

Generating Personality Character in a Face Robot through Interaction with Human

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Abstract

For the human-robot communicative interaction, it is difficult to design robots behavior which is preferable to human. In this paper, therefore, we propose an approach to personality characterization of the face robot generated by reinforcement learning with human instruction, and investigate its characteristics from some real human-robot interaction. We found that the face robot personality character is generated through communicative interaction learning done by human partner's instruction and pointed out the importance of the learning algorithm and human instruction procedure.

1. Introduction

For the face robot that looks like a human face and is equipped with a CCD camera sensory vision system and with motor-output system of artificial facial expression muscles[1], it seems to be difficult to learn by herself what kind of actions such as facial expression, nodding or voice should be taken in complicated human-robot communicative interaction. We thus think that the supervised instruction by a human partner of the face robot may be useful for the robot to acquire this kind of intelligence, since improvement in human behavior is usually done by such supervision. Based on this psychological background speculation, we developed an approach to the generation of personality character in the face robot through applying a reinforcement learning algorithm under the communicative interaction between the face robot and a human

partner.

Some researches about use of human instruction for reinforcement learning have been done, but these instructions are used as one example of the answer[2][3]. It is thus difficult for a robot to learn its behavior in the case when answer cannot be shown by human. For the emotional behavior in a robot such as facial expressions or the sophisticated behavior which need a great number of degree-of-freedom of actions, the answers are difficult to be determined accurately as well as to be shown to the robot. This paper presents, therefore, an approach to generation of face robot personality character with instruction/evaluation of robot behavior that reflect to the reward in the learning algorithm.

We prepared three experiments to investigate the face robot personality character which is appeared in the responsive behavior to the given behavior of the human partner. In the first and second experiments the test subjects observed the process of the face robot interaction with a human partner and classified the face robot personality character. Then we investigated the personality character generated in the face robot by a variety of the test subjects.

2. Face robot and its learning algorithm

The face robot used in the experiments has the following functions:

(1) The face robot is equipped with 18 small pneumatic actuators at proper locations inside the face struc-

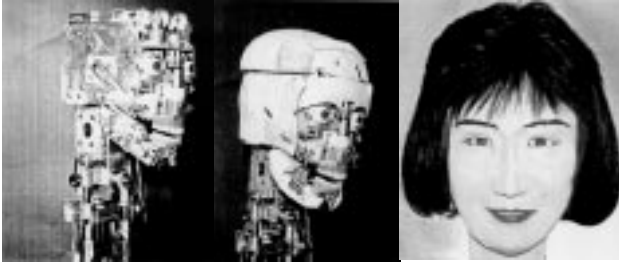


Fig.1 Appearance of face robot

ture to generate 6 typical facial expressions such as anger, surprise, fear, disgust, sad, and happy; and has 2 degrees of freedom in the eyeball rotation and 3 degrees of freedom in the head rotation.

(2) The face robot is implemented with a real-time vision system to identify the location of the face robot's partner and his/her facial expressions.

(3) The face robot is equipped with a conventional voice synthesizing system.

The size of the face robot was almost 120 % of a normal human head and her appearance is a young woman face as shown in Fig. 1.

For the learning algorithm, we employed a reinforcement learning to generate proper response to her partner's behavior such as approaching her or leaving her, in which the reward essentially needed in a reinforcement learning is given by the face robot partner to each of the face robot response to her partner's behavior, i.e., changes in the partner's position. This means that, when the response made by the face robot is preferable to the partner, the partner gives a positive reward to the learning algorithm and when not preferable, a negative one is given. The internal representation from state to action of the robot is described as $Q(s,a)$, where s means a certain state and a means a certain action. In a certain state s , the robot inclines to take the action whose $Q(s,a)$ is the maximum one. When a reward is given by the partner, $Q(s,a)$ is recalculated as follows:

$$Q(s,a) := (1 - \alpha)Q(s,a) + \alpha r \quad (1)$$

where α is a learning rate, r is a reward value that is +1 when positive reward is given, and -1 when negative one is given. As a whole, after certain runs of the interactive learning test with a human partner, the learn-

