Lexicon Acquisition based on Behavior Learning

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***Abstract*— Studies on lexicon acquisition systems are gaining attention in hope for a natural human-robot interface and a test environment for theories of infant lexicon acquisition. This paper presents a system that forms word categories based on object-oriented behaviors. By using physical experiences, the system is able to generalize names to objects with various visual features. The system was implemented to a mobile robot acquiring lexicon about object categories with different rolling preferences. The system successfully acquired the lexicon and generalized the names to objects with various visual features in accordance with their rolling preferences.**

I. Introduction

Young children are known to acquire lexicon in a very rapid style [1]. Considering the fact that there are infinite possible relations between objects and words [2], this rapid acquisition is an amazing phenomenon and still a subject of debate. On the other hand, many robots aimed to work in human society are developed today. These robots are expected to have a natural communication with their users, and sharing a common lexicon with human is one of the fundamental issues to be attacked for this goal. For these reasons, studies on lexicon acquisition systems are gaining attention today.

The problem of lexicon acquisition has been lively discussed in the field of psychology. To explain how infants find word meanings from few examples, many researchers proposed hypotheses that children possess cognitive constraints to limit the possibility of meanings [3] [4]. Although these rules explain some tendencies in early word learning, such constraints are not the only ability for lexicon acquisition. Recent studies have revealed that children can form categories for words by focusing on specific features or functions of objects. Nelson et al. [5] showed that 2-year-olds generalize names in accordance with objects' functions. This generalization of names seems effective since our environment is full of artifacts created for particular functional purposes. However, the mechanism underlying this process is unrevealed.

Recently, researches on lexicon acquisition have been extending their activities to the field of robotics. Although most language processing systems developed so far work in a virtual world [6] [7], some robots that ground words to sensory-motor experience are developed. The grounding process of words consists of clipping and forming categories from sensor information, and connecting labels to categories. The process is regarded as the first step toward solving the problem of symbol grounding [8], since relation of grounded word categories will lead to acquisition of more abstract words. For example, acquisition of nouns will lead to acquisition of verbs since verbs can be understood as relations of few nouns. Roy [9] developed a system that learns words from untranscribed acoustic and video inputs. Although the system solved many difficult problems such as segmenting words from infant-directed speech, there remains a problem that caregivers need to teach names whenever new objects with unfamiliar visual features are introduced. The problem is due to the fact that categorization is performed mostly in a passive style, where categories are formed based on similarity of visual features. Such an approach does not enable acquiring high level concepts such as functions of objects, and there are features that could only be recognized through actions such as "heaviness" and "softness". It is also pointed out by Steels and Kaplan [10] that feature based clustering methods might not provide the way to acquire word categories of visual features in real environments where light conditions change. Facing the problem of acquiring more realistic categories for words, the study by Fitzpatrick and Metta [11] is suggestive. They show the effectiveness of action in object identification, but the proposed system with fixed actions is insufficient for acquiring word categories.

In this paper, we propose a system which forms word categories based on object-oriented behaviors. The system regards objects handled in the same way belong to the same category. To acquire the word "door", for example, the system forms a category of objects that could be opened by grabbing, turning, and pulling the knob on them. The concrete system adopts a multi-module learning system [12] in which each module corresponds to an object-oriented behavior. The robot identifies the behavior oriented to the object based on effectivity of the behavior module, and form categories of visual features with same object-oriented behavior. The system is a model for the name generalization phenomenon found by Nelson et al. We implemented the system to a real robot learning a lexicon about objects that have different rolling preferences [11]. The robot successfully attained the lexicon and generalized the names to new objects according to their object-oriented behaviors.

II. System Overview

A. Basic idea

Lexicon acquisition we address here is to learn words of objects given by a caregiver (Fig. 1). By word, we do not mean unique name given to each object. The words that the learner aims to acquire are common nouns, such as “ball” which refer to spherical objects with various sizes and colors. A practical goal of the learner is to tell labels of objects in view. In order to accomplish this goal, the learner needs to know the corresponding labels for given visual features of objects. However, the learner needs to form and extend word categories of visual features by themselves since the caregiver cannot tell the names of all objects. The learner forms word categories of visual features based on forms of object-oriented behaviors, that is, it forms word categories by putting visual features of objects handled in a same way to a same category. By utilizing physical experience, the learner is able to generalize names to objects with unfamiliar visual features.

