A Low-Power Context-Aware System for Smartphone Using Hierarchical Modular Bayesian Networks

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Abstract. Various applications using sensors and devices on smartphone are being developed. However, since limited battery capacity does not allow to utilize the phone all the time, studies to increase use-time of phone are very active. In this paper, we propose a hybrid system to increase the longevity of phone. User's context is recognized through hierarchical modular Bayesian networks, and unnecessary devices are inferred through device management rules. Inferring the user's context using sensor data, and considering device status, context inferred and user's tendency, we determine the device which is consuming the battery most. In the experiments with the real log data collected from 28 people for six months, we evaluated the proposed system resulting in the accuracy of 85.68 % and the improvement of battery consumption of about 6 %.

1 Introduction

The most serious concern in mobile user is the duration of battery, according to the technical document of Qualcomm in 2013. Despite the improvement of battery capacity and various applications, most of the users have spare battery.

The data collected by sensors and devices of smartphone are used for inferring context of user and developing applications with appropriate services. However, because battery of the smartphone has not been improved significantly for all day use, user's demand for long use-time is increasing, so that it stimulates the active relevant research.

In this paper, we propose a low-power device management system for smartphone using hierarchical Bayesian networks which can infer unnecessary device and user's context. The proposed system infers the user's context using Bayesian network. Considering the user's context, tendency inferred and the status of devices, we can infer the unnecessary device which can consume battery excessively. As a result, the proposed system can improve the duration of battery. In order to reveal the usefulness of the proposed system, we evaluated the inference accuracy of unnecessary device by real data collected from 28 people. The usefulness of the proposed system is confirmed by comparing with the alternatives.

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2 Backgrounds

2.1 Related Works

Moghimi performed user's context-aware in smartphone, proposed method to manage devices. In this research, to reduce complexity of context-aware, he used fuzzy inference model [6]. Zhuang adjusted update-time-gap to gain location information [10]. Herrman proposed low-power system which can adjust state of sensor device according to context [12]. Previous works define static situation for low-power platform, and adjust limited-sensor device (Table 1).

Table 1. Related works on low-power platform

Author	Method		Description
	Context-aware	Device adjustment	
Moghimi et al. (2013) [13]	O	X	Fuzzy inference model of low computation complexity considering context-aware of user in smartphone
Herrmann et al. (2012) [12]	X	Sensor device	Low-power system adjusting power consumption of sensor device according to context of user
Weiss et al. (2011) [8]	O	X	Analysis of correlation of context-aware of user using accelerometer sensor in smartphone for 70 people
Zhuang et al. (2010) [10]	X	GPS	Adjustment of update-time-gap of location information about static state of user
Bettini et al. (2007) [7]	X	Power consumption	Investigated power consumption of built-in sensor such as accelerometer, microphone, GPS, Wi-Fi, and Bluetooth

2.2 Device Management Application

The previous applications for low-power system did not take account for the use pattern of users, and had a problem that user cannot configure the setting directly. Applications considering user pattern have problem of cold-start which takes a long time to recognize the pattern and has few data sample. In order to fix this problem, we propose a device management application which can adjust appropriate device for user through context inference. The proposed system supports the automatic adjustment of battery-saving mode in accordance with each situation. This system can improve the accuracy of situation inference through learning of user patterns. Table 2 shows the commercial low-power device management applications.

Battery Guru developed by Qualcomm can grasp use-pattern and optimizes the device function of smartphone. This application leads to decreasing battery consumption. But these previous applications have a problem which takes a long time to recognize pattern or relies only on user's configuration.

