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A Smartphone Management Method to Save Battery Using Bayesian Networks and Fuzzy System

Jun-Ho Kim
Department of Computer Science
Yonsei University
Seoul, Korea
barabarada@sclab.yonsei.ac.kr

Sung-Bae Cho
Department of Computer Science
Yonsei University
Seoul, Korea
sbcho@yonsei.ac.kr

***Abstract*— Conventional method for determining the policy to control devices have problems of the race condition of two contexts. It can be solved by combining the probabilities of contexts. In this paper, we propose a method to determine the device control policy from the contexts, which infers the necessity of devices using modular Bayesian networks, and decides the device control policy using fuzzy inference system. To evaluate the proposed method, we collected data with nine college students in two weeks and used the data to evaluate the accuracy of the proposed method. Also we conducted scenario based experiments with three graduate students in four days to confirm the battery saving effect. The proposed method shows 94.2% accuracy, and it saved 490mA more battery than the other method that use support vector machine in a day.**

Keywords—Mobile Device, Context Awareness, Low-power, Modular Bayesian Networks, Fuzzy Logic, Battery Saving System

I. INTRODUCTION

Proliferation of smartphone raises battery issue on mobile devices. Technology for communication develops rapidly and people can access internet on mobile devices with high speed, and the development of application market and improvement of web-accessibility on mobile device increase smartphone-using time. However, the capacity of battery cannot catch up with increasing of use time. The study by Saeid Abolfazli shows that battery consumption for a day increases as 600mWh annually, but battery capacity increases as 200mWh [1], resulting in that available time of using smartphone decreases annually.

To solve this problem, systems that reduce battery consumption are studied by many researchers and companies. Especially, battery saving systems using context are appeared to deal with the characteristics of mobile environment. They control the hardware devices of software to reduce the consumption of battery.

Conventional battery saving systems using context-awareness show the good performance to save battery. However, this systems have difficulties on situation that contexts are ambiguous. If two contexts are on race condition, conventional systems cannot determine battery policy precisely. Figure 1 shows the situation that “Shopping” and “Watching” contexts are on the race condition. Even if the current context is “Shopping,” conventional systems determine control policies by assuming the current context as “Watching” [2].

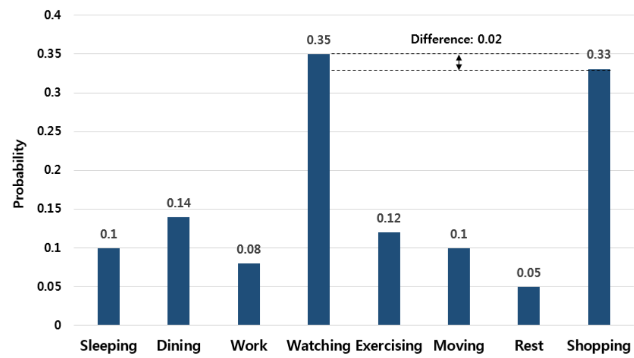

Figure 1. Context-aware Result on "Shopping"

We propose a method to determine the device control policy on context-aware system using modular Bayesian networks (MBNs) and fuzzy inference system (FIS). The MBNs infer the necessity of device from the probabilities of contexts, and the FIS infers device control policy from necessity of device and the remaining battery of device. We control the communication devices (WiFi, GPS, Bluetooth, and Data sync) to saving battery.

To evaluate the proposed method, we collected 1,837,917 data from 9 undergraduate student in two weeks. The accuracy is obtained to find the policy to control devices using our method. We compare our method with other classification methods, and conduct scenario based experiments to confirm that our method can reduce the consumption of battery. Scenario-oriented experiments are performed from three graduated students in four-days.

II. RELATED WORKS

Conventional battery saving systems use simple rules to control devices. Table 1 shows relevant studies on controlling a device in context-aware system. Herrmann proposed a method to control devices using finite state machine (FSM) [5]. It has states matched with context one by one, and each state has rules to control sensors when current context is changed. This method shows good performance when context is not vague, but otherwise, switching between states are not performed exactly.

