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Robot Feeling Formation Based on Image Features

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Abstract: Feeling and emotion are important to human being during his/her learning process, also valuable to be adopted into intelligent machines. This research presents a system which forms and expresses feelings of a robot. The vision information of robot is used and the environment features are categorized by a hierarchical SOM (Self-Organization Map). The proposed SOM here combines a feature map, an action map and a feeling map together, and the action policy of robot is modified by reinforcement learning rule, feeling degree is complicated by a dequantization algorithm. The experiments through computer simulation and an autonomous robot in the real environment showed robot's feelings formation process and its emotional actions.

Keywords: autonomous robot, emotional intelligence, feeling formation, image processing.

1. INTRODUCTION

The updated studies of neuroscience, psychology and cognitive science shows that emotion plays critical roles in learning process and intelligent behavior. Toward machine emotional intelligence, there are also some pioneer researches and practice in the field of autonomous robot engineering[1]. Computational emotion models are developed and their applications on robotics draw a bright future[2]. Meanwhile, the study on the human cerebral cortex showed that the motor cortex, somatosensory cortex, visual cortex and auditory cortex are represented by topologically ordered maps, and it brought out a successful classifier, *i.e.*, Kohonen's SOM (Self-Organizing Feature Maps)[3], [4], [5]. Furthermore,the studies on the psychology of animal learning gave us the last learning paradigm: reinforcement learning, which basic idea is that of awarding the learner for correct actions, and punishing wrong actions[6].

In this paper, we propose an autonomous intelligent system with active exploring ability, feeling formation function and emotional expression behaviors. The system adopts a new hierarchical SOM to classify vision information, *e.g.*, features of images, and uses reinforcement learning process to acquire environment information and stimulation for feeling formation. Though emotion models are still discussed in various scientific fields, a process of feeling formation is proposed here to show how a robot riches its feeling (happy or angry) degree during its environment exploring. We confirmed the effectiveness of proposed system by a simulation experiment and an experiment in environment using a mobile robot.

2. SYSTEM

The feeling of machine here we defined is expressed with 1-dimension vector space. Values of happiness and sadness are calculated from zero to one on the feeling axis , and 0.5 means normal emotional state. The feeling value changes after robot obtains reward from environment. The reward may be positive value or negative value according to the result of robot's probability behavior. The input information to the system is given by robot's visual sensor, a 3-CCD camera. And acquired images are classified by a hierarchical SOM proposed in the next subsection.

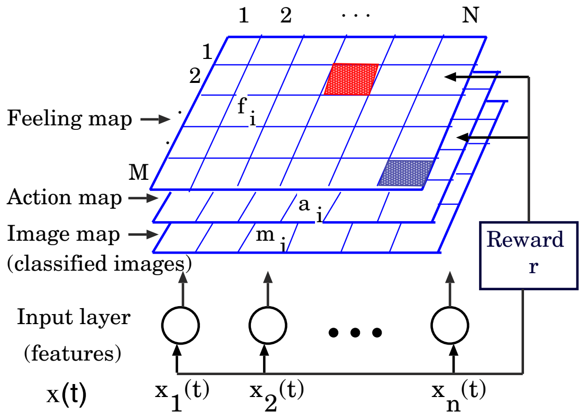

Fig. 1 Structure of a hierarchical SOM.

2.1 A hierarchical SOM

Kohonen's SOM (Self-Organizing Maps) is well known as an effective pattern classifier using unsupervised learning algorithm[3], [4]. In this research, to compel features of input images concerning with feeling vectors, a hierarchical SOM which consists of an image discrimination map, an action map, and a feeling map is proposed (Fig.1). The process of these maps is different from Carpinteiro's hierarchical SOM which combines 2 SOM together to realize sequence classification and discrimination. The process of each map in our hierarchical SOM is stated under.

The first map, image discrimination map, is a conventional SOM, classifying environments of robot using visual information, *i.e.*, features of images. The feature vectors are given by histogram of intensity in different region of a frame of image (after binarization), and they are arranged to a lower dimension space, usually, which is a 2-D map here. The model and learning algorithm is referred to standard SOM[3], [4]. The neighborhood function in our hierarchical SOM is just a kind of linear func-

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Table 1 An example of an action map on a learning step.

s_k	a_1	a_2	$\cdots$	a_i
1	3	2	$\cdots$	-5
2	8	1	$\cdots$	4
.			$\cdots$	
p	-27	3	$\cdots$	2
.			$\cdots$	
N×M	0	-4	$\cdots$	3

tion instead of the Gaussion function (Fig.2). The second

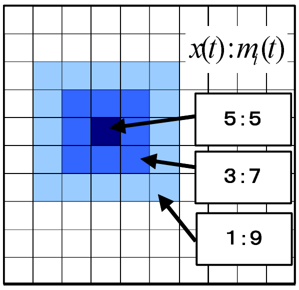

Fig. 2 Neighborhood function rate.

