi Manager: Every minute, this module logs the current Wi-Fi state (active, inactive) and access point information (connected and neighbor access points), such as MAC addresses, broadcasted SSID, hidden SSID, link speed, RSSI values, network capabilities, and each channel's frequency.

WatchDog: The WatchDog monitors the framework operation each minute, verifying that all the data logging modules are running and restarts any that are not. It also pings our server every 5 minutes to indicate that the framework is still alive and collecting data. A separate server process notifies the study participant by email to check her phone (and eventually reboot it), if it does not receive this ping for more than 30 minutes.

We stored all logged data into an SQLite database on the mobile's phone external storage (*i.e.* miniSD card), rather than using the phone's internal memory. Offloading the data from internal to external memory kept the phone's memory available for the proper operation of the device, reducing the influence of the framework on the device's operation.

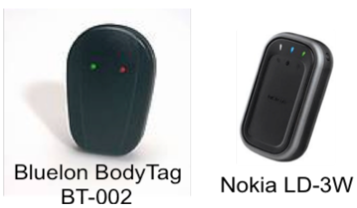

Figure 1. Bluetooth tags given to participants

Proximity Data Collection

To collect data on the proximity of users to their smart phones, we provided Bluetooth devices to our subjects, as in the original Patel paper. However, unlike the original work, we did not have enough of a single type of Bluetooth device, so we used a combination of BlueLon Bluetooth tags (3) and Nokia Bluetooth GPS devices (25) (Figure 1). We provided lanyards to each participant to wear the device around their neck. Every morning, participants received an automated email, reminding them to wear their device.Similar to the original study, the Bluetooth Manager in the AWARE framework performs a Bluetooth scan every 60 seconds, and determines the distance of the phone from the provided Bluetooth device using RSSI measurements. However, because we did not provide smart phones to our subjects and because we used a variety of Bluetooth devices, we collected calibration data for each user (smart phone-Bluetooth device pair). We collected a few minutes of RSSI data for each of the following: within arm's reach (1-2 meters), within the same room (5-6 meters) and unavailable (beyond 6 meters). After removing outlier RSSI values (using a quartile approach), we identified the range of valid RSSI values for each of our 3 distances. We do

Table 1: Demographic information, percentage data lost to framework errors. Also, ignoring lost data, percentage phone off and proximity without (and with) off data

	Gender	Profession	% bad data	% off data	% arm	% arm + room
1	F	Software eng.	4	16	47 (40)	95 (80)
2	M	Owner, moving company	25	24	45 (34)	78 (59)
3	M	Admin. Asst.	21	21	27 (22)	94 (75)
4	M	Driver	8	31	76 (52)	89 (61)
5	M	Student	16	21	76 (60)	99 (79)
6	M	AP coordinator	6	21	85 (68)	97 (77)
7	F	Designer	19	8	48 (44)	90 (83)
8	M	Web developer	54	17	53 (44)	72 (60)
9	M	PC technician	17	21	25 (19)	87 (68)
10	F	Software eng.	7	6	87 (82)	100 (94)
11	M	Graphic designer	14	23	30 (23)	68 (53)
12	M	Paramedic	15	31	65 (45)	99 (68)
13	M	Program manager	53	23	54 (41)	100 (77)
14	F	Researcher	16	23	32 (24)	44 (33)
15	M	Salesman	11	15	26 (22)	80 (68)
16	M	Collections agent	18	9	38 (34)	99 (91)
17	F	Librarian	9	8	74 (68)	96 (88)
18	M	Software eng.	5	7	47 (44)	100 (93)
19	F	Photo lab tech	22	16	51 (42)	66 (56)
20	M	Advertising agent	13	13	96 (83)	99 (86)
21	M	Software eng.	7	38	68 (42)	98 (60)
22	M	Systems analyst	11	21	43 (34)	86 (68)
23	M	Student	51	33	67 (45)	99 (66)
24	M	Teacher	18	54	38 (17)	82 (38)
25	F	Therapist	0	42	36 (21)	78 (46)
26	M	Social worker	7	16	38 (32)	93 (78)
27	M	Software analyst	37	30	34 (24)	84 (58)
28	F	Manager	9	18	73 (59)	99 (81)

note that even when using the same model of phone and the same model of Bluetooth tag, calibration was necessary, as different combinations of the same models resulted in different RSSI ranges.

