Phoneprioception: Enabling Mobile Phones to Infer Where They Are Kept

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ABSTRACT
Enabling phones to infer whether they are currently in a pocket, purse or on a table facilitates a range of new interactions from placement-dependent notifications setting to preventing "pocket dialing." We collected data from 693 participants to understand where people keep their phone in different contexts and why. Using this data, we identified three placement personas: Single Place Pat, Consistent Casey, and All-over Alex. Based on these results, we collected two weeks of labeled accelerometer data in-situ from 32 participants. We used this data to build models for inferring phone placement, achieving an accuracy of approximately 85% for inferring whether the phone is in an enclosed location and for inferring if the phone is on the user. Finally, we prototyped a capacitive grid and a multispectral sensor and collected data from 15 participants in a laboratory to understand the added value of these sensors.

Author Keywords
Context awareness; mobile sensors; phone placement

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
Throughout most of the world, mobile phones are ubiquitous – it is truly the uncommon case to find someone who does not own a mobile phone. While a few studies have examined the proximity of people to their phones [1,8] and where people have them while out and about [4], we still know relatively little about how people manage the burden of carrying a device. While intuitively we know the set of places that people put their phones (e.g. pocket, bag, table), we lack much in the way of real facts. What are the possible places that people keep their phones? What are the factors that influence where a person puts her phone?

If phones could reliably infer where they were placed, an entire set of new applications would be possible, including: placement-dependent notification settings, the ability to prevent accidental input when the phone screen had not been locked, supporting flexible authentication schemes, and adding context to other information that is being sensed and shared from the phone.

Our goal is to build a broad understanding of how people manage where they keep their phones across different contexts (e.g. walking, driving, at home), and assess the capability of a variety of sensors to infer where the phone is being kept. First, we carried out a series of in-person interviews and a Mechanical Turk survey to understand how people manage the location of their phone in a variety of contexts. From this dataset, we identified three phone placement personas: Single Place Pat, Consistent Casey and All-over Alex, who have distinct placement behaviors.

Informed by our understanding of phone placement, we then collected two weeks of accelerometer data from 32 participants' personal mobile devices. Using the experience sampling method (ESM), participants recorded how the device was being stored in-situ. To evaluate algorithms for inferring the placement or *proprioception* of the phone, we built and evaluated models using features from the in-situ accelerometer data. These models achieve accuracies of 85% for two different two-class models (Enclosed vs. Out and On Person vs. Not) and 75% for a four-class model (Pocket, Bag, Out, Hand).

Finally, we explored opportunities to improve the accuracy of the accelerometer-only models, using prototype sensors that leverage capacitive sensing (previously unexplored for this task), multi-spectral properties, and light/proximity sensing. We compare data gathered with these sensors in a laboratory setting, with resulting models achieving top accuracy levels of 85% to 100%.

Our results shed new light on where the phone is being kept and the tradeoffs between different sensing approaches for inferring phone placement. Specifically:

- We contribute an in-situ assessment of using accelerometer data for inferring phone placement, where prior work has focused exclusively on the laboratory.
- We assess the value of capacitive sensing for inferring phone placement, a modality not previously explored
- We directly compare new and existing sensors, where previous work has only examined the value of individ-

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ual sensing techniques without a direct comparison to related sensing techniques.

RELATED WORK

Prior studies on phone proximity, placement, and methods for inferring placement informed our research.

Studies Of Phone Placement

Recently, researchers have questioned how often a person's phone is in their immediate proximity. In 2006, Patel *et al.* found broad variation across participants with individual proximity levels for the phone being within arm's reach, ranging from 17% to 85%. Whether or not the person was home, sleeping, or if it was the weekend had the biggest impact on behavior [8]. Dey *et al.* replicated that study in 2011 with similar results: the phone was within arm's reach 53% of the time and within the room 88% of the time [1]. They also highlighted that a user's context and routine affected phone proximity, for example leaving the phone out when at home and carrying it in a pocket outside of the home. Our research complements these studies by examining the question of where the phone is being kept.

More closely related, in 2005, Ichikawa, *et al.* conducted a large-scale interview study asking 419 people in Helsinki, Milan and New York where they keep their phones when they are out, why they chose this place, and if it was the usual place [4]. Their results were strongly divided by gender, with 57% of men reporting that their phone was in their trouser pocket (8% for women), and 76% of women reporting that their phones were kept in a shoulder bag or backpack (10% for men). They also reported reasons that participants identified for placing the phone outside of the normal location, including variations in clothing (e.g. no pockets), expecting a phone call, or not wanting to be interrupted. Informed by this research, our phone placement interviews look more broadly at placement in different contexts, which also enables us to develop phone placement personas. Our work contributes the first large-scale dataset that examines where people keep their phones throughout the day and how they make that decision.

Inferring Phone Placement

To better understanding where people keep their phones, we explore the extent to which phones might be able to infer their placement. Several efforts have focused on detecting from accelerometer data where on the body an item is located while a user is walking [5,14], and also in combination with gyroscope data [11]. These systems leverage motion constraints of human anatomy to infer phone location, all reporting accuracies of approximately 90% in laboratory experiments. None of these approaches attempt to classify any off-body locations (e.g., in a bag or on a desk).