Fig. 1. Environment of lexicon acquisition.

B. Assumptions

The main problem we address here is to form realistic word categories and to acquire lexicon based on these categories in an effective way. In order to focus on these problems, we assume the following conditions in this paper.

1) Learner can extract object region from visual image.
2) Only one object is in view at a time.
3) Ability of object identification is not given, that is, learner does not know in advance whether different visual images belong to the same object or not.
4) Caregiver gives one label at a time.
5) Caregiver gives a label only when the corresponding object is in the learner’s view.
6) Object-oriented behaviors are not given. Learner acquires the behavior through trial and error process.

C. Lexicon Acquisition System

The overview of the lexicon acquisition system given to the learner is shown in Fig. 2. The system obtains three types of information about the objects as shown below.

1) System extracts an object region from the visual image by color based method and obtains *visual features* of objects such as colors and shapes.
2) The system obtains information for object-oriented behavior such as object’s position and direction. We call these kinds of information *state variables* in terms for reinforcement learning.
3) *Labels* of objects are given to the learner from the caregiver.

Visual informations about objects are classified into two kinds: visual features and state variables. These kinds of information can be interpreted as ones for identification and control. Such classification of visual information is also reported to exist in human brains [13]. The system identifies the object-oriented behavior of the given object based on sequence of state transition, and categorizes the visual features according to this identification.

The system acquires lexicon based on four different learning processes running in parallel as shown below.

1) Object-oriented behavior learning.
2) Visual feature space categorization based on the object-oriented behaviors.
3) Visual feature space categorization based on labels.
4) Correspondence learning between object-oriented behaviors and labels.

The system learns and identifies object-oriented behaviors with a *multi-module learning system*. The system then forms word categories of visual features based on the object-oriented behaviors. On the other hand, system also forms word categories of visual features based on the labels given by the caregiver. This means that there are two different process of categorization for the visual feature space. The categorizations are performed by *adaptive networks*. As the categories grow, the correspondence between the two groups of categories is learned by *Hebbian network*, connecting the categories selected simultaneously. When correspondence between label and behavior is found, the system can generalize the label to objects with same object-oriented behavior. Details of each learning system are explained in the following sections. III, IV, and V explain the learning process of multi-module learning system, adaptive network, and Hebbian network, respectively. The different learning processes are explained to run one at a time for simplicity, but the system is designed to works even when all the learning system runs in parallel. Scheduling of lexicon learning process is not needed.

D. Task

To show the validity of the proposed system, we implemented the system to a mobile robot (shown in Fig. 3 equipped with omni-directional wheels and a camera) learning lexicon about objects with different rolling preference. We used the objects shown in Fig. 4, and gave labels namely “ball”, “box”, “cylinder”, and “car”. After presenting the objects shown in Fig. 4(a), (b), (c), and (d) paired with the labels corresponding to them, we introduced new objects shown in Fig. 4(e), (f),

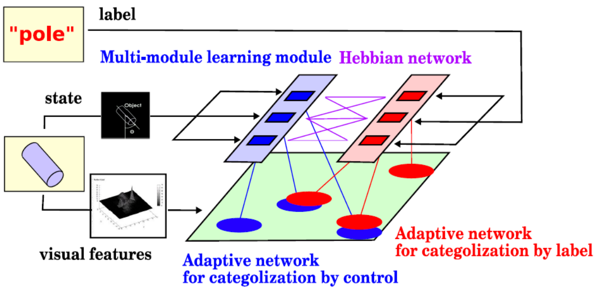


Fig. 2. Sketch of system for acquiring lexicon from physical experience.

