An Extended Q Learning System with Emotion State to Make Up an Agent with Individuality

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Abstract: Recently, researches for the intelligent robots incorporating knowledge of neuroscience have been actively carried out. In particular, a lot of researchers making use of reinforcement learning have been seen, especially, "Reinforcement learning methods with emotions", that has already proposed so far, is very attractive method because it made us possible to achieve the complicated object, which could not be achieved by the conventional reinforcement learning method, taking into account of emotions. In this paper, we propose an extended reinforcement (Q) learning system with amygdala (emotion) models to make up individual emotions for each agent. In addition, through computer simulations that the proposed method is applied to the goal search problem including a variety of distinctive solutions, it finds that each agent is able to have each individual solution.

1 INTRODUCTION

Reinforcement learning (RL) for the behavior selection of agents/robots has been proposed since 1950's. As a machine learning method, it uses trial-and-error search, and rewards are given by the environment as the results of exploration /exploitation behaviors of the agent to improve its policy of the action selection (Sutton et al., 1998). The architecture of RL system is shown in Fig.1. However, when human makes a decision, he finally does it using the various functions in the brain, e.g., emotion. Even the environmental state is the same; many different selections of the behavior may be done depending on his emotional state then.

A computational emotion model has been proposed by J. Moren and C. Balkenius (Moren et al., 2001). Their emotion model consists of four parts of the brain: "thalamus, sensory cortex, orbitofrontal cortex and amygdala" as shown in Fig.2. Fig.2 represents the flow from receptors of sensory stimuli to assessing the value of it. So far, the emotion model has been applied to various fields, especially, the control field of something. For example, H. Rouhani, et al. applied it to speed and position control of the switched reluctance motor (Rouhani, et al., 2007) and micro heat exchanger control (Rouhani, et al., 2007). N. Goerke applied it to the robot control (Nils, 2006), E. Daglari, et al. applied it to behavioral task processing for cognitive robot (Daglari, et al., 2009). On the other hand, Obayashi et al. combined emotion model with reinforcement Q learning to realize the agent with individuality (Obayashi, et al., 2012). F. Yang et al. also proposed the agent's behaviour decision-making system based on artificial emotion using cerebellar model arithmetic computer (CMAC) network (Fuping, et al., 2014). H. Xue et al. proposed emotion expression method of robot with personality to enable robots have different personalities (Xue, et al., 2013). Kuremoto et al. applied it to a dynamic associative memory system (Kuremoto, et al., 2009). All of these applications have good results.

In this paper, we propose an interesting reinforcement learning system equipping with emotional models to make up "individuality" for the agent.

The rest of this paper is organized as follows. In Section 2, a computational emotion model we used is provided. Our proposed hierarchical Q learning system with emotions is given in Section 3.

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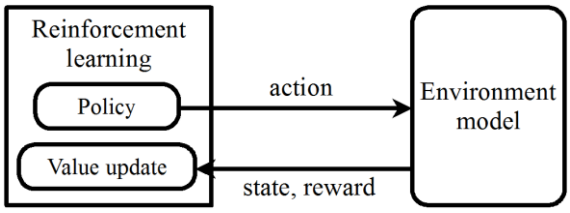


Figure 1: A reinforcement learning system (Sutton, et al., 1998).

A computer simulation using a grid world environment is carried out to evaluate the proposed system in Section 4. This paper is concluded in Section 5.

2 COMPUTATIONAL EMOTION MODEL

The computational emotional model is proposed by J. Moren and C. Balkenius (Moren, et al., 2001) consists of 4 parts of the brain, "thalamus, sensory cortex, orbitofrontal cortex and amygdala" as shown in Fig.2, it represents the flow from receptors of sensory stimuli to assessing the value of it. The dynamics of the computational emotional model are described as follows;

$$A_i = V_i S_i \tag{1}$$

$$O_i = W_i S_i \tag{2}$$

$$E = \sum_i A_i - \sum_i O_i \tag{3}$$

$$\Delta V_i = \alpha_{\text{amy}} (S_i \max(0, \text{Re}w - \sum_j A_j)) \tag{4}$$

