Activity-Object Bayesian Networks for Detecting Occluded Objects in Uncertain Indoor Environment

Youn-Suk Song[1], Sung-Bae Cho[1], and Il Hong Suh[2]

[1] Dept. of Computer Science, Yonsei University
134 Shinchon-dong, Sudaemoon-ku, Seoul 120-749, Korea
corlary@sclab.yonsei.ac.kr, sbcho@cs.yonsei.ac.kr
[2] The College of Information & Communications, Hanyang University
17 Haengdang-dong, Seongdong-gu, Seoul, 133-791, Korea
ihsuh@hanyang.ac.kr

Abstract. In the field of the service robots, object detection and scene understanding are very important. Conventional methods for object detection are performed with the geometric models, but they have limitations to be used in the uncertain and dynamic environments. This paper proposes a method to predict the probability of target object with Bayesian networks modeled based on activity-object relations. Experiments in indoor office environment show the usefulness of the proposed method for object detection, which produces about 86.5% of accuracy with environments.

1 Introduction

Recently the studies on service robots have been proliferated in many fields [1]. Especially demands of indoor services for elderly people have increased significantly during last decade. For the good service performance, it is very important for the robots to detect objects properly and efficiently. Traditional approaches to object detection is used to utilize only the information in the images so that they are likely to fail in the case that the objects are small or occluded by other objects in indoor environments [2].

In this paper, we propose a hierarchical Bayesian network model of singly-connected structure called activity-object Bayesian network for reasoning the probability of objects from the discovered objects as evidence. The proposed hierarchical Bayesian networks are efficient to model the relationship of objects because they are more informative than naïve Bayes structure and require much less computational power than multiply, fully-connected structure [3, 4]. For this 'common-cause' structures are adopted as building blocks for efficient design with reusability.

2 Backgrounds

2.1 Related Works

The studies for object detection in the images have a profound history. The traditional approaches are based on the two basic assumptions: "all objects are definable by a

R. Khosla et al. (Eds.): KES 2005, LNAI 3683, pp. 937–944, 2005.

relatively small number of explicit shape models" and "all objects have characteristic, locally measurable features" [5]. Under these assumptions, conventional methods use the geometry models to detect locations and directions of the object mainly in industries, but these approaches have limitations in the dynamic environment such as home, office, etc.

There are studies to improve these approaches by the knowledge based approach. Marengoni *et al.* tried to add the reasoning system to Ascender I which is the system to analyze aerial images for detecting buildings. They use hierarchical Bayesian networks and utility theory to select proper visual operator in the given context so that they can improve the cost of computation [6]. Torralba *et al.* proposed a method to recognize the place using Hidden Markov Model with the global vectors collected from images and use them as context information to decide the detection priorities [7]. This approach is useful to make detection more efficient but the errors are inherited from the place recognition systems [7]. In this paper, we propose a sophisticated model to predict the presence of target object more precisely from activity-object relations.

2.2 Bayesian Network

Bayesian network is the DAG (directed acyclic graph) model to evaluate the belief of variables using the dependency between them based on the Bayes' rule. The nodes represent random variables while the edges denote the dependencies of them: parent nodes for cause and child nodes for result. The edge between two nodes makes the joint probability distribution, so that the parent has prior probability $P(p)$ and the child has the conditional probability $P(c|p)$. Using the conditional independency, the joint probability distribution $P(x_1, x_2, x_3, ..., x_n)$ between the nodes can be factored as follows [8].

$$P(x_1, x_2, ..., x_n) = \prod_i P(x_i \mid Parents(X_i))$$

Each node has values which are mutually exclusive and exhaustive in it. In our model, all nodes take binary values.

3 Activity-Object Bayesian Network

3.1 Service Robot

We construct the activity-object Bayesian networks in the environment having 15 places and 29 objects. The environment is summarized in Table 1 and some of them are shown in Fig. 1.

When the service robot explores in indoor environments for detecting target object, he uses visual processor for recognizing where he is and predicting the presence of objects using place-object Bayesian network for glance-search [9]. After predicting the probabilities, we can decide whether the robot should perform the detailed analysis or not. This approach makes the search more efficient because we can save the costs for detecting the specific objects in images. Activity–object Bayesian networks are used for the detailed analysis for predicting the probability of the target object more precisely from the discovered objects. Activity is more elaborate and efficient classification than place for objects because several activities are occurred in the same place. While the robot does detailed analysis, we can decide again whether it is needed to do more detailed analysis near this place through activity-object Bayesian networks.