(a) ball

(b) box

(c) cylinder

(d) car

(e) new ball

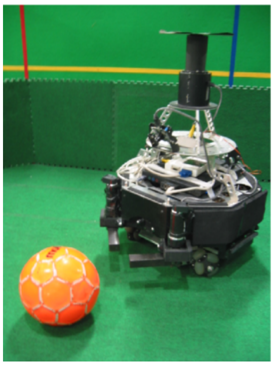
(f) new box

(g) new cylinder

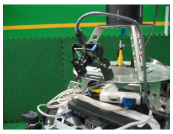
(h) new car

Fig. 4. Objects used in experiment.

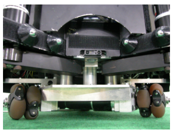
(g), and (h) without the corresponding labels. If the system successfully learned the relationship between object-oriented behaviors and labels, it should be able to generalize the labels to the new objects.



(a) robot



(b) camera



(c) omni-directional wheels

Fig. 3. Robot used in experiment.

III. Learning and Identifying Object-Oriented Behavior

A. Reinforcement Learning

Object-oriented behaviors are learned by reinforcement learning. The process enables an agent to acquire rational behaviors from trial and error processes based on the reward given by the designer. In general reinforcement learning, interaction between agent and environment is modeled as shown in Fig. 5. In every time step, agent obtains a discrete representation of the current state $s_t \in \mathcal{S}$ ($\mathcal{S}$ is the set of possible states), and selects an action $a_t \in \mathcal{A}(s_t)$ ($\mathcal{A}(s_t)$ is the set of possible action at state s_t). Then the next state $s_{t+1} \in \mathcal{S}$ and reward $r_{t+1} \in \mathcal{R}$ is determined, depending only to the state and action selected by the agent.

Task of reinforcement learning is to choose a policy $a = f(s)$ which maximizes the decaying sum of reward shown below,

$$\sum_{n=0}^{\infty} \gamma^n r_{t+n} \tag{1}$$

where γ is the decay factor larger than 0 and smaller than 1.

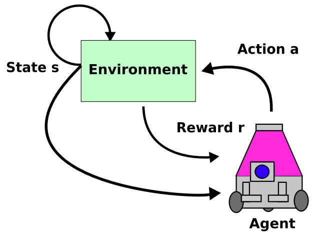


Fig. 5. Basic model of agent-environment interaction in reinforcement learning.

B. Behavior Learning Module

Agent in reinforcement learning builds two models for the environment. One is *state transition model* which is a set of possibilities of each state transition.

$$\hat{\mathcal{P}}^a_{ss'} = Pr\{s_{t+1} = s' | s_t = s, a_t = a\} \tag{2}$$

Another is *reward prediction model* which is a set of expected reward values for each state-action set.

$$\hat{\mathcal{R}}^a_s = \sum_{s'} E\{r_{t+1} | s_t = s, a_t = a\} \tag{3}$$

As the *state transition model* and *reward prediction model* are built, the agent calculates the *action value* $Q(s, a)$ (a set of expected decaying reward sum for every state-action set) based on dynamic programming method.

$$Q(s, a) = \sum_{s'} \hat{\mathcal{P}}^a_{ss'} [\hat{\mathcal{R}}^a_s + \gamma \max_{a'} Q(s', a')] \tag{4}$$

When $Q(s, a)$ converges, the rational policy for the environment is given as follows.

$$f(s) = arg \max_a Q(s, a) \tag{5}$$

C. Multi-module learning system

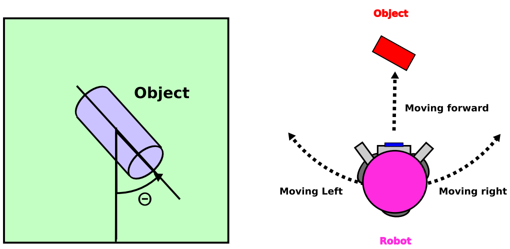
Since systems with a single learning module needs relearning whenever the environment changes, *multi-module learning system* is proposed [12]. We adopted this *multi-module learning system* to enable the system to obtain multiple object-oriented behaviors and switching the behavior according to the object. When the agent encounters an object, it identifies the behavior oriented to the object by choosing the learning module with the smallest action value error:

$$\Delta Q(s_t, a_t) = r_{t+1} + \gamma \max_{a_{t+1}} Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t). \quad (6)$$

When action value errors of all existing behavior modules exceed a predefined threshold, a new learning module is assigned to learn the behavior for the new object. The threshold should be balanced to avoid redundant computation and to acquire enough categories for object handling.

