A Robot Model That Obeys a Norm of a Human Group by Participating in the Group and Interacting with Its Members*

Yotaro FUSE†, Student Member, Hiroshi TAKENOUCHI††, and Masataka TOKUMARU††††, Members

SUMMARY Herein, we proposed a robot model that will obey a norm of a certain group by interacting with the group members. Using this model, a robot system learns the norm of the group as a group member itself. The people with individual differences form a group and a characteristic norm that reflects the group members’ personalities. When robots join a group that includes humans, the robots need to obey a characteristic norm: a group norm. We investigated whether the robot system generates a decision-making criterion to obey group norms by learning from interactions through reinforcement learning. In this experiment, human group members and the robot system answer same easy quizzes that could have several vague answers. When the group members answered differently from one another at first, we investigated whether the group members answered the quizzes while considering the group norm. To avoid bias toward the system’s answers, one of the participants in a group only obeys the system, whereas the other participants are unaware of the system. Our experiments revealed that the group comprising the participants and the robot system forms group norms. The proposed model enables a social robot to make decisions socially in order to adjust their behaviors to common sense not only in a large human society but also in partial human groups, e.g., local communities. Therefore, we presumed that these robots can join human groups by interacting with its members. To adapt to these groups, these robots adjust their own behaviors. However, further studies are required to reveal whether the robots’ answers affect people and whether the participants can form a group norm based on a robot’s answer even in a situation wherein the participants recognize that they are interacting in a group that include a real robot. Moreover, some participants in a group do not know that the other participant only obeys the system’s decisions and pretends to answer questions to prevent biased answers.

key words: social robot, group norm, reinforcement learning, human-robot interaction

1. Introduction

Recently, efforts to develop communication robots that can please people through emotional expressions and communicate with people naturally by behaving like living creatures have increased. However, to date, these robots did not have the ability to join a multiparty group or conversation. Moreover, to communicate more humanly in multiparty situations, such robots will need to learn sociality [1]. The aim of designing social robots is to enable them to interact with people or other robots in a human-like manner [2]–[4].

Robot models that consider sociality have been proposed previously [5]–[9]. These models enable robots to behave cooperatively. Carlucci et al. proposed a robotic system design that considers social behavior by implementing social norms. Within their model, the robots were able to behave cooperatively with humans. However, sociality is an endeavor to form a group and live with the group members. In every human society, people cooperate with many unrelated individuals [10].

To exhibit sociality in a human society, robots need to adapt to group norms that are formed by the members of the group. People conform to expectations and common group behaviors in human groups. Therefore, robots must also learn to behave as a member of a group by observing other members. These behaviors are known as group norms [11]. However, all humans have unique personalities. This reflects the dynamic integration of a person’s subjective experiences and behavioral patterns [12]. Because of the unique personalities, people have different criteria for making decisions and can respond differently from one another when facing the same situation [13]. Although people have different personalities and decision-making criteria, the criteria converge into one common criterion when a group is formed.

We therefore proposed a model for a robot that creates decision-making criteria by interacting with people in its group. A robot system using this model learns the criteria suitable for the group. We investigated whether the system can adjust its own behavior according to a suitable criterion in a group including humans, i.e., we investigated whether the people and system’s answers converge on their own to a suitable criterion when they answer easy quizzes that can have vague answers. We proposed two conditions for the experiments. First, one of the participants in a group only obeys the system, while the other participants are unaware of the system to avoid bias toward the system’s answers. Based on this condition, we investigated whether the answers of the system exhibit appropriate behaviors based on a normative criterion in a group, which is similar to how humans answer. Second, the participants should not be familiar with the social science concept of group norms, because it is assumed that this knowledge would influence the participants’ quiz answers. Convergences to suitable criteria in groups of people and the system had been observed [14].

---

*This research was supported in part by Ministry of Education, Culture, Sports, Science and Technology’s Program for the Strategic Research Foundation at Private Universities 2013–2017.

Manuscript revised August 10, 2018.
Manuscript publicized October 3, 2018.

