Adaptive Modeling of a User's Daily Life with a Wearable Sensor Network

Hyoungnyoun Kim, Ig-Jae Kim, Hyoung-gon Kim, Ji-Hyung Park
Korea Institute of Science and Technology
{nyoun, jhpark}@kist.re.kr, {kij, hgk}@imrc.kist.re.kr

Abstract

In an environment where the contexts of users are complex and the degree of freedom of user activity is very high, such as in daily life, several factors need to be considered for constructing user models. Such a model should include changes in the meanings of activities that reflect the user's situation both temporally and individually. In this paper we propose a novel approach for personalizing the user model and adapting it to individual circumstances with a wearable sensor network. We also describe the process for determining the repetitive activities of a user by using incremental clustering and Bayesian network. We show experimental results for an adaptive user model based on a real wearable sensor platform. Multimedia data of user experience are acquired from the multimodal sensors, and processed to metadata that have meanings.

1. Introduction

In a daily life, building a user model is a very challenging problem because it is expected that the contexts of the user are complex and a degree of freedom of user activity is very high. Previous context-aware systems are constructed to provide a user with appropriate services while assuming that the user modeling got accomplished. In the web not only the specific domains, like health or education, many systems for satisfying demands of users have been developed [1,2]. Several researches for analyzing the daily life are also in progress in the wearable computing environment [3,4,5]. They models behaviors of users that wear multimodal sensor networks. However it still remained as a principal problem how efficient we makes a system that saves, indexes, and searches information from multimedia streaming data. As to the build-up of a multimedia system, the reasoning - current contexts, abnormal behaviors, and future contexts - for providing services according to the intention of a user has to be included with. The system needs a user model that reflects a life pattern of a user, and we call the model as an adaptive user model.

A wearable sensor network extracts multimedia data (i.e. life-log data) from the daily life of a user. These data have some representative attributes, and determine methods for a user modeling. First, life-log data is streaming data that accumulate with user experiences. It includes old information that has appeared repetitively or new information that has not appeared according to the user context and the environment. Second, raw data acquired from sensors are saved as metadata that has unit of semantic, through preprocessing. We define these semantic metadata as primitives, which have characteristics of categorical data. Previous researches [3,6] dealt with the problem at feature level instead of semantic level to retrieve high-level activity from sensor data. Third, the metadata extracted from multimodal sensors has more than two types of information, which are potentially connected as causal relation. The relations discovered on user models have a significant role to infer user contexts. Furthermore, relations inside metadata can change its organization as both schemes of a sensor network and log data of user experience. Hence to be a adaptive model, we have to consider these potential relations.

In this paper, we construct a user model based on a probabilistic modeling approach in a wearable sensor network environment, where categorical metadata that has potential relations are incrementally accumulated according to user experiences. The created model allows personalization and incremental update of itself, and enables the system to infer user contexts from semantic metadata. Our approach discovers user activities that occur repetitively through entropy based clustering of categorical primitives, and performs both structure and parameter learning of Bayesian networks to detect relations between clustered primitives. The proposed clustering and network learning that are accomplished can process the incremental life-log data. Through a real experiment, we built adaptive user models based on life-log data of two people for two weeks. By showing the process of incremental update and personalization, we confirm that our approach is possible to apply to the wearable computing environment.

The rest of the paper is organized as follows. Section 2 describes the entire process of constructing adaptive user model from the acquisition of primitive data that forms the substantial elements of context, to constructing a modeling using clustering and Bayesian network. We then show experimental results based on a wearable sensor network in Section 3. Section 4 discusses our conclusions and possible future directions.

2. Adaptive User Modeling

Metadata of life-log data are divided into two levels: primitive, composite. *Primitive* data comprise the information based on a single modality as acquired from a sensor network through preprocessing. *Composite* data represent high-level context information inferred from more than two primitive data sets.

To extract information from a wearable sensor network, discriminated information is accumulated since not all of the users (1) wear the same sensors or (2) have the same experience. Primitive data can have the same meaning to different users, but the combination of various sets of primitive data varies with the user. The set of primitive data related to user experience is stored sequentially, and repeated patterns therein are considered to represent meaningful activity of the user. Therefore, the connection with primitive data and composite activity is important for user modeling.

To develop user-adaptive modeling, we obtain primitives of a user, extract composite activities, and discover the relationships between the activities. Figure 1 shows the process of our proposed user-adaptive modeling technique.

