CS 525M Mobile and Ubiquitous Computing: Getting Closer: An Empirical Investigation of the Proximity of User to Their Smart Phones

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Introduction

- Main problem: re-investigate the assumption about users’ proximity to smart phones
- Intention: smart phones vs. previous generation of mobile phones
- Value: implications on the development of mobile phone applications

    collect user and environmental context

    deliver notification to users

Three-fold

- evidence to understand the degree to which smart phones are an accurate proxy
- identify themes to explain, providing implications for future application
- build accurate predictive models of proximity using features about user activity

Related Work

- Activity sensing endeavors such as UbiFit, SenSay, and MotionBand
- In 2006, Patel *et al*. found the phone was on 81% of the time (within arm's reach 58%, within the room 20%), unavailable 38% of the day (23% of the on time and the time when the phone was off);

  small variance on proximity between weekday and weekends, waking versus sleep and home and away
- Classifiers determined whether the phone was within arm's reach with 86% accuracy

Methodology

- Original experimental setup
- Surveys
- 4-week long data collection
- Weekly interviews

Survey—collect subjects' perceptions about phone use and proximity

- how they used their phones and how close they kept phones in different situations
- mobile applications they use and frequency of use, as well as experience with the phone and expectations being met with respect to mobile communications.
- socio-economic status information of respondents

Data Collection

- Android AWARE Data Collection Framework

  developed by Android SDK 2.1

  collect proximity and contextual information

  SQLite database on mobile’s phone external storage

Sensing modules

- *Activity Manager*—active, inactive and background processes, current active activity on the screen, CPU and memory usage
- *Battery Manager*—battery-related events
- *Bluetooth Manager*—scans each minute for Bluetooth devices
- *Call Manager*—keeps track of incoming, missed and outgoing calls
- *Phone Manager*—captures the phone’s carrier information on the device

- *Location Manager*—collects the device's location every one minute (first network triangulation then GPS coordinates)
- *Network Manager*—network traffic and IP address along with network connections/disconnections
- *Screen Manager*—On/Off and unlocks/locks the screen
- *Sensor Manager*—sensor events
- *Messaging Manager*—SMS and MMS messages
- *Weather Manager*—weather forecast
- *Wi-Fi Manager*—Wi-Fi state /access point information
- *WatchDog*—framework operation/restarts modules that are not running

Tools

- combination of BlueLon Bluetooth tags and Nokia Bluetooth GPS devices
- scan every 60 seconds, determines the distance of the phone from Bluetooth using RSSI measurements
- calibration data: arm’s reach (1-2 meters), the same room (5-6 meters) and unavailable (beyond 6 meters)

Interview

- compared to the data logged by AWARE framework
- Day Reconstruction Method:

  break the day into episodes (activities, locations and time intervals, and location of phone)

Subjects—28 participants

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)

Results

- failed to collect Bluetooth proximity data 18% of the time
- turned phone or the application off for an average of 22% of the time