†The author is with Graduate School of Kansai University, Suita-shi, 564–8680 Japan.
††The author is with Fukuoka Institute of Technology, Fukuoka-shi, 811–0295 Japan.
††††The author is with Kansai University, Suita-shi, 564–8680 Japan.

Manuscript received February 28, 2018.

Manuscript revised August 10, 2018.
Manuscript publicized October 3, 2018.

E-mail: toku@kansai-u.ac.jp
DOI: 10.1587/transinf.2018EDP7077
so that we investigated whether the result has statistical significance or not. Additionally, we refer to related work regarding our study.

2. Related Work

The proposed model utilizes knowledge about human characteristics and machine learning so that a robot system can be enabled to find a suitable criterion in a group that includes human members. In this section, related research from the fields of individual differences, group norms, and machine learning has been described.

Humans have individual differences in their criteria for making decisions [15], [16]. They can respond differently from one another when they are faced with the same stimuli. However, people in a group are affected by social influence. Social influence is defined as a change in an individual’s thoughts, feelings, attitude, or behavior, which results from an interaction with another individual or a group [17]. Additionally, social influence comprises normative social influence and informational social influence. These influences affect an individual’s judgment [16]. When people do not know how to behave in an unfamiliar situation, they imitate other people’s behaviors. Sherif et al. revealed that forming a group norm in a human group occurs within few interactions in situations wherein the participants in the group attempt to answer vague questions that are a part of a quiz [13]. It is assumed that the influence of each participant in the group enables the participants to imitate each other’s answers, thereby forming a group norm about the quiz.

Herein, using the proposed model, we investigated whether human participants and a robot system in a group form a group norm and evaluated the social influence of the system’s opinion. To investigate this principle, we prepared quizzes about the descriptive terms of a quantity of dots for participants in an experimental group using a visual analog scale (VAS). VAS is a visual metric that is used to measure a characteristic or attitude that is believed to range across a continuum of values and cannot be easily measured directly [18]. For instance, a patient in a hospital subjectively assess degree of the amount of pain that she/he feels from 0 (no pain) to 100 (pain as bad as it could possibly be).

Moreover, the robot system learns through reinforcement learning, i.e., a framework for learning a suitable policy without training data [19]. Reinforcement learning is also used in robotics [20]–[22]. However, herein, the robot system has to adjust itself to a group without prior learning because the system does not have information about the group members’ personalities before the group is formed. After forming a group, humans adjust themselves to their group. Therefore, the system is unable to return an initial state in reinforcement learning. Additionally, participants in a group are unable to return a state of first meeting. Consequently, the system has to adjust to the group without prior learning by interacting with the group members. Interactive evolutionary computation (IEC) is used to solve problems without prior learning solely through the interactions with a user [23], [24]. However, IEC has a problem associated with the size of a search space because users’ fatigue arising from the interactions with the IEC system has to be considered. This experiment also has a problem associated with the size of a search space and limited interactions in few steps because human group members form their group norms in only a few interactions. Herein, the vague quiz offered a multiple answer that the system can select from when answering. However, the system cannot know how the other group members behave in the group but can learn a tendency of how people answer a certain quiz without advice before the quiz scenario. Therefore, the system decreases the search space by clustering some people’s answers against the quizzes prepared for our experiments through a k-means++, which is a way of clustering [25].

3. Group Norm Model

The proposed model enables a robot to create a suitable criterion, i.e., the group norm, for decision making by interacting with the people in a group through reinforcement learning. Figure 1 shows an overview of the group norm model. In this study, we aimed to investigate a robot system’s decision-making ability on the basis of group norms and determined whether this decisions-making approach resembles that of a human. For a robot to adjust its behaviors according to a group that includes human members, it needs to infer a specific way to behave in the group with regard to the other group members’ behaviors while a group norm is being formed. Therefore, before a robot behaves in a group on the basis of the robot system, we investigated whether the robot system, considering a group norm can make decisions.

3.1 Decision-Making Model

We proposed a model, as shown in Fig. 1, that a robot uses to generate a group norm. The robot’s behaviors within the group are determined by this model. The robot recognizes the behaviors of the other group members and compares its own behavior with these behaviors. Thus, it behaves cooperatively and creates a suitable group criterion by learning from other members’ behaviors.