2.1. Primitive Activity Detection

In a general definition, the high-level context comprises four main elements: time, location, object, and action [7]. Two types of primitive data are defined according to the properties of sensor data: sensor data related to the state of the user refer to an internal primitive, whereas data related to the state of environment are called an external primitive.

Internal primitives contain information on the static or dynamic actions and physiological states of a user. To analyze user actions, motion sensors such as an accelerometer and gyroscopic sensor measure body postures and gestures. The classified actions include standing, sitting, lying, walking, running, and going up stairs. In the same manner, body sensors acquire

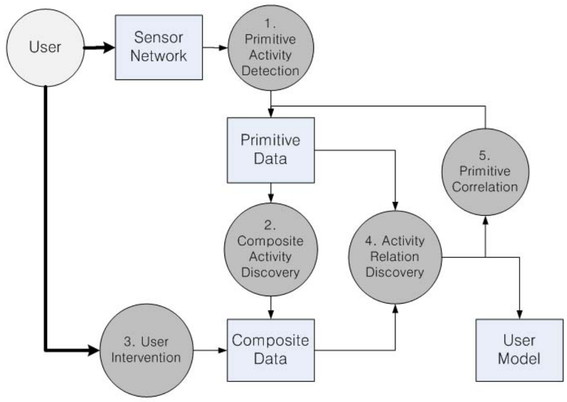

Figure 1. The overall process of user-adaptive modeling, which consists of five steps. Steps 2 to 5 repeat until the model converges.

information on the body state by measuring the temperature, heartbeat, and galvanic skin responses.

External primitives represent information about the environment around a user. We classify external primitives into private and public types. Private primitive data including faces and objects tend to vary with the user. These data are extracted using a camera, microphone, and RFID based on known definitions of the objects and manual definition by the user.

Public primitive data, which include times and locations, use the same preprocessing method for each sensor regardless of the user. The GPS (Global Positioning System) detects the position of a user outside. Additionally, the GIS (Geographic Information System) can be used by all users to obtain their positional information autonomously. Time is commonly defined by users as an absolute concept from dawn to midnight.

2.2. Composite Activity Discovery

The information group of primitive data that includes time, objects, and actions is an attribute. Each attribute has concrete value data, and the set of acquired attributes at any time is called the instance.

The step of composite activity discovery involves discovering repetitive instances through clustering between primitive instance set, which involves the following considerations. First, primitive values are not numerical and ordered, but rather non-ordered and categorical data. Therefore, clustering methods for categorical data [8,9] are more useful than methods for numerical data. Second, primitive instances are streaming data that accumulate with user experiences. Hence, after an initial clustering step for the stored data pool, newly gathered data can affect the previous clusters. Likewise, new clusters that were absent from the previous data pool can be discovered, representing a user's activity patterns. The third consideration is the potential presence of relations between primitive attributes. Clustering generally involves defining independent relations among the attributes. However, two attributes (location and object) are related when a user encounters a particular object whenever he or she is in a specific location.

We apply a clustering method that can process a data set containing categorical values and streaming instances. The presence of asynchronous data (as the third consideration) is a problem related to the definition of instances. Potential relations (as the last consideration) are processed after this clustering step. Figure 2 shows a flow chart for the incremental clustering of categorical data. In order to complete this clustering, we combine information entropy and quality threshold (QT) clustering [10].

In the clustering step, information entropy is applied because of the characteristic of categorical data. According to the QT clustering we find the candidates of cluster centers. Then we choose the most similar instances from the data pool to cluster based on the selected two candidates. Each instance must be the one that results in the smallest increase in cluster entropy. Since all instances are investigated one by one, the cluster increases by adding instances that satisfy the conditions. Two clusters stop expanding their ranges when the entropy of each cluster exceeds the fitting threshold. New clusters are discovered by repeating this process, and clustered data are transmitted to the next step and labeled, and the remaining data stays in the data pool.

The meaning of each discovered cluster is labeled by users. This labeling process deals with instances that represent the repetitive pattern in all of the instances, so users can define the adaptive meaning of each context with a minimum of effort. The general model that divides daily life into the activity categories selects composite activities such as sleeping, eating, drinking, cleansing, shopping, housework, attending, and leaving. In some cases, users indicate manually the meaning of the activities as a composite activity.

2.3. Activity Relation Discovery

This step involves finding the potential relation between primitive attributes and composite activities, after primitive instances guarantee labels of composite activity through clustering and labeling from unlabeled primitive data. The method of relation discovery is as follows.

