Enriching Location Information: An Energy-efficient Approach

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ABSTRACT
Off-the-shelf modern mobile devices come with a number of inbuilt sensors, e.g., GPS, WiFi, GSM, accelerometer, compass, gyroscope, NFC and Bluetooth. Equipped with all these sensors and internet connectivity, modern mobile phones are enabling continuous sensing and increasingly many emergent mobile applications are using sensed context on the phone to understand users' needs and improve usability. However, limited battery power is a big hindrance to the deployment of continuous sensing on mobile devices and without any intelligent sensor management, the battery lasts only few hours. In this research, we emphasize on location-awareness and address the challenges in developing ubiquitous positioning solutions, cross-device indoor localization, position and trajectory tracking and inferring high-level contexts using machine-learning techniques on sensor data in an energy-efficient way.

ACM Classification Keywords
C.2.4 Computer-Communication Networks: Distributed Systems

General Terms
Algorithms, Experimentation, Measurement

Author Keywords
Energy-efficiency, Positioning, Mobile computing, GPS, Trajectory simplification, Particle Filtering

MOTIVATION AND RESEARCH GOAL
Location technologies are an important part of ubiquitous computing and especially localization has been an active area of research [10]. Modern mobile phones readily support localization using a number of technologies such as GPS, WiFi and GSM. Equipped with a large number of sensors and pervasive connectivity, modern mobile phones have become the most widely used devices in ubiquitous computing. Moreover, improvements in mobile user interfaces and the ease in development of custom mobile applications have resulted in a proliferation of *location based services* (LBS). The success of LBS mainly depends on good positioning accuracy and user experience on the mobile domain.

In terms of positioning, GPS provides accurate location estimations outdoors but becomes unreliable in regions where the line of sight to the satellites is obstructed, e.g., indoors and in regions with high-rise buildings [14]. Indoor positioning using beacons such as WiFi, RFID, IR and ultrasound achieves higher accuracy, but typically requires additional infrastructure investments as well as maintenance efforts. On the other hand, accuracy of GSM cell positioning depends on the density of GSM towers [24] and often additional hardware, e.g., a GSM modem, is required for obtaining higher accuracy. Thus, a ubiquitous location technology that is accurate, low-cost and easily deployable remains elusive [10]. In addition to the accuracy, coverage and cost of deploying positioning technologies, their use on mobile platform poses challenges in terms of energy efficiency. For example, high battery consumptions of integrated GPS receivers and WiFi radios on a mobile phone make them unattractive for continuous positioning [11, 18]. Moreover, existing commercial indoor localization techniques require detailed radio-map of the indoor environment and often works using specialized hardware receiver. To support localization on various heterogenous mobile phones current solutions require maintaining device specific radio maps. One solution to overcome the need of multiple radio maps is to use Hyperbolic-fingerprinting [7].

LBS, such as tracking, while running on the device easily deplete the battery while sensing location data on the phone using GPS and sending location updates to a remote server. Care should be taken to decide when a client should send information about location changes to a remote server. Finding a balance between the accuracy of location information and overall battery life of a mobile device is challenging. Trajectory simplification and update protocols have been traditionally addressed in the moving object databases literature using line simplification methods. However, these methods have been solely designed to guarantee sufficient position accuracy, not to simultaneously optimize the battery life of a mobile device. Development of robust and energy efficient trajectory tracking techniques for the mobile device would thus be highly beneficial for emerging LBS, e.g., real-time logistics, share-ride recommender and collaborative sensing.

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Emergent LBS require high level context information for adaptability, usability and improved user experience. Location data can be utilized to identify high-level contexts such as personally meaningful places, activities, transportation modes, routes and movement models [12]. High-level contexts provide better indications of a user's current situation, communication contexts and information needs. Utilizing the high-level contexts, LBS can adapt their behavior appropriately to assist the user. Moreover, most emerging LBS suffer from difficulties in associating sensor retrieved measurements to personal contexts [6].

Contributions

The first contribution of this research is to develop accurate, energy efficient, easily deployable on-device positioning techniques with wide coverage area. This provides ubiquitous positioning capabilities to modern mobile phones and opens up new possibilities of location-aware computing. The second contribution is developing a hybrid-localization technique that operates indoors, as well as, outdoors with adequate accuracy across various devices. This method helps to overcome the burden of device specific radio map generation with the help of Hyperbolic fingerprinting techniques. The third contribution is the development of methodologies to enable energy-efficient, robust position and trajectory tracking. While performing tracking, we employ on-device simplification of sensed locations to minimize the size of a moving object database and minimize the cost of data transmissions over the Internet. The fourth contribution is developing machine learning techniques for inferring high-level contexts on the device in a way that do not adversely drain the battery of the device. Correct inference of high-level personal context improves the usability of emergent LBS.

