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ConaMSN: A context-aware messenger using dynamic Bayesian networks with wearable sensors

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ABSTRACT

With the growth on the concern about context-aware applications, it becomes important to recognize and share user context. Even though there are some applications, it is still limited in managing simple contexts. In this paper, we propose a context-aware messenger application that exploits dynamic Bayesian networks to automatically infer a user's context and shares contextual information to enrich electronic communication. It collects various sensory information and displays representative user contexts such as emotion, stress, and activity in the form of icons in the messenger program.

1. Introduction

People want to enrich their social relationship by communicating with each other, and implicit situational information, called context, is beneficial to increase the richness of communication (Griswold et al., 2004; Ranganathan, Campbell, Ravi, & Mahajan, 2002). However, it is hard to share the context of users who are far apart from each other. Recently, a messenger (like Windows Live Messenger) for chatting with someone electronically provides a function to show a simple context such as online or offline, in business or in break, etc. Even though these kinds of information might be useful to properly contact with others, it is still limited to share the wide variety of contexts that could be sensed in a face-to-face conversation. We thus aim to create a system that could recognize various contexts such as the level of stress, the type of emotion and activity.

Our goal is to recognize a user's context based on information collected from wearable sensors and to share the context through a messenger application. Our system, context-aware messenger (ConaMSN), manipulates the large number of raw data to enlarge the simplicity of conventional context-sharing systems. From a user's physiological information and movement collected by using Armband and accelerometers, ConaMSN infers various contexts with modular dynamic Bayesian networks (BNs) and visualizes them with a set of icons.

By exchanging contextual information of users, ConaMSN lets them know their buddies' situation and improve electronic communication. For example, users can give words of encouragement to their friends in a gloomy mood. Also, they can expect a slow response, since they already know that their buddies are involving in some activity.

2. Related work on context-sharing systems

Sharing contextual information is a hot issue in building social relationships. Many researchers have studied how to construct a sensor platform, collect and preprocess features, design a recognition model, and visualize the contextual information. SenSay (Krause, Smailagic, & Siewiorek, 2006) and ContextPhone (Raento, Oulasvirta, Petit, & Toivonen, 2005) are representative platforms of context-aware services, which collect sensory information by using some embedded or wearable sensors and recognize contexts. Korpipaa, Mantyjarvi, Kela, Keranen, and Malm focused on how to manage raw sensory information of multiple heterogeneous sources. They constructed context ontology which might be useful to handle imprecise information from multiple sensors (Korpipaa et al., 2003).

Recently, many studies have dealt with the recognition method of contexts, where probabilistic models are the most popular one. Krause et al. used BNs to infer user preferences (Krause et al., 2006), while Oliver et al. proposed layered hidden Markov models to model human activities (Oliver & Horvitz, 2005). Cho, Kim, Hwang and Song used an ensemble of BNs to automatically detect events from log data (Cho et al., 2007). ConaMSN integrates various kinds of sensory information and uses the ensemble of dynamic probabilistic models to recognize more complicated user contexts.

There are other related works on context-sharing such as ConChat (Ranganathan et al., 2002) and ContextContacts (Raento et al., 2005). ConChat is an instant messaging system that shows people's contextual information, but it requires users to select their contexts manually. ContextContacts, a context-sharing application

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implemented based on ContextPhone, lets users automatically represent and exchange their contextual information such as location and profile. Since it uses a simple sensor like GPS, it can only provide simple situation cues. Favela, Rodriguez, Preciado, and Gonzalez developed a mobile hospital information system that indicates the presence and location of users (Favela et al., 2004). Table 1 shows some context-sharing applications.

3. ConaMSN

We have designed and prototyped ConaMSN consisting of five modules as shown in Fig. 1. After ConaMSN logs and preprocesses raw data, it infers three user contexts such as emotion, stress, and activity, and converts them into the icons of the buddy list. We have constructed a set of dynamic Bayesian networks (DBNs) in a modular manner, where DBNs are one of the most efficient models of inferring situations given a certain amount of uncertain or partial serial information.

