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Activity Recognition Using Sensor Network

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Abstract

In the implementation of a smart home, activity recognition technology using simple sensors is very important. In this paper, we propose a new activity recognition method based on Bayesian network (BN). The structure of the BN is learned by K2 algorithm and is composed of sensor nodes, activity nodes and time node whose state is quantized with reasonable interval. In the proposed method, the BN has less complexity and provides better activity recognition rate than the previous method.

Key Words : Bayesian Network, Smart home, Context-aware, K2-algorithm, Activity recognition

1. Introduction

As civilization advances, human used place like cave which they can live comfortably and safely. And as progress, these places became home. Originally, the concept of home was protecting oneself and own family from surroundings. As times goes by human pursued convenience in home, so human installed many convenient facilities, like water purifier. As these everyday wants gradually progress, lately homes can have home control system which controls home applications automatically [1], [2]. And these homes can also have robot system which relieves us from domestic affairs and environmental control system which controls domestic temperature and humidity. Concept of home automation which human need not adjust home application, but automatically controlled was started in the middle of 1940. Because we shorted device network technology which connects between home applications and control technology at that time, attempt to home automation was not activated. However, since 1980 home network technology has been developed and particularly in 1990's high speed internet service like ADSL and Cable modem was installed in home, namely home network infrastructures has been equipped. All these developments of technology mean construction of basis that connects home applications and composes home network. With this construction of basis, decreased price of detecting sensors that obtain information about home circumstances and habitants, progress of activity recognition technology and signal processing made contribution to smart home which means that home itself recognize circumstances and respond suitably.

By the way, in activity recognition technology that is one of an important factor of smart home, two method can be used [3]. First, activity recognition technology using cameras or microphones. Second, activity recognition technology using small state-change sensors. But, in these days using sensors such as cameras or microphones for activity recognition is decreasing because they are perceived as invasive and threatening by some people. So, in these days, activity recognition technology using small state-change sensors are more frequently used in smart home. If we suppose we can find some activity data using small state-change sensors, to utilize these sensor data in activity recognition, several probability models can be used. First, Hidden Markov Model (HMM). Second, Decision tree. Third, Bayesian Network (BN). They have merits and demerits each, but nowadays, almost people use BN in activity recognition because it matches perfectly [4]. People have used naive Bayesian Network in activity recognition which is most simplest model of BN [7]. If we use naive Bayesian Network for activity recognition and make as nodes not only sensors but also sensor relationships, the following naive Bayesian Network structure will be complex and load much to system. On the other hand, there are many continuous values in home. Time, location, temperature, humidity are all have continuous values, and it is not efficient to use these values intact in BN. So, generally quantization of these values is needed to use in BN. If we quantize these values too detailed, it will load much to system. And if we quantize these values too large scale, it will not quantized ordinarily.

In this paper, we propose activity recognition method to solve presented problems. First, to meet reducing number of nodes in BN and representing sensor relationship, we use not naive Bayesian Network but BN whose structure is learned by K2 learning algorithm. Second, to prevent loading too much to system or losing of important data, time is quantized with two hour interval. For simulation, we use BN tool box for MATLAB from [5].

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2. Backgrounds

2.1 Bayesian Theory

Two classical approaches to probability are the most frequent approach and the Bayesian approach. In the most frequent approach we assign relative frequencies (occurrence ratios) to different events and call these probabilities. The Bayesian approach, on the other hand, assigns subjective probabilities to events. These probabilities are also called the degree of belief for an event. The subjective approach is called Bayesian because unknown probabilities are calculated from known ones using the Bayes rule that is given in equation (1)

$$P(\Theta|X) = \frac{P(X|\Theta)P(\Theta)}{P(X)} \quad (1)$$

In the above equation, $P(\Theta)$ represents our current belief of an event Θ. For example, in a classification task $P(\Theta = i)$ would represent our current beliefs that the right class to assign with this data is the class i. Continuing with the classification example $P(X|\Theta)$ would represent the probability of the attributes given this class; this is also called the likelihood of the attributes. The likelihood measures our beliefs about the class being Θ, when the attributes are X. The denominator $P(X)$ is called the normalizer and its task is to normalize the values so that their sum is one. The left-hand side of equation (1) is called the posterior distribution of Θ given X. Using the Bayesian rule we can update our beliefs given new data and this interpretation is the basis of all Bayesian methods. Bayesian methods are especially useful in modelling tasks. First we need to generate(or gather) some data and build a model for that data. In some cases we already have some parts of the model ready so we must update our new model so that it best fits the data. After we have a suitable model we can predict future actions based on our model an keep updating the model so that it also takes new samples (evidence) into consideration.