Weekly Interviews

When our deployment subjects returned to our office each week over the 4-week study, we interviewed them for ground truth about their proximity to their mobile phone. This information was compared to the data automatically logged by the AWARE framework. Similar to the original study, participants completed a diary of the previous 24-

hour period wherein they record their activity and the relative location of their mobile phone, as suggested by the Day Reconstruction Method [13]. This method breaks the day into episodes described by activities, locations and time intervals, and the location of the phone during these times. During the interview, users explained, in more detail, the factors influencing their proximity. This way causalities and relations between proximity and user behavior could be identified, and any inconsistencies in the AWARE framework data could be clarified. As well, they indicated when they forgot the phone/tag, or took the tag off.

SUBJECTS

Thirty subjects were recruited using Internet advertisements in <city removed> using the survey described above as a screener. We compensated subjects with $250 each for participating in the entire study. Subjects' ages ranged from 18 to 45, and included 9 females and 21 males. They came from a range of ethnic and cultural backgrounds and had varying income levels and occupations (see Table 1). Two subjects withdrew from the study: one on the second day of data collection and the other after completing only the first 2 weeks. In the following section, we present the results of our analysis of the collected data from the remaining 28 participants, using Droid, Droid X and Nexus One phones.

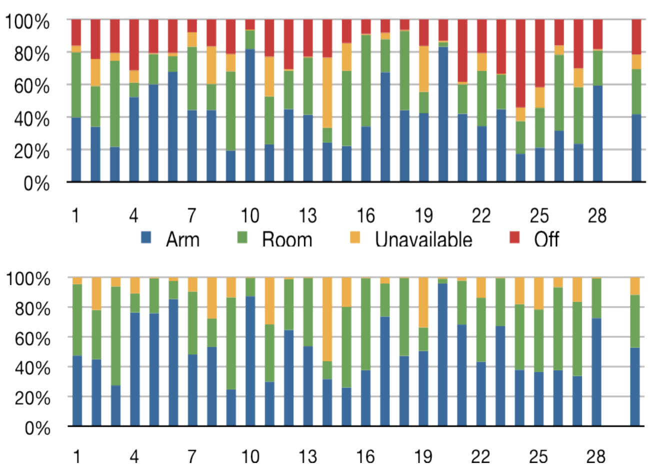

Figure 2. Distribution of proximity levels for each of the 28 participants, with (upper) and without (lower) off data, with the last bar representing the average across all participants.

RESULTS

Participants ranged in their participation from 27 to 30 days. On average, our phone failed to collect Bluetooth proximity data (but collected other data) 18% (std. dev. 15%) of the time. This number is high particularly because for some subjects we only noticed that there was a data collection error at the weekly interview, and that no data was collected that week. The remainder of our results and analyses will not include this data. Of the remaining time, users either turned their phone or just our application off for an average of 22% of the time (Figure 2). One reason this was so high is that users turned their phones off to conserve battery when they did not think they would use them or could not use them. One subject, S24 was a teacher who turned off her phone during school hours and at night. S17 was pregnant and turned off her phone in the evening and night. Despite our attempts to keep the AWARE framework's energy footprint low by making it mostly event-driven, some of our subjects complained about the impact it had on their phone battery and having to recharge more frequently.

Proximity Results

We acquired between 13430 and 37564 proximity samples (*i.e.*, number of minutes) from our subjects, with the average being 26474. Because not all subjects participated for the same number of days, these results are best viewed as percentages of participation (not including framework data acquisition errors, but including time when the phone was turned off) range from 46 to 94%, averaging 78%.

In *contrast* to our hypothesis that users of smart phones carry their phones with them (*i.e.*, within arm's reach) more than users of the previous generation of mobile phones, we found that our participants had their phones within arm's reach on average for only 53% of the time when the phone was on. This is similar to what Patel *et al*. found in 2006: 58% (see Table 2 for proximity percentages that include the time the phone was off). However, participants' perceptions were that their phone was within arm's reach 91% of the time. While most participants grossly overestimated their proximity, there were 3 subjects (S1, S26, S27) whose estimation was ~58%, much closer to the actual proximity.