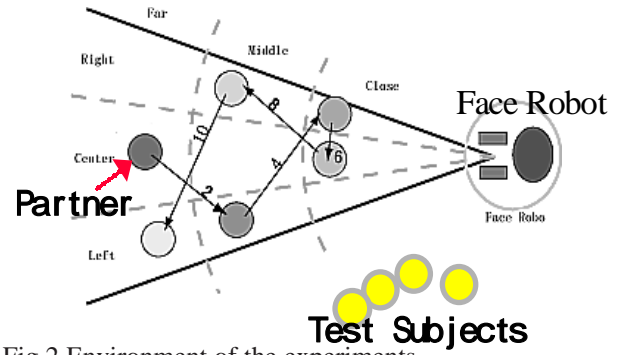


Fig.2 Environment of the experiments

ing may be converged to a certain sensory-input to action-output coordination, i.e. a personality character in the face robot.

3. Experiment 1

To analyze the personality character in terms of certain behavior patterns of the face robot, we initially employed the following experiment. We prepared 9 small sections in the fan-like region in front of the face robot and a human partner changes his position from one section to another after the face robot took a responsive action of turning her head and made a voice of hello according to the recognition of the partner's position, as shown in Fig.2. We set three cases of responsive behavior patterns for the face robot, one (pattern A) is a follower type personality, i.e., the face robot tries to look toward the partner and make a hello voice to him at each change in the partner's position. The second one (pattern B) is a selfish personality with ignoring the partner's movement and making a hello. Then we implemented the reinforcement learning algorithm in the face robot computer and, by means of the partner's instruction, a follower personality was generated. The initial state of the face robot personality was set to the selfish one. This is pattern C.

With the observation of the responsive behavior of the face robot, the test subjects (10 college students) were asked to answer the 12 categories of personality classification which is usually employed in Y-G personality analysis[3]. The results are shown in Fig. 3, which shows the distribution of scores obtained with

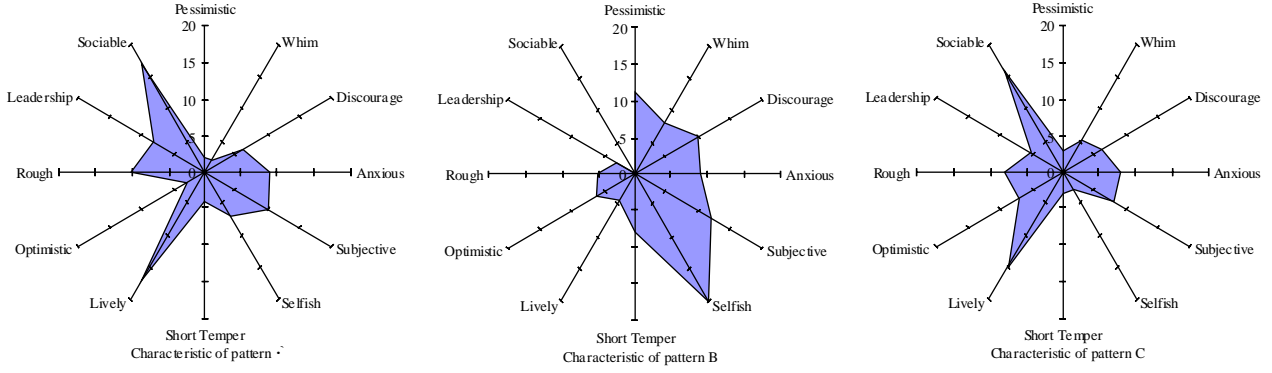


Fig.3 Evaluated personality character for pattern A, B, and C

respect to the 12 axes of Y-G personality analysis. Patterns A and B show the same personality characters as those designed respectively. Pattern C shows the similar distribution to that in pattern A, which indicates that the learning was successful to generate a personality character in the face robot through communicative interaction with a human. We investigated the major factors influential to the evaluation of the personality character with face robot responsive behavior by means of analyzing the answer data of 10 subjects. Table 1 shows what kind of feature of the face robot contributed to the evaluation of the face robot responsive behavior from the view point of personality character. The most influential factor was the manner of interaction of the face robot with the human partner, and then the dynamic hardware feature of the face robot such as speed of head rotation was another major factor.