Other approaches aim to be activity invariant by incorporating data from other sensors either in addition to or instead of the accelerometer. Sensay [12] used a light sensor in a lab environment to determine when a phone was in a trouser pocket or out of the pocket. Discovery [7] used features derived from listening on the microphone and a multi-round classification approach to infer whether the phone was in a pocket or not with approximately 80% accuracy.

The Polite Ringer II system [13] uses a combination of gyroscope, accelerometer, compass, light, and proximity sensors to infer when the user picks up the phone to receive a call so that the ringtone volume could be muted when the phone is picked up. HandSense [15] contains two capacitive sensors on each side of a phone-shaped prototype to determine how the user is holding the device, which they can use to classify six different hand-grip configurations.

In contrast to these unobtrusive techniques, others have explored approaches that could be observable by users. For example, activating the vibration motor on the device and detecting movement using the accelerometer [10], and a combination of active vibration and the emission of short 'beeps' while listening on the microphone and accelerometer to fingerprint the environmental response [6]. A potentially less noticeable active approach uses a photo resistor and a light-to-frequency converter for sensing light from five LEDs (red, green, blue, infrared, and ultraviolet) [3]. Using their device, Harrison and Hudson tested 27 different placements and achieved an average accuracy of 87% in their testing. We replicated this device and include it in our laboratory study for comparison.

Overall, this wide range of previous inference approaches covers disjoint pieces across the range of possible phone placement sensing methods with data collections and experiments conducted in controlled laboratory settings. Our research goes beyond previous contributions by collecting data in-situ and directly comparing a range of existing and new sensing techniques for inferring phone placement.

PHONE PLACEMENT INTERVIEWS

We began our investigation of phone placement with 50 short, semi-structured interviews with desk-based office workers in their usual office setting at our company. We approached participants in their offices and if they agreed to participate we asked:

- What was the current location of her mobile phone.
- Where she normally keeps the phone at work, at home while sleeping and awake, in the car, and while out walking around.
- How she decides where to put her phone.
- In how many of ten pre-identified places had she ever put her phone, and which of those places had the phone been in during the past 24 hours

These interviews lasted five to ten minutes, and participants were offered entry into a raffle for a $30 dining voucher. In addition, we administered a modified version of this same survey (omitting the "right now" question) to participants in our ESM and laboratory studies (some participated in both and were only interviewed once). We had a total of 93 (37 female) office worker participants (OWork).

To understand the broader generalizability of our results, and avoid any possible bias from an internal office worker population, we deployed a survey based on our interview questions on Amazon's Mechanical Turk (MTurk) to 600 participants (242 female) located in the U.S. and paid each respondent U.S. $0.25. We made a few formatting changes to suit the nature of an online survey. Most notable is that instead of providing a free-text response for "How do you choose where to keep your phone?" we provided checkboxes with the categories identified from the interview responses. There was some evidence MTurk respondents have more diverse jobs than our internal population, e.g. 65% spend less than 6 hours on a computer.

After carefully comparing responses from the OWork and MTurk populations, we determined they were similar in most respects (e.g. median number of places participants reported putting their phones, most common places to put the phone right now, gender differences, etc.) giving us confidence both in the validity of the MTurk survey responses and generalizability of the behaviors observed. Given the similarity, we present all results together and note any large differences.

In total, we report on data from 693 respondents (M: 414, F: 279). Most of our participants were between 20 and 39 years old (76%, 527). Some MTurk participants were under 20 (8%) and the rest of our participants were 40 and older. Respondents' phone OSs were distributed across Android (39%), iPhone (24%), feature phones (22%), Windows Phone (8%), Blackberry (4%) and the rest (2%) were MTurk participants that did not indicate operating system. MTurk respondents had a larger percentage of Android and feature phones than the OWork respondents.

How many places do people put their phone?

From prior work [1,4,8], we identified 10 places that participants might put their phone: a Front Trouser Pocket, Back Trouser Pocket, Jacket Pocket, Shirt Pocket, Purse, Backpack/Bag, Case on Belt, Out on Table or Desk, Out in Car, and In Hand. Of these, participants reported putting their phone in 2.8 places on average (med: 3, max: 8) in the last 24 hours, and 4.8 places on average overall (med: 5, max: 9). Our female respondents reported keeping their phones in significantly more places than men both overall (5.3 vs. 4.5, $t(691) = 7.06$, $p<0.001$) and for the previous 24 hours, (3.1 vs. 2.6, $t(691) = 5.97$, $p < 0.001$). Additionally, 8% of participants used a free response Other option to mention places including bed, nightstand, kitchen counter, and bra.

Where is the phone?

We asked 650 participants (M:394, F:256) where their phone was Right Now, (excludes ESM and lab study participants). The most common location was Out on Table or Desk reported by 68% of respondents. Next was Front Trousers Pocket (13%), Purse (4%), Bag/Backpack (2%), Hand (2%), Back Trousers Pocket (1%), Case (1%), Car (1%), and Shirt (<1%). The places mentioned by the 7% of participants that answered Other, mostly MTurk respondents, suggest participants were not in an office including having the phone on a bed or couch.