However, while there was not an increase in the amount of time the phone was within arm's reach, we did find a *substantial increase* in the amount of time that our subject's smart phones were outside of arm's reach but were in the same room as them: 35% in our study vs. 20% from the previous study. Combining both within arm's reach and within the same room (arm+room) results in a total of 88% for our smart phone study and 78% for Patel *et al*.'s mobile phone study.

Table 2: Comparison of proximity between original study and ours, not including (and including) off time

	Arm's Reach	Room level	Arm + Room
Original	58% (47)	20% (16)	78% (63)
Our study	53% (42)	35% (28)	88% (69)

Proximity and Contextual Factors

We also examined the impact of different contextual factors such as day of week, time of day, and location. There were no differences in the proximity of the phone between weekdays and weekends: 53% and 52% within arm's reach for weekdays and weekends, respectively; and 89% and 87% for within room (and arm's) reach, respectively. This matches participants' perceptions that there was little difference between weekends and weekdays. The original paper reported similar results of 59% and 53% for within arm's reach for the weekdays and weekends, respectively.

The phone was within arm's reach 56% of the time when subjects were sleeping (estimated between 11pm and 7am), and 51% of the time, at other times of the day, whereas the

Table 3: Comparison of proximity at different times of day

	Arm	Room	Arm + Room
Morning (7-9am)	57% (46)	30% (23)	87% (69)
Daytime (9am-6pm)	51% (40)	36% (28)	87% (68)
Evening (6-11pm)	48% (37)	40% (31)	88% (68)
Night (11pm-7am)	56% (46)	33% (26)	89 %(72)
Not Night (7am-11pm)	51% (40)	37% (29)	88% (69)

Patel paper showed a different trend with percentages being 52% and 61%, respectively. There was less distinction at the arm+room proximity: 89% while sleeping and 88% at other times. Table 3 shows the distribution of proximity for different times of the day.

The phone was within arm's reach 46% of the time when subjects were home (Patel: 50%), and 54% of the time (Patel: 71%) when in named locations other than home, and within room and arm's reach cumulatively 83% (Patel: 77% when at home), and 85% (Patel: 82% when not at home), respectively. Table 4 shows the distribution of proximity for different categories of locations that our subjects identified in our initial interview. While proximity at the arm level varied, proximity at the arm+room level stayed relatively stable. Most subjects reported that their proximity to their phone was not different between work and home, and that perception bears true.

We also checked to see if there was a correlation between proximity at the arm or arm+room level with either time spent talking on the phone or the number of SMS/MMS sent. However, these factors were not correlated.

Table 4: Comparison of proximity in different locations

	Arm	Room	Unavailable	Arm + Room
Home	46%	36%	17%	83%
Not Home	54%	31%	15%	85%
Work	48%	33%	18%	82%
Shopping	62%	20%	17%	83%
Leisure	50%	37%	13%	87%
Family	56%	33%	10%	90%
Friends	51%	30%	18%	82%
Gas	74%	3%	22%	78%

Factors Affecting Phone Proximity

We now discuss factors that impact users' proximity to their phone, based on qualitative information collected from the 28 participants in our data collection study, as well as the 339 additional subjects who responded to our survey but were not selected. Like the original study, we derived our factors using affinity clustering to group the self-reported factors from our interviews and surveys into themes, and from the features that contained the most information gain from our predictive models of phone proximity.

During the weekly interviews, as part of the day reconstruction method, we asked participants to describe their activities and the proximity of their phone over the past 24 hours. We asked them for additional detail about why their phone was in a particular location throughout this day. We first used this information and the survey data to identify the themes in the original study that we did and did not (light grey text below) have evidence for, and then to identify new themes.