Korpipaa and Moghimi used FIS to solve this problem [3, 4]. Korpipaa controlled screen brightness and font with FIS that infers control policy from contexts from Bayesian network, and

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Table 1. Methods for Battery Saving System based on Context-awareness

Author	*Context-aware Method*	*Policy Determining Method*	*Control Elements*	*Limitation*
Korpipaa (2003) [3]	Bayesian Network	Fuzzy Inference System	Font, Brightness	Used only an application
Priyantha (2011) [4]	Rules	Linear Function	Window size	Used only customized apps
Yashiro (2012) [6]	Rules	Rules	States of Sensors	
Moghimi (2013) [11]	No-Context	Fuzzy Inference System	Video Bit-Rate	Cannot infer exact context
Herrmann (2012) [5]	Rules	Finite State Machine	States of Sensors	Decision error on situation that changes contexts
Oliner (2013) [7]	Rules	Rules	States of Applications	
Chenren (2014) [2]	Markov Decision Pro cess	Rules, Action Function	Brightness, GPS Sampling Rates	
Yang (2015) [22]	Bayesian Network	Rules	States of Devices	

brightness. But this method only used current situation, not probabilities of context. Moghimi also used FIS to control applications. The study proposed frame-work for applications that need to control battery, but it has to set an application and cannot infer context exactly.

III. THE PROPOSED METHOD

The proposed method works on context-aware system. The system is shown in Figure 2. The system consist of context inference part and device control part. Context inferring part has data collection module, preprocessing module, and context inferring module. The part collect sensor data and infers current contexts. This part has the necessity of device inferring module and determining control policy the module. Necessity inferring module uses MBNs to infer the necessity of devices. Determining control policy module is designed with FIS. It determines a control policy of each devices with inferred necessity of device and remained battery.

Table 2. I/O of BNs for Necessity of Device

I/O	*State*	*Value*
Input	Sleeping	Yes/ No
	Dining	
	Studying	
	Working	
	Watching	
	Exercising	
	Moving	
	Resting	
Ouput	Wi-Fi	Yes/ No
	GPS	
	Bluetooth	
	Data Synchronized Device	

A. Inferring Necessity of Devices

The proposed method uses Bayesian networks (BNs) to infer necessity of devices. At this step, BNs are modularized for efficiency of inferring process and reducing complexity of networks.

First, we define input and output elements. Each output element is connected with input element that have the relation with each output. In the proposed BN, each device is connected with contexts that are related. Table 2 shows the input and output of BNs that infer the necessity of devices.

Second, we make hierarchical structure with nodes. Hierarchical structure minimizes the complexity between parent and child nodes. If a child node has more than three parent nodes, middle node is inserted between child and parents to minimize the size of conditional probability table [12].

Lastly, we constructed the network structure and parameters. In general BNs, parent node represents the cause and child node represent result, but the proposed BNs are constructed in the opposite direction to reduce complexity.

Suppose that N is the set of necessities, and the set N can be expressed by $N = \{n_{device} |\ device = \{WiFi, GPS, Bluetooth, Datasync\}\}$. The function of inferring necessity of device is set as $InferNecessity_{device}$, and the inferred contexts is set as C. Then we can define n_{device} with equation (1).

$$n_{device} = InferNecessity_{device}\ (C). \qquad (1)$$

B. Fuzzification of Necessity and Remained Battery

In this step, we fuzzify the infered necessity of device and remaining battery using membership function. The fuzzified result is used with the input of fuzzy inference system. We use Mandani fuzzy model to construct fuzzy inference system [16],