$$\Delta W_i = \beta_{\text{amy}} S_i (E - \text{Re}w), \tag{5}$$

here, S_i denotes input stimuli from the sensory cortex and thalamus to the ith neuron in the amygdala, i = 1, 2, ….. , N_{amy}, where N_{amy} corresponds to the number of neurons in the amygdala and A_i denotes the output of the ith neuron in the amygdala. Likewise, O_i denotes the output of ith neuron in the orbitofrontal cortex. E is the output of the amygdala after subtracting the input from the orbitofrontal cortex. $\alpha_{\text{amy}}, \beta_{\text{amy}}$ are learning rates, V_i, W_i are synaptic weights of connections between the sensory cortex and amygdala, as well as the sensory cortex and orbitofrontal cortex, respectively. Primary reward Rew is the reinforcing signal.

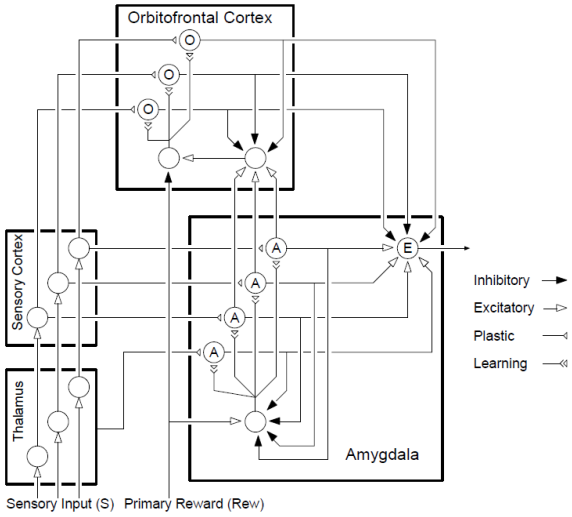


Figure 2: A computational emotional model proposed by J. Moren, et al. (Moren, et al., 2001).

3 HIERARCHICAL Q LEARNING SYSTEM WITH EMOTIONS

When a person saw an exciting landscape, he feels it pleasant or unpleasant. In this paper, we introduce the degree of - (pleasant-displeasant) impression of the image using the colour characteristics of the image as one of the emotional state to be defined in the internal robot. Figure 3 shows the proposed extended reinforcement learning system with emotional models and integrated emotional state model. It has a hierarchical structure, the first layer is an image processing model, the second layer is a fuzzy inference model, the third layer is emotional models by Moren, the fourth layer is the integrated emotional state model by Russel and the fifth layer is the proposed extended reinforcement Q learning system (Obayashi, et al., 2012). In the next subsections short contents of them are described.

3.1 Image Processing Model: First Layer

In the first layer, RGB values of each pixel of the image acquired from the environment is converted to the HSV (Hue, Saturation and Value) values, using the following (6). These are transmitted to Fuzzy inference model of the second layer,

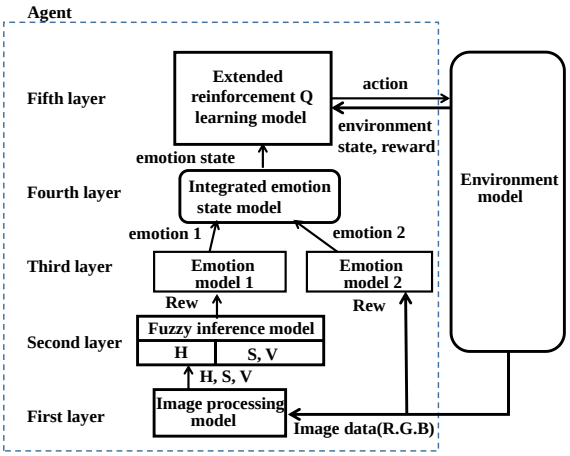


Figure 3: The proposed hierarchical reinforcement (Q) learning system with emotional models.

$$H = \begin{cases} \text{undefined} & \text{if } MIN = MAX \\ 60*(\frac{G-R}{MAX-MIN}+1) & \text{if } MIN = B \\ 60*(\frac{G-R}{MAX-MIN}+3) & \text{if } MIN = R \\ 60*(\frac{G-R}{MAX-MIN}+5) & \text{if } MIN = G \end{cases}. \quad (6)$$

$$V = MAX.$$

$$S = MAX - MIN.$$

where Max = max{R, G, B}, MIN = min{R, G, B}.