map, action map, is a kind of labeling process table which combines one pattern of environment with a correct action using reinforcement learning algorithm[6]. Table 1 shows an example of values of action map in a learning step (for example, at the initial step). The column of s_k means different states of environment classified by the first map ($k = 1, 2, \cdots$, N×M), a_i means selectable actions or behaviors ($i = 1, 2, \cdots, I$). $Q(s_k, a_i)$ which example values are the numbers in the table express values of actions. Using a stochastic policy, *e.g.*, according to a probability given by Eq.1 (Boltzmann/Gibbs distribution) to select an action, and an evaluation rule given by Eq.2, robot is trained to act easily to obtain reward, and avoid to be punished.

$$p_{ki} = \frac{e^{\frac{Q(s_k,a_i)}{T}}}{\sum_{j\in A} e^{\frac{Q(s_k,a_j)}{T}}} \tag{1}$$

where T is temperature, p_{ki} is the probability to select action i on the state s_k. A is a set of actions. $Q(s_k, a_i)$ is updated when robot accepts a reward r after action a_i is executed (Eq.2).

$$Q_{t+1}(s_k, a_i) = Q_t(s_k, a_i) + r \tag{2}$$

In a case that an autonomous robot searches goals (food, energy, etc.) in the unknown environment, the reward can be designed that it takes a negative value when robot crashed an obstacle and a positive value in other cases. This reward is also used in calculation of feeling map.

The third map, feeling map, combines the reward or the punishment from environment with feeling vector. The detail of feeling formation process is given in the next subsection.

2.2 Formation of feeling

Motivation of a creature's behavior may be affected seriously by its feelings, and emotions can be derived partly from feelings. The feeling of machine here is defined by an 1-dimension vector space, which includes a direction of happiness and a direction of angry (or sadness).

Let $f_i(t), i = 1, 2, \cdots$, N×M express feeling value of robot in different environments. These feelings correspond to nodes of input layer SOM which classified the input patterns. We set $f_i \in [0.0, 1.0]$, where $f_i = 0.0$ means the most happy value, $f_i = 0.5$ means calm value, and $f_i = 1.0$ means the most angry value. The feeling of each state is changed by reward r:

$$f_i(t) = \begin{cases} f_i(t-1) - r, if r \neq 0 \\ f_i(t-1) - \alpha * f_i(t-1), if r = 0. \end{cases} \tag{3}$$

here $0.0 < \alpha \ll 1.0$ is a constant to give excitant for exploring. To realize more happy more exploring philosophy, Eq.2 is refined by:

$$Q_{t+1} = \begin{cases} Q_t + r, if r \geq 0 \\ Q_{t+1} = Q_t + r * f_i(t), if r < 0. \end{cases} \tag{4}$$

Eq.3 and refined action value function Eq.4 make robot to have more experience, and to form as more rich feelings as more rewards it obtained in experience.

Eq.3 just describes how to calculate feeling's value, does not evaluate the kinds or levels of feeling, i.e., we need to express how happy or how angry the robot is by literary description. Here we give a dequantization algorithm to realize how to form complicated feelings from low level.

A dequantization algorithm of computational feeling.

step 1 Initially, for a random feeling value $f_i(t)$, set up a threshold of happy H_0 and a threshold of angry A_0. Let $0.0 \leq H_0 < f_i(t) < A_0 \leq 1.0$.

step 2 Tune H_0 or A_0 after an action by:

if $r > 0$, then

$$H_{age+1} \leftarrow H_{age} + \beta * f_i(t+1) \tag{5}$$

if $r < 0$, then

$$A_{age+1} \leftarrow A_{age} - \beta * f_i(t+1) \tag{6}$$

if $r = 0$, then

$$H_{age+1} \leftarrow H_{age} \tag{7}$$

$$A_{age+1} \leftarrow A_{age} \tag{8}$$

where β is a constant, $0.0 < \beta \ll 1.0$.

step 3 Yield a new feeling area if necessary. If $H_{age} - A_{age} > \gamma$, then

$$H_{age+1} = (H_{age} + A_{age})/2.0 \tag{9}$$

. If $H_{age} - A_{age} < \varepsilon$, then

$$A_{age+1} = H_{age+1}, \tag{10}$$

.

step 4 Back to *step 2* if exploring.

An example is given in Fig.3 where 10 levels kinds of feeling was formed. Parameter's values were: $H_0 = 0.5, A_0 = 1.0, \beta = 0.1, \gamma = 0.2, \varepsilon = 0.01$, and the stop age was set to 9.