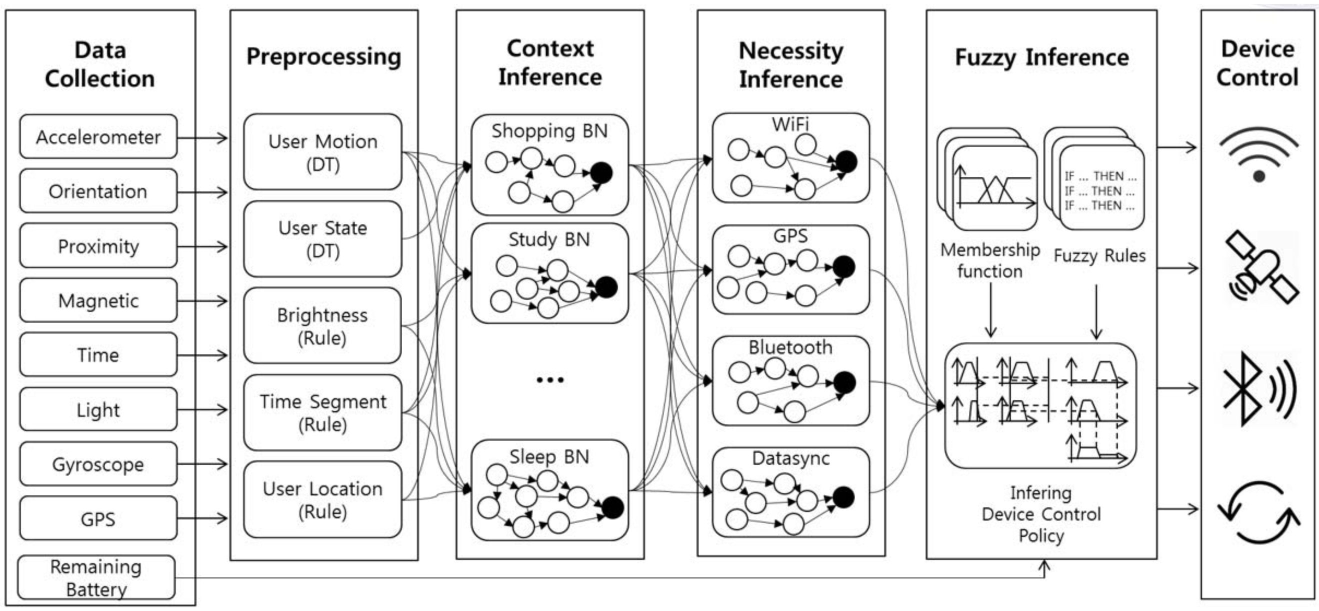

Figure 2. System Overview

and the membership function is designed with trapezoid shape. The membership function μ_{Xi} is represented by equation (2).

$$\mu_{Xi} = \begin{cases} 0 & (x < a_{Xi0}) \\ p_{Xi0}x + q_{Xi0} & (a_{Xi0} \le x < a_{Xi1}) \\ 1 & (a_{Xi1} \le x < a_{Xi2}) \\ p_{Xi1}x + q_{Xi1} & (a_{Xi2} \le x < a_{Xi3}) \\ 0 & (x \ge a_{Xi3}) \end{cases} \quad (2)$$

a_{xik} means area of function, p_{xik} means slope of function, and q_{xik} means intercept of function. They are calculated by (3).

$$\begin{gathered} \text{Area of Function} \quad A_{Xi} = \{a_{xik} | 0 \le k \le 3\} \\ \text{Overlapped Area} \quad O_{Xi} = \{o_{Xik} | 0 \le k \le 1\} \\ a_{Xi0} = \textstyle\sum_{k=0}^{i} s_{Xk} - o_{X(i-1)1} \\ a_{Xi1} = \textstyle\sum_{k=0}^{i} s_{Xk} + o_{Xi0} \\ a_{Xi2} = \textstyle\sum_{k=0}^{i+1} s_{Xk} - o_{X(i+1)0} \\ a_{Xi3} = \textstyle\sum_{k=0}^{i+1} s_{Xk} + o_{Xi1}. \\ s_{Xk}: the\ width\ of\ area\ for\ the\ kth\ function\ in\ \mathrm{X}. \end{gathered} \quad (3)$$

The slope of function is determined with the overlapped area. Overlapped area o_{Xik} is set to 30% of each area. o_{Xij}, and p_{Xij} is calculated by equation (4).

$$\begin{gathered} \text{Slope of Function} \quad P_{Xi} = \{p_{xik} | 0 \le k \le 1\} \\ o_{Xi0} = \textstyle\sum_{k=0}^{i} s_{Xk} \text{-} \sum_{k=0}^{i-1} s_{Xk} \\ o_{Xi1} = \textstyle\sum_{k=0}^{i+1} s_{Xk} \text{-} \sum_{k=0}^{i-1} s_{Xk} \\ p_{Xij} = 1/o_{Xij}. \end{gathered} \quad (4)$$

The area of membership function for fuzzifying the necessity of device is calculated from surveys. Response item was constructed as "Never", "Rarely", "Sometimes", "Often", and "Always". The response ratio is set to R, and it can be expressed by $R = \{r_k | 0 \le k \le 4\}$. $r_0 \sim r_4$ means each response item.

