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Automated Bayesian network Integration based on Ontology for Reasoning Object Existence of Service Robot

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Abstract: Object detection of service robots is very important for their service. Most of services such as delivery, errand of users are related to objects. Conventional methods are based on the geometric models in static industrial environments, but they have limitations in uncertain and dynamic indoor environments, because interest object can be occluded or small in the image according to the robot's location or angle. For solving these uncertain situations, it is helpful to predict the probability of target object, because it can give important information for their next action. Our idea is to use observed objects as context information for predicting target one. For this, we adopt Bayesian networks and ontology together for modeling domain knowledge and reasoning objects in probabilistic frame. We verified the performance and process of our method through the experiments.

1. INTRODUCTION

The studies of object detection using visual sensors for service robots are active. Conventional approaches mainly applied to industrial environments get the interesting information in the images predefined geometric models, but they have limitations when the uncertain situations occur. Since the service robots move around their place of residence and the environment can be changed, it is easy to happen that the target objects are small in the image or occluded by one other one [1]. It is very important to manage those situations for object detection performance.

For solving these uncertain situations, we use knowledge-based approach in which we make object relationship for exploiting observed objects as context information to predict target one. For this, we propose the method to use Bayesian network and ontology together. Bayesian network is useful to represent the confidence of object being present. Ontology is good way to share the domain knowledge between expert and systems for modeling Bayesian networks. Therefore, it is used for deciding and making reasoning model autonomously when the robots find objects, because it can give the information about integrating pre-defined Bayesian networks according to conditions. This approach is very useful to design and reason the knowledge models, because it reduces redundant Bayesian network models and it solves the problem of choosing appropriate model.

In section 2, we'll explain the related works about object detection. We'll describe the service robot and its object detection process in section 3. In section 4, we explain our proposed method including description of overall system with control algorithm, the way of constructing ontology and Bayesian network, and the integration issues.

2. RELATED WORKS

The studies for improving object detection performance with context information exploit various kinds of context. Torralba et al. proposed the method in which location information was used to improve object detection performance [2]. They used the hidden Markov model (HMM) to model the transitions of location and global vectors extracted from the images to recognize the location. The location was used to determine the detection priorities of the objects and to predict the prior probabilities of the objects being present. Marengoni et al. attempted to use recognized features as context information for the Ascender I system, which analyzes aerial images [3, 4]. The system detects objects such as buildings, houses, parking lots, etc. They designed Bayesian networks according to hierarchical stages of feature. Throughout each stage, they were able to predict which features existed and what would be the proper visual operations next. In this way, they were able to improve the performance of system in the aspects of accuracy and the costs of visual operations. Socher et al. used speech information as context for detecting objects [5]. In their works, Bayesian network was able to manage different kinds of noisy sensors and integrate them. This approach shows the flexible and well suited way to improve the performance of the system through integrating large variety of different information.

In our works, we use objects as context information for predicting target object being present, because it can be occluded or small in indoor environments.

3. SERVICE ROBOT

The inputs-outputs of service robot, and the processes of object detection are shown in figure 1.

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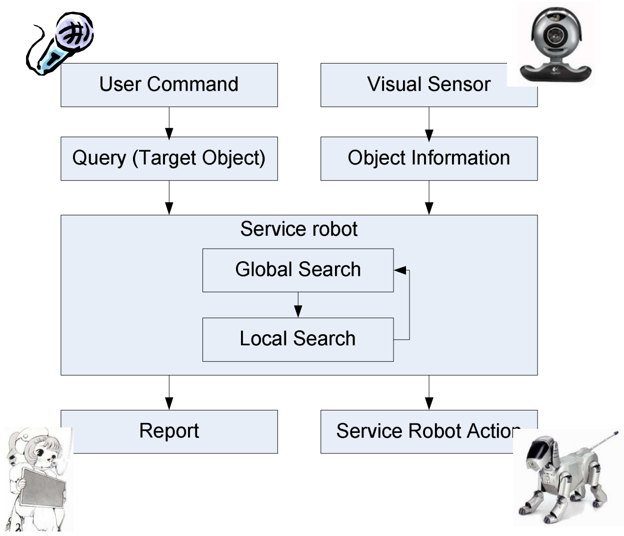


Figure 1. Service robot

The robot accepts the user's request. After that, he uses a visual processor for recognizing places and predicts the presence of the target object using prior knowledge about place-object relationship. He decides whether to perform the local search or not based on the probability of the existence of the target object (global search). If he performs local search in a particular place, proposed method is used for deciding whether to continue detection or not through predicting the probability of the existence of the target object from the previously observed ones. If he finishes the object detection in all places, he reports the results of detection and if possible, brings the target object to the user.

