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Towards Cognitive Agents: Embodiment based Object Recognition for Vision-Based Mobile Agents

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Abstract

In this paper, we propose a new architecture for recognizing objects based on a concept "embodiment" as one of primitive functions for a cognitive robot. We define the term "embodiment" as the size and shape of the agent's body, locomotive ability and its sensor. According to embodiment, an object is represented by reaching action paths, which correspond to a set of sequences of movements taken by the agent for reaching the object. Such behavior is acquired by the trial-and-error method based on the visual and tactile information. Visual information is used to obtain sensorimotor mapping which represents the relationship between the change of object's appearance and the movement of the agent. On the other hands, tactile information is utilized to evaluate the change of physical condition of the object caused by such movement. By means of this method, the agent can recognize an object without depending on its position and orientation in the environment. To show the validity of our method, we show an experimental result of computer simulation.

1 Introduction

Recognizing an object based on visual information is essential and useful function for the agent which can behave in the real world. In the computer vision area, so-called model-based approach is popular for recognizing an object based on the visual features. Since human designers always prepare the model of the object from the designer's viewpoint in such approach, it is ambiguous whether such model is suitable or not for the agent having the model-based object recognition system. Therefore, such model should be constructed by the agent itself from the agent's viewpoint.

Recently, there have been many researches regarding to the development of the intelligent agent which have an internal model considering agent's embodiment [4][3][1]. Embodiment roughly means property of agent's body such as size, shape, and locomotive ability. In their researches, the model is expressed by using features of agent's embodiment. Nehmzow et al.[3] proposed a location recognition method in enclosure environment by means of sequential motor command of turn action and elapsed time between commands. Fukuda et al.[1] proposed an object recognition method by hand shape. They assume that an internal representation of object in human brain is expressed as hand shape for grasping it.

In our work we use the assumption that an internal representation is expressed by agent's embodiment. It is almost the same assumptions to above researches. Locomotive ability is commonly used to model the environment [4][3]. In addition to is, we argues that the size and shape of an agent also plays very important role in modeling it. It is because the representation of its environment depends on the size and shape of the agent's body. For example, a chair is an instrument to sit for a human, but it does not have any meaning of tool to sit for an ant which has different embodiment. In other words, the significance of existence of the object depends on the embodiment of the agent.

In this paper we propose an object recognition method considering agent's shape, size, and locomotive ability. In our method, an object is represented by a set of all possible action series to it. An action series is a path that starts at current position and terminates with touching state in which agent's body touches to an object. We call such a path as "Reaching Action Path". A reaching action path is acquired by the trial-and-error method based on the visual and tactile information. Because of an object has it's own size and shape, features of a set of paths vary depending on them.

Because reaching action paths as internal representation represents an object, recognizing an object by vision is to estimate the reaching action paths from visual input. In next section, we will show a method of generating reaching action path from visual input. In section 3, we will show a method of make a representation of an object from reaching action paths. In section 4, we show an experimental result of computer simulation to show the validity of our method. By means of our method, the agent can recognize an object without depending on its position and orientation in the environment.

2 Reaching Action Path

Objects are considered as an area in which an agent can not exist. In other words, objects are represented by paths each of which terminal is perceived by tactile information. We call these paths as reaching action paths. The agent can discriminate objects by means of reaching action paths because they reflect the shape of objects. In order to represent an object by reaching action paths, we extract several features from them. We call these features as a shape characterizing vector.

On the other hand the agent cannot receive any information directly about an environment by vision. In order to recognize the physical world by vision, the visual information should be concerned to tactile information, which is an only modality to receive physical information directly. If the agent knows the visual features which associates with tactile information, it can generate reaching action paths mentally. In our method the relation is learned by means of dynamic programming.

2.1 Assumed Agent and Environment

We assume that the dimension of an agent and an environment is 2, that is, the agent can move only on the 2D plane. Figure 1 shows the agent and the environment assumed in our work. The shape of the agent is circle and the agent is equipped with tactile sensors around its body. We put a camera over the environment as its eye so that the agent can see both its body, object and contact state. We also assume that the agent can generate 6 action commands. We define an action unit as a segment of the agent's movement until a change of state is observed. The agent also has a gyro sensor so that it can perceive rotation of body.

2.2 Calculation of Reaching Action Path

A reaching action path means an optimal path, which starts at a point on agent's body and ends at a point on boundary of physical object.