3.2 Fuzzy Inference Model: Second Layer

In the second layer, the colour features (Saturation, Value which represent modifier: dull thin, dark-bright-dark, and Hue which represents basic colour name: red, blue and green) provided from the first layer is converted to a degree of pleasure-displeasure using Mamdani type simplified singleton fuzzy inference.

The membership functions of Saturation, Value and Hue used in this paper are shown in Fig. 6, 7 and 8, respectively. They are set corresponding to their values. The fuzzy rules of Saturation and Value, Hue are shown in Table 1 and 2. The impressions I_{sv} and I_H in these Tables are decided according to our human impression. In Table 2, the Impression (I_H) of red is set to high and that of blue is set to low. This represents to express the vitality impression with the colour.

Concretely, we inference the impression (I^*_{SV}) from the Saturation and Value, taking the minimum value between the grade of S and V for each rule, and then taking fuzzy singleton inference for defuzzification. The impression (I^*_H) from the Hue are calculated as same as I^*_{SV}. Then, it is integrated to obtain an impression value (I_{HSV}) for a pixel by (7). This operation is applied to all the pixels. Then the emotion of the entire image (Image impression: Imi) is obtained by taking the average of all of the impression values (8). Calculating Imi for each direction of the image, sum of them is input to emotion model 1 (the third layer) which is responsible for pleasure-displeasure as Rew.

$$\text{Impression } (I_{HSV}) = \text{Impression } (I^*_H) \bullet \text{Impression } (I^*_{SV}) \quad (7)$$

$$\text{Image impression (Imi)} = \frac{\sum_{\text{pixel}} \text{Imression } (I_{HSV})}{\text{pixel length}} \quad (8)$$

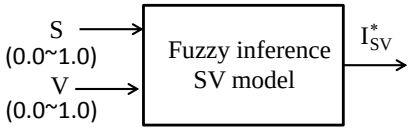


Figure 4: Impression (SV) fuzzy inference model.

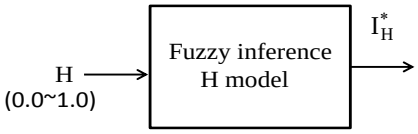


Figure 5: Impression (H) fuzzy inference model.

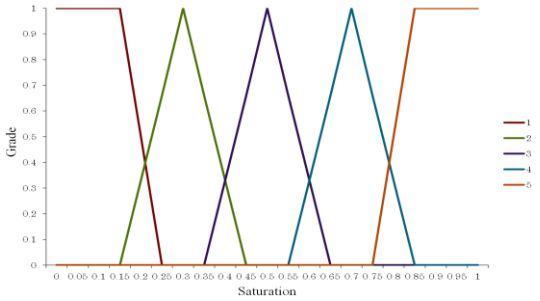


Figure 6: Membership function for Saturation (S).

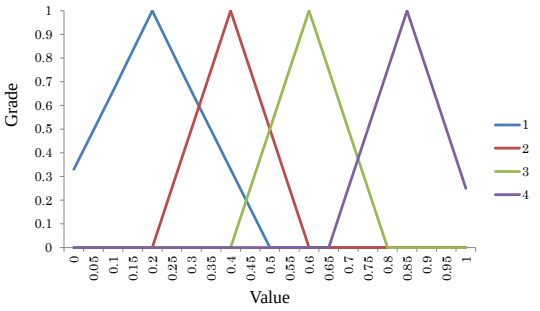


Figure 7: Membership function for Value (V).