4. PROPOSED METHOD

In this section, we explain about our reasoning method. In our system, the Bayesian networks called as primitive Bayesian network designed by experts are used for predicting object being present and are integrated autonomously based on ontology. In section 4.1, we'll explain about our reasoning system and later we'll describe the algorithm for controlling the reasoning process.

4.1 Proposed Reasoning System

The overall system for reasoning target object is shown in figure 2. It is composed of three kinds of manager: Robot Manager, Ontology Manager and Bayesian network Manager. The roles of them are below:

- Robot Manager: Interfaces between user and reasoning modules. It has control algorithm, and controls reasoning process.
- Ontology Manager: Gives the information for deciding and making reasoning models using ontology which contains domain knowledge.
- Bayesian network Manager: Reasons the probability of target object and integrate pre-defined Bayesian networks through the information from ontology manager.

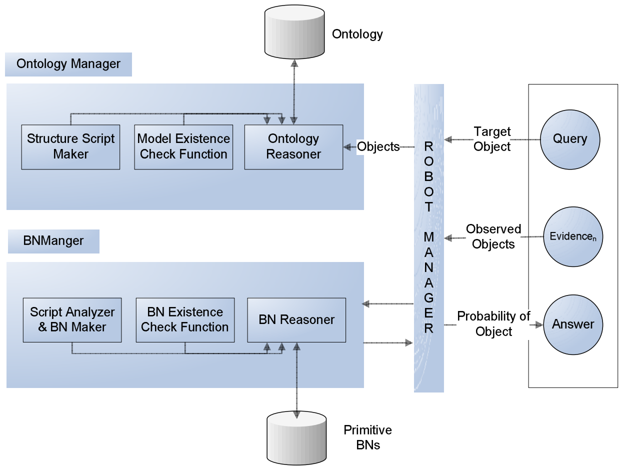


Figure 2. Overall reasoning system

The Propose & Revise (p&r) algorithm contained in Robot Manger controls the process of reasoning according to query and evidences (observed objects). We'll explain about the p&r algorithm in the next section, because it shows more explicitly our method for reasoning objects.

4.2 Proposed & Revise Algorithm

The p&r algorithm is a simple one for controlling the reasoning process between Bayesian networks and ontology. In the p&r algorithm, two different parameters exist. The one is a target object and the other is a value of integration degree.

The parameters of p&r algorithm: a target object, an integration degree of Bayesian networks.

An Integration degree: a degree which gives and takes influences among Bayesian networks when they are integrated

The related figure for p&r algorithm is below.

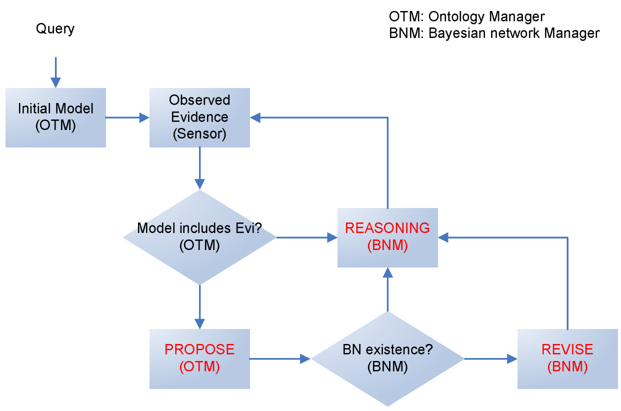


Figure 3. Propose & Revise algorithm

When the robot asks if the target object exists or not, the p&r algorithm would choose the smallest reasoning model initially. The smallest reasoning model is called as primitive Bayesian networks, which is previously designed by experts. The initial model is found by ontology manager. Afterwards, if a new object is observed, the p&r algorithm uses it for deciding whether other model is needed by ontology manager again based on the present model and a new found one. In this paper, the way of determining whether a new model is need or not depends on the fact that present model includes new evidence or not. If current model doesn't include the new one and there is new model including them, the p&r algorithm try to propose new reasoning model (propose).

