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Exploiting Energy- Aware Localization with Social Network Based Interaction in Mobile Phones

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ABSTRACT: Observational research on the social impact of cell phone usage in public places suggests that the mere presence of cell phones in public conflicts the private and public spheres and inhibits social interaction with proximate others,saving the energy of the mobile phones , storage of user profile data and make sharing quickly becomes difficult. In addition to mobility, another defining characteristic of mobile systems is user social interaction. To manage this entire problem two methods have been proposed, initially E-Shadow method is proposed for distribute mobile local social networking system. E-Shadow has two main components: (1) Local profiles. They enable E-Shadow users to record and share their names, interests, and other information with fine-grained privacy controls. (2) Mobile phone based local social interaction tools. E-Shadow provides mobile phone software that enables rich social interactions. In second design and prototype an adaptive location service for mobile devices, a-Loc, that helps reduce this battery drain. The proposed design is based on the observation that the required location accuracy varies with location, and hence lower energy and lower accuracy localization methods. It continuously tune continually tunes the energy expenditure to meet the changing accuracy requirements using the available sensors. A Bayesian estimation framework is used to model user location and sensor errors. Experiments on real world Windows Mobile phones and large-scale simulations show that our system disseminates information efficiently; it helps receivers find the direction of a specific location with accuracy. The experiments demonstrate that can recognize not only whether a social interaction is taking place, but also the type of social interaction, distinguishing between formal and informal user social settings.Focusing on helping behaviour in particular, Results Indicate That While On The Cell Phone, Users Are Less Likely To Offer Help.

Index Terms- E-Shadow, Mobile Phone, Layered Publishing, Direction-driven Matching, Energy- Aware Localization, Bayesian Estimation framework and Social Interaction Network

I.INTRODUCTION

Recent news articles are reporting a dramatic increase in the use of battery-powered,mobile, lightweight, handheld devices often equipped with wireless interfaces [1-2]. Examples of such ubiquitous devices include cell-phones and PDAs, music players like Zune, and gaming devices like PSP. The number of mobile systems for these devicesis also quickly growing. Their key challenge is providing functionality in a dynamicand often unreliable network environment. This need has led to a flurry of research on the design and implementation of new protocols and applications that can handle and perhaps exploit the primary characteristic of this new environment user mobility.

In addition to user mobility, another defining characteristic of mobile systems is user social interaction. A variety of new applications focus on facilitating social activitiesin pervasive systems. For example, new Internet dating services allow clients to use their cell-phones' Bluetooth radios to detect when they are in the proximity of a person that matches their interests [3]. Other companies are offering file-sharing softwarefor mobile phones that allows users to share ring-tones, music, games, photos,and video [4]. In these new mobile systems, information exchange is driven by the users' social interactions: friends use their cell-phones to share photos or song collections;strangers with similar dating profiles are notified when they are near each other.

Cell phone usage can be defined as any application of thecell phone as a tool, including talking, text messaging, gameplaying or the sheer accessibility of the instrument. Originallythe cell phone served as a tool for business management.Now, cell phones serve as a tool for social connection,in other words, managing social relationships. Across qualitativeand quantitative studies, users of the cell phone allreport using their phone for social purposes. However, scholarshave argued the cell phone might actually serve as a toolfor social isolation [5]. Therefore, thesocial use of cell phones has proven to be a rich area forcommunication research, with researchers exploring variousways in which cell phone use affects social interaction, bothisolating and connecting involved persons. In the wave of human centeredpervasive computing [6], mobile phones are becoming amajor driving force to lubricate social networking amongpeople with its powerful communication and sensingcapabilities [7], [8].

Monitoring of social interactions using mobile phones istypically based on sensing proximity or on detecting speechactivity. A frequently applied approach for inferring socialactivity through the detection of proximity relies on the useof Bluetooth [9-10]. Since the Bluetooth communicationsrange is in the order of ten meters, this approach providesonly a coarse spatial granularity in recognizing interpersonaldistances; therefore, the knowledge about proximitybetween individuals is used to model the dynamics of socialinteractions at large scale rather than detecting each singlesocial encounter which takes place at small spatio-temporalscale. As an alternative, Wyatt et. al [11] proposed the methodof extracting audio data features using microphones froma pair of co-located mobile phones, in order to detect whowas speaking and when thus detecting face-to-face interactions.The algorithm does not capture raw audio databut a set of features which does not contain verbalinformation. However, the microphone-based approachesare sensitive to false positives as nearby conversationscan be unintentionally picked up. In addition, activatingmicrophone typically entails compromising privacy andethical issues – in a number of situations audio data cannot be obtained due tolegal or ethical norms [12].