Although an equivalent percentage of male (67%) and female (69%) participants reported having their phone on the table right now, we saw a similar gender difference in phone placement around trouser pockets and purses to what Ichikawa [4] observed. A significantly higher percentage of men (20%) reported having their phone in their front trouser pocket compared to women (4%, Pearson chi-square $\chi^2(1, N=650)=35.48$ $p<0.001$). Conversely, all 27 participants that reported having their phone in their purse right now were female (11% of females asked).

More generally, the most common places all 693 participants reported putting their phones in the last 24hrs (participants could specify multiple) were similar to the Right Now results. On a Table or Desk was selected by 83% of respondents followed by Front Trouser Pocket (64%), Car (51%), Purse (28%), Bag (19%), Back Trouser Pocket (16%), Jacket (13%), Shirt Pocket (4%), and Case on Belt (3%). Not surprisingly, a significantly larger percentage of men (84%) put their phone in their Front Trouser Pocket in the last 24 hours as compared to women (34%, $\chi^2(1, N=693)=178.48$ $p<0.001$). We did find it somewhat surprising that the 16% of participants who indicated they used a Back Trousers Pocket (16%), had a higher percentage of women (23%) compared to men (11%, $\chi^2(1, N=693)=15.74$ $p<0.001$). Again, a significantly higher percentage of women (69%) reported putting the phone in a Purse compared to men (<1%) and also for non-purse bags (29% vs. 12%, $\chi^2(1, N=693)=31.26$, $p<0.001$).

Where is the phone for different contexts?

Table 1 shows where participants told us they put their phone in four different contexts: Walking, Driving, Home While Awake and in the Office. Participants could indicate more than one location and the average number of locations ranged from 1.4 (Driving) to 1.6 (Walking). For simplicity we merged three categories that received few responses into other categories. Trousers includes both front and back pockets as back pocket was less than 1% except when Walking when it was 8%. Jacket includes shirt pocket which was less than 1% for every context and Other includes case on belt which was 3% or less for every context.

At Home or in the Office about half our participants put phones on a table, and slightly under half of our participants keep their phones out while Driving. Response rates appeared consistent across men and women for these places. Combinations of contexts and places for which a significantly higher percentage of male or female participants

	Walk	Drive	Home (awake)	Office*
Trousers	**50%** $^{M+}$	26 % $^{M+}$	20% $^{M+}$	24% $^{M+}$
Purse	14% $^{F+}$	13% $^{F+}$	5% $^{F+}$	7% $^{F+}$
Bag	8% ^{F}	5% ^{F}	2%	7%
Jacket	9%	4% ^{M}	2%	7%
Hand	14%	3%	11%	0
Table	1%	<1%	**52%**	**49%**
Out In Car	<1%	**42%**	1%	1%
Other	4%	7%	7%	4%
Total	1083	1002	1039	135

Table 1: Where participants place their phone in different activities and locations. Respondents could indicate more than one place. Most popular place is bolded per column. *N=693 for each column except office where locations were only asked of the 93 OWork participants. ^{F} denotes a significantly higher percentage of female participants indicated this location based on Chi-square, ^{M} for males. $^{+}$ denotes Chi-square significance p< 0.001, all others p < 0.01

indicated that combination are annotated with an ^{M} or ^{F} respectively. Again we see the preference of men for trouser pocket and women for purses across contexts. We were somewhat surprised how few people indicated their phone was in a purse or bag at Home. The larger percentage of Other locations for Driving include passenger seat, cupholder, and center console. In several of the at-Home Other responses, participants indicated they had no particular place for the phone and were likely to carry it with them.

We also asked participants about where they kept their phone while sleeping. Based on the interviews we added the options of nightstand and bed to the MTurk survey. Nightstand (39%), Table (35%), and Bed (16%) accounted for 90% of the 920 locations participants reported. We were surprised by the prevalence of bed responses; two participants even used the Other option to tell us they kept the phone under the pillow. Another surprise was that 16 of the Other responses were floor. In the interviews, participants explained that the phone had to be on the floor because that was the location of the nearest plug to the bed. The only gender difference was that a significantly larger percentage of male respondents (52%) specified table as a location as compared to women (37%, $\chi^2(1, N=693)=16.37$ $p<0.001$).

How consistent are participants?

To understand whether participants tended to choose a single location to keep their phone across activities (e.g. in their trouser pocket or purse), used a consistent but different location for different context (e.g. purse while walking, out in car when driving), or had many different places they put their phone we examined the number of places respondents indicated they put their phone for each context.

Only 7% (47) participants indicated they put their phone in the same place regardless of activity or location, we termed this group *Single Place Pats*. Given the common usage of the front trouser pocket by men, we initially thought these participants might all be men. We found to our surprise this group had a similar percentage of male (32, 8% of male respondents) and female (15, 5%) participants. However, not surprisingly the single location where participants kept the phone differed by gender. Male participants primarily used the front trouser pocket (28 participants, 25 male), and women used purses and bags (13 total, 11 female). In addition a few participants indicated their single location was a belt case (2), car (2), jacket (1), or back trouser pocket (1).

37% (259) of our participants were *Consistent Caseys* who specified a single, but different place for each of walking, driving, and at home. Again both men (38%) and women (37%) reported this behavior. Slightly more than half of these Consistent Caseys (57%) specified a different place for each activity, while the rest (43%) had two of the same places and one different; consistent with Single Place Pats, front trouser pocket was the most common duplicated place for men and purse for women.

