A Non-GPS Low-Power Context-Aware System using Modular Bayesian Networks

Kyon-Mo Yang, Sung-Bae Cho
Dept. of Computer Science
Yonsei University
Seoul, Korea
kmyang@sclab.yonsei.ac.kr, sbcho@yonsei.ac.kr

***Abstract*—The proliferation of smartphones has lead to the development of a large variety of applications and the inverstigation on the use of various sensors through context-awareness, in order to provide better services. However, smartphone battery capacity is extremely limited, so that the applications cannot be effectively used. In this paper, we propose a low-power context-aware system using modular Bayesian networks. Bayesian networks are known to respond flexibly to uncertain situations. However, probabilistic models, such as Bayesian networks, have high time complexity, resulting in high power consumption. To reduce the time complexity, we modularize the network based on the Markov boundary, and eliminate the use of GPS because it consumes a lot of power. We compare the accuracy of the system using a combination of sensors and confirm the decrease in the time complexity. Experiments with the real data collected show that the proposed Bayesian networks yield an accuracy of 92.47%.**

Keywords-Low-power system; context-awareness; modular Bayesian network; Markov boundary.

I. INTRODUCTION

With the widespread production of smartphones along with its diverse array of applications and sensors, the trend of smartphone applications has shifted towards the personal and intelligent service route. Many researchers have investigated the possibility of intelligence techniques for context-awareness. The battery capacity of a smartphone, however, is well behind the development of applications. In a typical case, the user has to carry an extra battery or charge it frequently. There is the critical issue of how to reduce battery consumption for the context-awareness on the smartphone [1].

In this paper, we propose a low-power context-aware system using Bayesian networks. We focus on the configuration of input sensors and the inference time of the system. In the configuration of input sensors, the GPS sensor is a very important tool for situational context-awareness because the state of the user is closely related to the location. However, GPS usually consumes the highest amount of power and induces the need for a large location database in order to convert semantic location. For this reason, we choose to infer the user position not by GPS, but by determining whether the user is indoors or outdoors using the temperature and humidity sensors. In terms of reduction of time complexity, the Bayesian Network (BN) is modularized based on the Markov boundary [2].

We compare the accuracy using different combinations of sensors and evaluate the inference time of the proposed method against a monolithic network. In addition, we verify the low-power consumption feature of the proposed method in a real smartphone environment using the power tutor application.

The paper is organized as follows. Section 2 presents the related works for context-awareness, battery consumption, and Bayesian networks. Section 3 describes in detail the proposed low-power context-aware system. Finally, Section 4 reports the experiments conducted to compare the power consumption of the proposed system with the conventional system.

II. RELATED WORKS

A. Context aware services in smartphone

A context can be defined as information that can be used to characterize the situation of an entity, such as the person, place, or device that is considered relevant to the interaction between the user and the application [3]. Context-aware applications recognize the situation and provide services. The services have been studied using various sensors, as shown in Table I.

TABLE I. CONTEXT AWARENESS IN SMARTPHONE

Authors	Sensors	Services
Otebolaku, et al. [4]	Accelerometer, Orientation, Rotation	Mobile media content recommendation
Wang, et al. [5]	Accelerometer, Gyroscope, Brightness, Bluetooth, GPS	Music recommendation for daily activities
Santos, et al. [6]	Accelerometer, Brightness, Temperature, Humidity, Microphone, Time	Social networking application
Phithakkitnukoon, et al. [7]	Accelerometer, Microphone, GPS	Alert mode control
Chon, et al. [8]	GPS, GSM, Wi-Fi, Accelerometer, Thermometer, Digital compass	Location-based service

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Otebolaku and Andarade developed a context-aware mobile application [4]. The system used classifiers for recognizing high-level contexts from low-level sensor data. Wang, et al. presented a probabilistic model to integrate contextual information with music content analysis to offer music recommendation for daily activities [5]. Santos et al. described the architecture, operation and potential applications of a prototype system developed within the User-Programmable Context-Aware Services (UPCASE) project [6]. Phithakkitnukoon and Dantu proposed a three-step approach in designing the model based on the embedded sensor data for controlling alert mode [7]. Chone and Cha presented the smartphone-based context provider [8]. The system used the activity, connectivity, location and environment for inferring the current context. However, these previous works focus on the high accuracy of awareness using as much information as possible. These researches do not consider the power consumption of the context-aware system.

