Expert Systems with Applications 36 (2009) 12065–12076

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

# Landmark detection from mobile life log using a modular Bayesian network model

Keum-Sung Hwang, Sung-Bae Cho *

*Department of Computer Science, Yonsei University, 262 Seongsanro, Sudaemoon-ku, Seoul 120-749, South Korea*

A R T I C L E  I N F O

*Keywords:*
Modularized probabilistic reasoning
Mobile application

A B S T R A C T

Mobile devices can now handle a great deal of information thanks to the convergence of diverse functionalities. Mobile environments have already shown great potential in terms of providing customized services to users because they can record meaningful and private information continually for long periods of time. Until now, most of this information has been generally ignored because of the limitations of mobile devices in terms of power, memory capacity and speed. In this paper, we propose a novel method that efficiently infers landmarks for users to overcome these problems. This method uses an effective probabilistic Bayesian network model for analyzing various kinds of log data in mobile environments, which were modularized in this paper to decrease complexity. We also present a cooperative inference method, and the proposed methods were evaluated with mobile log data generated and collected in the real world.



## 1. Introduction

Mobile environments have very different characteristics from desktop computer environments. First of all, mobile devices can collect and manage various kinds of user information, for example, by logging a user's calls, SMS (short message service), photography, music-playing and GPS (global positioning system) information. Also, mobile devices can be customized to fit any given user's preferences. Furthermore, mobile devices can collect everyday information effectively. Such features allow for the possibility of diverse and convenient services, and have attracted the attention of researchers and developers. Recent research conducted by Nokia is a good example (Nokia LifeBlog). Especially, the context-aware technique that has recently been widely studied is more applicable to mobile environments, so many intelligent services such as intelligent calling services (Schmidt, Takaluoma, & Mntyjrvi, 2000), messaging services (Lo, Thiemjarus, & Yang, 2003), analysis, collection and management of mobile logs (DeVaul, Sung, Gips, & Pentland, 2003; Gemmell, Williams, Wood, Lueder, & Bell, 2004; Korpipaa, Mantyjarvi, Kela, Keranen, & Malm, 2003; Krause, Smailagic, & Siewiorek, 2006; Raento, Oulasvirta, Petit, & Toivonen, 2005; Siewiorek et al., 2003; Zheng & Ni, 2006) have been actively investigated.

However, mobile devices present some limitations. They contain relatively insufficient memory capacity, lower CPU power (data-processing speed), smaller screen sizes, awkward input interfaces, and limited battery lives when compared to desktop PCs. In addition, they have to operate in the changeable real world, which means that they require more active and effective adaptation functions (Dourish, 2004).

In this paper, we propose a novel method of analyzing mobile log data effectively and extracting semantic information and memory landmarks, which can be used as special ways of helping recall specific functions (Horvitz, Dumais, & Koch, 2004). The proposed method adopts a Bayesian probabilistic model to efficiently manage various uncertainties that can occur when working with mobile environments, including real-world irregularities, like varying levels of attention and emotions, inaccuracy of sensors, and uncertain causal factors. The proposed model uses a cooperative reasoning method with a modular Bayesian network (BN) in order to work competently in mobile environments. We also discuss how to learn and update the Bayesian inference model by using the proposed BN learning method with training data. The proposed method was applied to several experiments using both synthetic data and real mobile log data collected with a smartphone for a month in the real world. In Hwang and Cho (2006), we proposed a method for identifying landmarks on mobile devices, which was a modularized BN model designed by human manually.

There have already been various attempts to analyze log data and to support expanded services by using the probabilistic approach. Li and Ji used a probabilistic model for active affective state detection of user (Li & Ji, 2005). They utilized a dynamic Bayesian network and the utility theory to reason the 'fatigue,' 'nervous,' and 'confused' states. They showed that the probabilistic approach was good at management of uncertain information like affection.

Ji et al. used also a dynamic Bayesian network method for real-time monitoring human fatigue (Ji, Lan, & Looney, 2006). They

* Corresponding author. Tel.: +82 2 2123 2720; fax: +82 2 365 2579.
*E-mail addresses:* yellowg@cs.yonsei.ac.kr (K.-S. Hwang), sbcho@cs.yonsei.ac.kr (S.-B. Cho).

0957-4174/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2009.03.002

concerned and combined many conditions such as light, heat, humidity, time, napping, anxiety, temperature, weather, and work type. Zhang and Ji proposed an active and dynamic information fusion method for multi-sensor systems with dynamic Bayesian networks (Zhang & Ji, 2006). This showed the usefulness of Bayesian approach for information fusion. These works showed the Bayesian probabilistic approach was good tool for handling, reasoning, and combining uncertain information.

Krause et al. clustered the sensor and log data collected on mobile devices, discovered a context classifier that reflected a given user's preferences, and estimated the user's situation in order to provide smart services (Krause et al., 2006). The context classifier was constructed using the BN model, which was based on a general learning method for a small domain of classification subjects. Horvitz et al. proposed a method that detected and estimated landmarks by discovering a given human's cognitive activity model from PC log data based on the Bayesian approach (Horvitz et al., 2004). Their approach showed a good performance for recognizing and learning everyday-PC-life of humans.