4. Experiment 2

According to Experiment 1, the personality character can be analyzed in terms of the interaction feature and dynamic hardware feature. In the second experiment, therefore, we pay attention to three aspects of face robot response based on dynamic hardware and interaction features in Experiment 1 as an indicator of personality character. The first one, i.e., voice, is used to measure how happily the subjects feel with the voice of the face robot during the communicative interac-

Table 1 Number of answered feature

Feature	Pattern			Total
	A	B	C	
Static	3	0	0	3
Dynamic	7	0	5	12
Interaction	8	15	9	32
Learning	0	0	4	4

tion. The second point, speed, is to measure how fast the subjects feel with the head rotation. The third one, face direction, is for evaluating whether the subjects can recognize the face robot's tendency to take the action of looking toward the partner. The more happily the voice sounds, the faster the rotation is felt, or the more strongly the face robot tends to look toward the partner, the higher scores to the attention points are given. To investigate the transition of personality character of the face robot, 5 test subjects were asked to observe the same communicative interaction between the face robot and a human partner as that in Experiment 1, and answer the score to each of these attention point at 5-step rating. 30 steps of the responsive actions of the face robot were employed for each of 3 patterns A, B and C.

In Fig.4, which shows the average scores of attention point for each pattern, the results of patterns A and B can be clearly distinguishable, i.e., in pattern A the score is positive and high for these 3 aspects. On the other hand, in pattern B it is negative and lower. This result indicates that these attention points are influential to evaluation of the personality character of the face robot. In addition, with the increase in the learn-

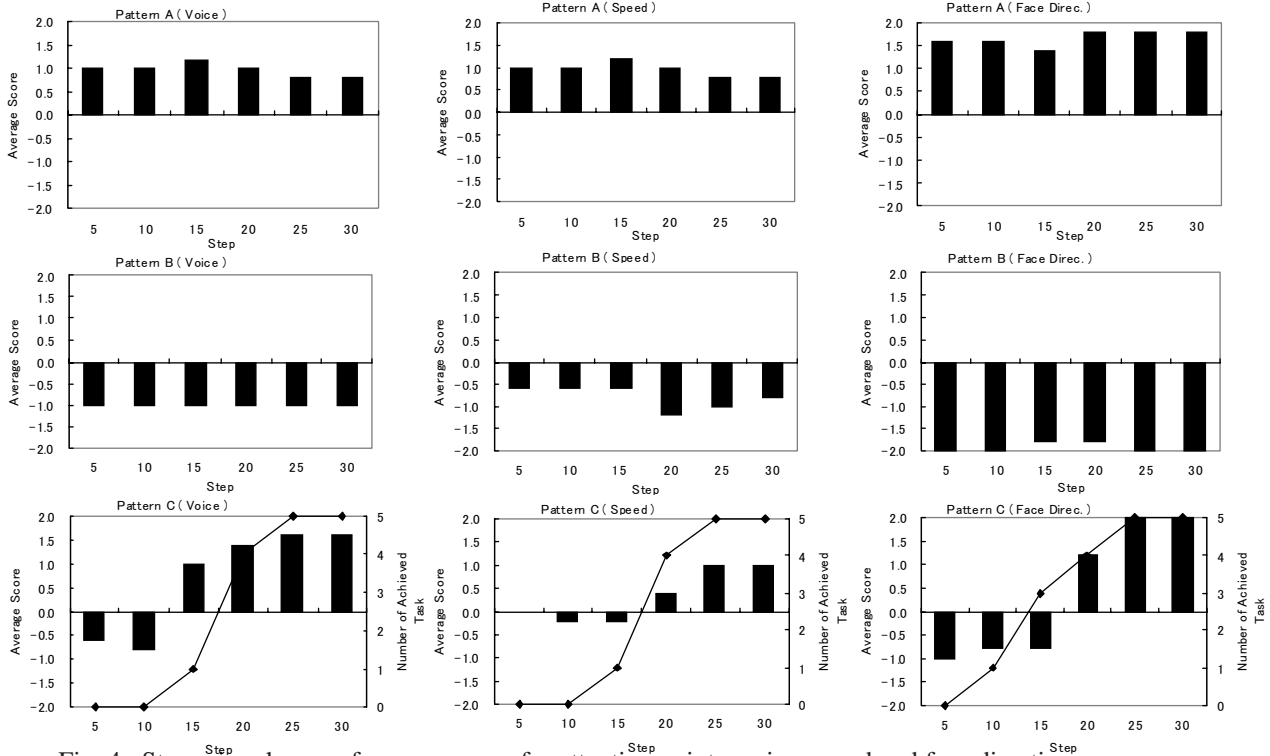


Fig. 4 Step-wise change of average score for attention points; voice, speed and face direction