Table 2. Commercial device management applications

Application	Saving mode	Configuration	Use pattern
Battery Guru	2	O	O
Battery Doctor	3	X	X
King of Energy Saving	3	O	X
2 Battery	2	O	X
Green Power	2	O	X
MX Battery Saver	4	X	O
DU Battery Saver	3	O	X
Battery Saver 2	2	X	X

3 The Proposed System

3.1 Structure Overview

In this paper, we analyze the correlation between situation and tendency of user and devices to develop low-power platform through related works and data collected. The sensor data are processed by decision tree and rules to provide input to Bayesian network. It is simple to implement rules and decision tree which have advantage of high accuracy when processing information such as acceleration data. As a movement of user, we distinguish state (walk, run, and stop) using acceleration sensor. As a posture of user, we distinguish posture (sit, stand, and lie) using orientation sensor, and distinguish user location of indoor and outdoor based on rules as information of GPS. In order to design Bayesian networks, we have to collect data and analyze the correlation.

Situation of user can be inferred by using modular Bayesian networks with tree structure using low-level data after preprocessing. Bayesian network is a good model for handling with uncertain input in smartphone environment. Because they are designed as tree structure, they can infer situation with low calculation complexity compared to the conventional Bayesian network. It has an effect on making low resource use of CPU. As network can be a powerful model through cumulated massive data learning, researchers are investigating the learning data in real time.

In order to process decision tree algorithm in mobile environment in real time, we implement it in C language and used Android application through NDK. In case of implementing in C, it can recognize fast because it does not use Java virtual machine, and decision tree has advantage of fast learning time (Fig. 1).

Figure 2 shows variation of sensor data according to state of user. This shows that we can classify data using time series sensor data on movement of user. In this paper, we extract movement of user from sensor data using decision tree. To detect movement state of user, we need to extract feature value as input of decision tree first. Sensor data used in decision tree are from acceleration, magnetic and orientation sensors. We use the equations below for these data.

$$sum\_X = \sum_{i=1}^{N} |x_i - x_{i-1}| \quad (1)$$

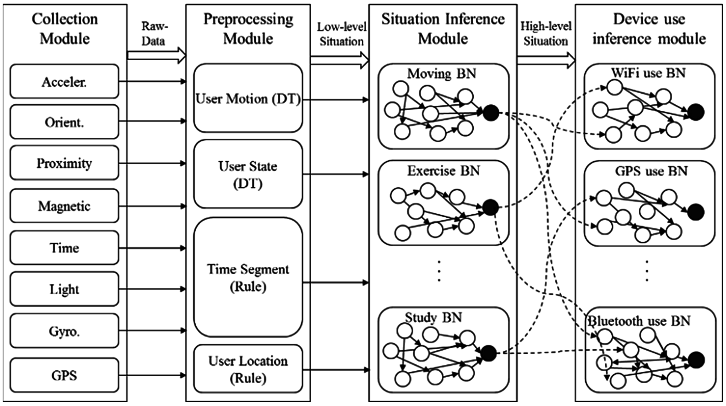

Fig. 1. The overall system structure

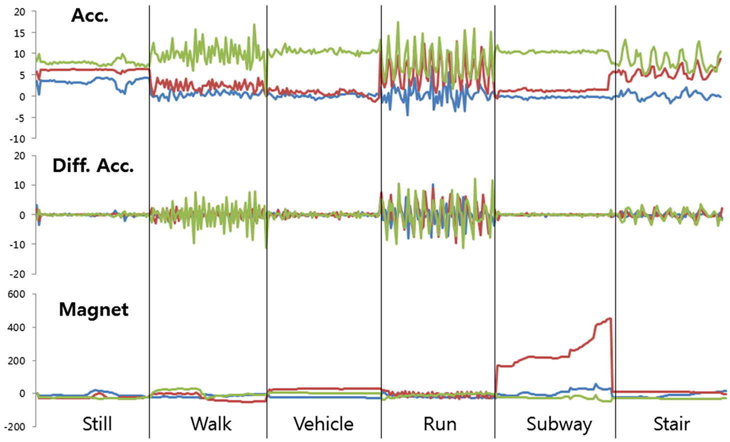

Fig. 2. An example of sensor data for each movement state

$$mean\_X = \frac{\sum_{i=1}^{N} \sqrt{(x_{i+1} - x_i)^2}}{N} \tag{2}$$

$$std\_X = \sqrt{(\sum \sqrt{(x_{i+1} - x_i)^2} - mean\_X)^2} \tag{3}$$

$$SMA\_X = \sum_{1}^{N} (|x_i|) + (|y_i|) + (|z_i|) \tag{4}$$

Here, X represents sensor, x means the value at present time of i, and N means the total data of amount in a window. Basically, we use 4 as feature value for each sensor. Table 3 is the list of total feature value used for decision tree.