1. *Routine*: The phone's proximity was linked to users' flow of usual activities, *e.g.*, a) at home, leaving phone in a fixed/central position such as on a coffee table or shelf or at work, leaving it on their desk; b) at home, the phone is with the user to support using different applications substituting for a PC or to call a spouse inside a big house; c) outside the home, carrying the phone in a pocket or on a belt clip by a male, and in a purse or bag by a female (depending on her outfit).
2. *Environment*: The phone's proximity is related to the physical constraints of the space. For example, at home, users kept their phones in the same rooms as them, while in the car, the phone was most often within arm's reach.
3. *Physicality of person/activity*: The phone's proximity is related to the physicality of the person or the person's activity. For example, while playing sports or exercising, we found that users chose to keep their phones with them to listen to music. While the theme matches that of Patel *et al*., we find the opposite result.
4. *Disruption to others*: In contrast to the original study, we have not identified any evidence suggesting that a user's phone proximity is based on how it might affect other people or the environment. This could be because social norms around cell phone use have evolved over the last 5 years [1].
5. *Disruption of self*: The phone's proximity takes into account the impact of proximity on the user. For example, at home, users kept phones in central places with the idea that it could get their attention regardless of their location. Others who responded to our survey reported that they put their phones "away" on weekends so as not to be bothered.
6. *Regulations*: We identified a number of situations where users turned off their phones in certain locations due to legal or other specific regulations preventing use. For example, one subject was a teacher who had to turn off her phone in school. Similarly, others turned off their phones in churches and hospitals, and in other locations where camera phones were forbidden.
7. *Use of phone by self*: Users made choices about the phone proximity based on their anticipated use of the phone. Unlike the earlier study, rather than keeping them close for making a phone call, our subjects did this for access to data, *e.g.*, carrying the phone inside the house to be able to check something quickly on the Internet. In addition, from our survey respondents, we saw that some people used their mobile phones to check their private email accounts while at work.
8. *Use of phone by others*: The phone's proximity was affected by the idea that someone else would want to

contact the subject. For example, users would keep their phone in a fixed/central location in their home to hear phone calls (similar to the previous study), or be notified about email/SMS arrivals (new in our study).

9. *Use of phone both by self and by others*: We primarily saw evidence of this theme through descriptions of coordination efforts. For example, some kept the phone close by to make it easier to coordinate efforts for going out with friends on the weekend, while the moving company owner did it to coordinate his staff.
10. *Use of handset by others*: We did not identify any evidence suggesting that a user would make a choice about the phone proximity based on the expectation that somebody else would physically use the device. This could be because smart phones and cell phones have become widely available [4,14] and, therefore, are becoming more personal devices.
11. *No need for use of phone*: When users believed they were not going to use their phones soon, users were willing to be further away. While only about one-half of our subjects had a landline phone, for those who did, the expectation that a caller could reach them using this line, was evidence of this theme. While at work, having access to a PC for relevant data/Internet supplanted use of the phone and affected its proximity.
12. *Technical resources*: The phone's proximity is impacted by technical considerations inherent to limitations of the phone. We saw evidence of this theme when users limited the mobility of their phone when charging (USB or AC adapter). In addition, survey respondents physically moved with their phone to acquire improved signal reception in their home.
13. *Quick trips*: Unlike the previous study, we found that users did not leave their phones behind when taking quick trips. Our subjects tended to take their phones with them when going on a coffee break and when going to the bathroom. This may be related to theme #19 about the use of the phone during idle periods.
14. *Memory and forgetfulness*: We saw multiple instances where users simply forgot their phone at home or work or left/forgot it someplace temporarily.
15. *Protection of phone from others*: Similar to the previous study, we saw that users made choices about phone proximity to protect the phone from tampering. For example, users put their phone out of reach while playing with children. Similarly, survey respondents reported leaving their phones behind when going out for fear their expensive smart phones would be stolen.

In addition to the analysis of the 15 themes identified in the original paper, we identified 5 new emergent themes:

16. *Costs associated with usage*: The phone's proximity is associated with monetary costs related to phone usage. While everyone in our study had an unlimited data plan, they still had to pay for data usage when traveling abroad. As such, the few subjects that left the U.S. during our study tended to keep their phone off.
17. *Personal Utility applications*: The phone's proximity is related to use of its applications in a given context. For example, phones were often used as an alarm in the bedroom while subjects were sleeping, to support nutrition or sports training in the gym, and to replace the use of a PC at home.
18. *Data privacy on the phone*: The phone's proximity is related to access of data applications holding or accessing private data on the device, *e.g.*, checking private email on phone while at work and having access to a corporate network while not at work.
19. *Idle time in between activities*: The phone's proximity is related to time spent on mobile data applications while waiting for some activity to start. For example, users checked their email or accessed the web while waiting for a friend, waiting for a bus, or even while on the toilet.
20. *Applications for planning or scheduling coordinated tasks*: The phone's proximity is related to tasks requiring the management of coordination and cooperation. For example, some users used shared grocery lists or to-do lists with a partner, used Google Calendar to add new group events, and then accessed this information at later times.
21. *Protection of phone from environment*: The phone's proximity was affected by users' beliefs that the phone had the potential to be damaged. Survey respondents reported leaving their phones behind when going fishing (wary about water damage) and when cooking in the kitchen (wary about water and heat damage).