RELATED WORK

A simple solution of GSM localization is to use the location of the serving base station as the estimated location of the mobile phone. The accuracy depends on the cell size, cell density and environment characteristics of the area and typically varies from hundreds of meters in urban areas to several kilometers in rural areas [24]. The accuracy can be improved with the knowledge of nearby cell towers and performing weighted averaging of tower locations with corresponding observed signal strengths [14]. Fingerprinting is a positioning methodology that uses pattern matching techniques to locate a device by analyzing the radio model of the surrounding environment [10]. Laitinen et al. [13] applied a fingerprinting technique for outdoor positioning using measurements from up to 6 neighboring GSM base towers. The authors reported 90-percentile accuracies of 90 m and 190 m respectively within urban and suburban areas in Helsinki, Finland. The Place Lab, developed by Lamarca et al. [14], employs a sensor model, combined with a Bayesian particle filtering achieves location accuracies between 100 and 200 meters. Chen et al. [4] have shown that the GSM fingerprinting approach to positioning is most accurate in downtown areas with an accuracy around 100 meters and pointed out good generalization performance of the Gaussian process model in case of GSM training data collected by different devices. Fingerprinting algorithms can be applied to WiFi signals and was introduces by the RADAR system [2]. While estimating client location by matching observed signal environment to stored radio map, probabilistic models can be applied as in the work by Roos et al. [22]. However, when the device used to create the radio map differs from the device used to estimate positions, the accuracy in fingerprint-based positioning suffers. This is due to the presence of significant variations in observed network measurements on different devices. One approach to mitigate the problem is to use Hyperbolic fingerprinting [7].

While performing the task of client's position tracking, existing systems, such as EnTracked [9], focus on sensor managements, i.e., selecting sensors with lower power consumption whenever possible. The RAPS system [21] uses GSM information to predict when GPS accuracy is poor and during that period uses other less accurate and energy-efficient positioning methods. Previous work on trajectory tracking [15] focus on collecting and simplifying trajectory data. However, majority of previous work have been designed to improve accuracy and do not address the problem of excessive power consumption.

High-level contexts such as user's personally meaningful places, destination, transportation mode, activity and route can be inferred from location data and applications including intelligent environments, surveillance, human robot interactions and assistive technology for the disabled can utilize the contexts for adding values to services. A simple approach for identifying a user's destination is to learn transition probabilities between her personally meaningful places and to train a Markov model to predict the destination [1, 17]. Liao et al. [16] use dynamic Bayesian networks to learn transportation modes and activities from GPS measurements.

METHODOLOGY AND OBTAINED RESULTS

The research proposed in this paper will be carried out following a bottom-up approach where we start with positioning, i.e., obtaining location of a device, followed by collecting location measurements over a period of time in an energy-efficient manner. Later we continue with deriving secondary contexts that provide new opportunities for LBS.

The first endeavor in this research is to develop an energy efficient positioning technology that is easily deployable, accurate and has large coverage area. The positioning algorithm relies on a grid representation of the world and we use GSM signal strength measurements to learn a probability distribution of GSM signal fluctuations within each grid cell. Position estimation is based on the resulting probability distributions, and particle filtering is used to smooth the resulting trajectories over time. The algorithm for on-device GSM positioning has already been developed and it is described in [20]. The median error of our proposed algorithm was found to be within 150 meters and for the majority of the time the estimated location is within 500 meters of the actual location. Currently we are developing a positioning solution that can operate seamlessly outdoors as well as indoors. The indoor environment in our case is a large scale hypermarket where we need positioning accuracy in the order of couple of meters. We are developing an extension of our grid-based model combined with Hyperbolic fingerprinting for WiFi access points, so any user can use her personal mobile phone to determine her position. For successful deployment we need to overcome challenges in positioning particularly in retail environment, such as signal interference, attenuation, blocking and presence of crowd during rush hours. We are running extensive empirical studies to derive the best structure of the indoor grid using self-organizing map (SOM) and organic development of the radio map using muti-dimensional scaling (MDS) technique. We are particularly interested in accurate positioning in retail environment at the grid level, such that our previously developed navigation system for retail environments (MONSTRE) [3] can be run on majority of mobile phones. Moreover, we plan to collect a huge set of calibration data from couple of medium sized European cities and test the storage requirement of our proposed radio map. We are also interested to employ the grid structure in a hierarchical way to support positioning solution at different granularities, e.g., city level, suburb level and street level. Additionally, with the knowledge of a number of users' activities tied to grid hierarchy we could come up with novel social applications using average activities in different areas.