Table 3. Feature value used for decision tree

Feature value	Description
sum_accX	Summation of X-axis acceleration
sum_accY	Summation of Y-axis acceleration
sum_accZ	Summation of Z-axis acceleration
std_accX	Standard deviation of X-axis acceleration
std_accY	Standard deviation of Y-axis acceleration
std_accZ	Standard deviation of Z-axis acceleration
sum_orientation	Summation of orientation
sum_pitch	Summation of pitch
sum_roll	Summation of roll
std_orientation	Standard deviation of orientation
std_pitch	Standard deviation of pitch
std_roll	Standard deviation of roll
sum_magX	Summation of X-axis magnetic field
sum_magY	Summation of Y-axis magnetic field
sum_magZ	Summation of Z-axis magnetic field
std_magX	Standard deviation of X-axis magnetic field
std_magY	Standard deviation of Y-axis magnetic field
std_magZ	Standard deviation of Z-axis magnetic field
SMA	Signal magnitude area

The proposed system consists of data collection module, preprocessing module, situation inference module, and device use inference module. Data collection module collects mobile sensor data and status of device. In preprocessing module, in order to decrease the time complexity, we preprocess the data using decision tree and rule-based method as shown in Table 4. Situation inference module infers user's context using the input data preprocessed. Considering the tendency of user, battery status, and inferred situation, device use inference module can infer unnecessary device and adjust automatically.

Table 4. The result of preprocessed sensor data

Method	Type	Use pattern
Decision tree	Acceleration, direction	Walk, run, stop
	Magnetic, Gyro	Sit, stand, lie
Rules	Light	Very bright, bright, normal, dim, very dim
	Time	Morning, afternoon, evening, dawn
	GPS	School, home, library, theatre, cafeteria
	Battery amount	Low, normal, high

Input:

User situation, tendency of user, mobile state

Output:

State of devices unnecessary

Device $=\{d_1,d_2, \ldots ,d_i\}$

Select inference module through the state of devices;

Configure the input value for each module;

Calculate linearly probability;

Decide the state of unnecessary device based on critical value;

Repeated for selected inference module;

Fig. 3. Inference algorithm of unused devices

3.2 Hierarchical Probabilistic Model

Our previous work proposed to recognize low-power situation of user using linear inference [3]. We recognized situation of rest, sleep, dining, exercise, work, shopping and lesson using the proposed modular situation inference. According to the criteria of situation classification of National Statistical Office, we define 8 situations. Unnecessary device was not being utilized. Because this device is turned on, this can consume battery. For example, in outdoor, if Wi-Fi device is turned on, we did not use Wi-Fi. But that device always can try to search access point or Wi-Fi connection nearby. The inference technology proposed in this paper figures out unnecessary state of each device hierarchically considering the tendency of user and present mobile state. This technology reuses the result of user situation inference as evidence value. We use the tendency of user as Big-five tendency model proposed by McCrae and John [5]. Table 5 is the definition of I/O of probability model of each device.

3.3 Inference and Management of Unnecessary Device

When we infer unnecessary device, we calculate as the Eq. (5) based on linear inference algorithm by Das considering only coincidence of state value about cause-and-effect relationship of output value.

$$P(S) = \sum_{j=1}^{n} \omega_i p\left(S|Comp(I_j = i_j^{S_{j_j}})\right) \tag{5}$$

$\mathrm{Comp}\left(I_j = i_j^{s_j}\right)$ is the value of CPT on coincidence situation of node i. W_i means node i influence to the final situation.