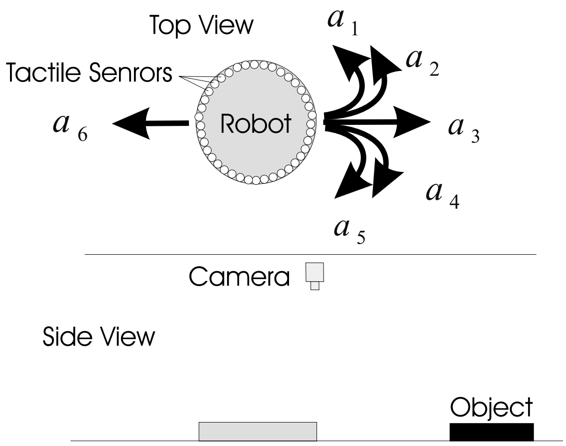


Figure 1: Assumed agent and environment.

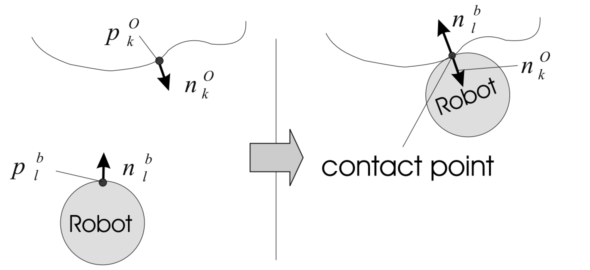


Figure 2: Contact condition.

Suppose a point $p_l^b \in \boldsymbol{R^2}$ on the surface of an agent's body and a point $p_k^o \in \boldsymbol{R^2}$ on the surface of a physical object (Figure 2). When the agent's body is touching the object, a tangential line of the agent's body coincides with that of the object at a contact point. In other words, the point on agent's body coincides with that of the object, and a normal vector of the agent's body and object have the same size and the opposite direction. This relation is expressed as following equation:

$$p_l^b = p_k^o \tag{1}$$

$$\boldsymbol{n}_l^b = -\boldsymbol{n}_k^o \tag{2}$$

where $n_l^b \in \boldsymbol{R^2}$ is a normal vector on the agent's body at the point p_l^b and $n_k^o \in \boldsymbol{R^2}$ is a normal vector on the object at the point p_k^b.

Next, we explain a method for learning the reaching action path using visual input. Consider an input image like Figure 3 which includes both the agent's body and an object. We treat an input image as a set of several small areas. The small area may include

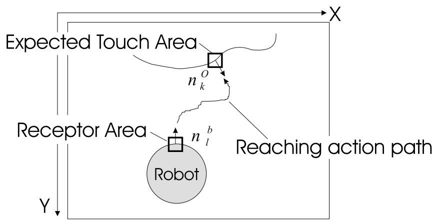


Figure 3: An input image and small areas.

the surface of agent's body and/or the object. We call an area that includes the point of agent's body as Receptor Area (RA), and an area that includes the point of object as Expected Touch Area (ETA). An expected touch area indicates an area in which physical contact will be observed after certain action series, i.e., reaching action. We define the coordinates of expected touch area as (x^{ETA}, y^{ETA}) and an angle of a normal vector as θ^{ETA}, the coordinates of receptor area as (x^{RA}, y^{RA}) and, a normal vector as θ^{RA}. In a goal state of reaching action path, the state of each area should be as follows;

$$x^{ETA} = x^{RA}, y^{ETA} = y^{RA}, \theta^{ETA} - \theta^{RA} = \pi \tag{3}$$

We use dynamic programming as a learning method for the optimal policy to generate an optimal reaching path. Given an utility function U and if a state transition holds Markov property, optimal policy for Markov decision problem is calculated as follows;

$$f(i) = \arg\max_a \sum_j M^a_{ij} U(j) \tag{4}$$

where M^a_{ij} is the probability of reaching state j if action a is taken in state i, and $\arg\max_a f(a)$ returns the value of a with the highest value for $f(a)$. The utility of a state can be expressed in terms of the utility of its successors:

$$U(i) = R(i) + \max_a \sum_j M^a_{ij} U(j) \tag{5}$$

where $R(i)$ is a reward function which returns a value of reward in state i. In our work, a reward is given when the point of agent's body touches to an object, and M^a_{ij} indicates the transition probability of receptor area and it is obtained through experiences of random action.