Table 1: Fuzzy rule table for Saturation and Value.

Rule Number	If		Then	Impression (I_{SV})
	Number of membership func. of S	Number of membership func. of V		
1	3	1	Very Dark	0
2	3	2	Dark Grayish	0.3
3	4	2	Dark	0.6
4	1	3	Grayish	0.9
5	5	3	Deep	1.2
6	1	4	Very Pale	1.5
7	2	4	Pale	1.8
8	3	4	Light	2.1
9	5	4	Vivid	2.4

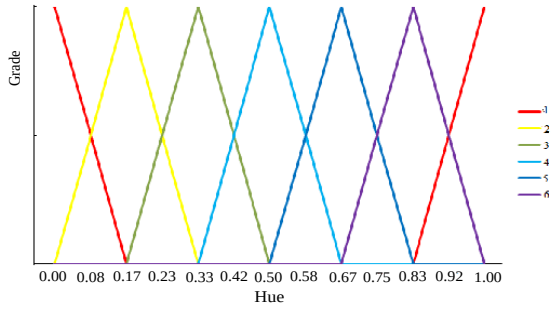


Figure 8: Membership function for Hue (H).

Table 2: Fuzzy rule table for Hue.

Rule Number	If	Then	Impression (I_H)
	Number of membership func. of H		
1	1	Red	2.0
2	2	Yellow	1.5
3	3	Green	1.0
4	4	Light Blue	-1
5	5	Blue	1.0
6	6	Purple	1.5

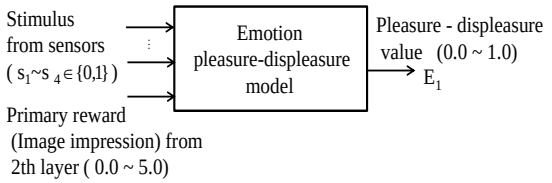


Figure 9: Emotion pleasure-displeasure model.

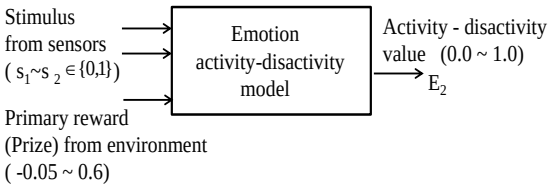


Figure 10: Emotion activity-disactivity model.

3.3 Emotion Model: Third Layer

Figure 9, 10 show the input and output for the pleasure-displeasure and activity-disactivity emotion models respectively. The structures of them are same and their learning method is explained in Section 2. The output of the emotion model for pleasure-displeasure is E_1, and E_2 is output of the activity-disactivity emotion model. These E_1 and E_2 are used for two axis for the integrated emotion state model in the fourth layer.

3.3.1 Emotion Model 1

The function of the emotion model 1 whose structure is same as the computational emotion model in Section 2 is to produce the emotion of pleasure-displeasure by making use of characteristics of the image. Its input and output components are shown in Fig.9.

3.3.2 Emotion Model 2

The function of the emotion model 2 whose structure is same as emotion model 1 is to produce the emotion of activity-disactivity by making use of the primary reward given by the environment. Its input and output components are shown in Fig. 10.

3.4 Integrated Emotion State Model: Fourth Layer

In this paper we use the circumplex emotion model (Russel, 1980) as the integrated emotion state model. The circumplex emotional model proposed by J.A Russel consists of two axes that are pleasure-displeasure (horizontal axis) and activity-disactivity (vertical axis); it is shown in Fig. 11. The figure shows unidimensional scaling of 28 emotion words on the plane. Russel said that all the emotions of the living body can be dealt by this circumplex model. This model decides the current two dimensional emotional states of the agent using two inputs E_1 (displeasure–displeasure value) and E_2 (activity–disactivity value) from the third layer as shown in Fig. 3.