2.2 Bayesian Networks

A Bayesian Network is a model that combines graph theory, probability theory and statistics [6]. Before we give a definition of a BN we need to revise some basic graph theory. A directed graph is a pair (V,E), where V is a finite and nonempty set. The elements of V are called nodes. E is a set of ordered pair of (distinct) elements of V and its elements are called edges. A DAG (directed acyclic graph) is a directed graph, with no cycles. A cycle is a set of edges (also called a path) $\epsilon = \{E_1, \cdots, E_n\}$ where the start and end nodes are the same. A graph that has no cycles is called acyclic. Suppose that ς = (V,E) is a DAG. If all the nodes are conditionally independent of their non-descendant nodes given their parent nodes, then the DAG satisfies the Markov condition. The Markov condition allows us to represent the probability of the whole network (the joint distribution of the variables) easily. For example the probability of the whole network shown in fig. 1 is given by

$$P(X)P(Y)P(Z)P(U|X,Y)P(V|Y,Z)P(P|U)P(Q|V) \quad (2)$$

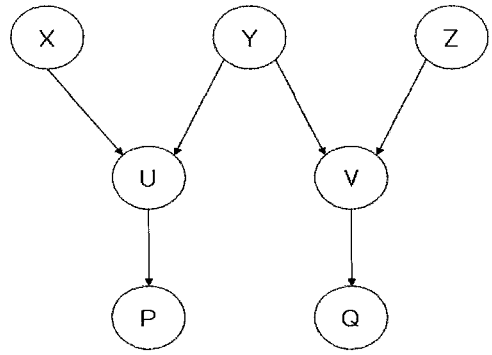

Fig. 1. A Bayesian network

2.3 Structure Learning

If we adopt a Bayesian approach, structure learning means returning a posterior distribution over all possible graphs, or at least computing the expected values of functions(e.g., which indicate the presence of certain features, such as edges) with respect to this distribution. If we adopt a non-Bayesian approach, structure learning means finding the single "best" model. "Best" can either mean the one that satisfies all (and only) the conditional independencies observed in the data (the constraint based approach), or one that maximizes some scoring function, such as penalized likelihood (e.g., MDL/BIC) or marginal likelihood. Given observational data alone, it is not possible to distinguish between membets of the same equivalent class. However, it is simple to modify the scoring function to exploit interventional data: simply don't update the parameters of nodes that have been set by intervention. This enables one to learn causal models from data, which is useful in such domains as bioinformatics. An alternative to searching in graph/edge space is to search in feature space, and then use the Gibbs-exponential distribution to define the model. Features provide a much "finer granularity" than edges, and often lead to models that perform better in terms of density estimation or predictive power.

3. Previous Activity Recognition Method

In [7], one group of reachers have obtained real time data using small state-change sensors. They installed the state-change sensors in some important locations in home. And employing people not affiliated with the research group, collected sensor data corresponding to his or her activity for 2 weeks. An example of the type of data that was acquired by the state-change sensors is shown at table 1.

To use these data in activity recognition, they excluded activity that happens less than six times, used all categorized sensors and sensor relationships nodes, used naive Bayesian Network with connection activity node to all sensor and sensor relationship nodes, quantized time in 3 minute interval, and 1 day cross validated the data. The corresponding struc-

Table 1. Sensor data example.