The final group of participants with distinct placement behavior were *All-over Alexs* who reported more than 2 places for each of walking, driving and at home when awake. This was 17% of our participants (121) and was made up of similar percentages of men (16%) and women participants (19%). These participants indicated on average 7.6 different places across Walking, Driving and at Home.

How do you decide where to keep your phone?

To understand how participants decide where to put their phone, we analyzed the responses to an open-ended question asked during the OWork interviews. First, one author generated codes for 50 of the responses. Then two authors independently coded all responses. Conflicting codes were resolved through discussion. These codes were used as options on the MTurk survey. We believe the ability to select reasons rather than provide a free response explains why MTurk participants on average selected more reasons (2.8) as compared to our OWork interviewees (1.7). Note that the percentages do not add up to 100 because responses could be coded for multiple categories. We saw no gender differences in the reasons reported.

Accessibility/Receive Notifications (83%): Participants in this category wanted to have their phones on their body or as convenient as possible to reach. 426 of the 575 participants (74%) in this category explicitly noted they wanted the phone to be close so that they would be able to receive notifications and calls. As one participant said "[I] need to be able to hear/feel it, needs to be accessible, so no purse."

Don't Lose/Habit (77%): These participants had a default location where they would put their phone, often because they did not want to forget where they had put their phone.

Of the 537 people in this category, 383 (71%) people explicitly indicated not wanting to lose their phone.

Safety of the Phone (49%): Participants in this category wanted to ensure that their phone was secure and protected. Specific concerns included falling out of a pocket, getting scratched by keys, or being sat on in the back pocket. Interestingly, a larger percentage of All-over Alex participants (67%) indicated safety as a decision factor than Consistent Caseys. (47%, $\chi^2(1, N=380)=13.04$, $p<0.001$).

Comfort (38%): Participants identified that some places they would otherwise like to keep the phone were uncomfortable. A few participants were concerned about health and radiation, but for most the concern was physical discomfort from keeping the phone in a trouser pocket, particularly while sitting. Comfort concerns may lead to more locations; a higher percentage of All-over Alex participants (50%) selected comfort compared to Single Place Pats (23%) and Consistent Caseys (32%) ($\chi^2(1,N=169)=10.63$, $p<0.001$, $\chi^2(1,N=380)=12.36$, $p<0.001$).

Minimize Distraction (11%): Participants put their phone in particular places so that it would not interrupt them. This is the opposite of the first category, although some participants fit into both categories: "alarm at night so [it needs to be] close by, pockets aren't big enough so hand or purse, keep it close by unless [I] don't want to be disturbed."

Other (3%): A few participants mentioned other reasons, the most common was charging as a factor that affects where they put their phone. e.g. "[I] like to keep it plugged [in], tend to keep it nearby, comfort is important."

ESM PHONE PLACEMENT STUDY

To collect sensor data in-situ that we could use to train and evaluate phone placement models we used the experience-sampling method (ESM) to collect accelerometer data from 32 participants' personal smartphones in conjunction with a ground-truth label describing the phone's placement. These in-situ labels complement the retrospective self-report data from the Phone Placement interviews. While interview participants were undoubtedly as complete as possible, in-situ survey data enriches our understanding of where users choose to keep their phones.

Data Collection

We built a data collection application, "Where's Your Phone?" (WYP) on the Windows Phone 7.5 platform. WYP collects 10 seconds of accelerometer data (three dimensions at 50 Hz) roughly every 30 minutes. It then prompts the participant to answer "Where was your phone at XX:XXpm?" Below this question, participants were given 6 choices including Other and I Don't Know. Each category had a few sub-categories. (See Table 2 for all 23 sub-categories). We chose categories based on the Phone Placement interview responses to minimize the number of situations when ESM participants would need to enter free-text Other responses.

Unanswered surveys expired when the next set of accelerometer data was collected and unlabeled accelerometer data was deleted. Participants specified a bedtime at which WYP turned off and a wake time at which it resumed. Participants could also "snooze" WYP for up to two hours at a time. Survey responses and corresponding accelerometer data were automatically uploaded to a server.

We recruited 32 participants (16 M, 16 F) from a Windows Phone 7.5 email list. Fifty-nine percent of participants were between 20 and 39 years old and the rest were older. Participants received \$10 plus \$0.25 per survey response (max \$4 /day) as a gift card at the conclusion of their two week study period after a short final interview.

ESM Survey Responses

Our participants submitted 5,524 ESM responses, although the number submitted varied across participants (med: 147.5, min: 29, max: 358). The total number of responses from male (52%, 2847) and female (48%, 2677) participants was similar. It is important to acknowledge the potential limitations in the comprehensiveness of the ESM responses; times when phones are away from their owner would be under-reported.

We believe the ground-truth labels are most useful for showing the breadth of places participants placed their phones, especially the additional sub-categories we coded from the Other responses (see Table 2). To account for the differing number of responses per participant, we calculated how many different participants reported putting their phone in a particular place in addition to total number of responses for a category, so we could see which categories are common across participants.