ing steps that is shown for pattern C in Fig. 3, the personality character of the face robot changed from its evaluation similar to that in pattern B to the one in pattern A and finally was evaluated as pattern A. This also supports the result obtained in Experiment 1, i.e., the personality character tends to be evaluated by the convergent responsive behavior.

5. Experiment 3

To clarify the variety of the personality character generated in the face robot through the instruction given by different partners, in this experiment the subjects are asked not only to evaluate the score to each of the attention point defined in Experiment 2, but also to play the role of the robot partner, i.e., they change their position and give a positive or negative reward in response to the action taken by the face robot. In this experiment the subjects are not explained when they give a positive/negative reward or which reward they give, but explained only about the task; “Try to make

the face robot look toward you and say hello to you by judging the responsive action of the face robot in terms of a positive or negative reward at each interaction step.” This task includes 2 sub-tasks in the face robot: (1) to turn her face to the direction toward the point where the partner is, and (2) to produce the proper voice. The learning algorithm implemented in the face robot did not converge to the follower type personality when the positive reward was not given in the case the face robot achieved both sub-tasks.

Table 2 shows the distribution of the number of positive or negative rewarding for each subject, which was given when each of sub-task was achieved or failed. In the table there are 2 distinctive types of reward number distribution patterns; one is correspondent to the positive rewarding in the case either sub-task was achieved, for example, subjects A and B, the other is to the positive rewarding in the case both of sub-tasks were achieved. Because of the reinforcement learning mechanism, these reward distributions affect the number of achieved tasks which is shown in Fig.4, i.e., the number of achieved tasks of subjects A and B are mark-

Table 2 Number of rewards given for the combination of sub-task accomplishment and failure
 Test Subject A Test Subject C Test Subject E

Sub-task		Reward		Sub-task		Reward		Sub-task		Reward	
Direc.	Voice	Pos.	Neg.	Direc.	Voice	Pos.	Neg.	Direc.	Voice	Pos.	Neg.
Achieved	Achieved	0	0	Achieved	Achieved	17	0	Achieved	Achieved	19	0
Achieved	Failed	14	3	Achieved	Failed	0	3	Achieved	Failed	1	3
Failed	Achieved	4	2	Failed	Achieved	0	4	Failed	Achieved	0	1
Failed	Failed	0	7	Failed	Failed	0	6	Failed	Failed	0	6

Sub-task		Reward		Sub-task		Reward	
Direc.	Voice	Pos.	Neg.	Direc.	Voice	Pos.	Neg.
Achieved	Achieved	4	0	Achieved	Achieved	18	0
Achieved	Failed	10	3	Achieved	Failed	0	3
Failed	Achieved	3	4	Failed	Achieved	0	3
Failed	Failed	0	6	Failed	Failed	0	6

edly smaller than those of subjects C, D and E. Fig. 5 also shows the scores of attention points for each subject, in which the distribution of the score obtained in subjects C, D and E is similar to that of pattern C in Experiment 2. On the other hand, the distribution of the score in subjects A and B is clearly not the same as those in subjects C, D and E, which means that the personality character generated in the face robot by the instruction given by subjects A and B are evaluated as different ones from those by subjects C, D and E. It is thus found that the responsive behavior of the face robot was changed by the different reward distribution patterns made by different subjects. As a result, the personality characters of the face robot generated by different partner were evaluated as different each other.

6. Conclusion

The personality character of the face robot, which may change the responsive behavior, can be generated by means of the supervised learning algorithm under the communicative interaction with her partner and be evaluated as a similar personality to the designed behavior. The personality character evaluation was mainly done by the interaction factor such as responsive behavior of the face robot. When the face robot was trained by different partners, the responsive behavior of the face robot can be changed and its personality

character can be evaluated as different. This fact suggests that the personality character of the face robot may become the one fitted to the preference of the partner when it is trained by him properly. Further discussion about the generality of human instruction and learning algorithm will be needed.

