International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6. 14 | Impact Factor (2013): 4. 438

Mobility Prediction with Minimum Energy Consumption

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Abstract: ***Nowadays mobile phones are very close to human life. For providing advanced services tracking user mobility is necessary. Previous works which are used for location sensing consume very much battery power. In this paper introduce new software called SmartDC. SmartDC perform mobility prediction with the help of adaptive duty cycling scheme. Previous works mainly focused on obtaining raw coordinates, with minimum energy consumption, this work focused on obtaining meaningful places with a given energy constraint.***

Keywords: Adaptive duty cycling, Accuracy, Markov predictor, Place detection, Prediction, Time series predictor

1. Introduction

Tracking human mobility is a necessary function to provide advanced services in mobile phones. Previous work that used for tracking human mobility focused only on maximizes accuracy to obtain raw coordinates. In this paper SmartDc runs as background in mobile phones. Mobile phones are mainly used for mobility tracking because phones are very closely related to human life and it include tracking techniques like GPS, Wi-Fi, WPS etc. For monitoring mobility, efficient method can be used is to sense the user location area continuously.

For continuously sense the location we cannot depend on GPS and other techniques since it consumes more and more battery power. Mobility learning is necessary service for tracking user's location. But the learning is not the primary function of mobile phones then it will be burden for users. So the main goal of this paper is to implement a system that continuously checks user location with minimum energy consumption and more accuracy. Main concepts used here are 1) Finding meaningful places 2) Find the randomness in human behavior. Here, the SmartDc system senses location on a predicted schedule. The main advantage is that when a user visits a place the location and the details of the location will be saved. When the user revisits that place there is no need to turn on the GPS again to detect that place. **The key challenges of this paper is that 1) it should perform learning and prediction simultaneously 2) should minimize the energy usage**

This proposed system introduces a new way to sense or locate a user. By tracking the human mobility it's very easy to provide advanced services in mobile phones.

2. Related Work

Before proceeding to this paper let's discuss the previous work on energy efficient sensing. We can classify the location sensing system according to the target context in two groups: raw coordinates and meaningful places. Most system uses a movement detector to reduce energy consumption. The main existing system that focused on location sensing with minimum energy consumption are1) EnLoc 2) Jigsaw 3) RAPS 4) CAPS 5) SensLoc

To track a user's raw coordinates, many approaches have been proposed to minimize energy consumption with adaptive sensor scheduling [5]. EnLoc uses a dynamic programming technique to minimize location error. Jigsaw detects a user activity by using an acidometer signal. Main disadvantages of Jigsaw method is that its use an acidometer which consume more and more battery power. RAPS which is Rate Adaptive Positioning System That uses a moving distance, space-time history, and cell tower based blacklisting to estimate uncertainty in a location. CAPS is Cell Aided Positioning System that detect the current user position.

SmartDC i.e., this proposed paper focused on detecting meaningful places with minimum energy consumption. And this method does not use an acidometer. Main advantage of this work is that this is the first system that implement a practical system that perform learning and prediction simultaneously.

3. Preliminary Study

Without adaptive duty cycling the continuous mobility learning is inefficient. The initial budget for the SmartDc is the remaining battery power in the mobile phone. List of sensors in the order of energy consumption are GPS, accelometer, Wi-Fi, and GSM. GSM consume less power because phones are always connected to a cell tower for voice communication. The duty cycle of the accelerometer should be carefully designed, since operating the accelerometer can incur significant energy usage. The application should lock the CPU to continuously use the accelerometer and prevent sleep state for continuous sensing. Although the accelerometer itself uses very little power, the continuous use of accelerometer needs to keep the CPU as well as associated high-power components active to access the sensor data.

Thus, computing the accelerometer signal with a 50 percent duty cycle at the lowest sampling rate (4-6 Hz) for 10 minutes consumes more energy than turning on a GPS with 1-minute intervals for 5 minutes. For this reason, most of the mobile platforms (e. g., Android, iPhone, and Nokia Maemo) restrict continuous sampling of acceleration while the screen is turned off [3]. Although a dedicated microcontroller may reduce sensing energy [2], even the latest smart phones do not employ such additional processor for sensing purpose. The proposed scheme, therefore, does not use an accelerometer for the pragmatic reason.