D. Behavior Module Configuration

The state space consist of direction of principal axis of the object $\theta \in [-90, 90]$ as shown in Fig. 6(a). The state space is quantized into 7, and another state is added to represent cases when principal axis is uncertain. The robot is able to choose three actions (Fig. 6(b)) namely, kicking the object forward, moving clockwise and anticlockwise around the object. Finally, a reward which value is proportional to moving distance of the object is given to the robot.



(a) state (b) action

Fig. 6. State and action for task.

E. Object-oriented behavior learning and identification experiment

The robot learned the rolling behavior for the objects shown in Fig. 4(a), (b), (c) and (d). The transition of the action value error while learning the behaviors is shown in Fig. 7 where each curve with different color corresponds to different learning modules. The robot experienced the objects in fixed order of ball, box, cylinder, and car. They interacted with the objects for 5 trials in the first 20 trials, for 3 trials in the next 12 trials, and after on, the object was switched after each trial. As shown in the figure, every time an unfamiliar object was introduced, the action error exceeded the limit $\Delta Q_{limit}(s, a) = 1.0$ and a new learning module was assigned. The figure also shows that the same learning module is selected for each object. This indicates that the system successfully acquired a set of learning module that can identify the object based on object-oriented behaviors.

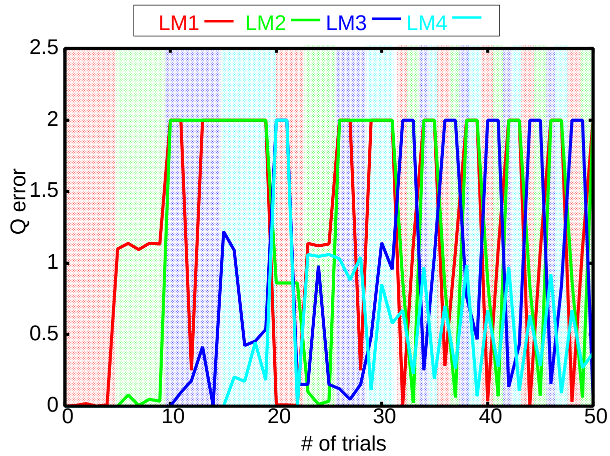


Fig. 7. Action value error of each learning module while learning object-oriented behaviors.

IV. Categorization of Visual Feature Space

A. Adaptive network

Adaptive networks, a modified radial basis function, is used for the categorization of visual feature space. The network consists of locally reactive units whose response is greatest at a central value $\boldsymbol{m}$, and decays exponentially around this central value.

$$z_j(\boldsymbol{x}) = e^{-\frac{1}{2}\sum_{i=1}^{N}(\frac{x_i - m_{ji}}{\sigma})^2} \quad (7)$$

Output of each category's network is a weighted sum of it's units,

$$y_k(\boldsymbol{x}) = \sum_{j=1}^{J} w_j z_j(\boldsymbol{x}) \quad (8)$$

and category with the greatest output is chosen as the best matching category.

The system categorizes the feature space by modifying the network weights and adding new units. When a training data (visual features with label or behavior) is given and categorization is successful, the network weight of the matching category is increased as shown below.

$$w_j \longleftarrow w_j + \beta z_j(\boldsymbol{x}) \quad (9)$$

If the categorization is not successful, a new unit is assigned. The weights are decreased whenever the network is modified.