Out was by far the most common top-level category with 63% of responses (3504) contributed by all 32 participants. The sub-category Desk made up 47% (1646) of these from 31 participants, then In-Hand (564, 32 participants), Table (442, 28 participants), Counter (314, 23 participants), and Nightstand (241, 23 participants). Several interesting places matching survey responses were reported in the Out-other responses across participants including couch/chair (134 from 24 participants), bed (53 responses from 14), floor (31 responses from 13), lap (19 from 7) and shelf (19 responses from 5). We saw only one difference in reporting based on gender, 61% of the Table responses came from women.

Pocket was the next most frequently reported top-level category (22%, 1230, from 29 participants). Consistent with the survey data, we saw gender differences, 74% of Pocket responses were from men and 26% from women. The Front Trousers Pocket was the most common sub-category (984, 26 participants, 15 M, 11 F). That gender split seems surprising; however, even though 11 women reported Front

Category	Original Sub-Categories	Sub-Categories from "Other" responses	Enclosed Class	On Person Class	4-Class
Bag	Backpack, purse, shoulder bag, other	None	Enclosed	Other	Bag
Car	Cradle, cup holder, dash-board, lap, passenger seat, other	Center console, pocket on door	Out	Other (except for 'lap')	Out
Out	Table, nightstand, in hand, desk, counter, other	Couch/chair, couch/chair arm, cradle/charge station, floor, lap, shelf	Out	Other (except for 'in hand' and 'lap')	Out (except for 'in hand')
Pocket	Trousers front, trousers back, shirt, jacket, other	Apron, armband, holster	Enclosed	On Person	Pocket

Table 2: Phone placement labels and corresponding classifications. Note that two more categories existed that were not included for any classifications: "Do not know", which participants answered when they weren't sure where the phone was, and "Other" responses which we could not code into any of the existing or newly created categories.

Trousers Pocket at least once, most of the responses (76%) are from men. Conversely, the 413 Bag reports (8% overall, 18 participants contributing) are 91% from women.

Though responses about phone placement while Driving are less frequent (270 from 26 participants), they do highlight the diversity of places people put their phones. Responses were split between Cup Holder (109, 15 participants), Passenger Seat (72, 13 participants), Cradle (48 from 7), Lap (15 from 9 participants) and others with smaller numbers including the Center Console, Dashboard and Door. Note that participants do not necessarily have a single location in the car; half of participants reported more than one location.

Using their Phone Placement interview data we calculated whether any ESM participants were Single Place Pats (1 participant), Consistent Caseys (6) or All-Over Alexs (4). The other participants either did not clearly indicate a single preferred location (overall or per context) or did not have enough locations to be considered All-Over Alexs.

Participants' ESM response behavior seemed to correspond with this categorization. 56% of the 307 responses by the Single Place Pat participant indicated his phone was in his front trouser pocket. He also only ever reported having his phone in 8 of the 23 sub-categories. Matching the behavior of having a few consistent locations, the three most common places the six Caseys reported having their phones accounted for an average of 73% of their responses. They also only ever reported having their phone in an average of 9.2 different sub-categories. From the four All-over Alexs, we saw reports from more sub-categories, 11 on average). Three of the All-over Alex ESM participants had over 100 ESM responses, which were fairly evenly spread across sub-categories; their top three categories accounted for only 61% of responses on average and they had on average 7 categories that each received fewer than 10% of responses.

The GPS data we collected with each ESM response allowed us to categorize responses that happened at a participant's Home, Work, Other or Unknown location (11% of responses do not have GPS data due to technical failures). We did not observe any surprises. For example, 69% of responses for the car were made in Other locations; people reported their phone being Out roughly evenly across Home (32%), Other (32%), and Work (26%); and Pocket is much more common in Other places (50%) than at Home (16%) or Work (12%).

The ESM study highlights the rich diversity of places that participants put their phones and allowed us to collect labeled sensor data in-situ.

Modeling Phone Placement from In-Situ Data

To evaluate whether phones can infer the places that people put their phones in the ESM and Phone Placement studies, we used the labeled accelerometer data collected in-situ by our ESM participants. We extracted the following features over each axis of one-second windows of accelerometer data as inspired by previous work [5,11,13,14]:

- mean; variance; RMS
- interquartile range; 25%, 50%, 75% quartiles
- the sum of detail coefficients across the first 5 wavelet levels

We used these features to evaluate models for three classification problems (below). All models were built using the Weka Tooklkit's SMO SVM with a polynomial kernel [2]. We chose these features and the SMO algorithm by experimenting with pilot data we collected earlier. Results are reported from a leave-one-participant-out cross-validation.

We chose each of the following classification problems based on the results from the studies in the previous section:

Enclosed or Out: whether the phone is out and potentially visible to a user, or if it is put away. Applications for this model include preventing pocket dial, and knowing whether or not visual notification mechanisms (e.g.: flashing light or screen) will be noticed. This model achieved a mean accuracy of 85.3%. The confusion matrix can be seen in Table 3a, along with precision and recall values.