However, these methods were not suitable for mobile devices that were limited in terms of capacity and power. For larger domains, the general BN and BN learning method require highly complex computation. This is a crucial problem when it comes to modeling everyday life situations with mobile devices. To overcome these problems, a more appropriate approach was required to reduce the complexity levels. Marengoni, Hanson, Zilberstein, and Riseman (2003) tried to reduce the complexity levels of the BN model by dividing it into several multi-level modules and using procedural reasoning of the connected BNs (just like chain inference). However, this method required procedural and classified properties of the target functions.

Tu, Allanach, Singh, Pattipati, and Willett (2006) proposed a hybrid BN model that allowed hierarchical hybridization of BNs and HMMs. However, it supported only links from lower level HMMs to higher level BNs without consideration of links between BNs of the same level. Hwang, Kim, and Zhang (2006) proposed the hierarchical probabilistic graphical modeling method, which constructed a hierarchical and distributed BN structure using generated hidden nodes and the links between them. However, this method is improper in mobile and private service environments since it leads to an increase of the number of nodes and does not keep the intuitive causal structure.

## 2. Landmark inference from mobile log data

The overall process of landmark extraction from the mobile log data used in this paper is shown in Fig. 1. Various mobile log data is preprocessed in advance, and then the landmark-reasoning module detects the landmarks. The preprocessing module is operated by the techniques of pattern recognition and simple rule reasoning. The BN reasoning module performs probabilistic inference. The update module learns the Bayesian network models and adapts to the user and environment by using the accumulated data.

BNs refer to models that can express large probability distributions with relatively small costs to statistical mechanics. They have the structure of a directed acyclic graph (DAG) that represents the link (arc) relations of the node, and has conditional probability tables (CPTs) that are constrained by the DAG structure (Korb & Nicholson, 2003). Fig. 2 shows an example BN that was designed by human and used for the application of this paper. It shows a DAG structure, node name, state name and inferred probabilities.

### 2.1. Collection and preprocessing

Table 1 shows log information collected on a mobile device and on the internet. The GPS log presents the places that the user visited, and the call and SMS logs show the user's calling patterns. The MP3 (a music file format) player log offers an idea of the user's emotions and the photograph log shows when the user wanted to memorize something.

Since logs have temporal properties, we considered their time spans, frequencies (per hour, daily, and weekly), and start/end times as well as their impact factors that reflect the density of given events. For example, the impact factor of time $t$, $IP_t$ can be calculated as Eq. (1), where $x$ represents the event and $\alpha(x)$ and $\beta(x)$ represent the increment/decrement constants and monitoring time-span for event $x$. We set the value $\alpha(x)$ as 1 for each event $x$, and the values for $\beta(x)$ are set manually as follows; $\beta$(GPS) = 1 h, $\beta$(Call) = 1 h, $\beta$(SMS) = 20 min,$\beta$(Pic. View) = 5 min, $\beta$(Photographing) = 30 min, and $\beta$(Mp3 Playing) = 30 min,

$$IP_t(x) = \begin{cases} IP_{t-1}(x) + \alpha(x), & \text{if event } x \text{ is occurred} \\ IP_{t-1}(x) - \alpha(x), & \text{if event } x \text{ is not occurred in } \beta(x) \\ & \quad\text{after prior event } x \end{cases} \tag{1}$$

The coordinates from the GPS log are used to get place names. In this paper, we divided the domain area into a lattice and then labeled each region. The user profiles and PIMS (personal information management system) datasets were used to find the user's social position (student, worker), gender, the position of their home, and the names and phone numbers of their friends and relatives.

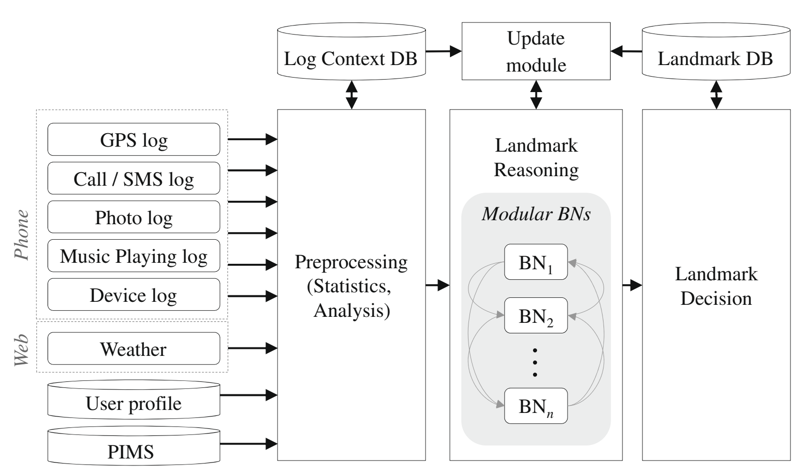


**Fig. 1.** The process of the landmark extraction from mobile log data.