B. Power consumption problem

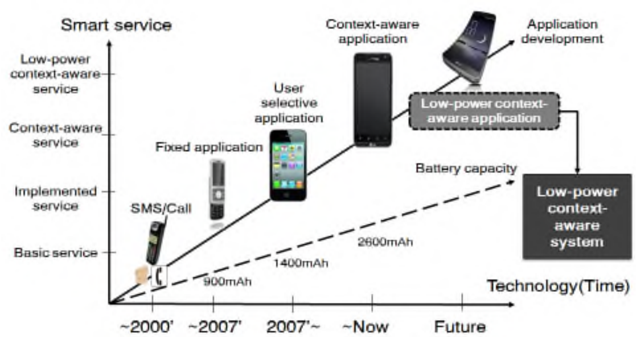

Figure 1. Trend of smartphone service

Various sensors have been implemented in smartphones, and the applications are utilizing these sensors. Although the battery capacity of smartphone has improved, it is insufficient to freely use a variety of applications. Fig. 1 shows the trend of smartphone services and the improvement of battery capacity. The energy consumption of these sensors is various, depending on the kind of smartphone. Abdesslem, et al. measured the energy consumption of different sensors [9]. Each sensor was run continuously on a Nokia N95 8GB smartphone until the battery was depleted. In this research, the power consumption of GPS was 623*mW*, which is 10 times more than the power consumption of the accelerometer senor. Wang, et al. measured the energy consumption using Nokia N95, as well [10]. In this research, the power consumption of GPS was 0.3308*W*, which is 7 times more than the power consumption of accelerometer. Although GPS sensor is more important for detecting user location, it has high energy consumption.

Many researchers proposed low-power applications using context-awareness to solve sensor problems. Herrmann et al. proposed to use context knowledge to dynamically adapt the behavior of sensing applications running on smartphones [11]. In the system, a context-aware application manager starts, suspends and changes the sampling rate of the sensors. Bareth and Kupper proposed a hierarchical positioning algorithm [12]. The algorithm dynamically deactivates different positioning technologies and only activates the positioning method with the least energy consumption. Seo et al. proposed a context-aware configuration manager for smartphones [13]. The system changes the configuration settings of a smartphone in response to changes in context, according to user-defined policy rules. These previous pieces of research focused on the management of the sensor, and they were not interested in reducing the power consumption of the inference module.

C. Context-aware service using Bayesian networks

Bayesian networks is a graph-theoretic concept for representing uncertain and incomplete knowledge using Bayesian statistics. BN has a structure of a directed acyclic graph which represents the link relations of the node, and has conditional probability tables (CPT). Assume that nodes are independent of each other.

$$\begin{aligned} P(U) &= P(A_1, A_2, \ldots, A_n) \\ &= P(A_1)P(A_2 \mid A_1) \ldots P(A_n \mid A_1, A_2, \ldots, A_{n-1}) \\ &= \prod_{i=1}^{n} P(A_i \mid pa(A_i)). \end{aligned} \tag{1}$$

The conditional probability distribution of variable A can be represented as $P(A \mid pa(A))$, where $pa(A)$ denotes the set of parent variables of variable A, where $U = A_1, A_2, \ldots, A_n$ is a set of nodes, and the joint probability distribution is computed by the chain rules as equation (1). For each child node, conditional probabilities are allocated for each combination of states in their parent nodes, so that the size of each CPT depends on the number of parent nodes and the number of their states, as follows:

$$size(CPT) = S \prod_{i=1}^{n} P_i \tag{2}$$

where S is the number of states, and P_i is the number of states in the i th parent node. Therefore, the size of the CPT can increase considerably with the number of parents, which can make the process of calculating the CPT intractable, especially if this is done through expert elicitation [14].

There are two approaches to identify the structure and parameter of a Bayesian network model. The first approach is the learning from the data on problem domains. The learning of structure is useful if we have a lack of understanding about the system. The method requires a sufficient amount of data, but it is not easy to obtain reliable data in many real-world problems.