The relation between the primitives and the composite can be drawn as a Bayesian network, which learns the structure of activities from training data, and hence reveals potential relations. Several methods of structure learning have been proposed based on the proper-

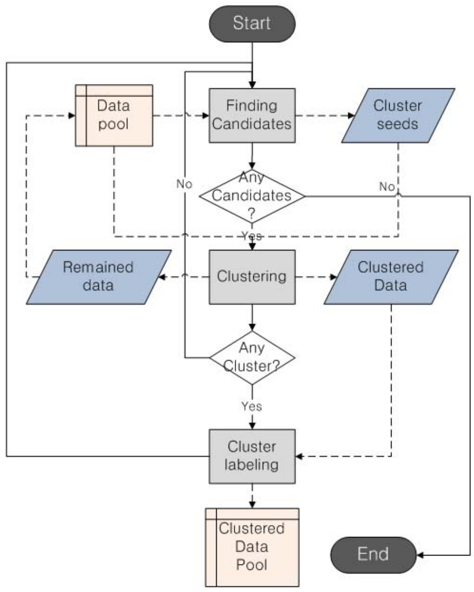

Figure 2. Flow chart for incremental QT clustering. Dotted lines represent the flow of primitive instances, and solid lines represent the process flow.

ties of training data [11, 12]. Among these methods, we applied the ORSearch algorithm that combines RADSEARCH [13] and Optimal Reinsertion algorithm [14]. This algorithm targets cases where no initial knowledge of the node ordering and fully observed data are assumed.

After structure learning, we discover the graphical model of primitives and simultaneously obtain the Conditional Probability Table (CPT) by parameter learning. Because both the CPT and network structure are based on the training data, repetitive learning of full training data is necessary to discover new clusters and to expand the primitive values.

The discovery of activity relations means that primitives and composite activities that rely upon user experiences form the basis for the construction of user-adaptive models. The relation between primitives and composite activities affects the process of inferring composite activity in a specific situation. Moreover, it is necessary to detect new activities and to expand the activity model through incremental clustering. The relation also changes with the clustering result. Therefore, by modifying the activity model, this modeling approach allows the model to adapt to the pattern of a user's daily life.

2.4. Iterative Correlation

We assumed that the primitive attributes are independent, and found the relations through entropy-based clustering. However, the constructed Bayesian networks indicated the presence of conditional dependencies between primitive attributes. Therefore, we define the user model whilst considering this contradiction related to dependency. We describe an iterative process that detects potential relations of primitives, discovers composite activities using those relations, and determines the structure of a user model.

The modified conditional entropy is used to discover the composite activity and activity relation. The iteration finishes when there are no changes in the relationship or there is no relationship in the primitives after clustering, which completes the user-adaptive modeling.

2.5. Inference

Two types of information can be inferred from the network model created through the process of user-adaptive modeling. The first is composite activity from a given primitive instance. A data-related user experience at a particular time point comprises primitive attributes but not composite activity. If the primitive data are substituted for the state of every node in the Bayesian user model, the model infers the composite activity in that case. On the other hand, the second type of information is the primitive data from a given composite activity. When a particular composite is predicted, the model can retrieve the most probable state in an unknown primitive node. This information increases the completeness of context information.

3. Experiments and Evaluation

The Life-log system aims to autonomously log and manage personal information whenever and wherever a user wants to recall their last experience, by recording, classifying, and summarizing contextual information related to user activities [15]. This system acquires, records, and manages user activity information such as location, time, action, and profiles obtained by users wearing multimedia sensors attached to the network and processing modules. The information is used by the system to recognize user context, analyze user interaction patterns, and increase user memory. Figure 3(a) shows a user wearing a sensor network. The process flow of the LLM system is presented in Figure 3(b).