3.5 Extended Q Learning with Emotion State

The Emotion extended Q learning (Obayashi, et al., 2012) is almost all of commonly used standard Q learning. The extended Q learning with emotion

state has the emotion state of the agent in addition to environment state of standard Q learning. The value function of the state, emotion and action in the extended Q learning is represented as $Q(s, s_e, a)$. The update equation of $Q(s, s_e, a)$ is as follows;

$$Q(s, s_e, a) \leftarrow Q(s, s_e, a) + \alpha\left[r + \gamma \max_{a'} Q(s', s_e', a') - Q(s, s_e, a)\right], \quad (9)$$

where s : current environment state, s_e : current emotion state with two dimensions from the fourth layer. a : current action, r : reward, s' : next current environment state, s_e' : next current emotion state, α : learning rate, γ : discount rate. We use the greedy method as selection policy of behaviors of the agent.

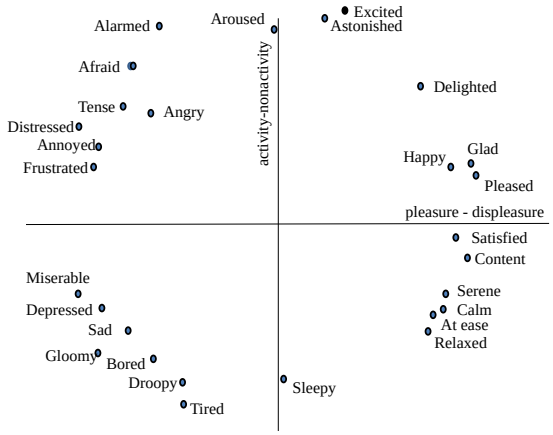


Figure 11: The circumplex emotional model by J.A. Russel (Russel, 1980).

4 COMPUTER SIMULATION

4.1 Preparation

4.1.1 Problem Description

To evaluate our proposed method, we carried out a computer simulation using a grid world environment as shown in Fig. 12. The wall surrounds around it. There are meaningful plural paths from start to goal. We found that each agent learned the different path from start to goal, forming the different emotions by use of the different parameter for learning of the emotion model.

4.1.2 Assumptions

In these simulations, next followings are assumed,

1) The agent knows his own position.
2) The action which the agent can take is "to move one cell to one direction among up, down, left and right".
3) If the agent collides with the wall, the agent stays at the position before collision.

4.1.3 Environment Used in the Simulation

In the simulation with environment shown in Fig.12, there are the cell which is locked and the switch cell to release the lock. It is necessary for the agent to visit the switch cell once to release the lock to get the goal. The agent has to take a circuitous route to get the red and blue foods and also has to take a hazard route to take the shortest path to the goal. So the agent has the dilemma, which route should be selected. It is verified the dilemma is solved by the individuality of the agent.

4.1.4 Emotion Formation in the Simulation

In this simulation, the number n of the sensory inputs s_n is 4 in the computational emotion model shown in Fig. 2, toward the information about up, down, right and left. If there is a food within 5 cells from the agent, s_i is set to 1, otherwise 0 (see Fig. 14). According to the distance between the food and the agent, Rew is set as following equations;

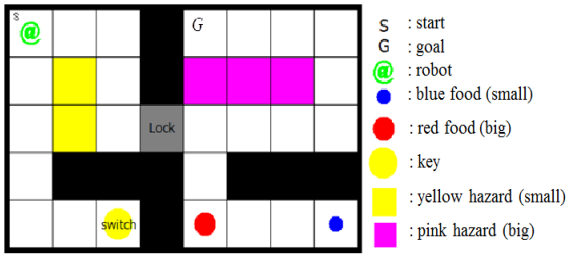
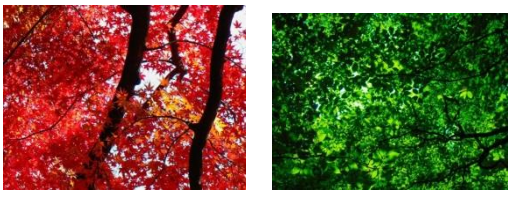


Figure 12: The environment used in the simulation.



(a) Image given as the red big food (b) Image given as the blue small food

Figure 13: The image used as input to Image processing model in the simulation.