This paper provides a solution that uses non-auditorysensors embedded in the current smart phones to detect theoccurrence of social interactions which occur on a smallspatio-temporal scale. Develop a system service, named a-Loc, that automaticallyadapts location energy and accuracy based ondynamically varying sensor characteristics as well as applicationneeds.Furthermore,demonstrate high predictive power of spatial parametersto detect social context of face-to-face interactions .The goal is toprovide a tool for acquiring a better insight into socialactivity of subjects and the contexts of individual socialinteractions thus to potentially support the research in socialnetworks analysis and the investigation of formal/informalstructures.

II. BACKGROUND KNOWLEDGE

People build expectations based on prior experiences andknowledge of similar situation. For example, do not expect to interact with strangers unless it is necessary (e.g., emergency). Therefore, it is safe to assumethat when one is on the cell phone, he or she does not expect to interact with strangers, for the chance of initiating a conversation with strangers is small to begin with. However, the social norm of helping others who are in need can break the usual interaction expectation with strangers. Although literature shows that are less likely to interact with unfamiliar social proximate others, argue that the presence of a cell phone further decreases the possibility of that interaction.

Raento et al. [14] were one of the first who proposed mobile phone data collection for large-scale context sensing. More recent algorithm for identifying social groups and inferring frequency/durationof meetings within each group was proposed by Mardenfeld et al. [15] who tested their approach on the Reality Mining dataset. In addition to modeling the patterns of person-to personinteractions, Do and Gatica-Perez [16] showed that it is possible to infer different interaction types using a probabilistic model applied on longitudinal Bluetooth data. However, Bluetooth scans indicate the presence of nearby devices in a radius of 10 m, which does not provide sufficient information to detect an ongoing social interaction which takes place on a small spatio-temporal scale; rather, such an approach is used to model the longitudinal dynamics of social interactions.

In order to address the limitation of Bluetooth scan to detect actual face-to-face proximity between subjects, the Virtual Compass project [17] estimates interpersonal distances using RSSI analysis of Bluetooth and Wi-Fi signals. By applying empirical propagation models, the approach achieves the median accuracy between 0.9 m and 1.9 m while also detecting position of subjects in 2D plane. However,the lack of subjects' orientation information might not be sufficient for modeling the occurrence of face-to-face social interactions.It is a peer-basedrelative positioning system that usesWi-Fi and Bluetoothradios to detect nearby mobile devices and places themin a two-dimensional plane.

E-SmallTalker [18] is a systemthat leverages Bluetooth Service Discovery Protocol toThis article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publicationexchange user-defined contents without establishing a connection are similar applications in this category.These applications also have some issues. First,applications like Nokia Sensor need users frequent interventionto manually configure Bluetooth or Wi-Fi connections.

Surroundsense [19] is a mobilephone based system that explores logical localizationvia ambiance fingerprinting collected from differentsensors embedded on mobile phones. E-Shadow doesnot need to decide a target's absolute position; instead,it uses a new human-assisted localization approach thatmainly focuses on deciding at which direction the targetlocates.

III. PROPOSED ENERGY AWARE BASED SOCIAL NETWORK FOR MOBILE PHONES

Introduce our solutions to efficient and selective information publishing designed for the E Shadow system. To have it continuously on and broadcast E-Shadow information will deplete the battery very soon. In this light, propose another solution, called layered publishingin total three layers:

1. WiFi SSID: On the first layer, 'abuse' WiFi nameto broadcast E-Shadow information within a range of40-50 meters. Put the information to share in WifiSSID field. Others can acquire the information by asimple scan, thus obviating annoying connection setupprocesses. However, the WiFi SSID field is very limited.It can contain only 32 bytes information on the WindowsMobile system.

2. Bluetooth Device Name: Back up WiFi SSID withBluetooth device name. May easily use

Bluetoothdevice names to publish hundreds of more bytes .This is the second layer. On this layer, also 'abuse'Bluetooth device name to disseminate information. Soit can also achieve unobtrusive information delivery,with the low energy consumption of Bluetooth as aplus. Interestingly, find that the Bluetooth devicediscovery range is more than previously thought. In ourexperiments, find it can typically reach up to 20meters .

3. Bluetooth Service Name: If Bluetooth device name isstill not enough, can publish more information inthe Bluetooth service name/discription. Its communicationrange is 10 meters. Then put the most detailedinformation on this layer. It may also include invitationfor further interactions, such as clues to solicit a messageor wireless connections.