3. EXPERIMENTS

A simulation experiment and a real environment experiment were carried out in this study.

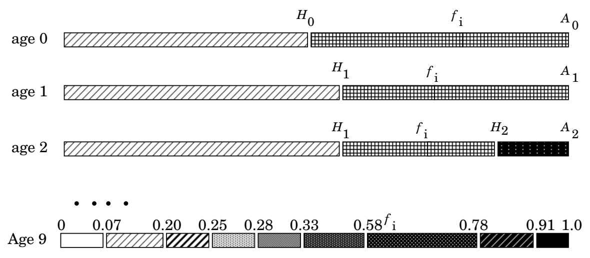

Fig. 3 An example for *dequantization algorithm of computational feeling*.

3.1 Simulation experiment

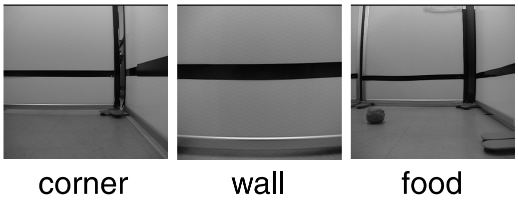

Fig. 4 Real images used in the experiment.

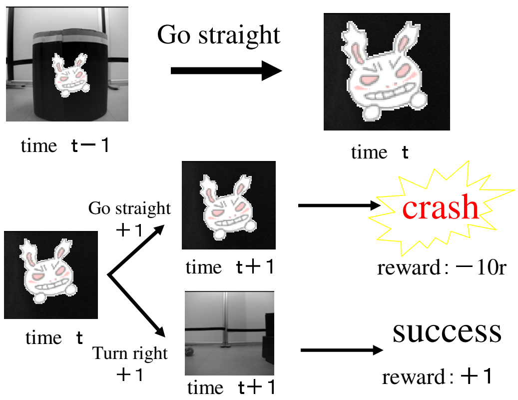

Fig. 5 Judgment of crash.

Computer simulation is designed in an environment shown in Fig.6. In the 5×5 maze space, a robot walks around all time to 4-directions availably, clashing with walls or obstacles, and sometimes a food. The input images were real images taken by a CCD camera, and 100 images captured in a room were used (4). The color of wall and floor was white, obstacles in the room were black, and a food is with red color. To distinguish wall and floor, black tapes were sticked at their conjunctions and corners of room.

One/Each image is divided into 40×40 area, and the brightness of each small area gives feature vectors of SOM. The judgment of crash was give by calculating the distance between 2 continuing image (Fig.5). Temperature parameter T in Eq.1 was set to be 50.0 which gave a best balance between convergence and exploration of action., and reward r in Eq.2 was 1.0 when there was no clash happened, but $r \leftarrow -10.0 * r$ after a clash. Parameter α in Eq.3 was 0.1. The training times of SOM was 1.0×10^5. Fig.7 shows the learning results of Image map (feature map of image) and Action map (selected actions in different probabilities). Random values were given at first, classifications were executed better according to iteration of training either on image map or on action map. Fig.8 shows the rate of image discrimination ascends by learning. Exploring steps continued 4.0×10^4 times, and the descent of rate of clash is shown Fig.9, concerning with iteration number of learning.

Fig.6 also shows results of feeling map. One can observe that nearby walls and obstacles, angry states exists completely. These simulation results serve to verify the effectiveness of proposed feeling formation method.

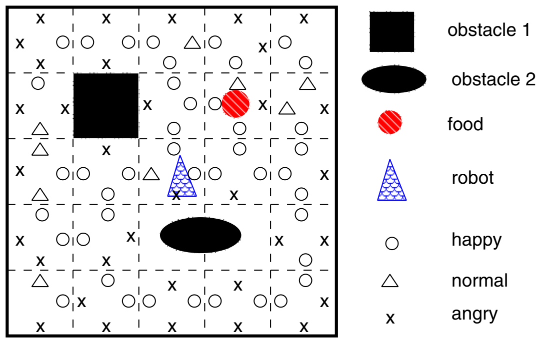

Fig. 6 The simulation environment and results of experiment.