![Fig. 1 Group norm model](image-url)
The model uses three stages to learn a suitable behavior: decision making, behavior recognition, and feedback acceptance. The inputs pass through these stages. Inputs to the model comprise the group members’ behaviors, and the output is the model’s behavior. Moreover, the decision-making module learns the group norm via reinforcement learning.

The decision-making component determines the robot’s behavior. The robot then inputs its own behavior into its behavior recognition component. Here, the robot learns a suitable behavior using the hypothesis that people also converge to a suitable behavior in a group.

The behavior recognition component receives both the system’s behavior and those of the other members. These behaviors are first input to the system’s behavior recognition component and are fed to the feedback acceptance component.

Based on a combination of the group members’ answers, the feedback acceptance component gives a feedback to the decision-making component. The feedback acceptance component judges whether the system’s behavior suits the group to which it belongs, resulting in the system receiving a positive or negative feedback. When the system’s behavior corresponds to that of one of the members, the system receives a positive feedback. However, when the system’s behavior does not correspond to those of the other members, it receives a negative feedback. The feedback is then input to the decision-making component, which uses the feedback to learn how to select suitable behaviors.

The system prioritizes the different behaviors that it can execute through the repetition of this process. The priority is based on whether the participants’ behaviors correspond to the system’s behavior. As the system’s behavior and other participants’ behaviors correspond to each other, the behaviors within the group become unified.

The decision-making component creates a suitable criterion for group participation by learning the group members’ behaviors through reinforcement learning. An agent in the decision-making component is used to make the decisions and has a role in learning suitable behaviors. The agent adjusts the value parameters of the different behaviors, which are the values of each behavior that the system can execute. After the agent selects a certain behavior based on the value parameters of different behaviors, it receives a feedback.

3.2 Reinforcement Learning Parameters

Reinforcement learning in this study involves actions, states, a value function, Q values, and rewards. The proposed model also employs a reinforcement learning environment in the decision-making component (Fig. 2). The robot system using the proposed model has a set of behaviors that the system can execute. When such a system operates in a real-world scenario, an agent in the decision-making component relies on the reinforcement learning environment and decides which behavior the system should select. In a group, each behavior is assigned a value that can be selected by the system.

There are \( N + 1 \) states and two actions, which constitute the reinforcement learning environment shown in Fig. 2. The \( n \)th state \( s_n \) represents a criterion that the robot comes up with at \( n \)th time in order to behave socially. \( N \) represents the maximum number of states. The actions are \( a_{dcs} \) and \( a_{next} \). \( a_{dcs} \) denotes that the agent decides when the robot exhibits its behavior based on a present state: a certain criterion. \( a_{next} \) shows that the agent moves from the present state to the next state.

There also are Q values, rewards, and a value function. The mechanism of the group norm model assigns a high value to the robot’s adjustment to the group that includes human members. A value function, \( V(s_n) \), shows the value of \( s_n \) as a criterion in a group. The Q value \( Q(s, a) \) denotes the value of a combination of a certain state and action. When a robot adjusts its behavior according to the group, the robot selects an appropriate way of behaving with the group by searching the space of states. The values of these ways are derived from the value function. In addition, rewards are used to renew the value function. Until the robot using the proposed model makes a decision in the group, the robot system executes \( a_{next} \) several times and \( a_{dcs} \) once while moving from the present state to the next state in the environment, as shown in Fig. 2. The \( a_{dcs} \) denotes that the agent decides that the robot carries out a behavior based on a present state: a certain criterion, that is, may be suitable for a group. The \( a_{next} \) indicates that the agent moves from a present state to a next state. When \( a_{dcs} \) is executed, the agent judges the present state is not suitable criterion.