After receiving the information from nearbypeople, the receiver may naturally want to know whoand where the E-Shadow owner is to facilitate furthersocial interactions.As a real-world example that provides a concrete testcasefor a-Loc, consider mobile search. Mobile searchis an important application for two reasons. First, there isa much larger number of mobile devices than desktops, andthese devices are rapidly becoming capable of obtaining informationfrom the Internet, through either full fledged smartphone browsers such as Mobile Safari or limited capabilitybrowsers using WAP, iMode etc. This has made mobilesearch the fastest growing mode of search usage. Secondly,mobile search is especially important to search serviceproviders such as Google, Yahoo, and Microsoft becausea significant fraction of mobile searches involve searchingfor local services or products. This type of mobile searchis easiest to monetize, not merely through advertisements accompanyingsearch results but also through transactions initiatedbased on those results.

At a high level, a-Loc considers multiple factors that affectlocation estimation, including a prediction of the user'slocation, the error performance of location sensors, energycosts, and application accuracy requirements. Figure 1 showsthe key components of our proposed system, and they arediscussed below.

Dynamic Accuracy Requirement: This block provides thelocation accuracy needed by the applications. For the mobilesearch-based applications, provide a method to computethe accuracy requirement based on the entities searchedbut in other cases, the accuracy need may bedirectly specified by the application.
Sensor Energy Model: These models characterize the energyused by each available location sensor for obtaining location. Then experimentally measure this for the modalitiesused and also compare the data to similar measurements onother phones.

Dynamic Sensor Accuracy Model: This model is developedfor each sensor to characterize the quality of locationinformation that it offers.

Sensor Selection Algorithm

The sensor selection algorithmdetermines the location sensor to be used at each timestep. The algorithm includes a method to model the user locationtrajectory and uses the sensor data as available to improvethe location estimates.A Bayesian estimation framework is used to combinethe sensor data and predicted location to provide a maximumlikelihood estimate.The goal of the selection algorithm is to determine the most energy efficient sensor to be used, such that the requiredlocation accuracy can be achieved.
variable x(t), that takes values in a two dimensional space.Suppose the location observation from sensing modality i attime t is denoted $z_i(t)$ as before. Suppose $\overline{z(t)}$representsall observations made up to the time instant t, ie$\overline{z(t)} = \{z(t), z(t-1), \dots z(0)\}$ for any i. Then, the probabilitydistribution of location at current time t given all previouslymade observations and prior models is given by $p\left(x \middle| \overline{z(t-1)}\right)$.Formally, thelocation estimate after using modality i is characterized bythe posterior probability distribution $p(x(t)|z_i(t))$. For eachsensor modality i, can use the spread of the distributionof $x(t)$, given a reading from that modality $z_i(t)$, as a measureof the error in the estimated location. The trace of thecovariance matrix is used to characterize this spread for thetwo dimensional distribution, much like variance is used forone dimensional random variables. The error for modality $i$given an observation, denoted $e_i(t)|_{z_i(t)}$, becomes,

$$e_i(t)|_{z_i(t)} = tr\{Cov\left(x(t)\middle|z_i(t)\right)\} \tag{1}$$

The computation of the covariance matrix requires the posteriordistribution, which can be computed using the sensoraccuracy model and the prior location distribution, via Bayesrule:

$$p\left(x(T)\middle|z_i(t)\right)\alpha\, p\left(z_i(t)\middle|x(t)\right)p\left(x\middle|\overline{z(t-1)}\right) \tag{2}$$

Compute the error that would resultfrom using modality i before spending the energy toobtain $z_i(t)$, compute multiple posteriors $p(x(t)|z_i(t))$for different possible $z_i(t)$, that may be observed, resultingin a different error estimate for each of the multiple possibleobservations, $z_i(t)$,. Then take a weighted average ofthese error estimates, where the weights are the probabilitiesof getting different observations $z_i(t)$for modality i. Theprobability of getting an observation $z_i(t)$, depends on thecurrent location, and since do not have the current location,use an estimate for the probability of getting observation$z_i(t)$. The probability distribution of the observationsis obtained using the distribution of predicted location as follows:

$$\hat{p}\left(z_i(t)\right) = \int_{\chi} p(z_i(t)) tr\{Cov(x(t)|z_i(t))\} dx(t) \tag{3}$$