The condition of proposing new model: $Object \notin Model_X \cap \exists (Object \cap Model) \in Model_{new}$

In the above conditions, the ontology manager gives information about integrating pre-defined Bayesian network for new reasoning model, if the proposed model doesn't exist in the Bayesian networks pool. We'll explain Bayesian networks integration in the section 4.5.

4.3 Ontology Modeling

Ontology is useful for sharing knowledge between experts and system [6]. Through the reasoning of ontology, we can find hierarchical structure of classes. We model the domain object relationship into ontology. The criterion of relationship is activity. Activity theory which Vygosky suggested in 1920s is the theoretical background of our idea that uses it as the criterion of defining objects relationship. Activity theory explains the objects are used for some activities (purposes). It helps us to explain why the objects exist together.

We define three kinds of classes for ontology regarding to activity theory: Activity, Action, Object. In table 1, We summarize their features and properties.

Table 1. Activity-Action-Object classes

Classes	Feature	Property	
Activity	Making relationship among the actions. These classes are used for Bayesian network integration	Has_Action Has_Activity	Subject ↕ Object
Action	Making relationship among the object classes if they are used for the same purpose. Knowledge experts make primitive Bayesian network using action classes after reasoning ontology.	Has_Object	
Object	Objects having the same function are modeled in the same class	-	

The structure of ontology and the example of reasoning is below

Ontology Structure:
- Objects
  Object= {ReadingMaterials, Monitor, Mouse, ... }
  ReadingMaterials= {Textbook, Paper, Novel, …}
  Monitor= {LCD Monitor, CRT Monitor}
- Action= {Reading, Computer Inputing, Audio Adjusting ... }
  Necessary & Sufficient Property of Reading:
  (∀Has_objects ReadingMaterials)
- Activity= {Indoor, Outdoor}
  Indoor= {Presenting, Lecturing, Washing, ... }

Reasoning:
→ Reading ∋ ReadingMaterials

As the result of reasoning, we can find the reading action class has reading materials that belong to object class as his child. We use this kind of result for modeling and reasoning Bayesian networks.

4.4 Bayesian Network Modeling based on Ontology

The Bayesian networks constructed by experts are tree structure based on common-cause structure, and each node has one parent and binary state, and they are composed of three kinds of basic nodes: action node , class node , object node . The summary for every node and the hierarchical relations are as follows.

- Object node: Representing observed objects or probability of target objects
- Class node: Criterion of detailed object relationship
- Action node: Root node, Criterion of primitive Bayesian network

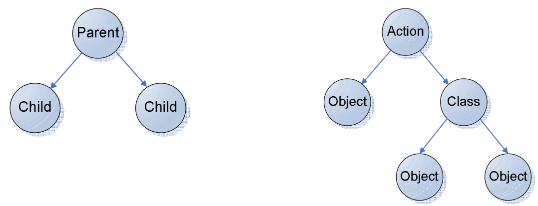


Figure 4. Common-cause and primitive Bayesian network structure

This kind of Bayesian network is called as primitive Bayesian network, because they can be used for another reasoning model. We set the value of CPT for primitive Bayesian network following to below formula.

$$\sum_{parent_i} P(child_{state} \mid parent_i) = 1 \;\; (parent_i \text{ is the state of } parent)$$

$$P(child_{yes} \mid parent_{yes}) = P(child_{no} \mid parent_{no})$$

The value of α, $P(child_{yes} \mid parent_{yes})$ is called as influence value and this setting method is called as binary cross setting method. This method keeps the probability distributions of all nodes uniformly after belief-updating without evidences if the prior probability of root node has probability (0.5, 0.5) in our structure. This is important for prediction. Next formula explains about this.

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

The influence of observed object A to B is calculated by following formula.

$$P'_{class} = \frac{P_{class}\, a_A}{P_{class}\, a_A + (1-P_{class})(1-a_A)}, P_B = P'_{class}\, a_B + (1-P'_{class})(1-a_B)$$

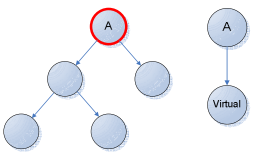
At first, A change the probability of class node, and then the class node influence to node B. This calculation occurs in reasoning process.