Based on the energy profile, we estimated the energy consumption of various mobility learning schemes. We made two assumptions: 1) A user spends 3 hours to move around outdoors each day [1]; and 2) the movement detector always recognizes user movements correctly. For example, SensLoc uses GPS and Wi-Fi every 10 seconds while a user moves, and the system activates an accelerometer with a 50 percent duty cycle when a user is stationary. Thus, the stationary state consumes 67. 8 mW and the moving state consumes 447. 8 mW, which is derived from the sum of the idle state (34. 5 mW), the GPS reading every 10 seconds outdoors (333. 2 mW), and the Wi-Fi scanning every 10 seconds (80. 1 mW). Fig. 1 presents the power consumption of several schemes. The expected battery lifetime is 29 to 48 hours if a Smartphone runs only mobility learning schemes. A previous study showed that, without mobility learning, 60 percent of people used their Smartphone from 14 to 41 hours with a single battery charge [4].

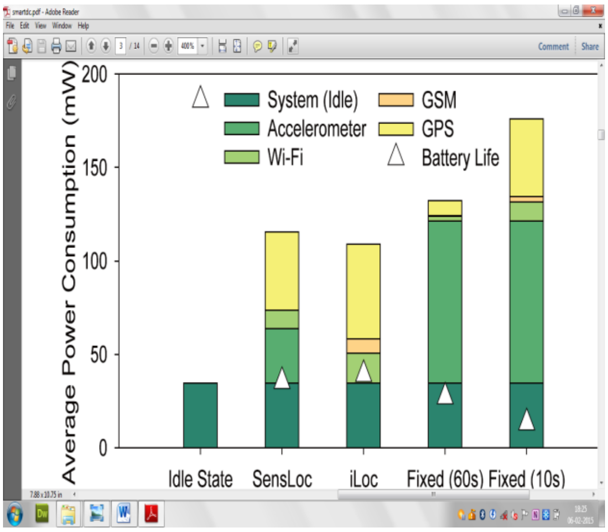

Figure 1: Power consumption of several schemes

This means that mobility learning may reduce battery lifetime by at least 16 percent and by 53 percent at most. Such energy consumption is a burden to users, since mobility learning is not a primary function of smart phones. Considering that the expected lifetime of idle state is 150 hours, previous learning schemes have room for lifetime improvement. The optimal scenario is that the system turns on sensors only when a user changes her states (i.e., entrance and departure moments). Our main idea is to adaptively sense the moment that includes a considerable possibility of state change. We predict the state change using the regularity of individual mobility patterns. The proposed system uses an energy budget as a constraint to customize sensing schedules to diverse usage.

4. SmartDC

The energy budget for SmartDC is the remaining battery of the phone. When a user stays at a place for a certain period of time then SmartDC will considered it as a meaningful place [5]. And stores the place and details related to that place such as location, Internet connection, Arrived time, duration time, and the Wi-Fi signal. Main three modules in this paper are 1) Mobility Learning 2) Mobility Predictor 3) Adaptive Duty Cycling. Fig. 2 shows the overall architecture.

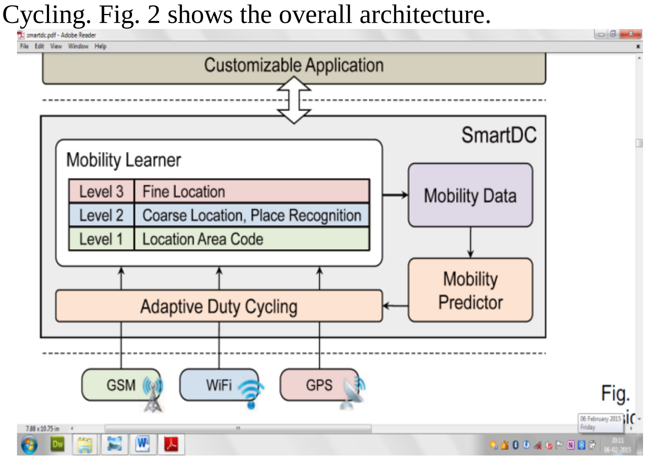

Figure 2: Architecture

Mobility learner deals with collecting individual mobility history without disturbing user. Mobility learner collect data through three levels. In first level it uses GSM to obtain the location area code (LAC). This first level updates the area code continuously with minimum energy consumption [6]. The second level uses Wi-Fi scanning to obtain the changing of places and revisited places. The basic concept is that if a user stays at a place for a certain period of time then the Wi-Fi signal is constant. When a user revisits a place, the system reuses the location and corresponding details stored. The third level then activates the GPS to detect the fine location. The third level activate only when the second level is failed to obtain accurate location details.

5. Result Analysis

This paper implemented in java programming language. The main advantage of this paper is that it help user to identify the location with minimum energy consumption. Also it provide the facilities available in that place with energy consumption.

Following screenshots represents the output of the work carried out on the project SmartDc Mobility Prediction.