On Person or Not: whether or not the phone is on the user. Applications for this model include dynamic notification

a) Enclosed vs. Out

	enclosed	out
enclosed	***1690***	599
out	337	***3742***
precision	0.74	0.92
recall	0.83	0.86

b) On Person vs. Other

	onPerson	other
onPerson	***2335***	402
other	511	***4120***
precision	0.85	0.86
recall	0.89	0.82

c) Pocket vs. Bag vs. Out vs. Hand

	pocket	bag	out	hand
pocket	***1570***	25	73	335
bag	141	***32***	85	28
out	188	25	***2961***	194
hand	124	44	308	***235***
precision	0.78	0.11	0.88	0.33
recall	0.78	0.25	0.86	0.30

Table 3: Results from the ESM study for each of three classification problems. For all three confusion matrices, the labels on the left represent the correct class, and the labels on the top row indicate the predicted class.

preferences (a primary concern from survey respondents, e.g. whether or not to vibrate) and progressive authentication (whether the user has to reauthenticate, based on whether she could have been separated from the phone since last authenticated). This model achieved a mean accuracy of 85.7% (Table 3b).

In Bag, In Pocket, Out, or In Hand: where the phone is at a finer granularity. This is useful for the "find my phone" functionality (e.g., "your phone has been in a bag since 11:22 am," a concern expressed in survey responses) and for sharing the user/phone's context to provide social awareness. The performance of this model was lower than for the previous two models, as we expect when increasing the number of classes. The model achieved a mean accuracy of 75.4%, with Out being the most accurately classified, followed by Pocket. Bag and Hand performed much worse.

Error Analysis and Discussion

In the case of the four-class model, several notable items stand out. First, it is important to note that Bag and Hand, which performed quite poorly, also had distinctly fewer instances in our dataset than Pocket and Out.

The accelerometer can be thought of as capturing the orientation of the device, however unlike sitting out on a table (where it usually sits flat either face-up or face-down), a phone may be placed in a bag any number of ways, depending on the style of the bag, the orientation of its pockets, etc. Furthermore, at any given time a bag may or may not be being carried by a person, which could make some of these features confusing with other classes (e.g, pocket).

INFERING PLACEMENT WITH MORE SENSORS

To assess what sensing modalities would be most useful to augment an accelerometer-only approach to inferring phone placement, we conducted a laboratory study. While a lab study loses some of the external validity of our previous in-situ study, we were able to test a variety of prototype devices that we could not deploy in the field.

Additional Sensing Modalities

With a focus on different ways of disambiguating confusing situations from the ESM study, we brainstormed sensors (some based on prior work) that might improve the classification. We identified several criteria as important for the set of sensors we would test. First, we wanted to maximize privacy and minimize computational expense, in hopes that our solution could run continuously in the background on mobile devices. These criteria combined to defeat computer vision or audio-based approaches. Another criterion was that the techniques should ultimately not disturb the user. This eliminated some of the previously proposed techniques, which emit sound [6] or activate the vibration motor [10]. This left us with the following sensors:

Proximity Sensor and Light Sensor: These sensors already exist on many of today's mobile devices. It would be preferable to collect this data in the field, but a combination of technical limitations for accessing those sensors and the variety of configurations that lacked these sensors on the device made data collection during the ESM study infeasible. In this study, we collected the data using a development phone that gave us access to all sensors on the device.

Two-Dimensional Capacitive Array: While nearly all mobile devices use capacitive technology in their touchscreens, most processing of the capacitive input is done in hardware. As a result, we built a prototype capacitive-sensing device similar to that of Saponas, et al.'s PocketTouch [9]. Our device reports a raw capacitance signal from a 10 by 20 grid at roughly 100 hertz. The device was designed in a form factor similar to that of today's mobile phones (see Figure 1a). The most apparent capability of this sensor is detecting when a hand grasps a phone. Perhaps less obvious is that this sensor also detects the presence of a person's leg through the lining of a trouser pocket.

Multi-Spectral Sensor: Following as closely as we could to the approach taken by Harrison and Hudson [3], we constructed a sensing device comprised of red, green, blue, ultraviolet, and infrared LEDs, a photo resistor, and a TSL235R light-to-frequency converter (Figure 1bc). The device was controlled by an Arduino Pro Mini, logging readings from the two sensors to an on-board microSD card. While the current form of the device does not fully satisfy our criterion of not disturbing the user, we believe

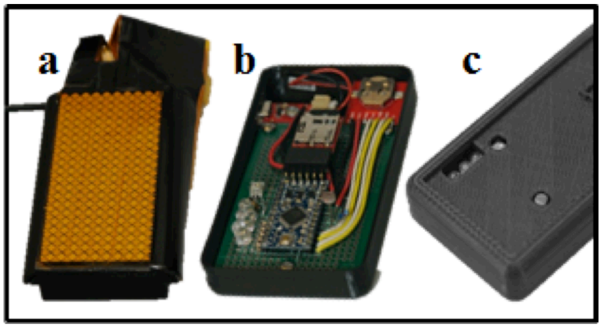

Figure 1: Sensor Prototypes. (a) Capacitive-sensing, (b) Multi-spectral sensor interior and (c) exterior.

that a carefully engineered version of this sensor might be nearly unnoticeable. Like the capacitive sensor, we constructed this device to mirror the form factor of a phone.

Data Collection

Using these three devices (development phone, capacitive-sensing prototype, and multi-spectral sensor), we collected data from 15 participants (6 Female). 73% of participants were between 20 and 39 years old and the rest were older.