Table 3. Fuzzy Rules to Decide the Policy

R_1	: IF (x_1 *is* b_1) *and* (x_2 *is* n_1) *THEN* (P *is off*)
R_2	: IF (x_1 *is* b_1) *and* (x_2 *is* n_2) *THEN* (P *is off*)
R_3	: IF (x_1 *is* b_1) *and* (x_2 *is* n_3) *THEN* (P *is off*)
R_4	: IF (x_1 *is* b_1) *and* (x_2 *is* n_4) *THEN* (P *is off*)
R_5	: IF (x_1 *is* b_1) *and* (x_2 *is* n_5) *THEN* (P *is off*)
R_6	: IF (x_1 *is* b_2) *and* (x_2 *is* n_1) *THEN* (P *is keep*)
R_7	: IF (x_1 *is* b_2) *and* (x_2 *is* n_2) *THEN* (P *is keep*)
R_8	: IF (x_1 *is* b_2) *and* (x_2 *is* n_3) *THEN* (P *is keep*)
R_9	: IF (x_1 *is* b_2) *and* (x_2 *is* n_4) *THEN* (P *is keep*)
R_{10}	: IF (x_1 *is* b_2) *and* (x_2 *is* n_5) *THEN* (P *is keep*)
R_{11}	: IF (x_1 *is* b_3) *and* (x_2 *is* n_1) *THEN* (P *is on*)
R_{12}	: IF (x_1 *is* b_3) *and* (x_2 *is* n_2) *THEN* (P *is on*)
R_{13}	: IF (x_1 *is* b_3) *and* (x_2 *is* n_3) *THEN* (P *is on*)
R_{14}	: IF (x_1 *is* b_3) *and* (x_2 *is* n_4) *THEN* (P *is on*)
R_{15}	: IF (x_1 *is* b_3) *and* (x_2 *is* n_5) *THEN* (P *is on*)

C. *Determining the Device Control Policy*

In this step, we deffuzifyng the fuzzified value using fuzzy rules and calculate the policy to control devices. Fuzzy rules are expression of relation between remained battery x_1 and necessity of device x_2, and output is device control policy $P = \{off, keep, on\}$. The fuzzy rules are expressed by Table 3. In the table, b_i is an element in remained battery *B, and* b_i is an element in necessity of device *N.*

The center of gravity (COG) method is used for deffuzification. This method determines the output by x location of COG. COG and fuzzy inference result $F(x_1, x_2)$ is calculated by equation (5) [17].

Table 4. Rules to Determine Device Control Policy

R1: $IF\ Max(\mu_{P1}(F(x_1,x_2)), \mu_{P2}(F(x_1,x_2)), \mu_{P3}(F(x_1,x_2))\ is\ \mu_{P1}\ THEN\ D_{device}\ is\ off$
R2: $IF\ Max(\mu_{P1}(F(x_1,x_2)), \mu_{P2}(F(x_1,x_2)), \mu_{P3}(F(x_1,x_2))\ is\ \mu_{P2}\ THEN\ D_{device}\ is\ keep$
R3: $IF\ Max(\mu_{P1}(F(x_1,x_2)), \mu_{P2}(F(x_1,x_2)), \mu_{P3}(F(x_1,x_2))\ is\ \mu_{P3}\ THEN\ D_{device}\ is\ on$

$$COG(x) = \frac{\int f(x)xdx}{\int f(x)dx} \quad (5)$$

$$F(x_1,x_2) = COG\left(Max\left(p_{x_1}\begin{pmatrix} \min(\mu_{B1}(x_1), \mu_{B2}(x_1), \mu_{B3}(x_1)), \\ p_{x_2}(\min(\mu_{N0}(x_2), \ldots, \mu_{N5}(x_2))) \end{pmatrix} \right)\right).$$

To control the devices using output value of FIS, the rules express the relation with the state of device. The device state is set $D_{device} = \{off,\ on,\ keep\}$ (keep the current state). The device control policy is determined by deffuzification result using the rules on Table 4.

IV. Experiment and Result

A. Experimental Environment

This experiment aims of verifying that the proposed method shows better accuracy of determined device control policy than other methods and confirming the reduction of battery consumption. To experiment, we collected 1,837,917 data with 9 ungraduated college students in 2 weeks. Data were collected a time in 10 seconds, and have sensor information, remained battery, and context at that time. The smartphone was located on left trouser pocket while collecting data. We collected accelerometer, gyroscope, orientation, proximity, magnetic, light, GPS, and time data using Samsung Galaxy S4 devices.

B. Inferring Necessity of Devices

To verify the accuracy of inferring the device control policy, we conduct 10-fold cross validation test with other machine learning methods and compare the results with the proposed method. We used comparing methods include support vector machine (SVM), multi-layer perceptron (MLP), K-nearest neighbors (KNN), Decision Tree (DT), and Naïve Bayes.