3.1. Experimental Setup

The Life-log system extracts six types of primitive data from the five sensors worn by a user: location, time, object, action, face, and voice. Outside locations are determined from the preset coordinates of the GPS, and indoor locations are determined using vision-based marker detection. Objects are classified and recognized

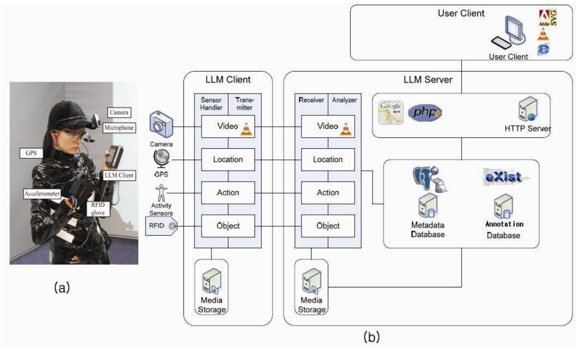

Figure 3. The Life-log system. (a) A user wears a sensor network that includes a camera, microphone, GPS device, RFID glove and accelerometers. (b) Process flow of the LLM system.

time	location	action	object	face	speaker
morning	house_bathroom	standing	shaver	none	none
morning	house_room	standing	bag, shoe	none	none
morning	house_front	standing	key	none	none
morning	bus	sitting	phone	none	none
morning	subway_hongdae	walking	card	none	none
morning	campus	walking	none	none	none
morning	campus_lectureroom	sitting	phone	none	professor
morning	campus_multimediaroom	sitting	mouse	none	none
morning	campus_multimediaroom	sitting	none	junior	junior
morning	campus_multimediaroom	sitting	mouse	friend	mine
morning	campus_multimediaroom	sitting	mouse	friend	friend
noon	campus_departmentbuilding	standing	phone	none	mine
noon	campus_departmentbuilding	standing	none	friend	mine
noon	campus_departmentbuilding	standing	none	friend	friend
noon	campus_front	walking	none	friend	mine
noon	campus_front	walking	none	friend	friend
noon	campus_restaurant	sitting	umpc	friend	friend
noon	campus_restaurant	standing	wallet	none	mine
noon	campus_restaurant	standing	wallet	none	friend
afternoon	campus_gym	standing	phone	none	none
afternoon	campus_gym	standing	none	junior	mine
afternoon	campus_gym	sitting	none	junior	junior
afternoon	campus_gym	standing	none	junior	none
afternoon	campus_multimediaroom	standing	none	none	none
afternoon	campus_multimediaroom	sitting	mouse	none	mine
afternoon	campus_multimediaroom	sitting	mouse	none	friend
afternoon	campus_departmentbuilding	standing	wallet	friend	mine
afternoon	campus_departmentbuilding	standing	wallet	friend	friend
afternoon	campus_lectureroom	sitting	can	none	professor
afternoon	campus_departmentbuilding	standing	phone	none	mine
afternoon	campus	walking	none	friend	mine
afternoon	campus	walking	none	friend	friend
afternoon	subway_hongdae	walking	none	none	none
evening	bus	sitting	phone	none	none
evening	street_house	walking	none	none	none
evening	house_front	standing	key	mother	mine
evening	house_front	standing	key	mother	mother
evening	house_bathroom	standing	none	none	none
evening	house_livingroom	sitting	tvremotecontrol	none	mother
evening	house_livingroom	lying	tvremotecontrol	none	none
evening	house_room	sitting	mouse	none	none
evening	house_room	sitting	phone	none	mine
night	house_room	sitting	mouse	none	none
midnight	house_room	lying	phone	none	none

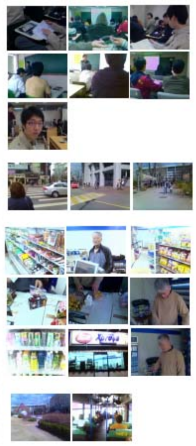

Figure 4. Experience data sets representing the captured daily lives of an undergraduate student and the captured images.

by attaching RFID tags to things that a user touches. Action information is defined as simple postures and gestures such as sitting, standing, walking, running, and lying down. Faces and voices are recognized through vision and audio-based machine learning algorithms.

Currently the Life-log system does not apply autonomous annotations and restoration of multimedia since problems related to battery capacity and privacy are not solved yet. We capture snapshots using a camera at 30-minute intervals and annotate logs of the primitive activity manually to prepare the experimental data set. This set comprises experimental logging data obtained over 2 weeks. In the first week, data are acquired from a user's daily life, and in the second week primitive data are created virtually. Figure 4 shows examples of primitive activities gathered for the daily

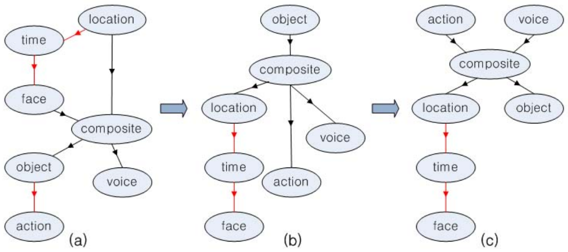

Figure 5. Results of an iterative modeling test. Arrows indicate related nodes, with red arrows representing the relations between primitives.

lives of an undergraduate student and captured images. In this section, we show three topics in adaptive modeling respectively: iterative, updated, and personalized modeling.