Although, as mentioned above, a reaching action path is defined such a path between a receptor area and an expected touch area, we can define multiple reaching action paths. If there are m expected touch areas on boundary of the object and n receptor areas on boundary of the agent's body, $m \times n$ reaching action paths are defined.

Table 1: Example of Relation between action and code.

action	a_1	a_2	a_3	a_4	a_5	a_6
code	-2	-1	0	1	2	0

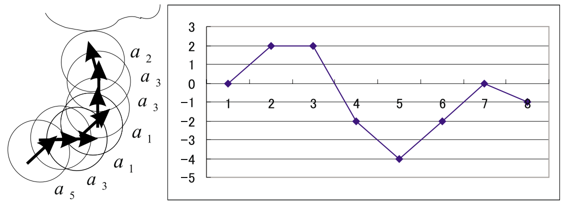


Figure 4: Chain coding.

3 Characterizing Objects by Embodiment

In order to represent objects by agent's embodiment we use reaching action paths. Reaching action paths are calculated depending on the variety of a size and shape of agent's body. In this section we explain methods to represent the physical properties of object by means of reaching action paths. Physical properties mean pose, i.e., position and orientation, and shape of an object. Before explaining these methods precisely, we explain a method to represent the reaching action path.

3.1 Representation of a Reaching Action Path

In order to represent a reaching action path, we utilize a chain coding which is a popular coding technique in the fields of image processing and shape analysis [5]. In our method, a code indicates an angle of rotation of a motor command. Table 1 shows an example of relation between action and code. The ratio between code values is similar to that of rotation angle. However, the moved distance and the angle of rotation corresponding to the action are indeterminate, since one action terminates when change of state is observed. In order to overcome this problem, we adopt an average value of rotating angle to calculate the ratio. Figure 4 shows a summation of code value in each time step corresponding to an action series of reaching action. The summation of the code value indicates a relative angle to the starting point, and the length of the chain code indicates the moved distance of the agent. Consider an action series of a reaching action $a_1, a_2, \ldots a_u$ and a chain code corresponding to the action series $\boldsymbol{c} = \{c_1, c_2, \ldots, c_u\}$, the summation of chain code C is

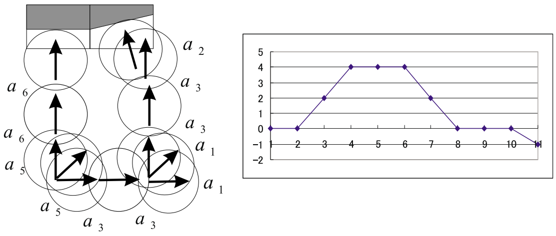


Figure 5: Local haptic motion.

Table 2: Objects used in our experiment.

name	shape	size
obj1	circle	radius 2.1
obj2	circle	radius 2.8
obj3	circle	radius 3.0
obj4	rectangle	3×5
obj5	rectangle	1.5×4
obj6	rectangle	3×3

represented as follows:

$$C = \sum_{i=1}^{u} c_i \tag{6}$$

and the length of the chain code L is:

$$L = u \tag{7}$$

3.2 Representation of Shape

Shape of an object indicates how the boundary contour of the object varies. The variation of the boundary contour can be perceived by a haptic motion. A local haptic motion is defined as an action series satisfying the following conditions.

1. The agent's body touches an object both at the starting and at the goal point.

2. The goal point is adjacent to the starting point.

We can calculate a reaching action path between starting and goal points, and a chain code of its action series. Figure 5 shows an example of a local haptic motion and a summation of code value $C = -1$ which represents a relative angle between the adjacent points on the object's boundary. The value of $|C|$ becomes larger in proportion to the relative angle of adjacent points.

In the example of Figure 5, $|C|$ can represent the relative angle directly because the same point of the agent's body touches the object both at the starting and at the goal point. If the different point of the agent's body touches the object at the goal point, $|C|$ does not represent the relative angle. In order to cope with this problem, we introduce C' which represents an action series that (1)the goal point of the physical object is similar to the starting point, and that (2)different points of the agent's body touch the object at the starting and at the goal point. As a result, in such situation, the relative angle is represented by $C + C'$.