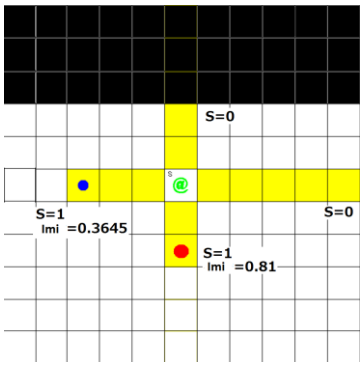


Figure 14: Example of the sensory input s and primary reward input (Rew) of the emotion model for making the pleasure-displeasure value (E_1).

$$\text{Prize} = 0.9^{\text{distance}}\ \text{Image impression (Imi)} \tag{10}$$

$$\text{Rew} = \sum_{i\text{mage}} \text{Prize}, \tag{11}$$

The images used as input to Image processing model in the simulation are shown in Fig. 13. A calculation example of values is shown in Fig. 14. The emotion model of activity-disactivity is as to "activity of the agent itself". The number of sensory inputs S is 2, as to the information, one is always S = 1, the other is S = 1 if the agent is in hazardous yellow area, or pink area, S =0 for otherwise. The value of Rew changes step by step according to the rules of Table 3. Parameters used in the learning of the emotion

Table 3: Primary rewards (Rew) for the emotion model 2 with activity-disactivity.

Initial value	0.4		
when after 1 step	- 0.005	blue food acquisition	+0.2
hazardous area : yellow	-0.02	red food acquisition	+0.6
hazardous area : purple	-0.05	when release the yellow switch	+0.4

Table 4: Parameters used in the learning of the two emotion models.

	pleasure - displeasure		activity - disactivity	
	learning rate α_{amy}	learning rate β_{amy}	learning rate α_{amy}	learning rate β_{amy}
Q+AE	0.4	0.3	0.2	0.5
Q+AE +S	0.4 ($E_1 < 0.3$)	0.3 ($E_1 < 0.3$)	0.2 ($E_2 < 0.5$)	0.5 ($E_2 < 0.5$)
	0.01 ($E_1 \geq 0.3$)	0.8 ($E_1 \geq 0.3$)	0.01 ($E_2 \geq 0.5$)	0.8 ($E_2 \geq 0.5$)

models are shown in Table 4. In Table 4, the method "Q + AE" is our proposed extended Q learning with emotion state, however, the parameters used in the learning of the emotion model are fixed while in the simulations. The method "Q+AE+S" is also our proposed method. The bigger the learning coefficient parameter α_{amy} is, the bigger the output of the emotion model is. In reverse, the bigger the learning coefficient parameter β_{amy} is, the smaller the output of the emotion model is. In the emotional model 1, the learning parameters α_{amy} and β_{amy} are changed in order to reduce the level of the pleasure when the level is over 0.3. The emotion model 2 about the activity is almost same as the emotion model 1.

4.1.5 Integrated Emotion State Model

The object of the integrated emotion state model in the fourth layer is to decide the two dimensional emotion states $S_e(i), (i = 1,\cdots,4))$, using the output E_1 and E_2 of the emotion models 1 and 2, respectively in the third layer and to transmit the state to the extended Q learning system in the fifth layer.

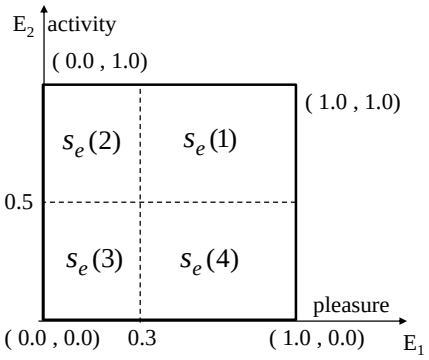


Figure 15: The circumplex emotion model used in the simulation.

4.1.6 Parameters and Rewards Used in the Extended Q Learning

Rewards given by the environment are shown at Table 5. The parameters used in the extended Q learning are given at Table 6.