PREDICTING USERS' PHONE PROXIMITY

Similar to the Patel paper, we also investigated whether we could predict users' phone proximity using information that are already available on the phone, rather than using our extra Bluetooth tag. For each subject, we use our Bluetooth tag proximity information as ground truth, and attempt to predict whether the phone was within arm's reach, or within arm+room. using the contextual information we collected with our AWARE framework. If the predictions are accurate, application developers can use our prediction models to determine when they can use the phone to collect contextual information from phone owners (arm's reach) or to collect contextual information about the owner's environment and deliver information to them (arm+room).

We created models that could classify phone proximity. We used a decision tree classifier using the ID3 algorithm so we could interpret the resulting trees and determine which features were most important to the classification task. Features near the root of decision trees usually have high predictive power and can be treated as important features.

We formulated the model building as two supervised learning problems, in which the class labels are three (arm vs. room vs. unavailable) and two (arm+room vs. unavailable) levels of proximity. Each data instance is a feature vector extracted with a one minute time window from the logged contextual data. We used three different feature sets to build our models. We ranked features for each subject using the Greedy Stepwise search method with Consistency Subset evaluation method from Weka [10], and used the top 3, 5 and all features. Figure 3 shows the 10-fold cross validation results using all the data from each subject for our 2 classification problems. We achieved 75 and 83% accuracy for the 3-class and 2-class problems, respectively, with large variations across our subjects.

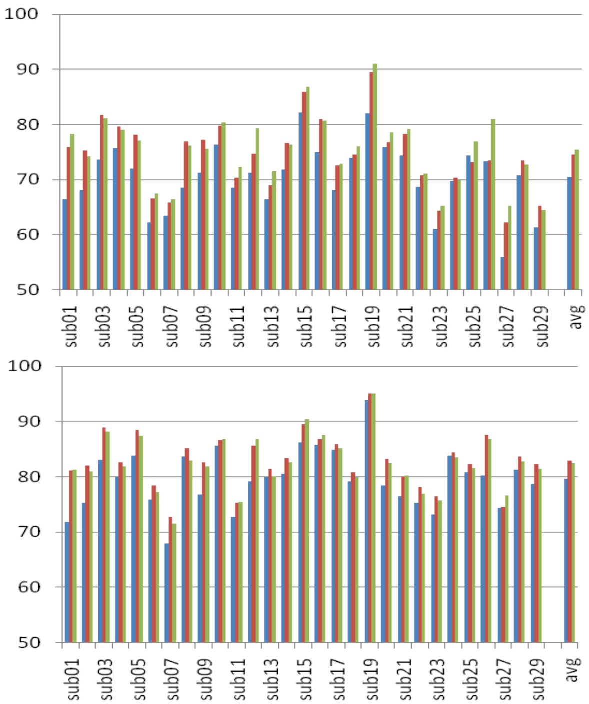

Figure 3. Classification accuracy for 3-class (upper) and 2-class (lower). Blue, red, green represent 3, 5 and all features, S3 (only 2 weeks of data) is included for completeness.

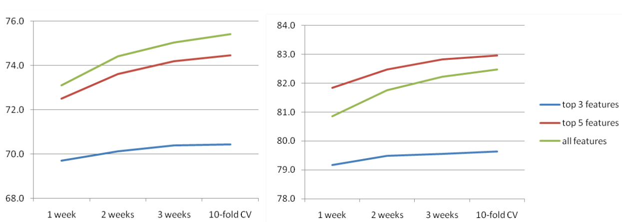

Figure 4. Analysis of the number of weeks of training required for accurate 3 –class (arm vs. room vs. unavailable) and 2-class (arm+room vs. unavail) models.

To determine how many weeks of data were needed to build a reliable model, we trained 3 additional models on the first one, two, and three weeks of data, testing on the remaining data using 10-fold cross validation. Figure 4 shows that while 3 weeks of data may not be enough for producing accurate models in the 3-class problem, 1 week of training provides reasonably high accuracy in the 2-class problem. Also, exploiting more features requires more training data to model their relationship with proximity.

