A Battery-aware Energy-efficient Android Phone with Bayesian Networks

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Abstract—Recently, as the number of smartphone users increases rapidly, various applications using GPS become widespread. Because GPS sensor has a drawback that consumes too much energy, we have to decrease the unnecessary usage of GPS receiver at indoors to reduce the energy consumption. Most of previous works focused on how to reduce the frequency or the period to use GPS. In this paper, we propose a method to save battery using Bayesian network inference with built-in sensors in a smartphone to get location information efficiently. In order to show the usefulness of the proposed method, we have developed an application in Android platform and performed experiments to evaluate Bayesian networks. Experimental results on real datasets has shown that it is possible to predict user's location at either indoor or outdoor. On weekday, accuracy is 77% which is higher than on weekend, 68%. Analysis implies that user lifestyle and life pattern in weekday have less changes than that in weekend. In terms of battery efficiency, active person and inactive person save energy of about 5% and 3% per hour, respectively.

Keywords—Battery saving, Smartphone, Bayesian network inference, Context-aware mobile application

I. INTRODUCTION

As the number of smartphone users increases rapidly, various applications such as social network, location based service, U-health care, and traffic service get proliferated. Unfortunately, GPS (Global Positioning System), to obtain the location information, is power-intensive, and its aggressive usage can cause complete drain of the battery [1][2]. It may not be used indoor as well as between tall buildings. Despite these drawbacks, the GPS sensor information is necessary to obtain accurate position. Therefore, the study on reducing the number of GPS accesses is required for location-based applications.

The energy saving system for location information has been extensively studied. RAPS, rate-adaptive positioning system for smartphone applications, applied GSM (Global System for Mobile communication) and WPS (Wi-Fi Positioning System) instead of GPS [3]. It could provoke not only positioning error but also high-energy consumption. GSM is not adopted in every country, and Wi-Fi has the same problem of high battery consumption with the GPS.

To avoid this, we propose a context-aware energy-efficient system. At the core of our approach lies a method to estimate user's contexts from built-in sensors based on probabilistic model.

This paper is organized as follows. Section 2 presents the related works about Bayesian network modeling and energy saving and management system. In Section 3, the proposed method using user contexts-based domain knowledge and Bayesian network modeling is described. In Section 4, experimental results are provided to show the usefulness of the proposed method, and Section 5 concludes the paper with summary.
II. RELATED WORKS

A. Bayesian network modeling

The algorithm to infer context of dynamic environment has been investigated in many studies. The probabilistic approach is the most successful method, though there are many methods to deal with user contexts [4]. Especially, there have been many studies on Bayesian network in AI (Artificial Intelligence).

There are a number of steps that a knowledge engineer must undertake when designing a Bayesian network [5][6]. These steps are as follows:

a) Identifying nodes and values: Firstly the features of interest in the domain must be identified. In other words, the knowledge engineer needs to identify what the nodes represent and what values they set up. In discrete nodes, the following types can exist: Boolean nodes, ordered values or integer values.

b) Finding the structure: The structure of the network represents causes and effects of relationships. It captures qualitative relationships between features. In particular, two nodes should be connected directly if one affects or causes the other, with the arc indicating the direction of the effect. Usually expert knowledge is used to build the structure.

c) Specifying conditional probabilities: Once the structure of the Bayesian network is determined, the next step is to quantify the relationship between connected nodes. In discrete variables, this is done by specifying conditional probability table (CPT) for each node.

Several methods to determine network structure and parameters are proposed. Typically, the model designed by experts is widely used. Marcot et al. proposed guidelines for the design. This work uses designed Bayesian network in ecological modeling method. Lee et al. presents a method to infer a person’s activities from mobile contexts using hierarchically structured Bayesian networks. Mobile contextual information collected for one month is used to evaluate the method [7]. It is not evaluated on a mobile device but the data collected in real mobile environment.

Laskey et al. proposed an engineering method of modeling Bayesian network [8]. In this work, Bayesian network has advantage that can be designed from experts having domain knowledge. In this paper, we design the inference model from mobile environment in difficult situations to collect training data.

B. Energy saving and management systems

Several power management systems have been proposed. Ravi et al. conducted research on rule-based system to predict whether he is at indoor or outdoor using mobile log data. It informs user of talk time and remaining time to recharge [9]. Rule-based system may cause inference errors from user’s dynamic behavior pattern and uncertainty, but it is difficult to save the energy radically.

Murao et al. proposed context inference system from body patch sensor in each joint. In order to save energy, it predicts what sensor is disuse in next behavior, and turn off the unnecessary sensors [10]. Higher accuracy was achieved with fewer sensors. In addition, in proportion to the remainder of power resources, the system reduced the number of sensors within the tolerance of accuracy.

![Figure 2. An example of sensor patterns through user behaviors.](image)
Moreover, the accuracy was improved by considering context transition. Even if the number of sensors changes, no extra classifiers or training data are required because the data for shutting off sensors were complemented by the proposed algorithm.