Table 5: Reward r given by the environment for the extended Q learning in simulation 1 or 2.

arrival to the goal	10.0	red food acquisition (Given as image of Fig. 14(a))	4.0
collision to the wall	-2.0	blue small food acquisition (Given as image of Fig. 14(b))	1.5
hazardous area : yellow	-0.5	when release the blue switch	5.0
hazardous area : pink	-2.0	others (when move 1 step)	-0.1

Table 6: Parameters used in the extended Q learning.

learning rate α	0.5	discount rate γ	0.95
policy	greedy method		

4.2 Simulation and Its Result

To confirm the performance of the proposed method, we compared with three methods: 1) the conventional Q learning method named "Q", the other two methods are our proposed methods, that is, 2) the method using extended Q learning with the learning parameter fixed emotional model named "Q+AE", 3) the method using extended Q learning with the learning parameter changed emotional model named "Q+AE+S".

The results of these three methods are shown at Table 7 and in Figs. 16~20. Table 7 shows average convergence steps to the goal of 100 times in each method. Fig.16 shows the number of steps to the goal for each method and episode. From these results, the conventional Q learning method could not get the goal at all. Our two proposed methods succeeded to get the goal. However, from Fig. 16 our two methods with success have a peak, after that the number of steps to the goal are decreasing according to progress of episodes. This means that the agent takes a lot of steps until the agent find that he has to proceed to the goal after pressing the switch. The reason why this could be achieved is that the emotion comes to be different from before and after the agent push the switch due to the emotional learning as shown in Figs. 17~20. The difference between the Q+AE method and the Q+AE+S method is their convergence steps, that is, in the Q+AE method the agent got the two foods although in the Q+AE+S method the agent got only the red food to be discovered firstly.

Fig. 17 and 18 show the simulation results of the Q+AE method. Fig.17 shows the convergence path along green cells in the four emotion states for the method. Fig 18 shows changes of the emotion state of the robot corresponding to the behaviour of the robot for the method. From Fig. 18, we can find that the agent starts with the emotion $S_e(3)$, passing through $S_e(4)$, $S_e(2)$ and $S_e(1)$, finally it got the goal with $S_e(2)$.

Table 7: Average convergence steps to the goal of 100 times in each method.

	Q	Q+AE	Q+AE+S
convergence step to the goal	---	32	28

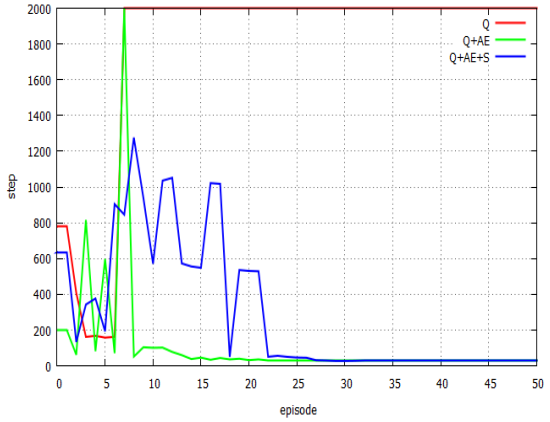


Figure 16: The number of steps to the goal for each method (average of 100 times).

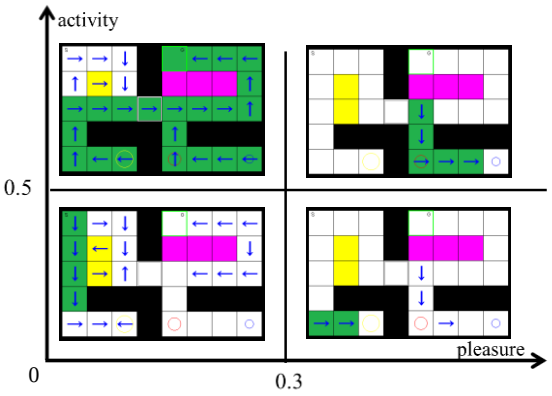


Figure 17: The convergence path (arrow direction with green) in the each emotion state for the proposed method named "Q+AE".