Table 1. Service environment

Classification	Contents
Places	Lecture room, Meeting room, Seminar room, Computer room, Prof. office, Admin. office, Guard office, Lab., Hallway, Stair, Hall, Elevator, Toilet, Former Toilet, Rest room
Objects	Table, Side Chair, Castor Chair, Lectern, Cabinet, Bookcase, Garbage can, Sink, Seat toilet, Wall clock, Air conditioner, Telephone, Desktop PC, Notebook PC, Mouse, LCD Monitor, Keyboard, Beam Projector, Projection Screen, Audio, Speaker, Microphone, Wall white board, Castor white board, Partition, Curtain, Water bucket, Door, Window

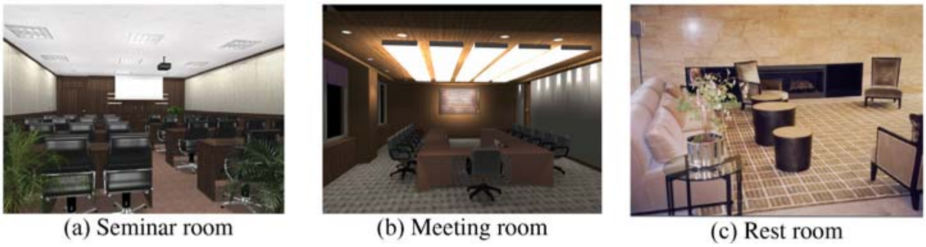

Fig. 1. Some pictures for related place

3.2 Structure of Activity-Object Bayesian Network

The activity-object Bayesian networks are singly-connected structure like tree. They are composed of three kinds of basic nodes: activity node, class node, and primitive node. Activity node is used for a root and class nodes are used for a root of sub-trees. Common-cause structures are used for sub-trees: it is one of the causal relationships between three nodes. It has two nodes that have another node as a parent commonly. This structure allows us to represent the relationship of objects more easily and precisely than simple causal chain because it is possible to assign the parameters to each node for representing the relevancy between them. Related concept on causality is proposed by H. Reichenbach in *The Direction of Time*, 1956. He proposed 'Principle of the Common Cause' as follows: *If two variables are probabilistically dependent, then either one causes the other (directly or indirectly) or they have a common ancestor* [10].

We also use a common-cause structure as a building block, and we can construct whole structure through combining them hierarchically. It is quite useful from viewpoint of design.

The nodes in the activity-object Bayesian networks have binary values. The primitive nodes are able to accept the evidences as inputs only. About this, we will discuss in the next section. In general, the activity node (i.e. root node) has two basic class nodes by design principles: public class node and private class node. Public class node is composed of sub-trees which can be reused in another activity-object Bayesian network. The relationship between the public class node and the activity node is adjusted through the parameters of public class node. Like this way, we can reuse the sub-trees belonged to the public class node for another Bayesian network just after re-adjusting the parameters of the root node in it. The descendants of private class node are composed of the nodes to have strong relationship with activity node. So the experts must design them with special domain knowledge. Some design principles are summarized in the following.

- Activity node has only two child nodes: public class node and private class node.
- Public class node is composed of the building blocks commonly used in another activity-object Bayesian networks and private class node is composed of the objects which are highly related with activity node.
- The parameter of class nodes means hierarchical relationship and that of primitive nodes means the relevancy between the siblings.

Basic structure of activity-object Bayesian network structure is shown in the Fig. 2.

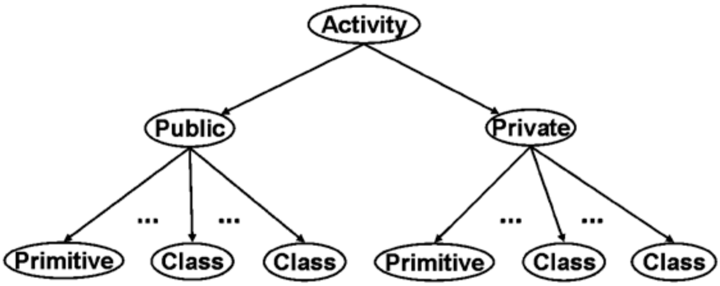

Fig. 2. Basic structure of Activity-Object Bayesian network

- Activity node: Root node. Criterion for making relationship among objects. It has a public and a private class node. Only used for output
- Class node: Root node of sub-tree. It correlates the objects. Its parameter means hierarchical correlation. Only used for output
- Primitive node: Leaf node. It represents objects. Its parameter means horizontal correlation between other primitive nodes in the same building blocks. Input for evidence. Output for probability of objects being present

This hierarchical structure is more informative than naïve Bayesian structures and requires less computational complexity than multiply, fully-connected Bayesian networks. The computational specifications of the structures are compared in Table 2.