Activity	Sensor ID	day	activation time	deactivation time	duration(sec)	room(opt)	object type(opt)
Preparing breakfast	PDA	12/1/02	08:23:01		10 min		
	23	12/1/02	08:23:03	08:23:07	4	kitchen	drawer
	18	12/1/02	08:23:09	08:23:17	8	kitchen	cabinet
	89	12/1/02	08:24:49	08:24:59	10	kitchen	fridge door
⋮ (many readings)							

ture is represented by fig 2.

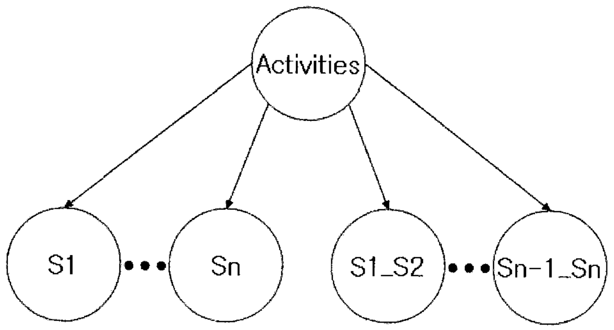

Fig 2. Naive Bayesian Network for Previous Method

In Fig. 2 Activities node have 13 states. Originally Activities node have 22 states. But because they had excluded activity that happens less than six, there exist only 13 states. And the number of sensor and sensor relationship nodes is 6694. Because they had used all categorized sensor and relationship nodes, there exist many sensor and sensor relationship nodes.

Because of many sensor and sensor relationship nodes and too detailed time interval, if we use this activity recognition method to real system, this can be load much to system. And because excluded activity that happens less than six, some important but rarely happened activities could be ignored. So in next chapter, we propose activity recognition method that is less complex but offers reasonable activity recognition rate in rough time interval.

4. Proposed Activity Recognition Method

In previous activity recognition method, made one activity node with 13 states to represent activities that happens not less than six times. But this activity exclusion can ignore some important but rarely happened activities. And because 13 activities converges to one activity node, and this activity node is connected to all sensor and sensor relationship nodes, if some disorder happens to this node, serious performance drop in activity recognition will happens. So, in proposed activity recognition method, make 22 activity nodes which represents each actually happened activities.

In previous activity recognition method, used sensor and sensor relationship node to represent sensors data. And the number of nodes needed to represent these sensors data is 6694. So, these many sensor and sensor relationship nodes can load too much to system. In proposed activity recognition method, we use only actually activated sensor nodes to represent sensors data and the number of sensor node is 72. In proposed activity recognition method, even if we omitted in sensor relationship nodes, some important sensor relationships will appear using K2 structure learning algorithm.

In previous activity recognition method, they made naive Bayesian Network without using any structure learning algorithm but just connecting one activity node to all sensor and sensor relationship nodes. And this BN structure can cause serious problems if the activity node has some disorder, and requires many nodes. In proposed activity recognition method, we had made BN structure using K2 algorithm. As previously mentioned, structure learning is to find structure of BN that explains the data at most. And one of the useful structure learning algorithm is K2 algorithm. K2 algorithm is greedy search algorithm that works as follows. Initially each node has no parents. It then adds incrementally that parent whose addition most increases the score of the resulting structure. When the addition of no single parent can increase the sore, it stops adding parents to the node.

The previous activity recognition method quantized time into 3 minute interval. This provides detail data about activity but burdens to system. In proposed activity recognition method, we quantized time into 2 hour interval.

5. Results

5.1 Bayesian Structure Learned Through K2 Algorithm

In this paper, we suggested that to find appropriate Bayesian structure of quantized data we use K2 structure learning algorithm which is greedy search algorithm that initially each node has no parents. After applying K2 algorithm to the quantized data completely, the final node relationship is like following Fig. 3.

In Fig. 3, nodes from number 1 to 22 represents actually happened activity, node 23 represents time that quantized 2 hour interval, and nodes from 24 to 95 represent actually activated sensor. We can find that after structure learning K2 algorithm, total 95 nodes are related much, and we can guess that the activity recognition rate will be better before structure learning.