4.5 Reasoning by Bayesian Networks Integration

We propose the method for integrating primitive Bayesian networks virtually with upper Bayesian network structure given by ontology. In the upper Bayesian network, the probabilities of root nodes in primitive Bayesian networks are used for influence value of virtual nodes. This is efficient way to make object relationship in the view point of reusability. The process of inference is as follows.

1. Compute P(root node | Evidence) of primitive Bayesian networks
2. Construct the upper Bayesian network structure that has the value of integration degree as influence value referring to ontology. (But, the action node including query has influence value as 1).
3. Make virtual nodes that have influence value computed in step 1 as the child of corresponding action or activity nodes in the upper Bayesian networks
4. Set the evidence to virtual nodes and update the belief
5. Set the prior probability of primitive Bayesian networks with the new values of action nodes. Inference the value of target object.

The change of parent node's probability having virtual node explain why this method makes the same result to the Bayesian network structure having the whole nodes.



$$P'_A = \frac{P_A}{P_A a_V + (1-P_A)(1-a_V)} = \frac{0.5 \times a_V}{0.5 \times a_V + (1-0.5)(1-a_V)} = a_V$$

As shown in the above, the influence value of virtual node makes the probability value of parent A same with the original one in the primitive Bayesian network having node A. Therefore, we use virtual node for reflecting the value of previous Bayesian network for new created Bayesian network.

Figure 5 shows the overall reasoning process. The change of parent node's probability having virtual node explain why this method makes the same result to the Bayesian network structure having the whole nodes.

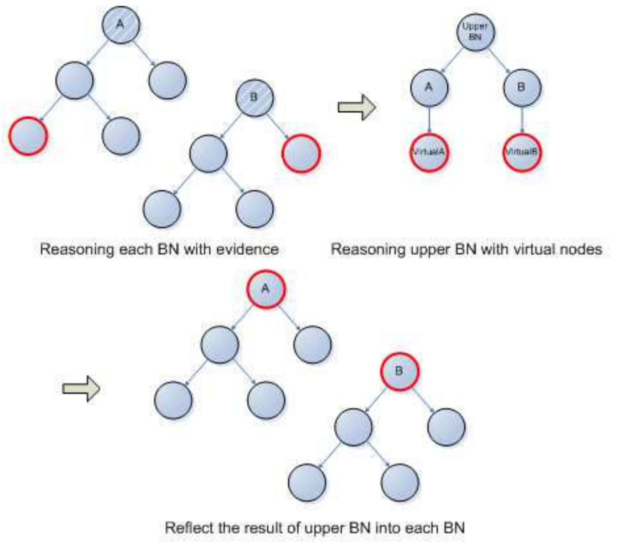


Figure 5. Bayesian network integration and reasoning

5. EXPERIMENT AND RESULTS

5.1 Reasoning by Bayesian Networks Integration

Experiments are carried out to verify the performance of proposed BN model in five different places for detecting beam-projector existing in Conference room. The objects existed in each place are summarized in table 2.

Table 2. The objects in each place

place	objects
Computer Room	Table, Chair, Lectern, Computer, Mouse, Mousepad, Monitor, Keyboard, Microphone, Speaker, Board, Chalk
Laboratory	Table, Chair, Lectern, Computer, Mouse, Mousepad, Monitor, Keyboard, Usb Hub, UBS Memory, Speaker, Board, Chalk, Bookcase, Book, Note, Pen, Pencase, File
Rest Room	Table, Chair, Round Table, Sofa, Cushion, Bookcase, Book, Note, Pen Pencase, File, Audio, Computer, Monitor, Mouse, Mouse Pad, Keyboard, USB Memory, USB Mouse, Vending Machine, Beverage
Conference Room	Table, Chair, Lectern, Book, Note, Pen, Pencase, File, Ruler, , Computer, Mouse, Mousepad, Monitor, Keyboard, Usb Hub, UBS Memory, BeamProjector, Screen
Guard Room	Table, Chair, Monitor, Keyboard, Mouse, Key, Television

We assumed that the service robot would move from place to place and the objects are detected randomly. We recorded the values and hit rates to predict the probability of target objects being present. The experimental conditions are summarized in table 3.

Table 3. Experimental Condition

Query	Degree of Integration	# of Detection	Threshold
Beam projector	30%, 60%, 90%	3,5,7,9	65%

5.2 *Experimental Results*

At the first experiment, we observe model selection according to observed object. The results are in the figure.