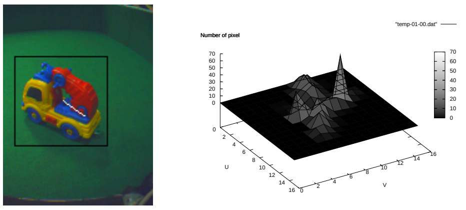
$$w_j \longleftarrow \alpha w_j \quad (10)$$

This process enables the system to forget unused categories, and keep adapted to changes of the environment. $\beta \in [0, 1]$ is a learning rate, and $\alpha \in [0, 1]$ is a decay factor. Each factor should be determined in relation with the other.

B. Visual feature

We adopt YUV color space and UV color histogram as visual feature in the experiment. UV space is quantized into 16×16, so the color histogram is a 256 dimension vector representing frequency of quantized color in UV space. Fig. 8 shows an example of the UV space histogram. The system uses χ^2-distance as distance metric.

$$\chi^2(A,B) = \sum_i \frac{(a_i - b_i)^2}{a_i + b_i} \tag{11}$$



(a) extracted image (b) color histogram

Fig. 8. Color histogram of object.

V. Learning Relation Between Object-Oriented Behaviors and Labels

A. Hebbian network

A Hebbian network is used for learning relation between object-oriented behaviors and labels. The relation is learned by increasing the connection strength between the behavior and the label whose category is selected simultaneously. The weight of the simultaneously selected categories are increased with the value δ_{inc},

$$w_{i,j} \longleftarrow w_{i,j} + \delta_{inc} \tag{12}$$

and other connections are decreased with δ_{inh} to disregard words unrelated to object-oriented behaviors.

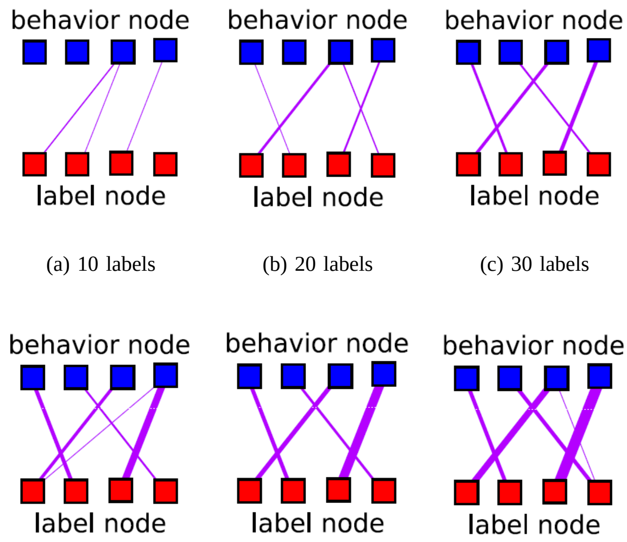
$$w_{i,j} \longleftarrow w_{i,j} - \delta_{inh} \tag{13}$$

δ_{inc} and δ_{dec} have positive values smaller than 1.

The Hebbian network enables the learner to generalize labels to other objects based on object-oriented behavior only when label and object-oriented behavior is related.

B. Lexicon acquisition experiment

After the robot learned the handling behaviors (described in section III-E) and categorized the visual feature space based on the behaviors, the caregiver gave the labels of the objects which the robot learned to handle (Fig. 4(a), (b), (c) and (d)) in random order. When the label was given, the system categorized the visual feature by assigning the visual features simultaneously given to the category of the given label. As the category of the label grows, the relationship between object-oriented behaviors and labels is learned by modifying the weight of the Hebbian network. Sketch of the Hebbian network weight transition recorded from real robot experiment in accordance with the number of times the label was given is shown in Fig. 9. The figure shows that the system successfully learned the one-to-one correspondence of object-oriented behaviors and labels.



(a) 10 labels (b) 20 labels (c) 30 labels

(d) 40 labels (e) 50 labels (f) 60 labels

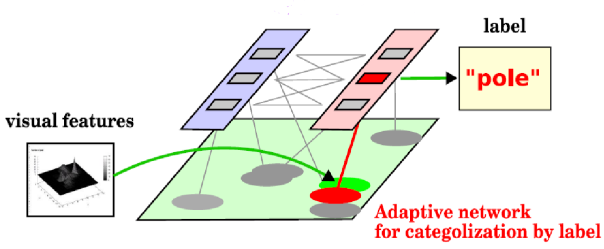
Fig. 9. Weight transition of Hebbian network. Width of connection represents connection weight.