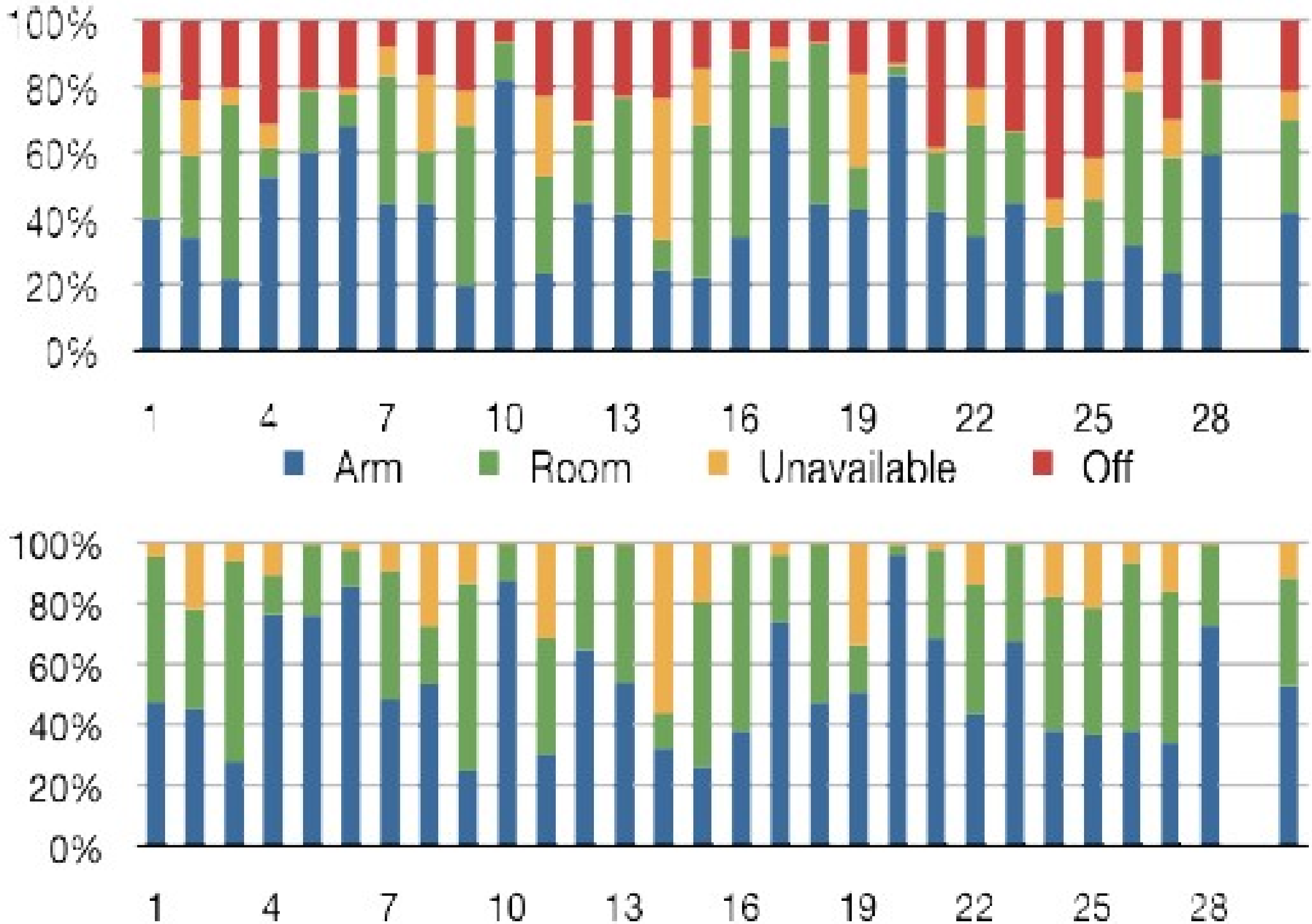


Figure 2. Distribution of proximity levels for each of the 28 participants, with (upper) and without (lower) off data, with the last bar representing the average across all participants.

Proximity Results

- average 26474 minutes—averaging 78%
- within arm's reach 53% vs. participants' perception 91%

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

- weekdays and weekends: 53% and 52% within arm's reach; 89% and 87% within room reach

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)