3.2. Iterative Modeling

We now test this iterative modeling process. The initial clustering discovered 14 clusters in 1 week of data for User A. Among 187 instances, 94 instances were classified to clusters and the remaining instances were left in the data pool. Each classified instance had six primitive attributes and one composite activity. Primitive attributes are represented by nodes in a Bayesian network. Structure learning yielded the initial trained model shown in Figure 5(a), which comprises seven relations between nodes and three relations with primitive attributes, with the other relations correlated with composite activity.

Once the computed entropy had changed, clustering revealed 119 instances covering 16 clusters. A new model was derived from the clustered data, as shown in Figure 5(b), in which two of the six arrows represent the relations between primitive attributes. Comparison with Figure 5(a) reveals that the relation between action and object has disappeared. According to the unchanged conditional relation, the third clustering based on modified entropy computation retrieved 120 clustered instances and 16 clusters. The final user model has the shape shown in Figure 5(c) with the relations between primitives being unchanged, unlike in Figure 5(b) where the relations of the composite differ. We therefore stopped the iterative modeling process at this time point. Parameter learning of the Bayesian network yielded the user model as shown in Figure 6. The system used this network model to infer the composite activity of a user in a specific situation.

3.3. Updated Modeling

Since it is insufficient to represent the ordinary life of a user, we added remaining virtual experience data into the data pool. In order to detect new activities that are repeated every week, we performed user modeling while adding 1 day's worth of data at a time. The instances added to the data pool were compared with the clusters of the created model: if the entropy of an aggregated cluster was less than a threshold of intracluster, the instance was used for inference; otherwise the instance was moved to the data pool where remaining data are restored. This resulted in a total of 186 instances being moved into the data pool for 5 days.

The analysis of 1 day's worth of data discovered 4 clusters that contained 16 instances, demonstrating that the added data facilitated the detection of clusters.
Table 1 lists the sequential variation of composite activities, data pool, and network according to the added instances.

Table 1. Results of an updated model showing changes in the data pool, discovered data, and network relation over 5 days.

		Day 1	Day 2	Day 3	Day 4	Day 5
Remaining data pool		67	75	81	93	103
Added data		36	34	37	38	40
Inferred data		12	20	25	22	23
Discovered cluster	Old	1	1	0	1	2
	New	3	1	0	1	0
Clustered data	Old	3	4	0	3	7
	New	13	4	0	3	0
Network relation change	Primitives	No	No	No	Yes	No
	Composite	No	Yes	No	Yes	Yes

The 5-day updates of the user model revealed additional composite activities that were not defined, and adapted the expansion of clusters and changes in relations between primitive attributes. Figure 6 represents the completed user model.

3.4. Personalized Modeling

We compared the results of adaptive modeling for each user to verify that our approach can create a personalized model as well as adapt to accumulated user-experience data by itself. Users A and B had their own lifestyles and experiences. We obtained models of these two users by analyzing the data sets comprising their real experience data and virtually created data. The models are shown in Figure 6. Even assuming that they have same sensor networks and primitive attributes, the values of each attribute differ between the users, as do the causal relations among primitives and composite activities.

We choose one instance of each of the following: time (afternoon), object (pen), action (standing), speaker (me), and face (none). In this situation the model of User A infers a composite of 'using a mobile phone', and that of User B infers the same activity as User A. However, if the action primitive changes from