VI. Word Generalization Based on Object-Oriented Behavior

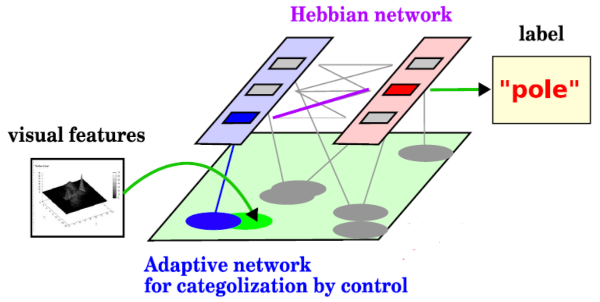
A. Word generalization policy

By learning the relationship between object handling behaviors and labels, the system can generalize words to unfamiliar objects based on object-oriented behaviors. When the learner encounters unfamiliar objects, it identifies the behavior oriented to the object by choosing the best matching behavior module in the multi-module learning system. Then, the visual feature of the unfamiliar object is assigned to the category of the selected behavior. To predict the label of the object in view, the system performs the following process.

1) The system selects a best matching category for the visual features of object in view, considering both adaptive networks of behaviors and labels. (Fig. 10)
2) If a category is selected from adaptive network of label, it is likely that the label of the object is already given, and the system outputs the selected label. (Fig. 10(a))
3) If a category is selected from adaptive network of behavior, it is likely that the label of the object is not given, but the object-oriented behavior of the object is known. In this case, the system outputs the label with the heaviest connection to the selected behavior. (Fig. 10(b))



(a) label guessing by label category



(b) label guessing by behavior category

Fig. 10. Label guessing process.

B. *Word generalization experiment*

After learning the relation between object-oriented behaviors and labels (described in section V-B), the robot was presented the new objects shown in Fig. 4(e), (f), (g) and (h) without labels. Since all the object-oriented behaviors of the new objects are known, the robot was expected to be able to generalize the learned words to the new objects. Fig. 11 shows the transition of ratio of correctly answered labels as the robot interacts with the new objects and identifies their object-oriented behaviors. The ratio of correctly answered label is only about 20% at the start, which indicates that existing methods are helpless for generalizing words to new objects. As the robot interacted with the new objects, it gradually generalized the category of object-oriented behaviors to new objects, and became to answer correct labels. The ability of word generalization is shown.

VII. Conclusion and Future Work

We proposed a lexicon acquisition system for generalizing names to objects with same forms of object-oriented behavior. The system was implemented to a robot learning words about objects with different rolling preference. The robot learned the rolling behavior for each object, formed word categories based on the behavior, and successfully generalized the words to newly introduced objects. For future task, we are planning to add shape information such as edge histograms into the visual features of objects. Such visual feature should be more

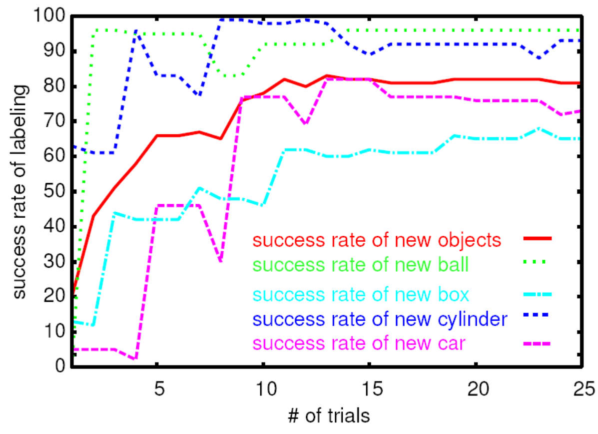


Fig. 11. Generalization of words to new objects.

suited for acquiring words about solid objects. Introducing other behaviors such as grabbing objects is also important since it introduces relation between categories. Considering the relation between word categories is the next step toward symbol grounding.

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