Our next research goal is to develop energy-efficient position and trajectory sensing strategies on the phone and intelligent update protocols that provide a balance between the freshness of location information and the battery consumption of a mobile device. We intelligently use on-device sensors such as, GPS, accelerometer, compass and radio to minimize overall power consumption at the same time maintaining robustness in terms of localization accuracy. Specifically, we employ distance-aware, movement-aware and heading-aware strategies and the sensor manager chooses the strategy with lowest estimated power consumption under the current tracking requirement. The power models are device specific and in our current work we generate the models empirically as described in [9]. Additionally, on-device simplification of the sensed trajectory is carried out to minimize power and cost of using mobile internet and also to restrict the size of moving object databases. Contrary to existing works, our proposed system $EnTracked_T$ decouples the task of position tracking and trajectory tracking at different application specific error bounds and is found to achieve higher energy-efficiency. This work is already completed and described in [8]. Our proposed system $EnTracked_T$ is found to achieve significant robustness in case of larger error bounds ($>$ 100 m), however new work is required to achieve similar accuracy at lower granularity of position tracking. We plan to further improve the robustness by optimizing sensor duty-cycles. Moreover, we observed that human movement pattern, e.g., transportation mode of the user, influences overall energy consumption. In our future work we plan to detect transportation mode automatically on the phone and use this context to further optimize on-device sensor management. Successful deployment of our tracking system can indicate the carbon foot print of the user and can encourage specific transportation mode for better living.

In a mobile environment the information needs of an individual vary depending on, among other things, her current location, time, activity, familiarity with the area and social interactions [5, 23]. Location data can be refined to produce high-level context information [12] and contexts can be used to enable novel location-enhanced applications. For example, colloquial place names are widely used in human communication [6] and hence they can be used to develop applications that support novel social interactions. In our previous work [19], we automatically identified personally meaningful places using GPS traces and showed generalization problem of most pervious algorithms across different users. Additionally, many of the algorithms can only be used offline and thus not suitable for mobile devices. Our future research will focus on developing novel algorithms for identifying personally significant areas that overcome the limitations of existing algorithms and enable detecting places on the device in an energy efficient manner, i.e., with minimal amount of computations and with minimal need for internet connectivity. To accomplish this task, we will look into sequential probabilistic approaches that integrate the energy-efficient location sensing and world grid model into an on-device place identification process. Additionally, the work of Church et al. [5], shows that the majority of user's information needs were reported while the users were moving and specifically in areas not previously known to the user. Hence, accurate knowledge of contexts such as transportation mode, destination, origin, whether the user is taking the best possible route and current activity will enable new possibilities of value-added LBS. The last phase of the research develops energy efficient machine learning techniques that extract different kinds of secondary contexts from sensor data. Existing work in this context has mainly focused on utilizing GPS and accelerometer measurements. In our research, we examine whether this can be effectively accomplished using GSM signals or a combination of GSM, accelerometer and other low power sensors.

Evaluation of energy saving

While evaluating the performance of LBS in terms of energy efficiency, one simple approach is to measure the average time between two successive recharges. Specifically, the LBS can be started when the battery of the mobile device is fully charged and the application is kept running until the phone is dead. To overcome influences of external factors, we plan to repeat all the experiments several times and take the average life time of the battery as an indicator for energy efficiency. Moreover, the battery condition is dependent on the amount of usage of the device. Hence, for generality, experiments should be conducted on several devices and the average performance should be taken as a better indicator. However, to better understand energy consumption of individual device modules, as well as applications running on a device, energy profilers (e.g., Nokia energy profilers for Nokia smart phones) can be used, as shown in our $EnTracked_T$ system. In the future we plan to take into account dynamic energy requirements of mobile modules, as well as the user's current activities to adapt the behavior of the application. For example, the sampling rate for retrieving sensor values can be adjusted dynamically depending on the current battery state and the activity of the user.

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