Each time the agent in the robot system moves to the next state, it has to make a small decision, i.e., to select either \( a_{next} \) or \( a_{dcs} \) in a certain state. The value of the small decisions indicates a Q value, which is derived from the value function. In this case, the equation for renewing the value function at the \( n \)th step is given in Eq. (1), where \( r \) is a discount factor, \( \alpha \) is the learning rate, \( S \) is a set comprising states, and \( r \) is the reward at the \( n \)th step. Moreover, the equation for deriving rewards \( r \) at the \( n \)th step is given in Eq. (2), where \( s_k \) is a criterion that each group member has in the group. Additionally, the initial Q values of each action are random numbers.

\[
V^{n+1}(s_n) \leftarrow V^n(s_n) + \alpha (r + \gamma \max_{s' \in S} V(s') - V(s_n))
\]

\[
r = \begin{cases} 
+1 & \text{(if } s_n = \text{a certain } s_k) \\
-1 & \text{(the others)}
\end{cases}
\]

Moreover, the equation for deriving Q values is given in

![Fig. 2 State transition](image)
Eqs. (3) and (4). The conditions of the variables in Eqs. (3) and (4) are \( m \in \{0, 1, 2, \cdots, N - 1\} \), \( n \in \{0, 1, 2, \cdots, N\} \), and \( l \in \{0, 1, 2, \cdots, N\} \). The agent selects an action that has higher value than its present state.

\[
Q(s_m, a_{next}) = V(s_{m+1}) \tag{3}
\]

\[
Q(s_l, a_{dcs}) = \frac{1}{V(s_l) - \max_n V(s_n)} \tag{4}
\]

Equation (4) has two cases corresponding to the value of \( V(s_l) \). When \( V(s_l) = \max_n V(s_n) \), Eq. (5) indicates the following scenario: the robot feels that \( s_l \) is appropriate as a group norm.

\[
(4) = \begin{cases} 
Q(s_l, a_{dcs}) \to \infty & \text{(if } V(s_l) = \max_n V(s_n)) \\
Q(s_l, a_{dcs}) < 0 & \text{(the others)}
\end{cases} \tag{5}
\]

In other words, the agent moves in the environment by executing \( a_{next} \) or \( a_{dcs} \) on the basis of the Q value of executing an action in a certain state. However, it is difficult for robots to come up with a certain criterion at the beginning of the experiment. Therefore, based on a limited scenario of experiments, a set of states is provided to the robot in this study.

4. Experiments

We carried out three experiments with 30, 15, and 4 participants in an investigation about descriptive terms, group experiments, and another investigation for the Mann–Whitney U test, respectively. The 30 participants in the investigation do not include the 15 participants in the group experiments. Moreover, the four participants are different from the 30 and 15 participants.

We did not use a real robot in our experiments, because we aimed to investigate whether group norms occur or not even if one of the group members make decisions in accordance with making-decisions of the robot system. We developed the proposed model for robots to socially make decisions in a group. Therefore, we use the word “robot” in this study, although a real robot does not participant in these experiments.

4.1 Quiz Environment

In this study, we prepared quizzes about the descriptive terms of a quantity of dots using VAS for participants in an experimental group. Each participant answering this quiz can describe her/his degree of the amount of some descriptive terms as the number of black dots in a white box. Each participant answers the same quiz by clicking a button on a laptop. All participants recognize each participants’ answers after the participants answer once. This procedure is repeated several times. At first, each participant does not know the correct answer; thus, the participants answer the quiz on the basis of their criteria. However, each participant’ answer is affected by other participants’ answers and the participants change their criteria because they do not know the right answer and recognize each answer in the group.

Figure 3 shows an input screen on the laptop and an example of a participant’s answer. Figure 3(a) shows the input screen in its initial state. Figure 3(b) shows the input screen after a participant has answered. Figure 3(c) shows the results of the three answers after the participants have finished the quiz.
Table 1  Six descriptive scale

| Japanese  | English                                           |
|-----------|---------------------------------------------------|
| A Hodoyoku | You see a moderately large number of dots         |
| B Sokosoko | You see a somewhat large number of dots           |
| C Dochirakato-ieba | If you had to choose, you would say that you could see a large number of dots |
| D Warito  | You see a comparatively large number of dots      |
| E Kekko   | You see quite a lot of dots                        |
| F Kanari  | You see a considerably large number of dots       |

Figures 3(a) and 3(b) have two buttons beneath the white box: BUTTON and FINISH. If the participant clicks on BUTTON once, a black dot appears on the input screen. The number of BUTTON pushes represents the number of dots that equals the descriptive term. Each time the participant clicks on BUTTON once, a black dot appears at a random location in the white box. The number of dots indicates the answers of a participant in a quiz for the application. Each black dot appears in accordance with a same pattern. However, the pattern makes it difficult for participants to expect where a next black dot appears in the white box. Additionally, the quiz allows participants to click to a maximum of 100 times. Although the participants are unaware of this limit, they can determine the number of dots in their own answer.