The second one is to construct the model based on the domain knowledge. The experts identify the structure and set of parameters according to their knowledge, if we do not have enough data in the domain. In the context-aware service, Bayesian networks have been used for sensor fusion [15]. Lee and Cho proposed two-layered Bayesian networks for inference on a mobile phone [16]. This network was designed with the domain knowledge. The performance of Bayesian network using the domain knowledge can be evaluated through the scenarios or collected data [17]. In the field of context-awareness on the smartphone, the number of the used sensors is proportional to the number of nodes in BN. Therefore, selecting the sensor used for context-awareness is very important to reduce the time complexity.

III. LOW-POWER CONTEX-AWARE SYSTEM

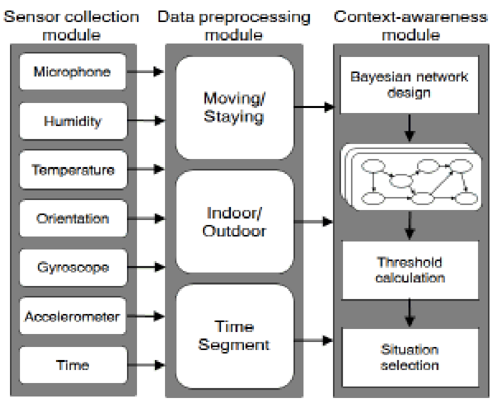

Figure 2. System archtecture

In this paper, we propose a low-power context-aware system. The system considers the power consumption and the sensors combination which are needed for inferring the user situation. Fig. 2 illustrates the system architecture for context-awareness. The system consists of three modules: sensor collection, data preprocessing, and context-awareness. In this proposed architecture, we do not use the GPS sensor because of the energy consumption. The sensor collection module obtains continuous sensor data in the smartphone. The data are sent to the data preprocessing module that discretizes them using a decision tree and a naïve Bayes classifier. The context-awareness module infers the user situation using a Bayesian network that is modularized based on Markov boundary. If the result of inference is higher than the threshold, it is the current situation. However, if all the results of a situation are less than the threshold, the module does not infer the current situation.

A. Data preprocessing

The purpose of data preprocessing is to reduce the time complexity of the Bayesian network modules. The number of states of input node is proporional to the size of CPT, because the parameter S in equation (2) is selected as the number of states. There are two discretization methods for input data. First, the input can be divided into a predefined number of intervals of equal width such as 0~1, 4~8, 8~12, 12~16, and so on. Second, it can be divided using statistical methods. For instance, a range between 22~27℃ represents 'normal', 10~22℃ is 'cold' and 'hot' indicates between 27℃ to 34℃. Table II shows the result of preprocessing. In this paper, we use the two preprocessing methods: Decision tree and naïve Bayes classifier.

TABLE II. RESULT OF PREPROCESSING

Method	Type	Input sensor	Result
Decision tree	Indoor/ Outdoor	Temperature	{Very high, High, Normal, Low, Very low}
		Humidity	{Very high, High, Normal, Low, Very low}
	Noise	Microphone	{Very high, High, Normal, Low, Very low}
	Time	Time	{Morning, Afternoon, Evening, Night}
Naïve Bayes classifier	User state	Accelerometer	{Stay, Moving}
		Gyroscope	
	User position	Accelerometer	{Sitting, Lying, Standing}
		Orientation	

A decision tree is a powerful and popular tool for classification. This method makes rules which can be understood by humans. The inputs such as temperature, humidity, microphone, and so on, make the rules as a range of the division using the decision tree, because the input data do not need to change into the semantic data. It just needs to divide each range.

A Naïve Bayes (NB) classifier is a simple probabilistic classifier based on applying Bayes' theorem with strong independence assumption. We infer the user position and state using NB classifier, because some input data need to be converted into semantic data, because if each input data are independent, we do not need Bayesian network. We use the two methods for preprocessing because the methods have low complexity.

B. Tree structure modular Bayesian network

This section presents a modular method of the types of situation. We design the tree structure Bayesian network for reducing the time complexity. We identify the three types of input nodes: The set of situation nodes $S = \{s_1, s_2, ..., s_i\}$, the set of type nodes $T = \{t_1, t_2, ... t_j\}$, and the set of preprocessing result nodes $R = \{r_1, r_2, ..., r_k\}$, where the type node t consists of the set of associated result nodes; $\{r_1, r_2, ..., r_m\} \in t$. The situation node S consists of the associated set of type nodes.