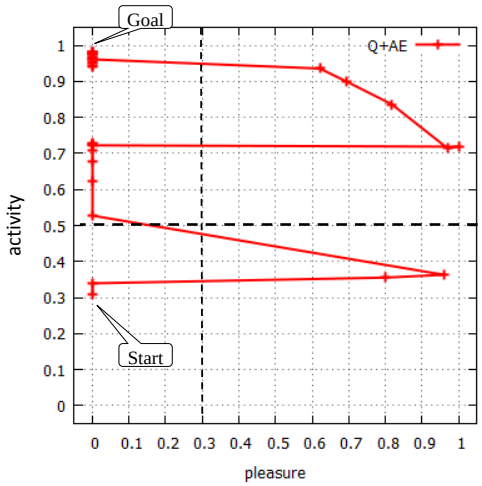


Figure 18: The change of emotions from start to the goal for the proposed method named "Q +A E".

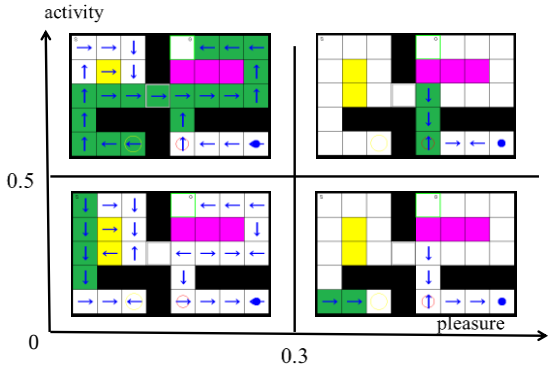


Figure 19: The convergence path (arrow direction with green) in the each emotion state for the proposed method named "Q+AE+S".

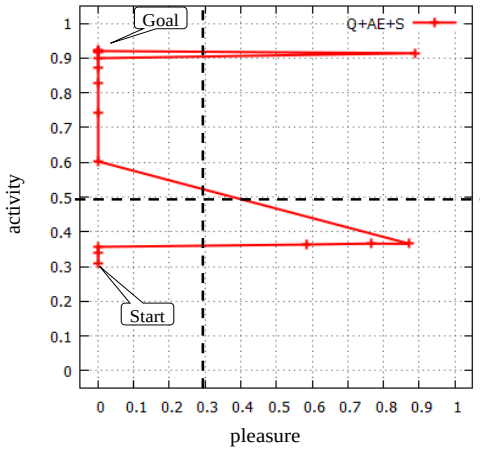


Figure 20: The change of emotions from start to the goal for the proposed method "Q +AE+S".

Fig. 19 and 20 show the simulation results of the Q+AE+S method. How to see both Figures is as same as Fig.17 and 18. Comparing Figs. 17 and18 with Figs. 19 and 20, it is found that although the result of the Q+AE+S method is the same as in the Q+AE method until the agent gets the red food to be firstly discovered on the path, the robot in Q+AE method, besides, gets the blue food, although it in Q+AE+S method moves to the goal, by changing the learning coefficients $\alpha_{\text{amy}}, \beta_{\text{amy}}$ of the emotion model to reduce the reaction for the emotion. This is the reason why the agent didn't visit the cell the blue food is placed in the Q+AE+S method.

5 CONCLUSIONS

In this study, we proposed an extended reinforcement Q hierarchical learning system with emotion state to make up an agent with individuality. We generated the emotions in the robot using the emotion models. In the computer simulation for a path-finding problem with plural meaning paths, that is, having a dilemma, it was verified that the agent could get a variety of behavior patterns by setting the different learning parameters in emotional model learning. This means that by giving the different learning parameters mentioned above to each agent, it is able to make each agent give different individuality, i.e., each agent get the goal achieving any different and meaningful things.

In this study, we considered the single agent case. In the future, we would like to try to the multi agent case, i.e., to problems to be solved by multi-agents.

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