Answers in this study are white images with black dots, like Fig. 3. In this study, good answers do not exist because the quiz does not have a clear answer. However, the meaning of the answers depends on the human’s or robot system’s perspective. When a participant pushes BUTTON X times, a white image including X black dots is created. If he/she is satisfied with the image as an answer of a quiz, he/she pushes FINISH and the image becomes his/her answer. However, the robot system regards answers as the numbers of dots in the white images regardless of the location of these black dots.

Table 1 provides a list of the descriptive terms that the three quizzes use. The participants answered a quiz that required them to follow this instruction: “continue pushing BUTTON until, in your opinion, you see X.” The label X is replaced by a descriptive term that is selected in an experiment. It is substituted with one of the English translations of the descriptive terms (A, B, C, D, E, or F) listed in Table 1. In addition, we informed the participants of the existence of the six descriptive terms in the quizzes before the test. We also informed them that they could make their own criteria for each descriptive term. For example, the quiz asks participants to continue clicking BUTTON until, in their own opinion, they see a considerably large number of dots.

We investigated 30 university students’ answers to six quizzes before experiments were performed for the system in order to use the results as a dataset for clustering. These participants indicated their descriptive scales by entering an answer on our laptop. In these experiments, the number of dots represented the participants’ descriptive scales.

4.2 Flow of the Experiment in a Group

Figure 4 shows an environment wherein the experiments were performed. A laptop was placed on a table, and a chair was placed near the table. In addition, three participants and a quiz host sat on the table. Therefore, in this study, a group comprised three human participants. A place surrounded by a dotted line where the participants sat was referred to as the “waiting area,” whereas the other place surrounded by a dotted line next to the quiz host was referred to as the “answering area,” as shown in Fig. 4. Additionally, the people in the waiting area were not able to see the display of the laptop in the answering area. This was done to prevent them from being aware of the other participant’s opinion because the people in the waiting area can use this information to seek advice to answer the quiz.

Figure 5 shows a flowchart that defines the experiment controlled by the quiz host. At first, all participants who intended to join our group experiments answered the six quizzes without any advice in order to enable a comparison between individual answers and answers in a group before performing the experiment. Next, a quiz host taught the participants how to use the laptop before the experiment was performed. Then, the quiz host selected only three participants as group members in a single experiment, of which two answered differently in the same descriptive term quiz, i.e., the individual difference between each of them is large.

Here, one out of the three participants in a group, who is referred to as “Participant” and is our collaborator, knows the aim of these experiments. At this point, the “Participant” only obeyed the system on the laptop, answered based on
the proposed model, and pretending that he was answering by himself while the other participants answered the quiz on our laptop. In this experiment, a robot system was included in the application (Fig. 3). When the third participant attempted to answer, the application automatically displayed the robot system’s answer as the third participant’s answer. This was the phase of forming a group, i.e., at this point, each participant considered the other participants as group members.

Next, the quiz host decided who answered the quiz at first such that the first and second participants were human members, whereas the third participant was “Participant.” When it one of the participants turn to answer a quiz, he/she sits on the chair. The quiz host ensures that there is no discussion about this experiment while someone is answering a quiz on the laptop. Then, the three participants see each other’s answers. At the same time, the robot system on the laptop checked the human participants’ answers and registered this information for learning the participants’ behaviors. When the numbers of dots of human participants’ answers were \( k_1 \) and \( k_2 \), the robot system recognized their answers as \( s_{k_1} \) and \( s_{k_2} \), respectively, and renewed the values using Eqs. (1)–(4). The participants repeated this procedure five times. At the beginning of each step, they did not know the each others’ answers. However, at the end of a step, they had this information. We thought if the participants had already known all of the information in Table 2, they would be affected by one another’s answers and change their own answers.