Table 5. Input and output of inference Bayesian network of unnecessary device

Classification	Type	Description
Input	Sleeping	We consider co-relationship between the result of situation inference of user and device use based on the situation classification of National Statistical Office
	Dining	
	Work	
	Lesson	
	Watching	
	Exercising	
	Moving	
	Rest	
	Battery state	Considering usable device or not via battery state
	Screen state	Considering the state of screen be turned on or off
	Extroversion	We consider co-relationship with the tendency of user based on Big-five model
	Openness	
	Congeniality	
	Sincerity	
	Faithfulness	
Output	Device	Wi-Fi, GPS, Bluetooth, Data synchronized device

Figure 3 shows the inference algorithm to find unnecessary devices. First, we choose the inference module in order to understand the state of device d_i. We configure evidence value of input node of smartphone and the tendency and situation of user which is needed for inference module, and calculate probability value of unnecessary node. Next, we calculate conditional probability value and intermediate node. Finally, calculate probability value of result node which means the state of unnecessary device, and decide the unnecessary state of device based on a threshold. This process is repeated for device management inference module. Through the repeated result, we carry out device management. Figure 4 shows the graphic user interface of device management for each situation. GUI is designed to configure battery-saving level, and user can confirm to configure setting and working system.

To show the usefulness of the developed application in low-power environment, we designed a scenario which is effective for battery-saving and utilizing device management application. The scenario aims to show the effect of device management application through situation inference and alteration of state of device in addition to situation and tendency of user.

4 Experimental Results

4.1 Evaluation of Performance

The performance of decision tree to identify the type of transportation is evaluated first. User's movement state can be classified into stop, run and walk. The type of transportation is classified into vehicle, subway, train and taxi. As input value, we use sensor value of acceleration, magnetic, and orientation. After preprocessing, the accuracy of