If there are m expected touch areas on boundary of an object, the shape of the object is represented by $\boldsymbol{c}= \{c_1, c_2, \ldots, c_m\}$. We call this vector as a shape vector. The shape vector can represent the characteristics of the object's shape. For example, an object which consists of only straight lines and right angles, namely, rectangle, $\boldsymbol{C}$ can be $\{0,0,4,0,0,4,0,0,4,0,0,4\}$, and in the case that the variation of the object boundary contour is regular like an circle, $\boldsymbol{C}$ can be $= \{1,1,1,1, 1,1,1,1,1,1\}$. Note that the shape vector does not change in spite of the change of position and orientation. Because the shape vector includes various information about shape, we should select appropriate features so that it can represent the object adequately. The primary feature is the length of $\boldsymbol{c}$ which corresponds to neighbor the circumference of an object, i.e., $f_1 = |\boldsymbol{C}\ |$. The feature of characterizing an object is represented by frequency analysis such as Fourier transformation. Consequently, $f_2, f_3, \ldots$ is the Fourier coefficient. We call $\boldsymbol{F}= \{f_1, f_2, \ldots\}$ as a shape characterizing vector.

3.3 Object Recognition

Object recognition is mainly divided into two procedures; (1)learning of the representation of objects, and (2)object recognition by this representation. The learning procedure is as follows:

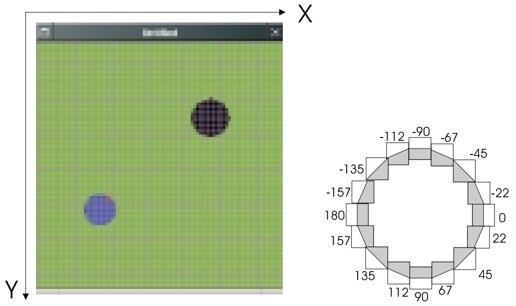
- Estimation of transition probability.

- Collect examples of various shapes of objects from experience, and store shape characterizing vectors. Note that the agent can generate reaching action paths mentally, i.e., without actual motion, after the agent knows the transition probability.

Object recognition is accomplished by means of NN (nearest neighbor classification). Sample data of NN is collected examples of shape characterizing vectors.

4 Experimental Results

In order to show the validity of our method, we had an experiment by computer simulation. In this experi-



(a) (b)

Figure 6: (a)An input image and (b)angular discretization rule.

ment, the aim of the agent is to recognize objects from any position and orientation, and categorize them correctly. Table 2 shows objects used in our experiment. Note that the size of each object represents the size in the simulated world not in the input image. Figure 6-(a) shows an input image used in computer simulation. The size of image is 160×160 pixels and the size of expected touch area and receptor area is 3×3 pixels, therefore there are 53×53 possibilities for them. A circle on the left lower side in the image shows the body of an agent and another one on the right upper side shows an object (obj3). Figure 6-(b) shows the angular discritization rule applied to both the body of the agent and the object. The angle of a normal vector of the surface is discritized into 16 steps. As a result, the number of state is $53 \times 53 \times 16$.

In this experiment, we assume that the agent has only one contact point in front of the surface of its body.

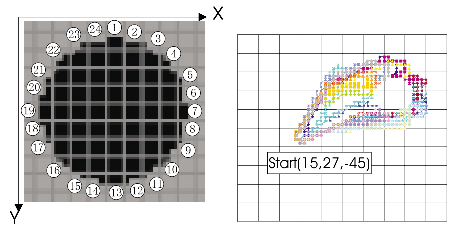
4.1 Learning of the Representation of Objects

4.1.1 Transition Probability Estimation

Consider a state in an image $S_i(x_i, y_i, \theta_i)$, the possible number of the next state $S_{i+1}(x_{i+1}, y_{i+1}, \theta_{i+1})$ is $a \times m \times n$, where a is a number of actions, m is a number of adjacent cell in the image, and n is a number of angular discritization. We assume that transition probability from any (x, y) in the image is equal.

4.1.2 Calculation of Reaching Action Path

Next we calculate reaching action paths by dynamic programming using transition probability calculated above. Figure 7-(a) shows the detected 24 expected touch areas from Figure 6-(a). We put an agent on the starting point where detected receptor area is $(15, 27, -45)$.