4.3 Individual Differences and Clustering Dataset

We investigated 30 university students’ answers to six quizzes before the experiments were performed. Table 2 shows the averages and standard deviations of the number of dots generated from each university student’s answers. These results revealed that there were individual differences among participants’ quiz answers. The standard deviations indicated the existence of individual differences in the quizzes when the participants answered without any advice. As the average increased, the standard deviation increased (Table 2).

In reinforcement learning, the agent in the robot system selected the actions in a given state from a set of 100 states. Then, the system selected some states as representative states using the k-means++ clustering algorithm in order to reduce the search space. The states corresponded to answers concerning the number of dots. The number of states was 100 because the system pushed BUTTON from 1 to 100 times when the participants answered a quiz. Therefore, we set the number of clusters to four. Consequently, \( N = 4 \), which is the maximum value of the number of states. The system used the results of the experiments to investigate the individual differences among quizzes (Table 2).

The system separated the resulting dataset into four clusters and considered the four centers of the clusters to be representative answers. Thus, the agent in the system selected a certain action in a given state from the four representative states. We presumed that clustering diminished the choices of states and accelerated the system’s convergence to a group norm. In addition, the system considered the other members’ answers as a certain representative state that was closest to the four representative states.

4.4 Test of Convergences in the Experiments

We ran the Mann-Whitney U test to investigate whether the answers in Fig. 6 converged or not [26]. The three participants’ answers in a group affect each other’s opinions, so that their answers converge. In other words, mutual influences cause convergence of their answers in a group. We investigated whether such influence exists by using the Mann–Whitney U test.

We prepared two samples to use the Mann–Whitney U test. These samples are depended on whether the participants in a group recognize the other participants’ answers. One sample is a set of variances of each group answers

| Descriptive Scale | Average | Standard Deviation |
|-------------------|---------|--------------------|
| A                 | 18.70   | 11.35              |
| B                 | 20.03   | 11.51              |
| C                 | 24.87   | 11.92              |
| D                 | 27.80   | 12.34              |
| E                 | 34.73   | 19.53              |
| F                 | 50.73   | 20.85              |

Table 2 Results of investigating descriptive scale
Fig. 6 Results and standard deviations
We must investigate whether change of answers in a group would depend on if participants in the group recognize one another’s answers or not. If the change exists, mutual influences and convergences in groups also exist. Therefore, we investigated answers of human groups where the participants do not recognize the others’ answers.

To observe change of answers in case participants in a group do not recognize one another’s answers, we also investigated four extra participants’ answers without advice on their own in four descriptive terms (A, B, C, and D). The four participants answer each quiz five times, that is, a total of 20 times. In the experiments (Fig. 6), we did not use descriptive terms E and F, so the participant does not answer the quizzes about the term E and F.

If we pick three participants from the four participants, we can regard the three participants as a group. Moreover, the group including the three participants answers four kind of descriptive term quizzes. Therefore, \( \binom{4}{3} \times 4 = 16 \) groups can exist. We define the group as pseudo-group.

We used the Mann–Whitney U test on between five experiment groups (Fig. 6) and 16 pseudo-groups. Then, the observation in each sample is a difference between the value of a variance of answers in a group at steps 5 and 1. These values mean changes of participants’ answers in each group.

### 4.5 Results

Figure 6 shows the results of the five experiments wherein two participants and the system in each group answered five questions per experiment. We selected two participants who had large individual differences for a certain descriptive scale in each experiment. The descriptive terms used in the experiments 1, 2, 3, 4, and 5 are D, A, D, B, and C, respectively, so that we do not use the descriptive terms E and F. Table 3 lists the parameters of reinforcement learning in each experiment. The horizontal axis shows the step number, whereas the vertical axis shows the number of dots that each participant answered (Fig. 6(a)-(e)). In addition, Fig. 6(f) shows standard deviations of the five experiments that indicate the degree of their individual differences in each step. Sherif et al. reported similar results using only human participants [13].

Table 4 shows two samples of experiment groups and pseudo-groups in the Mann–Whitney U test. Each value is a difference between the value of a variance of answers in a group at steps 5 and 1. These values mean changes of participants’ answers in each group.