We asked participants to bring anything that they might normally put their phone into including jackets, purses, or other bags. We collected data from each participant in any of the following places that they report having kept their phone: front trousers pocket, back trousers pocket, jacket pocket, bag/purse, and hand. We chose these based on our Phone Placement survey responses. To increase the external validity of this study, we did not have participants put our sensing devices in places that they would not normally put their phone. While this meant that we would capture more data for some participants than for others, it also maximizes the realism of our collected data.

For each place participants normally keep their phone, they completed a series of activities to simulate the various conditions that the device might encounter in everyday life while in the placement. For all placements except bag/purse, the activities were: sitting on a couch, sitting on a desk chair, standing in place, and walking around. We did not have participants sit for the back trousers pocket placement. For the bag/purse we had participants let the bag sit on the floor, stand while holding the bag, and walk while carrying the bag. Participants spent 20 seconds on each activity. Because each device had at least one sensor that was directional (e.g., toward leg in a trouser pocket), we collected all data for each placement with each device facing both inwards and outwards. We collected from two devices at a time to minimize the number of trials.

Surfaces

Unlike the other placements, most of the variation in placing a device on a surface involves finding a variety of surfaces. Thus we collected the surface-specific data ourselves, following a similar process to the other placements: we recorded data from each device in the two orientations of facing-up and facing-down. In total we collected data for 18 surfaces, including tables, desks, chairs, couches, on and in a metal filing cabinet, and even on a pillow.

Assembling the Data

For each placement (e.g., pocket or desk), we collected data from our three prototypes in two orientations each (e.g. facing-in and facing-out). We assembled these six sensor recordings for each placement into a single virtual-recording. This simulates a virtual device with the union of sensing capabilities from our three prototypes. This means that a single instance of collected data included: capacitive data (facing forward and backward), multispectral data (facing forward and backward), phone light/proximity sensor data (facing forward and backward), and phone accelerometer readings. We only considered one set of phone accelerometer readings because the second set from the phone facing the other direction was redundant.

Feature Extraction

We extracted features from the accelerometer facing one direction and our other sensors facing two directions. This allowed us to simulate a device with sensors on two sides.

Following Harrison and Hudson's approach, our multi-spectral features are one reading from each of the light-to-frequency converter and photo resistor for each of no-light, red, blue, green, UV, and IR. For the light and proximity-sensor on the phone, we took the mean over the 20 second window of the ambient-light level and the binary proximity state. Lastly, we took the mean over a one second window at each "pixel" in the capacitive sensing grid and computed three features over the grid: mean over pixels, median pixel value, number of non-zero pixels (pixels with some capacitance sensed). We used the same accelerometer features over a one second window as in the ESM study from the previous section.

Classification Technique

Our classification technique and evaluation followed that of the ESM study: a leave-one-participant-out cross-validation, where we counted each person or surface as a separate participant. We analyzed the lab study data by addressing the same classification tasks that we identified for the ESM study: Enclosed or Out, On Person or Not, and In Bag, In Pocket, Out or In Hand. Like the ESM data, we constructed Enclosed or Out models using Weka's SMO SVM with a polynomial kernel. When we experimented with pilot data, we discovered that the On Person or Not and In Bag, In Pocket, Out or In Hand problems were classified much better using Weka's implementation of Random Forest. Thus, we employ a Random Forest classifier for those problems in our lab study.

Results

Enclosed or Out

Perhaps unsurprisingly, the phone's light and proximity sensor seems to be the most useful sensor for classification,

	Enclosed	Enclosed P/R	Not Enclosed P/R	**On-Person**	On-Person P/R	Not On-Person P/R	**Pocket/ Bag/ Out/ Hand**	Pocket P/R	Bag P/R	Hand P/R	Out P/R
Accelerometer (AC)	89%	81/93	95/86	82%	80/79	84/85	79%	76/67	52/63	88/88	88/91
Light/Proximity (L/P)	98%	97/99	99/97	71%	55/69	82/71	70%	85/63	0/0	84/76	78/84
Multispectral (MS)	89%	91/86	88/92	80%	80/75	80/84	76%	6563	48/59	84/80	97/94
Capacitive (CAP)	58%	13/67	95/57	88%	87/85	89/90	73%	77/69	39/57	82/73	78/85
ACC + L/P	**100%**	99/100	100/99	84%	82/81	86/87	83%	81/72	45/58	95/91	95/98
ACC + MS	92%	89/93	95/92	82%	80/78	84/85	78%	77/63	24/36	88/94	98/97
ACC + CAP	85%	80/86	90/85	**90%**	88/88	91/91	79%	73/66	48/64	88/85	93/92
ACC + L/P + MS	99%	98/99	99/98	80%	79/74	80/84	81%	82/67	30/48	91/98	98/95
ACC + L/P + CAP	97%	99/95	96/99	**90%**	90/87	90/92	**85%**	82/77	52/61	91/89	100/100
ACC+L/P+MS+CAP	98%	98/98	98/98	88%	89/84	88/91	**85%**	85/72	36/63	96/95	100/98

Table 4: Accuracy and (P)recision/(R)ecall for all combinations of lab study sensors across the three classification problems.

yielding an average accuracy of 98%. Beyond this, there seems to be some evidence that the accelerometer can help to disambiguate the few errors made using light/proximity only, even achieving 100% accuracy in one case.