Where $p\left(z_i(t)\middle|x(t)\right)$ comes from the sensor accuracy model ,and$p\left(x(t)\right)$ comes from the location prediction .The weighted average of $e_i(t)|_{z_i(t)}$ for all the possible observations $z_i(t)$ becomes,

$$\hat{e}_i(t) = \int_{Z|x(t)} \hat{p}(z_i(t)) tr\{Cov(x(t)|z_i(t))\} dz_i(t) \quad (4)$$

Where $Z|x(t)$ represent the support of $\hat{p}(z_i(t))$.This $\hat{e}_i(t)$ quantitatively characterizes the expected error for modality i at the current time step. Having computed the estimated accuracy $\hat{e}_i(t)$ of sensor i the sensor selection problem can be expressed as ,

$$\hat{\iota} = \arg\min_{i\in\mathcal{L}} E_i(t) \quad \text{subject to} \quad :\hat{e}_i(t)<e_r^2(t) \quad (5)$$

Where e_r represent the desired location accuracy and $E_i(t)$ represents the energy used by modality i .Square of the desired accuracy is used since variances and trace of covariance matrix characterize error as a square of the variable estimated.

Direction-driven Matching

As the user is not very sensitive to the distancetraveled, allow him to walk a certain route to helpdecide the direction where the signal comes. In ourdesign, allow users to manually input the directionand distance every time he walks. Then the phonewill take the measurements and make calculations. Forillustration purposes, expound our mechanism usinga triangular route. Measurements are taken at every turningpoint. However, in open field, suggest users to walkalong a five-point semi-octagonal route, as is shown by$A \rightarrow B \rightarrow C \rightarrow D \rightarrow E$. This route is verynatural for a person to walk in a crowd, and providesinformation about RSSI change in all possible directions.After all RSSI measurements are taken in, compareeach pair of the RSSIs and then partition the space to get. If a line points from A to B, then RSSI at B is largerthan that at A. It means that the source is located nearerto B. If draw a perpendicular bisecting line of edgeAB, the source is in the subplane the arrow points at. It results in the upper-right cornerwith slant lines, where consider the source point islocated. This region may be infinite in range. However,can easily bound it with a circle of maximum wirelesscommunication range. Then draw a bisector of thisregion to give the direction.

IV.EXPERIMENTATION RESULTS

Proposed work has conducted extensive experiments and large-scale simulations to validate our design. The results are reported below.Evaluate the system performance whichincluding its collection time, energy consumptionand accuracy for deciding the walking directions.

Collection time

The experiments work is conducted to proposed work to show how fast a receiver can collect information from different wireless devices. In the experiments, have one device to be the receiver and let other mobile devices.

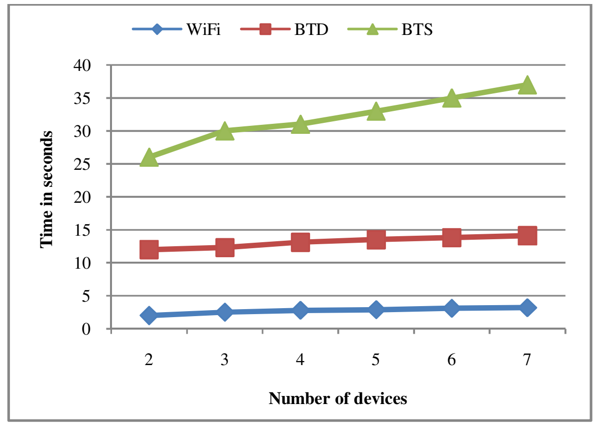

Fig. 1. The collection time for Exploiting Energy- Aware Localization with increasing number of devices

The Exploiting Energy- Aware Localization collection time on the receiverside is shown in Fig. 1. As can be seen from the figure,it takes the least time, i.e., at most 2 seconds, tocollect E-Shadow information on the WiFi layer. Thecollection time stays almost constant with increasingnumber of simultaneously working devices. However,it takes much longer on the BTD layer, i.e., around 10-15seconds. And on the BTS layer, need 25-35 secondsto find other E-Shadow profiles. The long delay can beattributed to Bluetooth's scanning mechanism. Bluetooth needs around 10 seconds to do device scanning. After other devices are found, it needs to query the devicefor the device name and the service names. The latteris normally much longer and hence takes more time,especially when the service does not exist.

Energy Consumption

Experimentation work is conducted to evaluate the power consumption of Exploiting Energy- Aware Localization, when it works in the server mode, i.e., broadcasting Exploiting Energy- Aware Localization, and the client mode, i.e., collecting Exploiting Energy- Aware Localization.