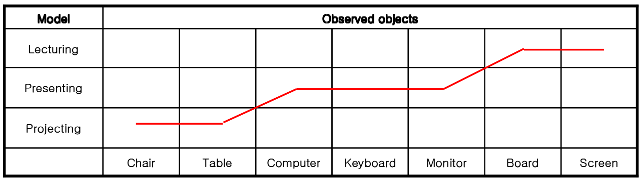


Figure 6. Model selection by p&r algorithm

According to observed evidences, p&r algorithm choose activity or action (reasoning model) defined in ontology and primitive Bayesian networks related to it. The primitive Bayesian network used in this experiment are below.

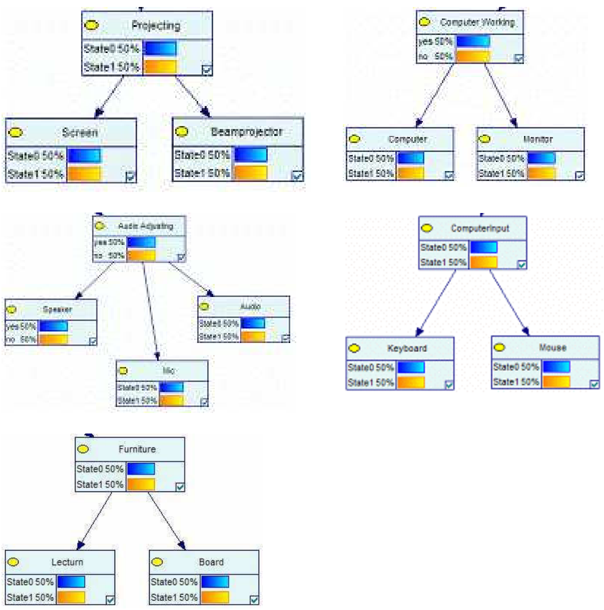


Figure 7. Primitive Bayesian networks

The hitting rate in the computer room and the conference room are in figure 7.

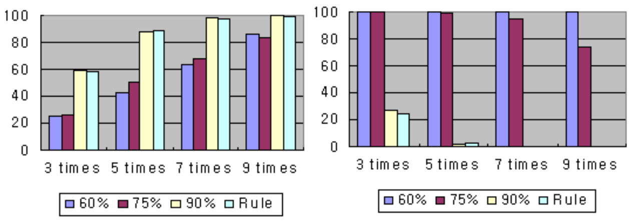


Figure 8. Conference room (left) and computer room(right)

The result of conference room shows that the conditions having many numbers of detection and high integration degree value have good performance, because the beam-projector exists there. In low degree integration, many evidences can help to improve the performance. This shows inductive reasoning is possible in Bayesian network frame. In the computer room, the rule and the high degree integration model have bad results around 0 ~ 20%, because false-positive errors occur in them. This means model selection is very important for high degree integration and rules, but in fact, it’s very hard to decide what the best model is for given conditions in real world. From this experimental result, the induction reasoning using Bayesian network is good choice for solving this uncertain problem.

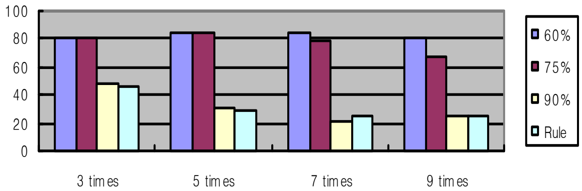


Figure 9. Overall performances

The above graph shows the average hitting rates in all places under conditions in table 3. It shows 60%, low degree of integration indicates highest points. Regarding rules, there are many cases of false-positive errors, so it concludes that a target object exists, even though it actually doesn't exist. It shows the low hitting rate, around 20%. We can conclude from these experiments that low integration degree and many evidences can be useful for uncertain situation, because they are robust against false-positive errors and model selection problem. This shows the merit of induction reasoning of Bayesian network.

6. CONCLUSION AND FUTURE WORKS

We propose a Reasoning model for the efficient detection of objects in uncertain environments. Using Bayesian network and ontology, we can infer the probability of the target object being present. For this, we define the role and relationship between networks and ontology, and then propose the way of controlling them. Our experiments show the merit of Bayesian network frame for solving uncertain situation compared with rules.

In the future work, we will use negative nodes for decreasing the probability and other context information.

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