(a) (b)

Figure 7: (a)Detected ETA and (b)calculated reaching action path

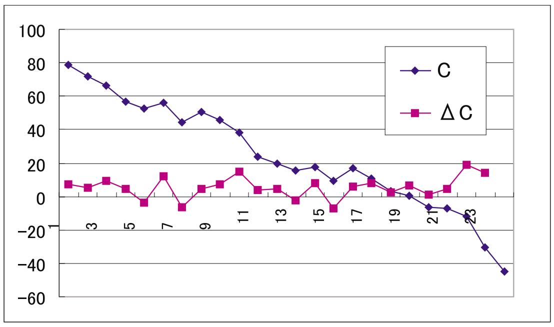


Figure 8: C and ΔC value.

Figure 7-(b) shows the calculated 24 reaching action paths. We also show the C and ΔC value of each reaching action paths on Figure 8. ΔC means difference value of C between the adjacent reaching action paths. Although the agent should do haptic motion in order to obtain ΔC value exactly, we use the ΔC value relatively obtained from the same starting point instead.

4.1.3 Extraction of a Shape Characterizing Vector

We extract shape characterizing vectors from ΔC. Extracted features in this experiment are described as follows. f_1 is the length of ΔC i.e. $|\Delta C|$. $f_2 \ldots f_5$ are Fourier coefficient extracted by discrete Fourier transform on ΔC;

$$\Delta C(n) = \sum X_k e^{-i\frac{k\pi n}{|\Delta C|}} \tag{8}$$

f_2 is a real part of X_1, f_3 is an imaginary part of X_1, f_4 is a real part of X_2, and f_5 is an imaginary part of X_2.

We provided four cases by changing the starting

Table 3: Average of shape characterizing value.

name	f_1	f_2	f_3	f_4	f_5
obj1	16	-1.2	-1.2	0.9	0.7
obj2	22	-0.4	-0.4	-0.9	0.1
obj3	24	-0.6	0.2	0.3	0.1
obj4	24	-0.8	1.9	0	-1.4
obj5	16	-1.0	2.9	0	-2.3
obj6	16	-1.0	-1.1	-0.2	-1.4

Table 4: Object recognition rate.

	obj1	obj2	obj3	obj4	obj5	obj6	average
rate	0.75	0.91	0.75	0.91	0.83	1.0	0.85

point, and calculated reaching action paths and shape characterizing vectors. Table 3 shows the average value of shape characterizing vectors for each object after 20 trials for each case.

4.2 Discrimination of Objects

We performed object discrimination tests using the extracted shape characterizing vectors above. We use NN(nearest neighbor classification) as discrimination method. We put each object of $obj1 \ldots obj6$ on 12 points and extract shape characterizing vectors and performed object discrimination tests. Table 4 shows the average recognition rate of each object. The highest value is 1.0, the lowest 0.75, and the average 0.85. One of the reasons to fail recognition is fail in path generation. Since the agent may fail to reach objects because of the scattering of transition probability and as a result, a correct shape characterizing vector is not

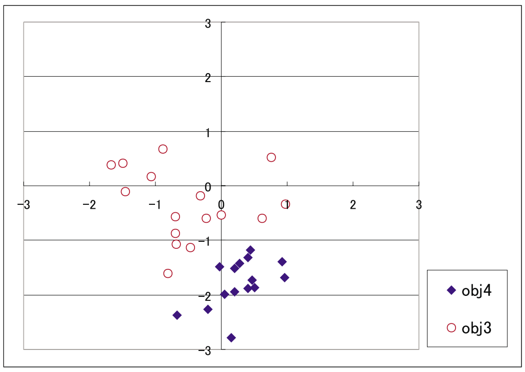


Figure 9: Shape characterizing value of f3-f4.

calculated.

Figure 9 shows the shape characterizing values of obj2 and obj4 used in the training and test. From this figure, we can see that divergence of an object is well formed, and that there are clear discrimination boundary. This implies that the agent can recognize objects from any position and orientation, and categorize it to the correct class.

5 Discussion and Conclusion

In this paper, we propose a method of embodiment-based visual object recognition. We define the embodiment as agent's own size and shape of body and locomotive ability. In order to represent an object by embodiment, we employ a reaching action path that represents the relation between surfaces of the agent body and the object. Then, agent can acquire the relation between vision and embodiment through learning of the path with visual input. By means of this method, the agent can recognize objects independently from its position and orientation without prior knowledge. In other words, acquired representation implies invariant advocated by Gibson [2].

In the future work, we will try to develop methods of situation recognition and behavior generation based on the same architecture.

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