3.1. Logging

By designing a sensor platform that integrates the Armband, accelerometers, a GPS receiver, and a smart phone as shown in Fig. 2, ConaMSN continuously collects four types of sensor information:

- Physiological information, related to emotion and stress, including a skin temperature, heat flux, and Galvanic skin response measured by the Armband;
- user movement, related to activity, including 3D acceleration, 3D angular velocity, 3D magnetic field of movements of head, right and left arms, right and left hands sensed by five accelerometers;
- user interaction, related to activity, including whether the user is indoor or outdoor, whether the user is using her phone or computer obtained by a GPS receiver and a smart phone; and
- physical environment, related to emotion, stress and activity, including weather and the time of day collected by a smart phone.

3.2. Preprocessing

Since raw data include continuous and discrete values collected from various types of sensors, it is required to unify them in a standard format. All the data are logged according to the time with the same frequency (in this paper, 20 fps). Continuous values are smoothed to remove sparking noises, and then discretized into three states (for example, low, mid, and high) by clustering. The smoothing uses a shifting window that moves on the sequence according to the time as shown in Fig. 3. It calculates the average of current and previous data within the window as follows:

$$f(W(t)) = \frac{\sum_k W_k}{s}, \quad W_k \in W(t) \tag{1}$$

where $w(t)$ stands for the window at time t, w_k is samples in the window, and s is the size of the window. Fig. 3 shows the effect of smoothing on the sensory sequence. The raw data includes some noises and rapid changes due to the sensitivity of sensors, but smoothing removes those rapid changes and captures only important patterns in the data.

After smoothing, we discretize the continuous value into several discrete states by using the K-means clustering algorithm for activity recognition based on BNs. It defines k centroids distributed over the given dataset, associates samples to the nearest centroid, and calculates new centroids again with the resulting clusters. It repeats the process until the centroids do not change any more, and aims to minimize the squared error function as follows:

$$V = \sum_{i=1}^{k} \sum_{xj \in s_i} (x_j - \mu_i)^2 \tag{2}$$

where there are k clusters, and μ_i is the centroid or mean point of all the points $x_j \in S_i$. The centroids are calculated for the training dataset in advance, and they are used in online activity recognition. In this paper, the cluster number k is set to 3 {High, Mid, Low}, which is the number of states of sensory nodes in DBNs. Table 2 shows the variables used for inferring contexts in ConaMSN after preprocessing.

Some information cannot be directly measured by sensors, so that we design a set of simple rules for setting values. For example, the location of users is determined whether the system detects (outdoor) or loses (indoor) the GPS signal. The usage of a computer is measured by the mouse movement and keyboard input.

3.3. Inferring user context

ConaMSN infers a user's three contexts such as emotion, stress, and activity, and Table 3 shows the available values for each context. Since contextual cues are gradually or instantly changed according to the corresponding context, a dynamic inference model is required to deal with the time-series sensor information. We used DBNs, which are BNs designed suitable for sequential data. Moreover, as sensor information is often missing, uncertain, and incomplete, we must deal with uncertainty and missing variables. DBNs can address such problems by providing a robust inference based on probability theory. Especially, we implemented the DBNs by using structural modeling, inference, and learning engine (SMILE), which is a popular BN library (http://genie.sis.pitt.edu).

Contrary to standard BNs, however, DBNs include time-series variables often leading a great complexity, and the overload also increases radically when a node has many states. In order to improve the scalability, therefore, we designed the inference module in a modular style by constituting an ensemble of multiple DBNs as shown in Fig. 4. ConaMSN has two kinds of inference models. Basically, three long-term models, which aim to manage the gradual change of contexts, infer the probabilities of all states of three contexts for given sensing information. Since activity is a context that instantly reflects on movements, seven short-term models detect the corresponding activity in addition to the long-term model of activity. ConaMSN integrates several outputs obtained by multiple DBNs based on the strategy used in our previous work (Hong, Min, Cho, & Cho, 2008). The three networks of the long-term model are manually designed to contain 37 nodes, 34 links, and 684 condi-

Table 1
Context-sharing applications.

Title	Sharing context	Sensor
ConNexus/Awarenex (Tang et al., 2001)	Location, activity	GPS
ConChat (Ranganathan et al., 2002)	Location, environmental context, mood, status, activity	External module
ContextContacts (Raento et al., 2005)	Location, profiles	ContextPhone
Ferscha, Holzmann, and Oppl (2004)	Location	RFID
Favela et al. (2004)	Location	External module
Hu and Wang (2007)	Location	GPS