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%

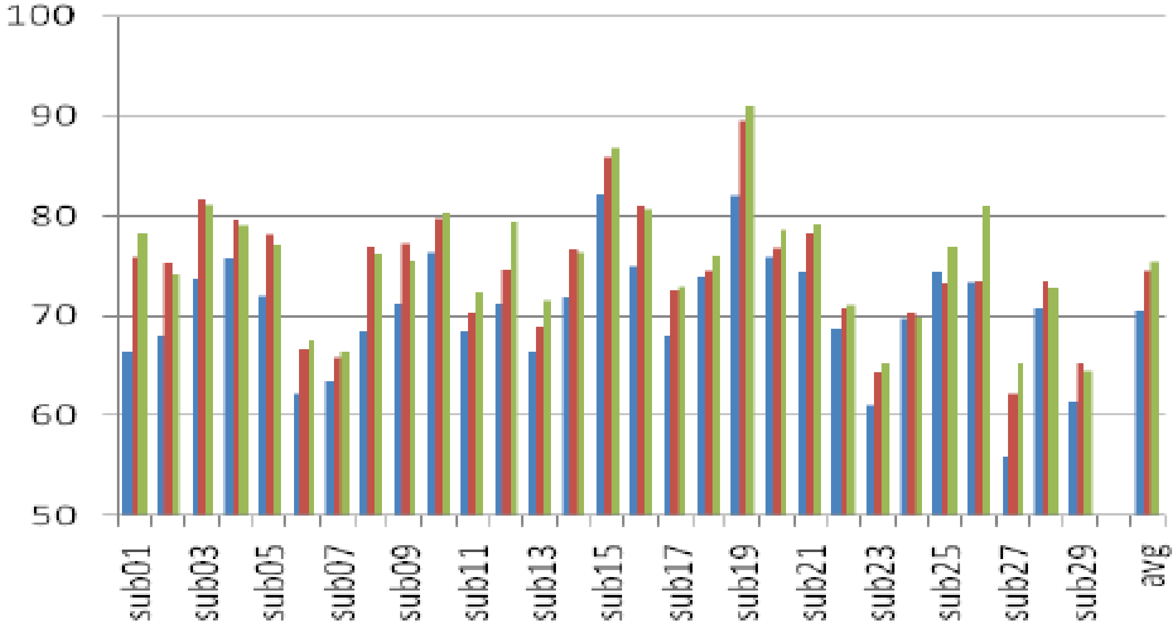
Factors Affecting Phone Proximity

- *Routine*: flow of usual activities
- *Environment*: physical constraints of the space
- *Physicality of person/activity*
- *Disruption of self*: impact of proximity on the user
- *Regulations*
- *Use of phone by self*
- *Use of phone by others*
- *Use of phone both by self and by others*

- *No need for use of phone*
- *Technical resources*: technical considerations inherent to limitations of the phone
- *Quick trips*
- *Memory and forgetfulness*
- *Protection of phone from others*
- *Costs associated with usage*
- *Personal Utility applications*
- *Data privacy on the phone*
- *Idle time in between activities*
- *Applications for planning or scheduling coordinated tasks*
- *Protection of phone from environment*

Predicting Users' Phone Proximity

- decision tree classifier using the ID3 algorithm
- model building as two problems—three class labels (arm vs. room vs. unavailable) and two class labels (arm+room vs. unavailable)
- Greedy Stepwise search method with Consistency Subset evaluation method from Weka, used top 3, 5 and all features
- 75 and 83% accuracy for the 3-class and 2-class problems



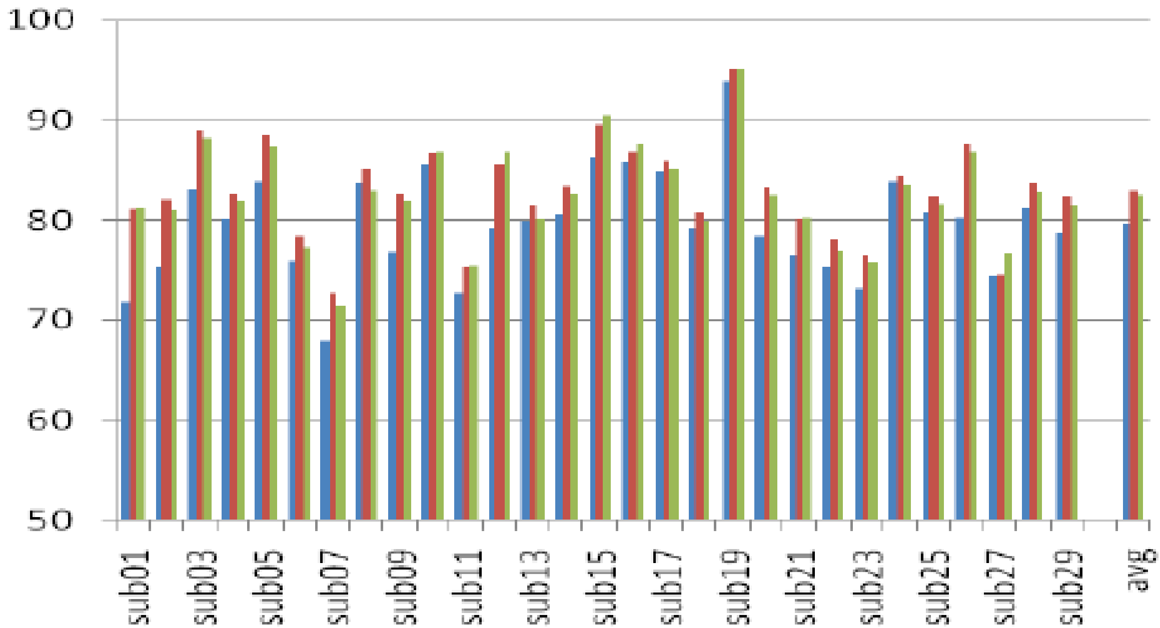


Figure 3. Classification accuracy for 3-class (upper) and 2-class (lower). Blue, red, green represent 3, 5 and all features, S3 (only 2 weeks of data) is included for completeness.