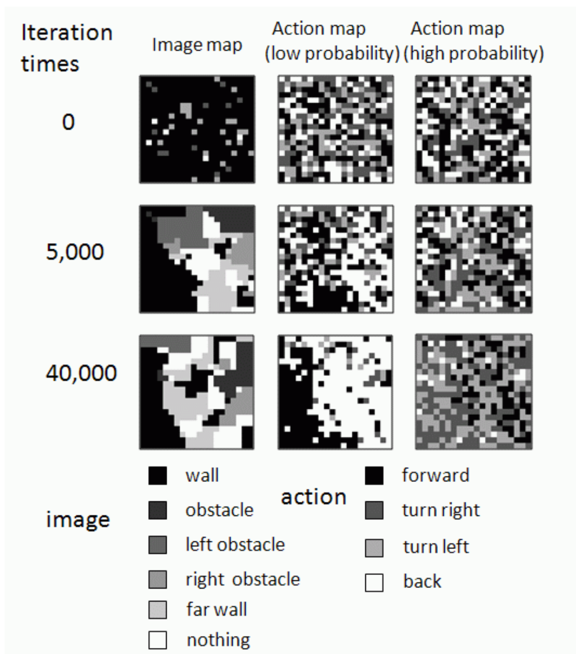

Fig. 7 Learning results of hierarchical SOM in simulation experiment.

3.2 Real environment experiment

We used a robot called Plat-F1[7] and a personal computer with an image processing board IP7500EB[8] to construct an autonomous system (Fig.10) and confirmed its effectiveness in a real environment. The state of environment was as same as description in simulation experiment. Robot was expected to move autonomously to find food (a red object) avoiding obstacles (2 black objects)

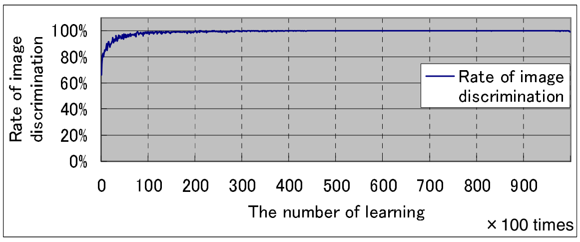

Fig. 8 Rate of image discrimination.

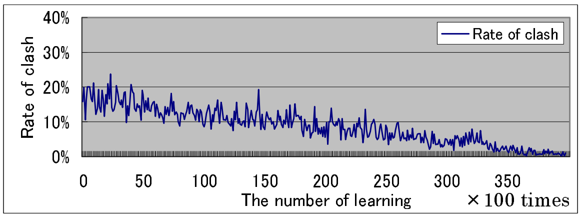

Fig. 9 Rate of crash.

and wall (white color objects above floor). The main specification of the robot and image processing equipment is stated in Table 2 and Table 3 respectively. The system used all parameters as same values as those used in simulation experiment. In this experiment, the robot walked around in the room actively, according to Eq.1, Eq.2 and Eq.3. To express feeling of robot, we set some special actions when feeling degree overred thresholds, i.e. "move ahead and back" for angry, "turn a round" for happy. As a result, robot played emotional actions with hesitation (move ahead and back), dancing (turn a round) vividly (Fig.11).

4. CONCLUSION

A hierarchical SOM for robot's feeling formation based on image features was proposed. The proposed system includes a feature map to classify images, an action map to select adaptive actions corresponding to states, and a feeling map to calculate feeling degree during robot's environment exploring. Competitive learning rule, reinforcement learning rule and a dequantization algorithm for computational feeling are adopted in the system efficiently. The effectiveness of proposed system was confirmed by experiments in simulation environment and in real environment.

Table 2 Main specifications of robot Plat-F1.

Running method	two driving wheels, steering wheel
Externals size	(W)30cm×(D)30cm×(H)10cm
Highest running speed	2000mm/sec
Weight	About 4kg
Weight capacity	10Kg
Running time	About 3 hours

Table 3 Main specifications of image processing equipment IP7500EB.

Hardware	IP7500EB, For crossing development PC
OS	IP7500EB: SH-Linux 2.4.2 Crossing development PC: RedHatLinux6.2
Compiler	SH Cross compiler gcc2.9
Software	IP7500EB Software development kit

Fig. 10 A robot (Plat-F1) with a CCD camera and a laptop computer

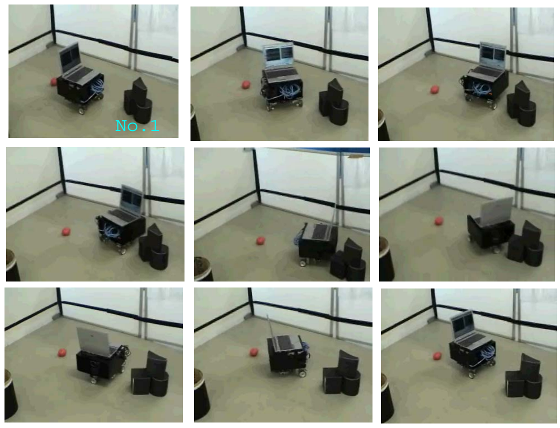

Fig. 11 Robot tried to find food avoiding obstacles and walls: found a food (images in the 1st line), became happy and turned right a round (images in the 2nd and 3rd lines).

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