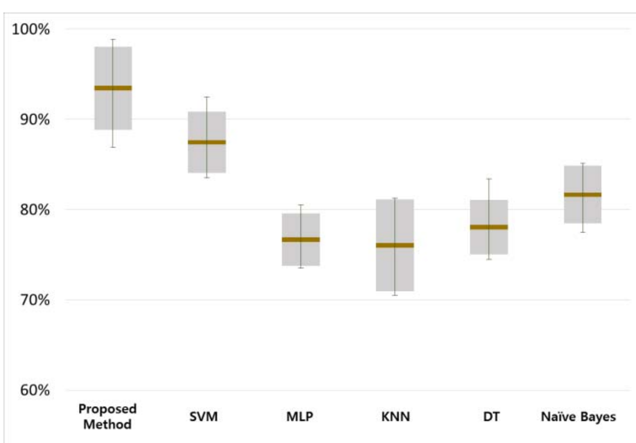

Figure 3. Experiment Results about Accuracy

At the result, the proposed method shows 94.2% accuracy, and other machine learning methods show 70%~80% accuracy.

Figure 3 is graph expression of experiment about accuracy. WiFi device shows the best accuracy with 98.9%, Bluetooth device shows the second accuracy with 97.66%. GPS devices shows the worst accuracy 81.74%. That results are expressed by confusion matrix in Table 5,6,7,8, and expressed by graph in Figure 4.

C. Experiments on Scenario

To verify the battery saving effect, we proceeded the scenario based experiment. Scenario is constructed based on Herrmann`s

Table 5. Confusion Matrices of Each Devices

WiFi		Actual	
		On	Off
predictal	On	429138	5828
	Off	14398	1388551

Bluetooth		Actual	
		On	Off
predictal	On	110305	2271
	Off	40754	1687157

GPS		Actual	
		On	Off
predictal	On	150245	263079
	Off	72508	1352082

Data Sync		Actual	
		On	Off
predictal	On	295348	21041
	Off	140689	1380837

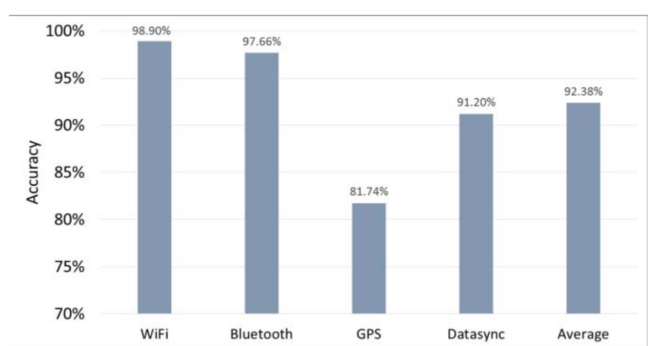

Figure 4. Accuracies with Each Device

Table 6. Experimental Scenario

Location	*Time*	*Context*
Company	9:00~9:30	Rest
	9:30~11:30	Working
	11:30~12:30	Rest
Moving	12:30~13:00	Moving
Restaurant	13:00~13:30	Meal
Moving	13:30~14:00	Moving
Company	14:00~15:30	Working
	15:30~16:00	Rest
	16:00~17:00	Working
Department	17:00~18:00	Shopping
Moving	18:00~18:30	Moving
Restaurant	18:30~19:00	Meal
Theater	19:00~21:00	Watching
Moving	21:00~21:30	Moving
Home	21:30~22:00	Exercising
	22:00~22:30	Rest

study [5], and modified it with contexts that our system can inferred. The scenario is shown as Table 6. For this experiments, we collected 10 scenario data from 3 graduated college student in four days.

We performed the experiments to compare the saved battery. The standards of saved battery is set the battery consumption with using SVM method that shows the best result on accuracy experiment. SVM is learned with data used for the accuracy experiment. The battery saving amount is shown in Table 7. The best, worst, and average amount of saving are 710mWh, 101mWh, and 490.9mWh. The average amount is 18.9% of battery capacity equipped on Samsung Galaxy S4 device.

Figure 5 shows the result of data 3 which occurred the best battery saving in real time. Green, horizontal striped area is saved battery and red, vertical striped area is wasted battery compared with SVM. At the time of switching between moving, working, and rest context, the proposed method has determined the necessary of device more precisely than SVM. Also, at exercising, the proposed method shows better result than SVM.