Neil proposed a method on how to separate large-scale Bayesian networks [18]. We define the two types of structure according to this research.

- Definition 1 (Result-Type structure): The network is used to reason about the uncertainty we may have about our own judgments. This structure represents uncertainties. We have result of preprocessing.
- Definition 2 (Type-Situation structure): Inferring the situation needs to reconcile independent source of evidence about a single attribute of a single entity, where these sources of evidence have been produced by

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different measurements or prediction methods. In this domain, the type nodes have different attributes and components. Therefore, the network is to reconcile independent response to the type node.

Locality of causal relation in a BN can facilitate decomposition of inference processes. A *d*-separation concept describes how different parts of BN can be rendered conditionally independent [2]. Pavlin et al. analyzed locality of causal relation with the *d*-separation concept [19].

- Definition 3 (Markov boundary of a set of variables): Markov boundary $B(V_i)$ of a set of variables $V_i \subset V$ in BN is the union of parents of set V_i and parent of children of V_i.

$$V(V_i) = Pa(V_i) \cup Ch(V_i) \cup (\bigcup_{\gamma \in Ch(V_i)} Pa(\gamma)) \qquad (3)$$

where $Ch(V_i)$ represents the children of V_i and $Pa(\gamma)$ is parent of γ.

We apply this locality of causal relation to the situation domain which has the response to type nodes as independent. For the independence, each module uses the sensor that is directly related to the situation instead of all sensory information. In the modules, the relations of nodes consist of two types: Type-Situation and Result-Type.

- Definition 4 (Type-Situation structure): The situation nodes represent the probability of the current situation. The type nodes denote the factors for inferring situation. For instance, the location, noise, time, and user is represented the type node. The situations such as viewing, moving, and studying are represented with the situation node.

- Definition 5 (Result-Type structure): The result nodes denote the obtained value of the sensor. For instance, the result node of the user state node denotes the values of user state: staying, and moving.

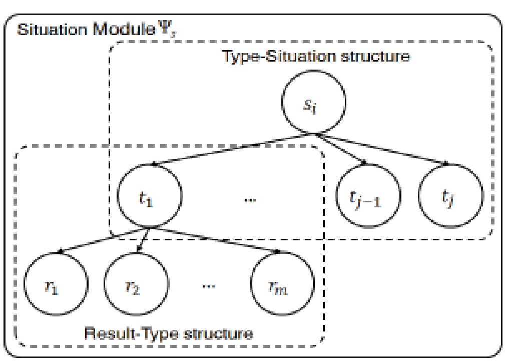

Figure 3. Modular structure for inferring user situation

Fig. 3 represents the situation module. Each situation module consists of one Type-Situation structure and one or more Result-Type structures.

C. Situation inference process

Input: Sensor data
Output: User situation

Preprocessing_sensor data

Repeat: all BN modules complete inference
    Setting preprocessed sensor data
    Executing propagation using (1)
    Getting result of inference R
  If ($R \geq$Threshold)
    Saving R *to current situation queue*
  Else
    Next module

Selecting the highest probability of R in current situation queue

Figure 4. Situation inference process

The inference process of the proposed context-aware system consists of multiple steps, as shown in Fig. 4. First, the system preprocesses the sensor data. Next, the system selects a Bayesian network module randomly. Then, the preprocessed sensor data set the values as evidence. The module propagates the probability and gets the result. If the result is larger than the threshold, the result is pushed to a current situation queue. The current situation queue has the candidate of the current situation. If the result is smaller than the threshold, the result is discarded. This step is repeated up to infer all BN modules. Finally, the system selects the highest probability of the result.