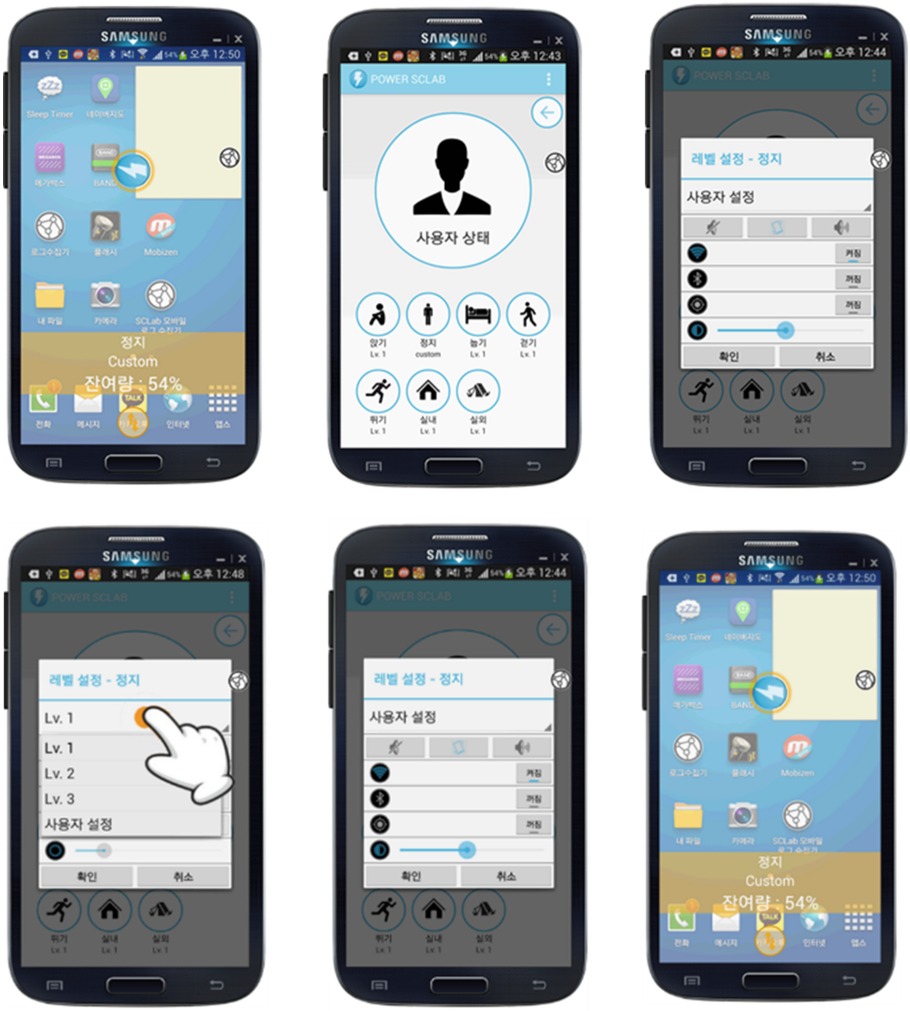

Fig. 4. Device management application

10-fold cross validation is used for classification of decision tree with the input of the variation of axis of sensor, standard deviation and SMA. Tables 6 and 7 show the result of accuracy of 10-fold cross validation.

Table 6. Accuracy of classifying the state of movement

Class	TP rate	FP rate	Precision	Recall	F-measure	ROC area
Staying	0.947	0.014	0.957	0.947	0.952	0.984
Walking	0.908	0.079	0.912	0.908	0.91	0.96
Running	0.848	0.042	0.828	0.848	0.838	0.966
(Avg.)	0.901	0.045	0.899	0.901	0.9	0.97

Table 7. Accuracy of classifying the type of transportation

Class	TP rate	FP rate	Precision	Recall	F-measure	ROC area
Train	0.873	0.052	0.885	0.873	0.879	0.957
Car	0.928	0.072	0.841	0.928	0.883	0.96
Subway	00762	0.051	0.863	0.762	0.809	0.914
Bus	0.91	0.02	0.833	0.91	0.87	0.969
(Avg.)	0.86	0.054	0.861	0.86	0.859	0.946

Tables 8 and 9 show the confusion matrix of the type of transportation and the state of movement using decision tree algorithm. In Table 8, the state of walking has higher performance compared with the other movement states. For the type of transportation, subway and train may be confused.

Table 8. Confusion matrix for movement state

	a	*b*	*c*
a = Staying	1020	43	7
b = Walking	45	1032	46
c = Running	0	69	746

Table 9. Confusion matrix for type of transportation

	a	*b*	*c*	*d*
a = Train	1038	47	94	10
b = Car	22	1024	32	25
c = Subway	105	130	860	34
d = Bus	8	16	10	345

Figure 5 shows the performance of each classifier for the type of transportation. We compared the classifiers such as decision tree, SVM, Multi-layer perceptron and RBF network. In Fig. 5, running time of decision tree is more stable and faster than the other classifiers.

4.2 Inference Accuracy of Unnecessary Device

In order to evaluate the inference accuracy of unnecessary device of the proposed system, we collected data of 6985 for 28 university students during 14 days. In total 8

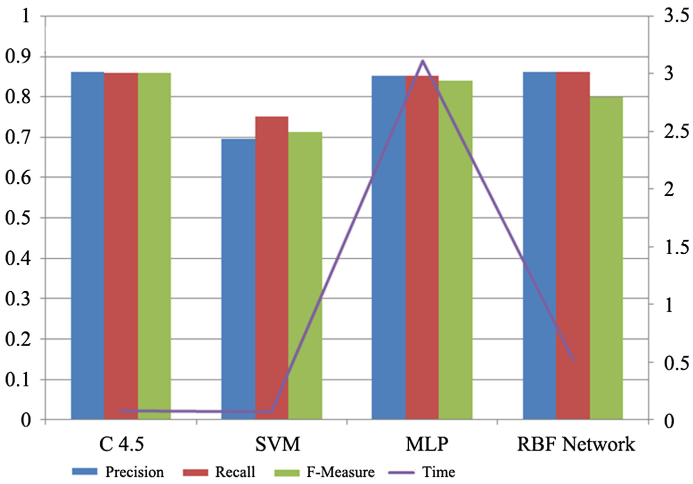

Fig. 5. Comparison of the accuracy and runtime for classifying the type of transportation