Table 2. The complexity of several structures

	Naïve	Fully-Conn.	Hierarchical. S.
# of objects	n	n	n
# of value	$2^2(n\text{-}1)+2$	$2(2^n\text{-}1)$	$2^2(n+\alpha\text{-}1)+2$
Complexity	$O(n)$	$O(2^n)$	$O(n)$

3.3 Conditional Probability Tables and D-Separation

It is important to maintain the probability distributions of all nodes to be $P(C{=}yes|P){=}0.5$ and $P(C{=}no|P){=}0.5$ after belief-updating without evidences in our problem. Suppose α represent the probability of $P(C{=}yes|P{=}yes)$ and assign 1-α to $P(C{=}yes|P{=}no)$ then by the following formula with uniformed prior probability of activity node we can maintain the probabilities of all nodes as (0.5, 0.5) in the case that there are no evidences in the network.

$$\begin{aligned} P(C_{yes} \mid P) &= P(C_{yes} \mid P_{yes})P(P_{yes}) + P(C_{yes} \mid P_{no})P(P_{no}) \\ &= \alpha \times 0.5 + (1-\alpha) \times 0.5 \\ &= 0.5 \end{aligned}$$

The examples of parameter settings are shown in Fig. 3(Left).

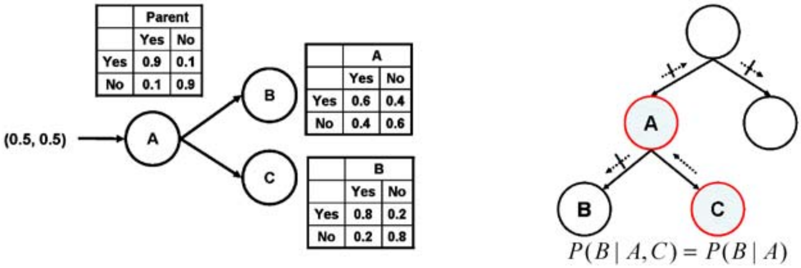

Fig. 3. Left: Example of conditional probability tables. Right: d-separation

Probability propagation is performed via a "flow of information" through the network[8] and there are two types of reasoning direction: diagnostic and predictive reasoning. Diagnostic reasoning infers from children to parents and predictive reasoning infers parents to children. D-separation is the notion that one node blocks the propagation between sets of nodes. In the case of common-cause structure, common-node given the evidence blocks the propagation not only between children but also between his ancestor and descendant (Fig. 3(Right)). To solve this problem, we suppose that the class node can be only used as the common-node. It allows us to be free from the problem of d-separation because class node cannot have evidence as input under the assumption.

4 Experiments and Results

4.1 Experimental Environments

The experiments are performed with a presentation activity-object Bayesian network for 6 places (Computer room, Laboratory, Rest room, Conference room, Seminar room and Guard office). The overall structure of the Bayesian network is summarized in Table 3 and shown in Fig. 4.

The purpose of our experiments is to observe the performance of activity-object Bayesian networks designed by experts for prediction of target object. We assume that the service robot moves from place to place and detects some objects randomly which are in the place. We record the probability values and hitting rate for predicting the probability of beam-projector in each place.

Table 3. The description of presentation activity-object Bayesian network

Node	Names	#
Activity	Presentation	1
Class	Public{Furniture{Basic1},ComputerRelated{Accessory},AudioTool}, Private{PresentationTools}	8
Primitive	Chair, Table, Mouse, Keyboard, LCDMonitor, Computer, Speaker, Audio, Lectern,Microphone x2,Board,ProjectionScreen,BeamProjector	14