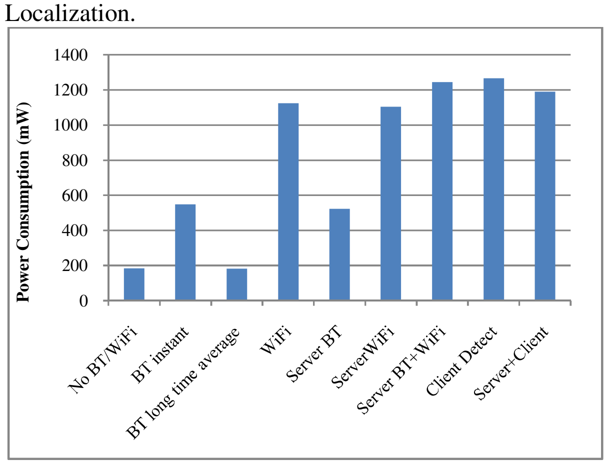

Fig. 2. Energy consumption of Energy- Aware Localization

Fig. 2 the energy consumption of eachpossible state of the mobile phone, where Exploiting Energy- Aware Localization system is installed. It is a common phone status of Exploiting Energy- Aware Localizationclient version. The power consumption is close to 185 mW. Alsoa working WiFi interface consumes 1145 mW, almosttwice the energy of a Bluetooth interface. However,over a long time, Bluetooth have much lower averagepower consumption at around 185 mW. If Exploiting Energy- Aware Localizationthe server version on with only WiFi, the powerconsumption is around 1312 mW. For E-Shadow withBluetooth aggressively broadcasting, this value is a littleover 550 mW. However, with both of them on, it onlyconsumes around 1300mW. On the Client side, assume both the WiFi and Bluetooth are open, and thepower consumption is about 1300 mW, when users arebrowsing and calculating directions. If the mobile phoneruns in both the server and client mode, the powerconsumption is similar to that of a fully operating Exploiting Energy- Aware Localizationserver.

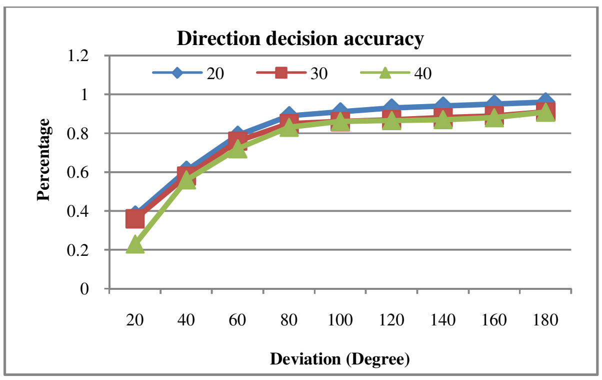

Fig 3. Directional Localization Simulation Results

The CDF distribution of the deviation angle is shownin Fig.3. Each CDF line is based on 10,000 samples.Start our tests from three distances, i.e., 40 meters,30 meters and 20 meters. Walk a semi-octogonalpath with edge length of 5 meters. At each turningpoint of the path, take 5 RSSI measurements with noise of 6 dB added . The algorithm may fail to give adirection due to noisy signals. It is an intuitive result, because the wireless signal at acloser range is strong and that helps the algorithm.

V.CONCLUSION AND FUTURE WORK

Understanding social interactions is important for a number of disciplines, including social psychology, epidemiology, medicine, economics and anthropology. The solutions for continuous (mobile) monitoring of social interactions are typically based on the use of dedicated devices which introduces a set of issues including subjects' stigmatization and consequently their behavioral change.Propose the E-Shadow concept is anelectronic personal image broadcast with one's mobilephone. The proposed method have also designed and implemented theE-Shadow system on real world mobile phones. The design can broadcast E-Shadow information efficientlyin a layered and dynamic manner.Presented the a-Loc system that can automatically tunethe location energy and accuracy trade-off by continuallyadapting to the dynamic location sensor characteristics andapplication needs. The end result is a system service that canfree applications of the burden of location error and energymanagement. The structured approach systematically modelsmultiple factors that influence location estimation usinga probabilistic framework.Inour future work, will further explore ways for cueingusers to connect with new people using E-Shadow, e.g.,by locally storing a list of contacted devices and highlightingdiscovered devices not on this list. Users shouldbe able to tell at a glance if there are nearby strangerswhom they might like to meet and their distance.

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