situations such as sleeping, dining, work, lesson, watching, moving and rest, we collected GPS, Wi-Fi, data synchronization, Bluetooth and state of battery. We investigate the tendency of users using NEO-RI-R survey. Using the collected data, we measure the accuracy comparing to result of inferred network of unnecessary device. Figure 6 presents average of 85.68 % accuracy. One of devices which have the highest accuracy is Bluetooth because of the definite usage distribution of data. Also, because GPS device is related in various situations, the accuracy was low.

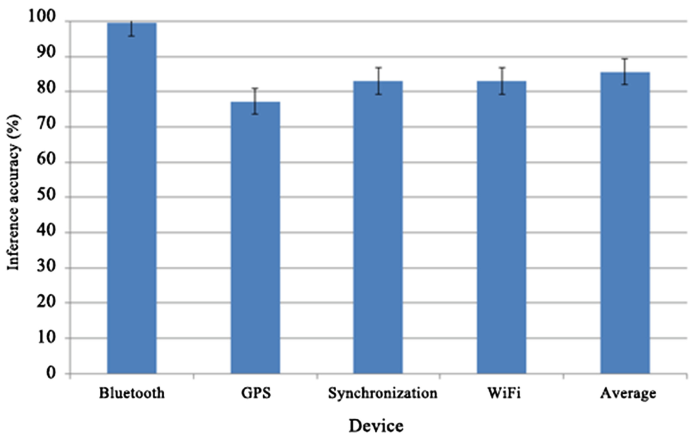

Fig. 6. Accuracy of inferring unnecessary devices

4.3 Comparing with Battery Level

In order to evaluate the performance of the proposed device management system, we compared the battery level for 1 day in environment with two Galaxy S4 smartphones.

One S4 device installed the proposed application. Figure 7 compares the battery level, resulting in the decrease of battery consumption about 6 % compared to existing one. This induced to increase the use time for about two hours.

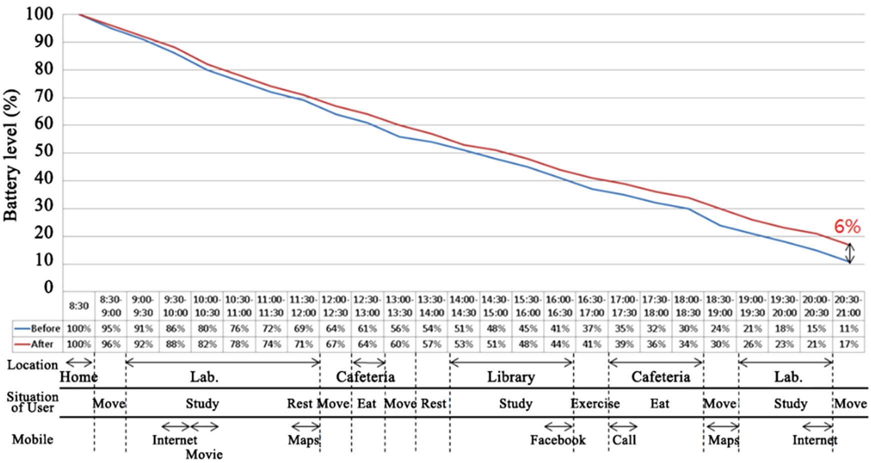

Fig. 7. Comparing battery levels

5 Concluding Remarks

In this paper, in order to increase the longevity of using smartphone through device management, we proposed a device management system based on hierarchical Bayesian networks inferring unnecessary devices and user's situations. In the experiments, we measured the accuracy of inference of the proposed system, compared the battery consumption, and confirmed the increased longevity.

Future works can be divided into short-term and long-term research. In the short-term, we need to incorporate a number of wearable devices and develop user-customized services based on them. In the long-term, we have to improve the context recognition model by learning larger data of more users.

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