- 3 additional models on the first one, two, and three weeks of data
- 3 weeks of data not be enough for producing accurate models in 3-class, 1 week of training provides high accuracy in the 2-class

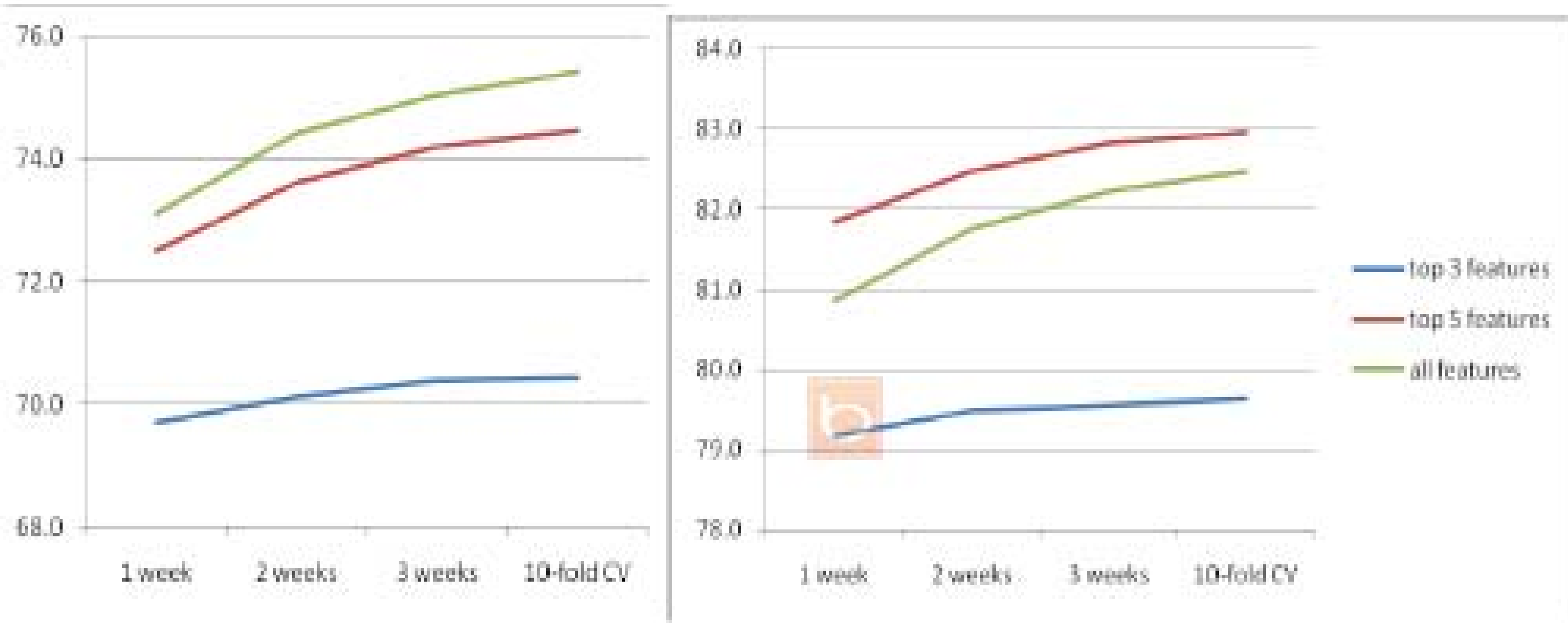


Figure 4. Analysis of the number of weeks of training required for accurate 3 –class (arm vs. room vs. unavailable) and 2-class (arm+room vs. unavail) models.

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

- **Actual Phone Proximity**

  why (decline at the arm's reach but increase at the arm+ room level)?

  Not require the phone to be within arm's reach

- **Perception of Phone Proximity and Individual Difference**

  proximity 10 hours a day rather than 22

  16 participants —arm+room level over 90% of on time assuming the phone is nearby—more accurate than models of proximity

- **Phone Proximity By Context**

  places (comfortable and familiar)—further away

  close by but not within arm's reach

  have their phones closer during sleeping hours

- **Predicting Phone Proximity**

  use active applications and more sophisticated features related to user activity to improve the accuracy of models

Limitations

- limited population for a limited period of time
- the amount of data we lost due to an automated task killer app
- not account for the amount of time the phone was off

Conclusion

- data collection-based study
- how mobile application designers leverage smart phones as proxies for users' environmental context, availability for delivering information and availability for accessing information
- predict user proximity with collected features about user activity

Future Work

- collect and leverage additional features regarding activity and user context to improve our predictive ability
- build into mobile applications as a demonstration of its effectiveness

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