Harris et al. made the system called a CAPM (Context-Aware Power Management) framework that employs Bayesian networks to support prediction of user behavior patterns from multi-modal sensor data for effective power management [11]. The use of acoustic data as an interesting context for predicting finer-grained user behavior also proposed. In experiments, it presents an initial evaluation of the resulting framework.

All these methods have led to save or manage energy. However, we need a more efficient system for mobile environment. Although resources are restricted in smartphone for probabilistic model, mobile device is a typical user-centered platform for context-aware systems. Probabilistic model can infer the user’s state in uncertain environment. In this paper, we propose a context-aware system using probability model based on user’s behavior patterns for energy saving.

The error rate for getting location in smartphone is high in the order of GSM-Positioning, WPS, and GPS. GPS can provide user with certain position, which is the most important sensor. Location-aware systems have been proposed either to replace other device or reduce frequency of devices.

Paek et al. proposed RAPS (Rate Adaptive Positioning System) in smartphone that predicts proper location sensors, such as GPS, WPS, and GSM-positioning, by using built-in sensors [12]. Input values of system are accelerometer, GSM cell tower information, and Bluetooth information. Accelerometer simply determines the cycle of collecting GPS signals. GSM cell tower can find out available GPS, and Bluetooth adjusts location information from nearby devices. Performance was evaluated by changing these inputs and cycles, i.e., 20 sec. and 180 sec. Through experiments, the method to use all sensors has running time of 35 hours. The next method, except Bluetooth, ran for 32 hours.

Wang et al. presented a novel design framework for an Energy Efficient Mobile Sensing System (EEMSS). It uses a hierarchical sensor management strategy to recognize user states as well as to detect state transitions [13]. By powering only a minimum set of sensors and using appropriate sensor duty cycles EEMSS significantly improves device battery life. Evaluation with 10 users over one week showed that the system increases the device battery life by more than 75% while maintaining both high accuracy and low latency in identifying transitions between end-user activities.

Zhuang et al. presented an adaptive location-sensing framework that significantly improves the energy efficiency of smartphones running location-based applications. The underlying design principles of the proposed framework involve substitution, suppression, piggybacking, and adaptation of applications’ location-sensing requests to conserve energy. It was implemented based on design principles on Android-based smartphones as a middleware. Experiment showed that the design principles reduce the usage of the power-intensive GPS (Global Positioning System) by up to 98% and improve battery life by up to 75% [14].

Figure 3. Bayesian network designed for saving energy on GPS usage.
These systems have some disadvantages. Input variables are neither independent nor correlated to each other. For this reason, the result of inference has weakness in environmental noise or uncertainty. Most of the related works model the system with rules that cannot be scaled up easily. In this paper, we propose a robust inference system to cope with the uncertainty, noise, and data error in mobile platform using Bayesian network.

III. BAYESIAN NETWORK BASED ENERGY SAVING SYSTEM

Bayesian network is a popular tool widely used for statistical knowledge representation. To apply this network, we model the energy saving system for GPS usage. The values from built-in sensors must pass through pre-processing because of making proper variable. These variables are inferred for GPS switching, which determines either on or off. Fig. 1 shows the overview of system.

A. Pre-processing for analog sensor signals

The sensor values from accelerometer, magnet sensor, and compass sensor need to be pre-processed to infer user’s behavior, because they are analog signals. It is essential to predict user’s and smartphone’s current state.

In this paper, user’s behaviors are classified into standing, walking, and running. Fig. 2 shows an example of sensor signal patterns about user’s behaviors. The accelerometer has different frequency for each pattern, but it can change by user’s velocity [7]. In order to overcome this, we should use information from other sensors such as magnet sensor and compass sensor.

B. Behavior patterns from user contexts

A user’s job and lifestyle can change context classification. In other words, the method of recognizing lifestyle is required in advance. In this paper, we model the system from the life pattern of graduate students who have constant and normal lifestyle.

Accelerometer is not only sensitive in little changes but also dependent on the user’s habits. It is also difficult to infer user’s state. Therefore, user’s behavior of standing, walking, and running can be inferred from accelerometer sensor, magnet sensor and compass sensor.

The signals from proximity sensor are not pre-processed because they are digital signal; if the object is sensed within 25mm, it outputs 0; otherwise 1. It is the evidence that the mobile device is in pocket, being used, or possessed by user.

Date information was categorized into weekdays and weekends, and time information was classified into rush hour, lunch, dinner, and leaving the office. Both the date and time information were classified roughly, but they can be fine-tuned by user’s job or lifestyle.