On Person Or Not

By contrast, when classifying whether or not the phone was on the participant, the light/proximity sensor performed the worst of each of the individual sensors (71%). In this case, the capacitive sensor was the single most useful sensor, achieving an accuracy of 88% on its own. Again the addition of accelerometer is most helpful, improving the accuracy to 90%, while the multispectral and light/proximity sensors do not seem to improve the accuracy. The capacitive sensing grid was likely so helpful because it can sense grasping of a device as well as detect a person's leg through the lining of many trouser pockets.

In Bag, In Pocket, Out, or In Hand

In the four-way classification, the accelerometer performs the best of any single sensor (79%), with the multispectral sensor also demonstrating its value (76%). Interestingly, the combination of these two sensors is not as valuable as the combination of the accelerometer with the light/proximity sensor, which achieved a combined accuracy of 83%. Ultimately, the combination of accelerometer, light/proximity sensor, and capacitive sensor is most effective, achieving an accuracy of 85%. The errors in this model come primarily from confusion over when the device is in a pocket or a bag. We had hoped that the capacitive sensor would be more valuable in this case, helping to disambiguate between being in a bag and being up against somebody's skin. Regardless, the overall improvement from accelerometer-only is still quite notable.

Comparison with ESM Data

Overall, there were not major differences between the accelerometer-only models in the lab study and those from the ESM study, even though the ESM data came from a broad variety of different devices and was collected in-situ.

DISCUSSION

Capacitive Sensing Best for Detecting "On Person"

Ensuring they would receive notifications was a primary factor in how our survey respondents decided where they put their phone. Results from the lab study show that the most successful sensing strategies for inferring whether or not the phone is On Person all involved the use of the capacitive sensor. This is particularly notable for several reasons. First, capacitive sensing has not been previously explored as a tool for inferring phone placement. Additionally, today's smartphones already employ capacitive technology in their touchscreens, though the raw capacitance is not accessible in software. Finally, if capacitive sensors were accessible, additional applications could benefit (e.g. [9]).

Challenges Detecting Placement in Bags

Survey data indicated that phones are frequently placed in bags and purses; however our models performed quite poorly on this class. This represents an important problem that remains unsolved by the techniques that we examined here. Our data suggests that there are enough differences between bags that generalized models may not be effective. Because most people use a fairly small number of bags, one solution (while clunky) would be to place RFID tags in the few places in a bag where users keep their phones, though a fully automatic phone-based solution is clearly preferable.

Applying Phoneprioception

Our promising Phoneprioception results enable several new interactive device capabilities we are excited to explore.

Placement-based Notification Preferences: Accessibility, primarily for receiving notifications, was the most common phone placement decision factor reported by our participants. Using Phoneprioception would enable a person to set placement-specific notification preferences (e.g., vibrate if in my front pocket; turn on the screen if sitting out on a table first and then ring, etc) and explore whether different phone placements coincide with a desire to change notifications preferences. For example, using vibration is a useful ringing preference when in a trouser pocket, but can be quite jarring if it vibrates while sitting on a hard surface.

Preventing Pocket Dial: Despite the fact that proximity sensors have become nearly universal on smartphones, accidental interaction with a phone's touchscreen remains a nuisance. Phoneprioception enables the phone to infer that input may be accidental. When a phone detects that it is "enclosed," it could lock the screen, or require some intelligent input before initializing a phone call.

Dynamic Authentication Requirements: Authentication on mobile phones can be painful, both because of the small interaction space and because of the frequency with which people interact with their phones. However, using Phoneprioception, if the phone was confident it had been "on person" since the last time the user authenticated, it might not require reauthentication or use a less rigorous form of authentication.

Phoneprioception As Contextual Information: At its most basic, Phoneprioception exposes a new piece of contextual information for the phone. We expect phone placement context could be useful to share with others (e.g.: predicting whether or not somebody will respond to a phone call) or as an additional piece of information for the "Find My Phone" service available on many platforms (e.g.: "your phone is at home in your backpack"), which could be quite useful to our All-over Alex participants.

As application developers consider using Phoneprioception we think it will be interesting to study people's response to applications that change behavior based on phone placement. What happens when there is an unintended behavior triggered by where the phone is placed? Will participants change their own behavior to fit this new capability of Phoneprioception or will they reject it?

Beyond the Phone

While we focused on smartphones, we believe the results have implications for a broad array of devices: mobile health technology, music players, cameras, remote controls, and of course tablets. While sensor placement may vary for some of these devices, and not all placements will be equally likely across the devices (e.g., many tablets do not fit in trouser pockets), the basic capabilities of Phoneprioception outlined in this paper should apply beyond the specific form factor of the phone.

CONCLUSION

Phoneprioception could be used in many ways to enable new user experiences. In this research we have broadly explored where people keep their phones throughout the day and in a variety of contexts through interviews and an in-situ ESM data collection. From this data we identified three placement personas: Single Place Pat, Consistent Casey and All-over Alex. We demonstrated that reasonably accurate classifications are possible with sensors that are already industry-standard, and that the addition of several other low-cost sensors further improve this performance.

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