V. CONCLUSIONS

The proposed method can improve the accuracy of context-awareness. Even in the situation that two contexts are in race

Table 7. The Battery Saving Amount of Scenario Data

Data	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*Avg.*
Battery Saving Amount (mWh)	701	604	710	101	504	515	341	412	401	620	490.9

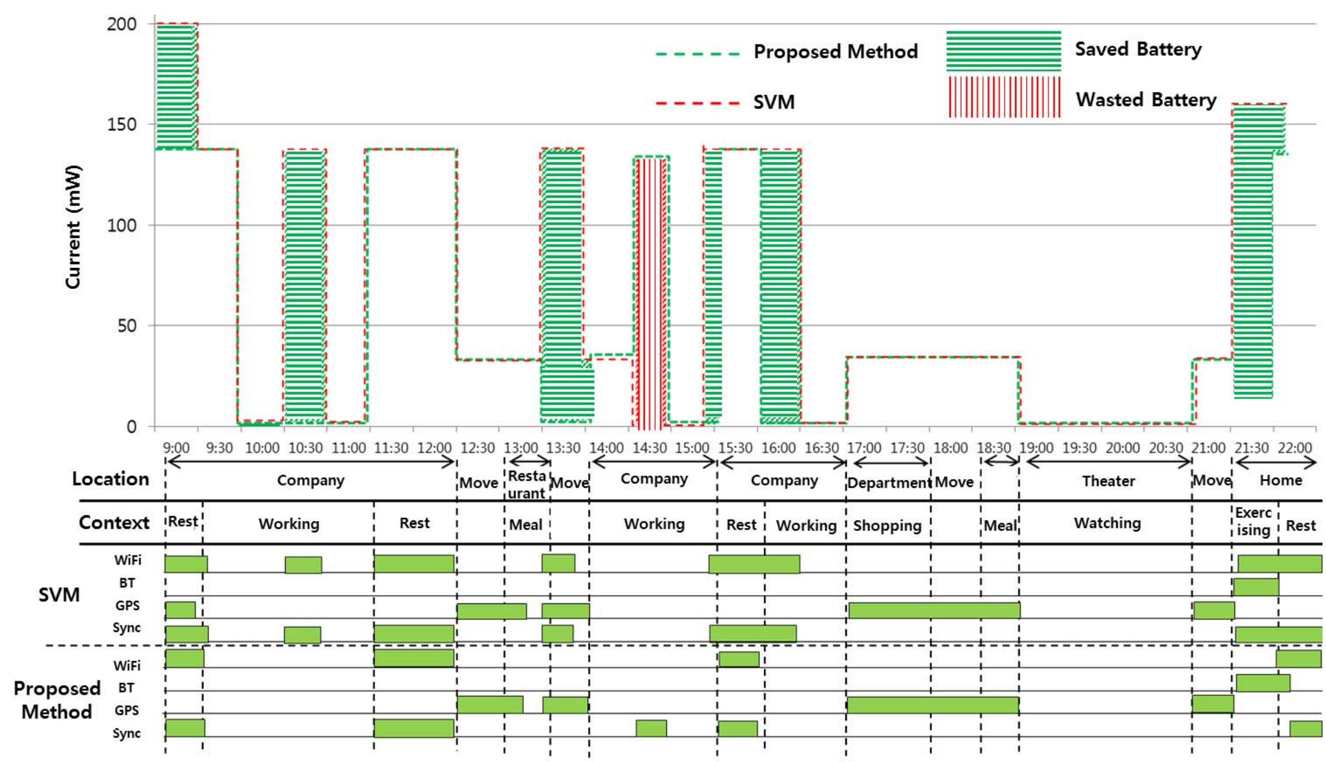

Figure 5. Real Time Result on Scenario Experiment

condition, the method can find the necessary devices more correctly than other methods. We verified the performance of the proposed method by experiments of accuracy and experiment based on scenario. At result, the proposed system produces better accuracy than other machine learning methods. In the scenario-based experiment, the proposed method showed the better battery saving compared with the SVM.

However, we could not compare with other methods in the relevant studies, because it was difficult to construct the same environment at the studies. In the future, we have to compare the accuracy and battery saving effect between the proposed method and the other relevant methods.

For the 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. We may also find a way to reduce the complexity of our method. In the long-term, we have to improve the context recognition model by learning larger data of more users.

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