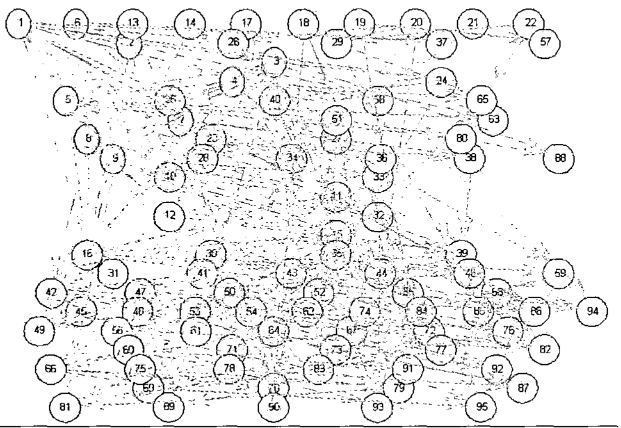

Fig. 3. Bayesian Network as the result of K2 algorithm

5.2 Activity Recognition Rate of Each Activity

After find the appropriate BN structure using K2 algorithm, we can find the each activity recognition rate by inference. In previous method, they cross validated one day data. That is to say, with all data except one day, performed parameter learning, and with one day data, performed inference. Likewise, we cross validated one day data to find activity recognition rate of each activity. And following table 2 represents activity recognition rate of each activity obtained by using previous activity recognition method and proposed activity recognition method.

From table 2, we can know that recognition rates of almost activities are improved. But there exist some activities that has not resonable recognition rate. In previous method, these activities are excluded before parameter and structure learning. However, cleaning that is one of the excluded activities in previous method could be recognized in proposed method with 0.25 recognition rate. Following table 3 represents several important differences of previous activity recognition method and proposed activity recognition method.

Table 2. Activity recognition rate using previous and proposed method

Activity	Recognition Rate Using Previous Method	Recognition Rate Using Proposed Method
Bathing	0.7917	0.65385
Toileting	0.4050	0.75532
Going out to work	0.1250	0.84615
Preparing lunch	0.7813	0.4
Preparing dinner	0	0.16667
Preparing breakfast	0.2083	0.55556
Dressing	0.1154	0.55556
Grooming	0.5625	0.62791
Preparing a snack	0.0833	0.5
Preparing a beverage	0.1818	0.58824
Washing dishes	0	0.22222
Doing laundry	0.2556	0.69565
Cleaning	0.0667	0
Washing hands	-	0
Putting away dishes	-	0
Putting away groceries	-	0
Putting away laundry	-	0
Lawn work	-	0
Watching TV	-	0.25
Going out for entertainment	-	0
Going out for shopping	-	0
Other	-	0
Average(13 activities)	0.2751	0.5052

Table 3. Differences of previous method and proposed method

	Previous Method	Proposed Method
Time Interval	3 Minute	2 Hour
Number of act node	1	22
Number of activity that recognized	13	22
Bayesian Structure	Naive Bayesian	Learn through K2 algorithm
Average recognition rate	0.2751	0.5052

6. Conclusion

Originally, the concept of home was protecting oneself and own family from surroundings. But as times goes by human pursued convenience in home, so human installed many convenient facilities, like water purifier. As these everyday wants gradually progress, lately homes can have home control system that controls home applications automatically. And that is called home automation or smart home. To realize home automation, activity recognition technology is important factor. And in these days, activity recognition technology using small state-change sensors are more frequently used in home automation than the others. And to use obtained data from sensor, these days almost people uses naive Bayesian Network in activity recognition which is one of the BN. But this naive Bayesian Network has problems like concentration of activity node, too many sensor and sensor relationship nodes, loss of activity that actually happened, and too short quantization time interval in activity recognition. So, in this paper, we propose the new activity recognition methods that has actually happened activity nodes, actually activated sensor nodes, BN structure derived from structure learning K2 algorithm, and reasonable quantization time interval. And from this proposed activity recognition method, BN has less complexity and provides better activity recognition rate.

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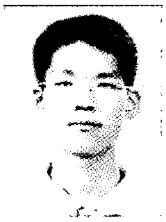

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