We also analyze the features selected using the search method (Feature in Table 5) and the features at and near the root of the decision trees (DT). Similar to the original study, we found hour of day and time of day to be quite predictive of proximity. However, location was not very useful. The other features we found to be useful were very related to activities that the user performs and interaction with the phone: acceleration, application used, battery level, battery temperature and screen status. Battery temperature is particularly interesting as high values are correlated with close proximity: carried in a pocket next to a warm body, or being used for CPU-intensive applications.

Table 5: Predictive features for 3-class and 2-class prediction problems. Number of participants using each feature from the search method (Feature) and decision trees (DT).

	arm+room vs. other		arm vs. room vs. other	
	Feature	**DT**	**Feature**	**DT**
mean acceleration (acc)	8	2	15	2
std deviation of acc.	5	0	12	3
application used	4	8	4	8
battery level	18	20	15	22
mean battery temp.	24	19	24	17
tower ID for CSDMA	0	3	0	0
day of the week	29	27	26	29
tower ID for GSM	1	0	1	0
hour of the day	28	24	28	26
screen status (on, off)	21	4	12	2
ringer status (on, off)	2	6	0	2
weather	5	1	3	3

DISCUSSION

We now discuss our hypothesis about the proximity of smart phones, the results of our study, and our analysis.

Actual Phone Proximity

We were very surprised to see that there was no increase in the proximity of users to their mobile phones, with the availability and widespread use of smart phones. Our intuition led us to believe that access to the Internet, the use of smart phones as entertainment devices, and the huge uptake in apps would increase proximity. In fact, we saw a slight decline at the arm's reach from 58% to 53%.

However, we did see a considerable increase in proximity at the room level from 20% to 35%, resulting in an overall increase at the arm+room level from 78% to 88%. We first describe the implications of this increase and then discuss the possible reasons for it.

Many ubicomp systems make the assumption that users always have their smart phones with them. If that assumption were true, it would allow these systems to:

- Collect user context (*e.g.*, motion, activity)
- Collect user's environment context (*e.g.*, sound)
- Get the user's attention at any time and present information (*e.g.*, notifications)
- Provide an always-available service for the user

However, our work and Patel's earlier work showed that users don't have their phones with them at all times. However, our work does demonstrate that users often are in the same room (or very close by) to their phones. While only a little more than half the time can the phone be used as a proxy for the user's physical context, almost 90% of the time, it can be used as a proxy for environmental context, a mechanism for getting the user's attention, and a medium for delivering always-available services.

From our interviews, surveys and our analysis of themes, we have a better understanding of why this change occurs in users' proximity to their phones. We heard several examples from each of our participants of placing their phone down on a table or desk, to keep the phone close by and easily reachable, but not immediately at-hand. It was enough to have the phone easily reachable in the case of notifications or phone calls, to look something up on the Internet or to use an app for a short period of time. None of these require the phone to be within arm's reach. Almost all the themes discussed (Patel's orginal and our new ones) help provide evidence for why people keep their phones nearby, but not necessarily within arm's reach: routine, environment, disruption of self, use of phone by self, use of phone by others, use of phone by self and others, use of handset by others, no need for use of phone, technical resources, quick trips, memory, personal utility applications, data privacy on the phone, idle time in between activities, applications for planning, and protection of phone from environment.

Perception of Phone Proximity and Individual Difference

On average, most of our participants believed they were in close proximity to their smart phones almost 22 hours a day! Half of our participants said they were *always* next to their phones. As we have shown, this number is closer to 10 hours a day, when taking *off time* into account. Users clearly tend to greatly overestimate their proximity. However, users are within arm+room level almost 16.5 hours per day, when considering off time. We do see considerable individual differences. From Table 1, 16 of our participants keep their phone at the arm+room level over 90% of the time the phone is on, with 13 of those at 95% or above. The remaining participants have arm+room levels ranging from 44 to 89% and average 76%.

For the 16 participants that keep their phones nearby almost all the time, it is unclear whether a prediction system is necessary for determining when the phone is nearby. With proximity rates of more than 90%, assuming the phone is nearby (arm+room) could be more accurate than many learned models of proximity. There are 7 users whose proximity at the arm level is 75% or greater, and the same statement can be made for them.