Reference

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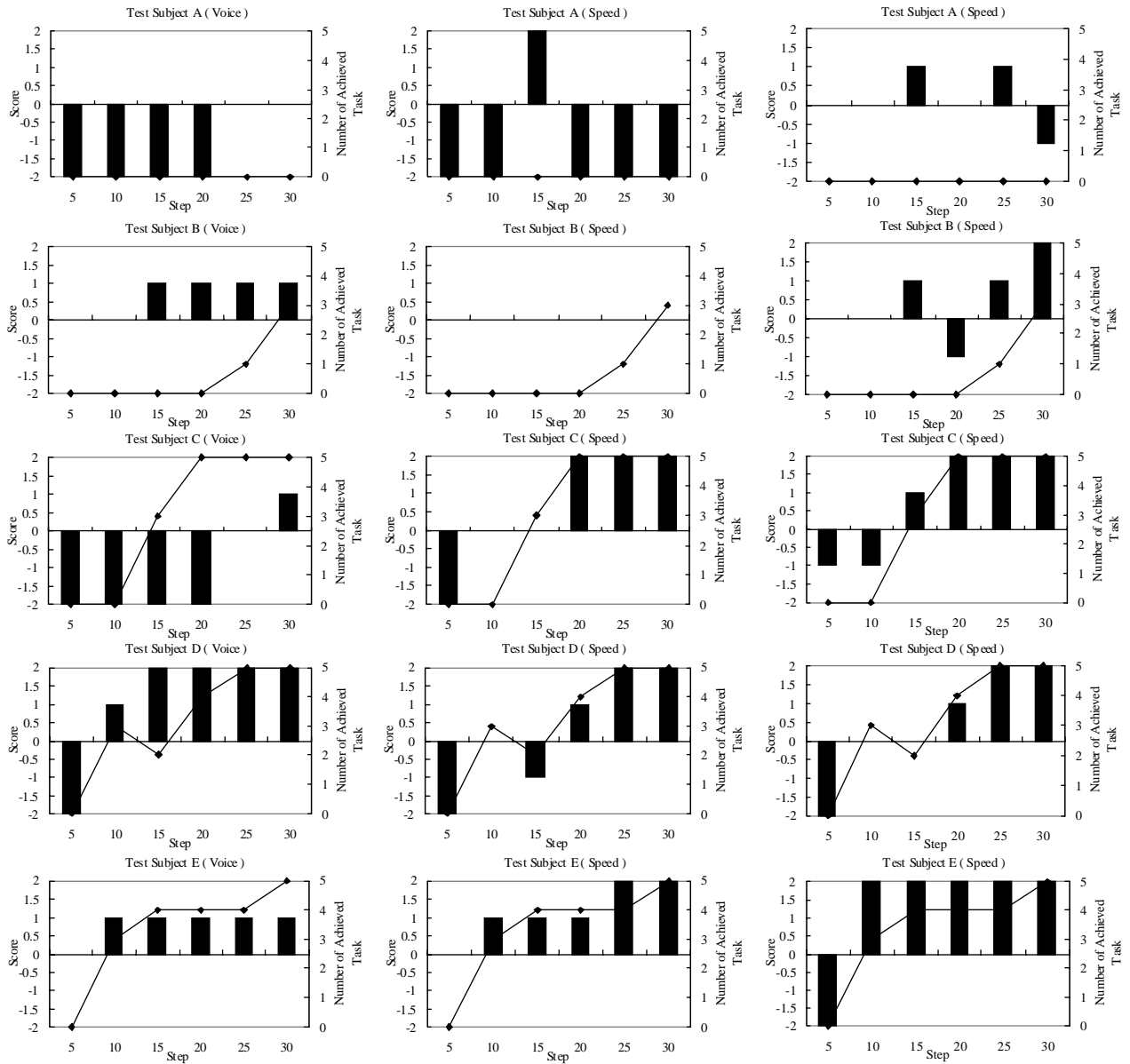


Fig. 5 Score change with steps for each attention point in Experiment 3