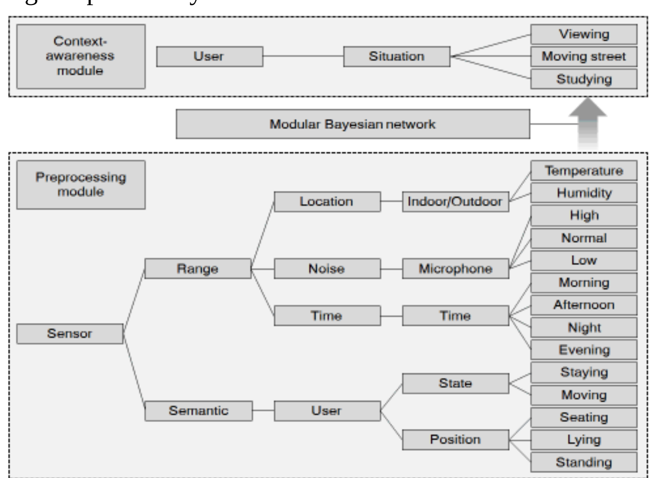

Figure 5. Formation of the context

Statistics Korea surveyed the time Korean people use to perform different activities [20]. In this survey, the students used a lot of time for sleeping, viewing, studying, and moving, in that order. We define the three network modules:

moving in the street, viewing, and studying to infer the situation of the student, because the user does not use the smartphone when he is sleeping. Fig. 5 shows the formation of context. In the preprocessing module, the input data include six types: temperature, humidity, microphone, time, state, and position. The sensor data are prepossessed and sent to the context-aware module. The module infers the three situations: viewing, moving in the street, and studying.

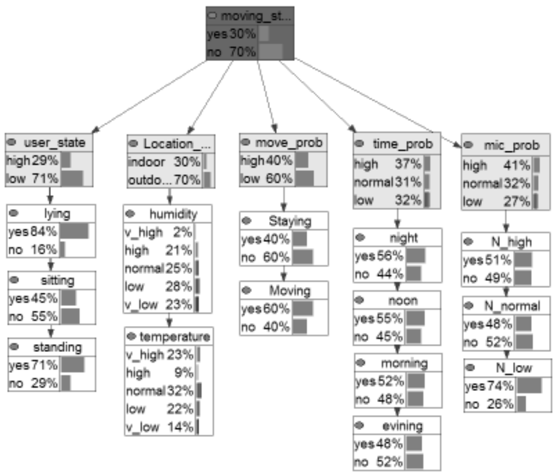

Figure 6. Example of moving street network

Fig. 6 shows an example of moving in the street network. In the network, the white color nodes are result nodes, the right gray nodes are type nodes, and the black node is situation node. The parameters are trained using Maximum Likelihood Estimation (MLE). This is the well-known method for learning the structure and parameters from data [2]. We collected the data for training parameters using MLE. The details about the data will be explained in the experimental section.

IV. EXPERIMENTS

This section describes the experiments conducted to evaluate the usefulness of the proposed method. For the experiments, the evaluation of the proposed method is conducted on Android phone datasets. The data was collected from five graduate students for one week. We used Samsung Galaxy S4. Android phone collected sensor data two times per second, and the amount of the collected data is 66,849 line. We collected data in three situations: studying, moving in the street, and viewing. The students selected the situation and conducted it. Android phone was put into their pocket.

A. *Combination of sensors*

Accuracy comparison for each combination of sensors verifies the accuracy of the method using sensor combinations except GPS. We conduct experiments of changing from one sensor to five sensors. Fig. 7 shows the accuracy comparison for each combination of sensors. As the result, the network using only GPS sensor has the highest accuracy among the networks using one sensor, because the GPS sensor can collect user location and relates closely to the user situation. However, the network uses about 0.3*W* per one time, which is not low. The accuracy of networks using two and three sensors combination, except GPS is less that of using GPS. The accuracy of network of four sensors; accelerometer, gyroscope, temperature, and humidity, is 94.25% whose power consumption is less.