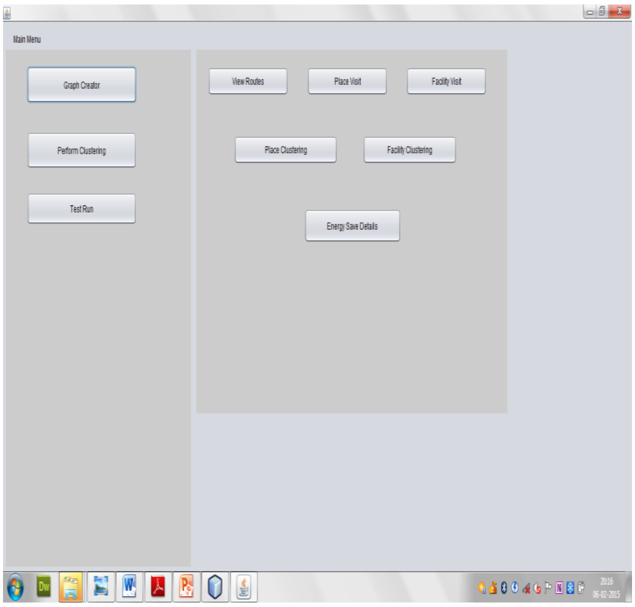

Figure 3: Main Menu

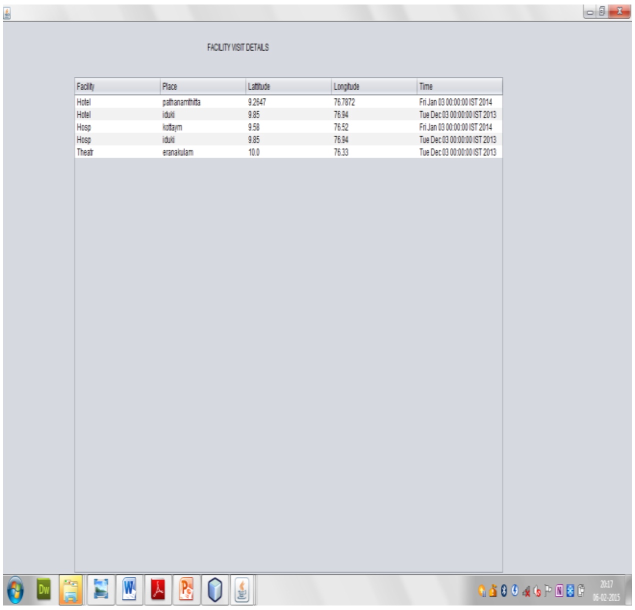

Figure 4: Facility Visit Module

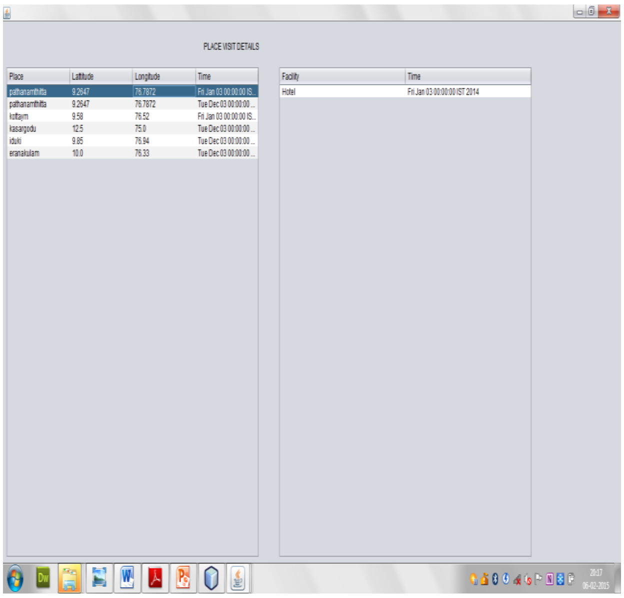

Figure 5: Place Visit Module

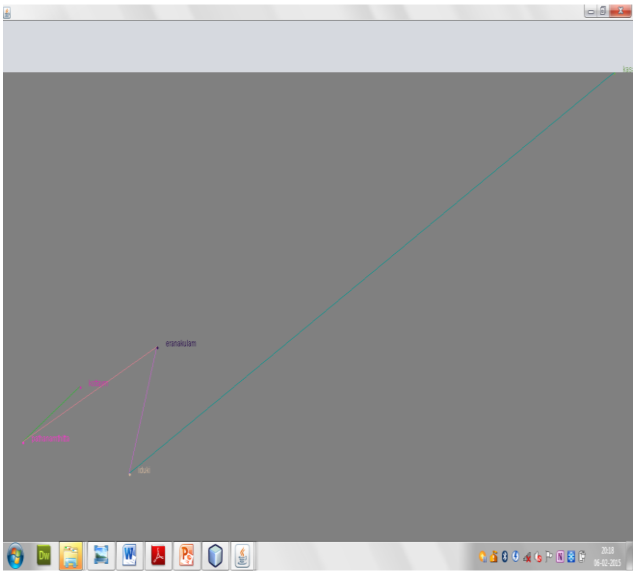

Figure 6: Route Map

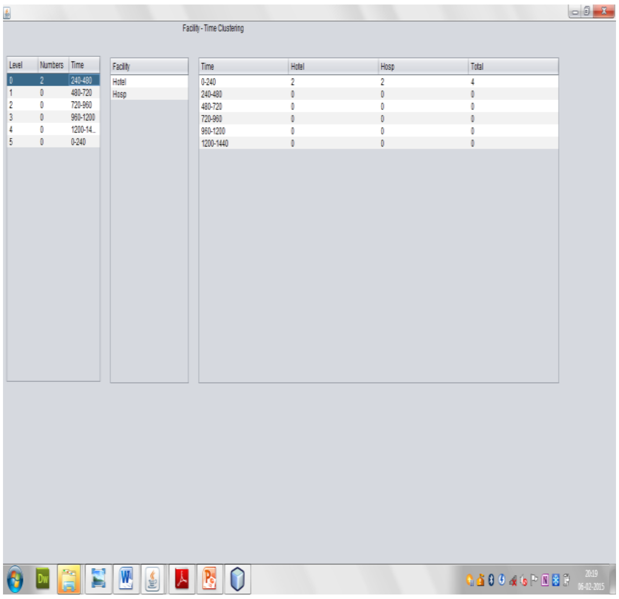

Figure 7: Perform Clustering

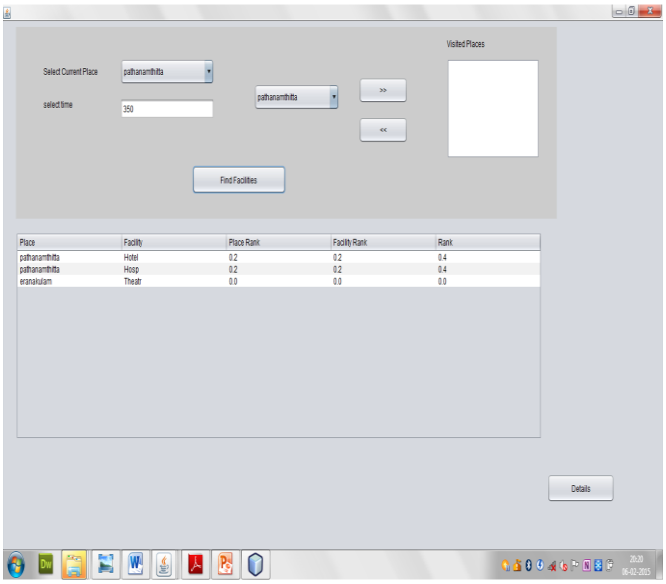

Figure 8: Finding Facility

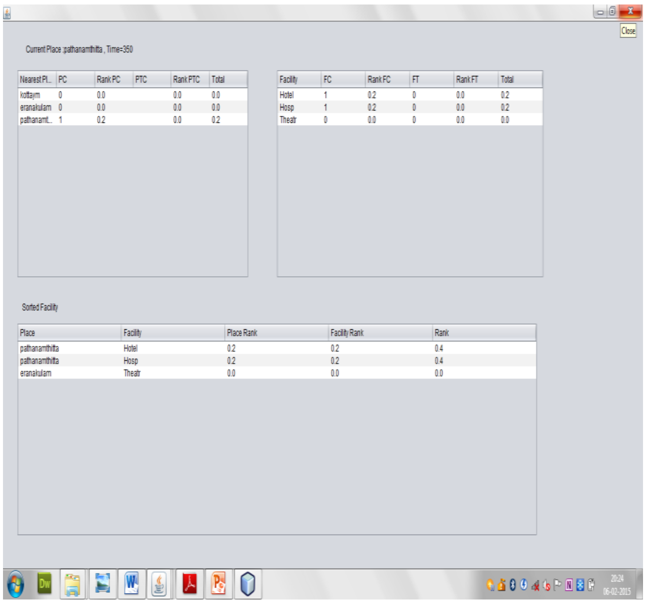

Figure 9: Energy Saving Details

This proposed method show that location can be continuously sense without turn on GPS. i.e., with minimum energy. Consumption. In this work it does not use an accelometer so the power consumption is very low as compared to previous works.

6. Conclusion

The proposed method SmartDC run as the background service in mobile phones. This is the first work that implement a practical system that simultaneously perform mobility learning and prediction. Uses different mobility predictor for prediction. And the experiment results show that this method saves 81 to 87percent energy than the previous work.

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