Phone Proximity By Context

Just as we were surprised by the lack of increase in proximity at the arm level with smart phones, we were also surprised that there was no difference in proximity between weekdays and weekends. There were some however, interesting differences in proximity at the arm level by location. Users were less likely to keep their phones within arm's reach at home, work, places of leisure, and at friends' residences. In contrast, they were more likely to keep their phones within arm's reach while shopping, buying gas, and visiting with family. The difference between proximity from home to other locations defined and geo-located by our participants was 46 to 54%. From our interviews with our participants, we found that in places where they were most comfortable and familiar, they tended to leave their phones further away from them: close by so they could use them, but not within arm's reach. As well, the 3 locations where phones were closer, tend to involve activities that allow for smart phone interaction during short idle periods.

Similarly, we saw differences in proximity by time of day. While proximity at the arm+room level was independent of this factor, proximity at the arm level was not. Participants tended to have their phones closer during sleeping hours than during other hours (56 vs. 51%). This can partly be explained by the use of smart phones as an alarm clock. Users were also closer to their phones during the morning hours (7-9am). Participants explained that they used their phones to check email and other Internet resources shortly after waking up, and during their commute to work. The times with the lowest proximity are the work hours and the time at home after work and before sleeping. Combined with the location results just described, the lower proximity values are not surprising. Both differences in location and time of day offer opportunities for designers of mobile phone applications to use the phone as a proxy for the user and their environment, and for communicating with users.

Predicting Phone Proximity

We produced models of proximity that used contextual factors from phone sensors that could predict when the phone was within arm's reach with 75% accuracy, and within arm+room with 83% accuracy. These models are not computationally intensive and can be executed quite easily on today's smart phones. There was large variability in accuracy by users, and in the features that were most predictive. This implies that a single population model or a small number of population models (as suggested by Patel *et al.*) may not be possible. It is interesting that all the most predictive features are directly related to user activities, both those in the real world (*e.g.*, movement) and those on the phone (*e.g.*, phone usage as measured by battery level and temperature). Perhaps by collecting information on the active applications on the phone and using more sophisticated features related to user activity we can improve the accuracy of our models. Certainly by taking into account those that were almost always within the arm+room level, and combining with the predictive models (taking the maximum accuracy for each subject), we can reach an overall predictive accuracy of 92%.

Limitations

As with the original study, our study has some limitations. We studied a limited population (28) of smart phone users for a limited period of time (4 weeks). As such, it may be difficult to generalize these findings to other populations of smart phone users. We provide this detailed exploration of how smart phone users use their phones and their proximity to their phones to illustrate the challenges and opportunities for designers of phone applications looking to use the mobile phone as a proxy for user context and attention.

One issue with our study was the amount of data we lost data due to issues with our data collection framework. We discovered that some of our participants had an automated task killer app on their phone. A task killer app removes processes (in our case, modules from our framework) that use up significant memory or CPU. This caused us to lose significant amounts of data (up to 54%, although most had data losses ~10% or lower) from some of our participants, until we identified the app and asked them to remove it. Another issue we did not account for was the amount of time the phone was off. While both we and the original paper report reasonably high proximity numbers from our studies, these numbers drop significantly when time when the phone is off is considered. Participants in our study had their phones off or our framework off 22% of the time. This results in our arm+room proximity to drop from 88% to 69%, when taken into account. As off time can be considerable, especially for some users (*e.g.*, paramedic, teacher, pregnant participant, foreign travel), off time needs to be considered when designing mobile applications that make assumptions about phone availability.

CONCLUSION AND FUTURE WORK

We have presented a field data collection-based study of 28 smart phone users to understand whether their phones can serve as proxies for their context and availability. We found that when their phones are on, they are only within arm's reach 53% of the time, but within arm+room 88% of the time. Based on these results, we build on the work of Patel *et al.*, and show how mobile application designers can leverage smart phones as proxies for users' environmental context, availability for delivering information and availability for accessing information. We demonstrate that we can reasonably predict user proximity with easily collected features about user activity, and when combined with knowledge about individual users and their normal proximity, we are very accurate (greater than 90%). In the future, we intend to collect and leverage additional features regarding activity and user context to further improve our predictive ability. We also will build this ability into mobile applications as a demonstration of its effectiveness.

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