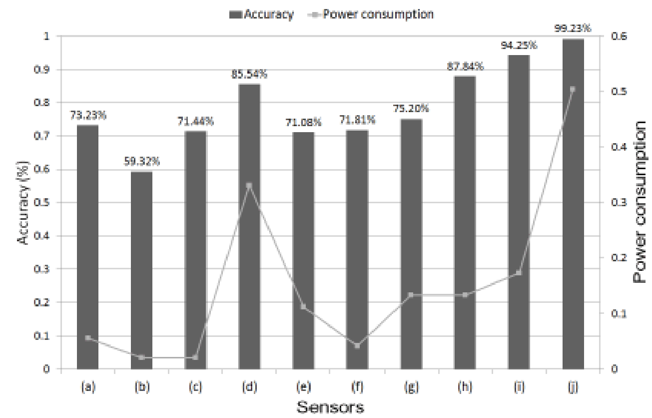

Figure 7. Accuracy comparision for each combination of sensors. (a): Accelerometer, (b): Temperature, (c): Humidity, (d): GPS, (e): Acelerometer+Orientation, (f):Temperature+Humidity, (g) Accelerometer +Gyroscope+Temperature,(h): Accelerometer+Gyroscope+Humidity, (i): Accelerometer+Gyroscope+Temperature+Humidity, (j): Accelerometer+ Gyroscope+Temperature+Humidity+GPS

The accuracy of the proposed method is higher than the accuracy of the network using GPS sensor only, because the proposed method collects user location using temperature and humidity sensors. Although the network using all sensors has the highest accuracy, its power consumption is very high too.

B. *Energy consumption*

To verify the relation of the inference time and power consumption, we calculate them. The PC configuration is Intel® Core™ i7-2600L CPU, 16.0 GB RAM, Window7. The inference time is calculated in the PC configuration. Table III shows the result of inference time, resulting in that the proposed method reduces more time of about 34% than monolithic BN. The structure of monolithic BN is trained using the Expectation Maximization (EM) algorithm [2].

TABLE III. RESULT OF INFERENCE TIME

BN type	Monolithic BN (BN)	Proposed BN (MBN)	Ratio (BN/MBN)
Moving street	1.178*ns*	0.095*ns*	12.3
Studying		0.084*ns*	14.0
Viewing		0.078*ns*	15.1
All module inferences		0.789*ns*	1.5

To verify the relation of power consumption, we calculate the power consumption using the power tutor application in Samsung Galaxy S4 [21]. The application infers 100 times per second. Fig. 8 confirms the difference of the time consumption of the BN and MBN. The BN consumes 45,241mW for an hour, whereas the MBN consumes 31,732mW for an hour.

C. Accuracy of proposed method

We conduct 10-fold cross validation to calculate the accuracy of each network, as shown in Fig. 9.

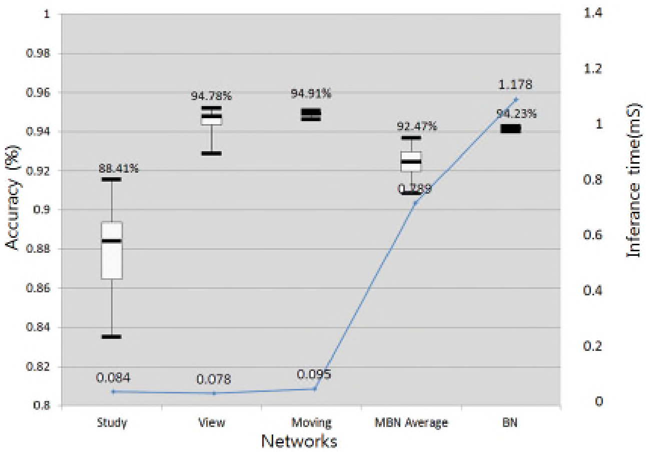

Figure 8. Accuracy and time comparion for each network

The accuracy of the average of MBN is 1.76% less than the BN while the inference time is 0.389mS more than the BN. The system for low-power context-awareness has to consider the inference time and the power consumption, the proposed method is better than the BN.

V. CONCLUDING REMARKS

In this paper, we have proposed a low-power context-aware system considering the power consumption and sensor combination. The system uses temperature and humidity to infer user location instead of using GPS sensor, because the GPS sensor has high power consumption. We use the Bayesian network considering the uncertainty of the situation and modularize to reduce the inference time. The system infers three situations: moving in the street, viewing, and studying. To verify the efficiency of the proposed method, we compare the accuracy of BN of the combination of sensors and calculate the inference time. In addition, we confirm the power consumption using power tutor application and verify the system has lower power consumption than the conventional method.

We will modify parameters using obtained data and will select the optimal time interval of inference. The system will apply to various context-aware service applications.

ACKNOWLEDGMENT

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