C. Bayesian network inference

Bayesian network is represented as a DAG (Directed Acyclic Graph) where each node corresponds to the probabilistic variable and the arcs among the variables correspond to the probabilistic dependency [15][16].

\[ P(B, \theta_B) = P(x_1, x_2, ..., x_n) = \prod_{i=1}^{n} P(x_i | \text{pa}(x_i)) \]  

Eq. (1) represents Bayesian network; B is network structure and \( \theta_B \) is probability variable. \( P(B, \theta_B) \) represents joint probability distribution among variables. Set of nodes is \( V = \{x_1, x_2, ..., x_n\} \), and set of arcs E when Bayesian network represents \( B = (V, E) \). In other words, Bayesian network can be represented by conditional probability tables [15][16].

This paper models the Bayesian network as shown in Eq. (2) by referring to Eq. (1).

![Figure 4](image-url)
Here, $n$ represents the number of all nodes, and union set, $U$, becomes all nodes. It is difficult to handle complex Bayesian networks on mobile devices because they require a large amount of memory, slow CPU processing speed, small screen size, interface constraints, and limited battery capacity.

The Bayesian network has been used as a robust model to solve problems in uncertainty. Mobile environments have much uncertainty because sensor information is not reliable. Therefore, the Bayesian network is a useful model to infer user context from mobile environments. It can be learned from data or be designed by experts with domain knowledge. In this paper, we manually designed Bayesian network models using domain knowledge on mobile contexts [17].

Fig. 3 illustrates the structure of the Bayesian network designed to infer location. It can infer location either indoors or outdoors.

In this paper, Bayesian networks were designed from the user’s daily life contexts. For example, if the user goes out for lunch, inputs are as follows: walking, mobile in pocket, and lunchtime. The system infers that the user needs the location information. It then informs the user of the alarm so that it can provide the location information.

IV. EXPERIMENT

A. System environment

Energy saving system for GPS has developed on smartphones of LG SU-660 based on the 2.2 version of Google’s Android as shown in Fig. 4. We always use a new and full-charged battery to conduct the experiments. The logging application records the voltage level of the smartphone, 5 minutes per period. We conducted two experiments to measure the accuracy and battery efficiency, respectively. In accuracy experiment, log data were directly gathered for 15 days by one person. In battery efficiency experiment, dataset was collected from two persons, active person and inactive person, having various patterns during an hour as shown in Table I.

B. Results

Logging application saves the states of the user’s location with the proposed system. It compares with labeled data from the user whether the result is right or not. The Experimental result is shown in Table II. On weekday, accuracy is 77%, which is higher than weekend, 68%. The result shows that user lifestyle and life pattern in weekday has less change than weekend.

In battery efficiency experiment, we assume that there are two patterns in person as shown in Table II. The result of accuracy by date is shown in Fig. 5. We also compare the voltage level with the default saving system on Android as shown in Fig. 6.

V. CONCLUSION

TABLE I. LOCATION OF USERS, 10 MINUTES PERIOD.

<table>
<thead>
<tr>
<th></th>
<th>Active person</th>
<th>Inactive person</th>
</tr>
</thead>
<tbody>
<tr>
<td>~10 min.</td>
<td>Indoor</td>
<td>Indoor</td>
</tr>
<tr>
<td>~20 min.</td>
<td>Outdoor</td>
<td>Indoor</td>
</tr>
<tr>
<td>~30 min.</td>
<td>Indoor</td>
<td>Indoor</td>
</tr>
<tr>
<td>~40 min.</td>
<td>Outdoor</td>
<td>Outdoor</td>
</tr>
<tr>
<td>~50 min.</td>
<td>Indoor</td>
<td>Outdoor</td>
</tr>
<tr>
<td>~60 min.</td>
<td>Outdoor</td>
<td>Outdoor</td>
</tr>
</tbody>
</table>

TABLE II. INFERENCE RESULT ON WEEKEND/WEEKDAY.

<table>
<thead>
<tr>
<th></th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekday</td>
<td>77.27</td>
<td>78.57</td>
<td>84.62</td>
</tr>
<tr>
<td>Weekend</td>
<td>65.38</td>
<td>68.42</td>
<td>81.25</td>
</tr>
<tr>
<td>Total</td>
<td>70.83</td>
<td>72.72</td>
<td>82.76</td>
</tr>
</tbody>
</table>

Figure 5. The result of accuracy; weekday, weekend, and total.
We have proposed an energy-efficient system for GPS sensor on smartphone using a probabilistic model. This system can offer user to control the GPS. The proposed system has various built-in sensors that use low power, and date and time are inputted to the Bayesian network designed. Bayesian network infers whether user locates in indoor or outdoor. Input values are made via pre-processing. Finally, we confirmed the higher performance of the proposed system with two experiments. The first experiment shows that weekday has higher accuracy than weekend. Accuracy on weekday is 77%, and weekend is 68%.

This implies that user’s job and lifestyle are very important in performance. Next, the proposed system is suitable for active person. The energy is wasted to use the inference for inactive person because computational load of inactive person’s smartphone is bigger than that of active person.

For the future work, we will consider more diverse user patterns, and the parameters and network structures will be optimized from learning with more features. The features, which could affect the inference, will be dealt with other contexts such as temperature, weather, humidity, and schedule, and so on.

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