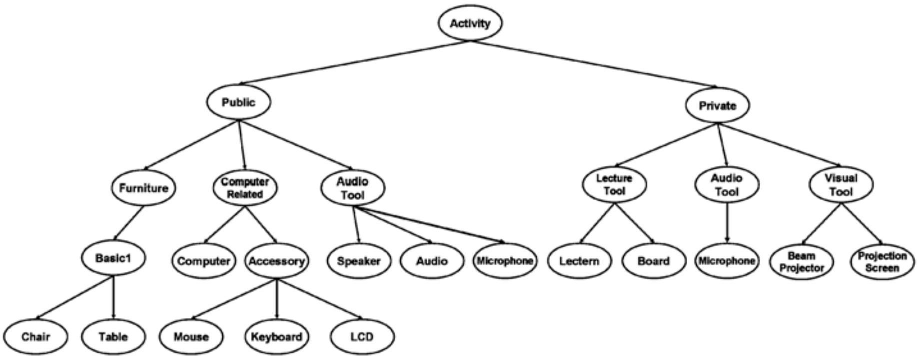

Fig. 4. Overall structure of presentation activity-object Bayesian network

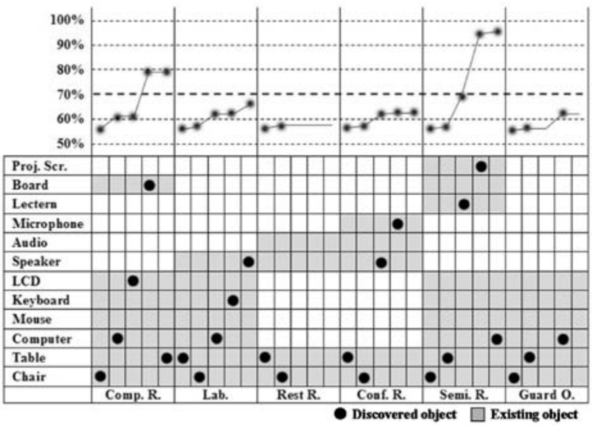

Fig. 5. Probability of beam projector in each place

4.2 Experiments Results

The probability for beam-projector in each place is shown under threshold 70% until the robot finds 5 objects (Fig. 5). Predictions seem reasonable except one case. We can see the robot predicts that a beam projector exists in the computer room and seminar room but not computer room actually. This fact denotes that false-positive error is likely to occur in the similar environment from the result of accumulating evidences. It is important to decide the threshold value and number of times for finding objects for the performance. The hitting rate is summarized in Fig. 6. For this experiment we try to test ten times in each place and try again ten times whole processes. This result also confirms the same fact with the previous one. The overall result is 86.5 %, which shows the proposed method is reliable to predict objects being present.

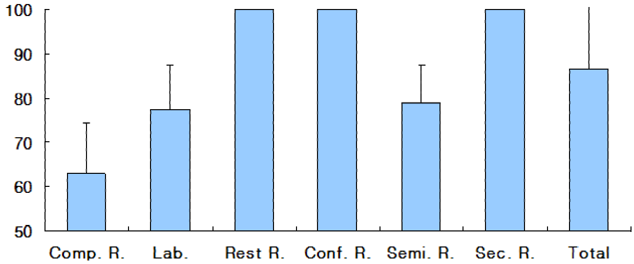

Fig. 6. Hitting rate of predicting the beam-projector

5 Summary and Conclusion

We propose a Bayesian network model for the efficient detection of objects in uncertain environments. Using the hierarchical Bayesian network structure, we can infer the probability of the target object being present. Also, we have tested why this structure is good for our problem including some related issues (posterior probability of nodes without evidences and d-separation) and the useful aspects in terms of design. Our experiments show the reasoning of object being present is helpful for object detection.

In the future work, we will use negative nodes for decreasing the probabilities and try various activity-object Bayesian networks for real robots.

Acknowledgement

This paper was performed for the Intelligent Robotics Development Program, one of the 21st Century Frontier R&D Programs funded by the Ministry of Commerce, Industry and Energy of Korea.

References

1. P. Dario, *et al.*, “Robot assistants: Applications and evolution,” *Robotics and Autonomous Systems*, vol. 18, pp. 225-234, 1996.
2. K. Murphy, *et al.*, “Using the forest to see the trees: A graphical model relating features, objects, and scenes,” *Proc. Neural Info. Proc. System*, vol. 16, pp. 1499-1506, 2003.
3. J. Pearl, *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*, Morgan Kaufmann, 1988.
4. E. Gyftodimos and P. A. Flach, “Hierarchical Bayesian networks: A probabilistic reasoning model for structured domains,” *Proc. European Conf. on Machine Learning*, pp. 25-36, 2003.

5. T. M. Strat and M. A. Fischler, "Context-based vision: Recognizing objects using information from both 2-D and 3-D imagery," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 13, no. 10, pp. 1050-1065, 1991.
6. M. Marengoni, *et al.,* "Decision making and uncertainty management in a 3D reconstruction system," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol 25., no. 7, pp. 852-858, 2003.
7. A. Torralba, *et al.*, "Context-based vision system for place and object recognition,"*Proc. Intl. Conf. on Computer Vision*, pp. 273-280, 2003.
8. K. B. Korb and A. E. Nicholson, *Bayesian Artificial Intelligence*, CRC Press, 2003.
9. K. S. Hwang, *et al.*, "Bayesian network design for high-level context reasoning in uncertain indoor environment,"*Soft Computing Lab. Tech. Report*, 2005.
10. H. Reichenbach, *The Direction of Time*, University of California Press, 1956.