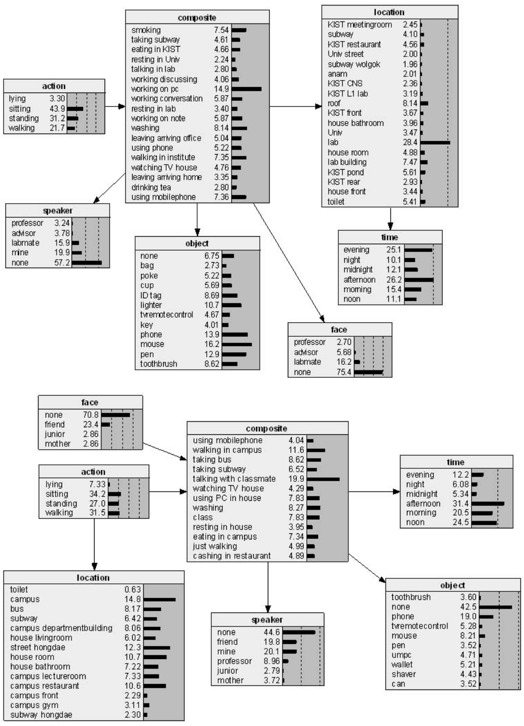

Figure 6. Bayesian networks after updating the user model over 5 days. The experience data of User A and B were used to train these models.

'standing' to 'sitting', the models of Users A and B represent 'class' and 'working with conversation' activities, respectively.

The result of inference provides a crucial cue to apply a user model in a service domain. The service involves the system making an offer to a user, which differs between attending a class and working in a laboratory. In previous researches, the same information from a sensor network retrieved the same inference. However, our approach attempts to consider the personalized lifestyle when inferring the context.

4. Conclusion and Future works

This paper dealt with the problems of adapting and personalizing the model of a user's daily life. We applied a machine learning method that combines clustering and a Bayesian network to extract meaningful activities by analyzing data acquired from a wearable sensor network. Through experiments we constructed an adaptive user model that can be updated and personalized. Moreover, the model would be more adaptive to the user as accumulating user experience to that model.

We are trying to record user experience data in real-time by setup of a wearable sensor platform. Although metadata that includes primitives and composites does not represent all of user's daily life, it would increase according to the log database. We expect that our modeling approach can be applied to many types of systems that need information adapted to a user context.

5. Acknowledgements

This work was supported by the IT R&D program of MIC/IITA. [2006-S-032-03, Development of an Intelligent Service technology based on the Personal Life Log].

6. References

[1] E. Fraias-Martinez, G. Magoulas, S. Chen, and R. Macredie, "Modeling human behavior in user-adaptive systems: recent advances using soft computing techniques", Expert Systems with Application, 2005.

[2] E. Fraias-Martinez, S. Y. Chen, and X. Liu, "Survey of data mining approaches to user modeling for adaptive hypermedia", IEEE Trans. On SMAC, 2006.

[3] A. Krause, A. Smailagic, and D. P. Siewiorek, "Context-aware mobile computing: Learning context-dependent personal preferences from a wearable sensor array", IEEE Trans. on Mobile Computing, 2006.

[4] A. Kapoor, R. W. Picard, and Y. Ivanov, "Probabilistic combination of multiple modalities to detect interest", In ICPR'04 Conference Proceedings, 2004.

[5] B. Mark, "Real-time context recognition", Master's thesis, Swiss Federal Institute of Technology Zurich (ETH), 2005.

[6] J. A. Ward, P. Lukowicz, G. Troster, and T. Starner, "Human activity recognition using body-worn microphones and accelerometers", IEEE Trans. on PAMI, 2005.

[7] A. K. Dey and G. D. Abowd, "Towards a better understanding of context and context-awareness", Technical report, GIT, 1999.

[8] N. Durand and B. Cr. Ecclat, "A new approach of clusters discovery in categorical data", In KBSAAI'02 Conference Proceedings, 2002.

[9] T. Li, S. Ma, and M. Ogihara, "Entropy-based criterion in categorical clustering", In ICML'04 Conference Proceedings, 2004.

[10] L. Heyer, S. Kruglyak, and S. Yooseph, "Exploring expression data: identification and analysis of coexpressed genes", Genome Res., 1999.

[11] W. L. Buntine, "Operations for Learning with Graphical Models", J. of AI Research, pages 159-225, 1994.

[12] D. Heckerman, "A tutorial on learning with Bayesian networks", Technical report, Microsoft Research, 1996.

[13] A. W. Moore and N. Friedman, "Real-valued all-dimensions search: Low-overhead rapid searching over subsets of attributes", In UAI'02 Conference Proceedings, 2002.

[14] A. W. Moore and W. K. Wong, "Optimal reinsertion: A new search operator for accelerated and more accurate bayesian network structure learning", In ICML'03 Conference Proceedings, 2003.

[15] I. J. Kim, S. C. Ahn, H. Ko, and H. G. Kim, "Persone : Personalized experience recording and searching on networked environment", In CARPE'06 Conference Proceedings, 2006.