![Fig. 7 Statistical distribution of two experiments samples and two-sided p-value](image)

The result revealed a statistical significance \( p = 0.0019 \), two-tailed test. Therefore, we can see that when participants recognize the others’ answers, they will be affected by the others’ answers.

These results showed that each participants’ answer in all groups converged to a criterion of the number of dots at the fifth step. This confirmed that their answers converged to become the group’s norm in all experiments. However, the standard deviations decreased as the number of steps increased. These findings revealed that groups with a high value of individual differences at the first step tended to converge more strongly.
4.6 Discussions

As a result of learning, we observed that if the standard deviation was comparatively lower at the first step, the participants did not feel the need to change their answers at the next step. However, it appeared that if the participants changed their answer at the next step, they felt the need to find a more suitable answer by considering the answers of the other group members. We also observed that the system’s answer affected the participants’ answers. For instance, compared to the answers at the first step, it appeared that the answers of Participant 2 were closer to those of the system at in second and third steps (Fig. 6(a)). We assumed that the participant felt that the system’s answer was as natural as a human’s answer because the participants in the group formed group norms considering the system’s answers. However, we cannot completely conclude that the system’s answers were as natural as a human’s when considering the fact that the third participant only obeyed the system because the system gave the same answers unnaturally in a row (Fig. 6(c)). Moreover, the third participant only obeyed the system and pretended to answer in a way similar to how humans answer. The other participants were unaware of this information. We cannot conclude that the system’s answer was as natural as a human’s answer solely by considering that the first and second participants knew that the third participant only obeyed the system.

From the results of these experiments, we concluded that the robot system made decisions in groups involving human members by considering the group norms. Moreover, we concluded that human participants in groups made decisions considering the robot system’s behaviors. The proposed model enabled robots to make decisions socially in order to adjust their behaviors to common sense not only in a large human society but also in partial human groups, e.g., local communities, because these robots can learn group norms when joining a group. Therefore, we presumed that these robots can join human society by adjusting their behaviors according to their interactions with group members.

Further studies are required to investigate whether using the proposed model, a real robot can adjust its behavior to be in line with human participants’ behaviors and whether participants could create a suitable criterion for decision-making by interacting with the group. The proposed model enabled robots to make decisions socially in order to adjust their behaviors to common sense not only in a large human society but also in partial human groups, e.g., local communities, because these robots can learn group norms when joining a group. Therefore, we presumed that these robots can join human society by adjusting their behaviors to the group norms.

As a result of learning, we observed that if the standard deviation was comparatively lower at the first step, the participants did not feel the need to change their answers at the next step. However, it appeared that if the participants changed their answer at the next step, they felt the need to find a more suitable answer by considering the answers of the other group members. We also observed that the system’s answer affected the participants’ answers. For instance, compared to the answers at the first step, it appeared that the answers of Participant 2 were closer to those of the system at in second and third steps (Fig. 6(a)). We assumed that the participant felt that the system’s answer was as natural as a human’s answer because the participants in the group formed group norms considering the system’s answers. However, we cannot completely conclude that the system’s answers were as natural as a human’s when considering the fact that the third participant only obeyed the system because the system gave the same answers unnaturally in a row (Fig. 6(c)). Moreover, the third participant only obeyed the system and pretended to answer in a way similar to how humans answer. The other participants were unaware of this information. We cannot conclude that the system’s answer was as natural as a human’s answer solely by considering that the first and second participants knew that the third participant only obeyed the system.

From the results of these experiments, we concluded that the robot system made decisions in groups involving human members by considering the group norms. Moreover, we concluded that human participants in groups made decisions considering the robot system’s behaviors. The proposed model enabled robots to make decisions socially in order to adjust their behaviors to common sense not only in a large human society but also in partial human groups, e.g., local communities, because these robots can learn group norms when joining a group. Therefore, we presumed that these robots can join human society by adjusting their behaviors according to their interactions with group members.

Further studies are required to investigate whether using the proposed model, a real robot can adjust its behavior to be in line with human participants’ behaviors and whether participants could create a suitable criterion for decision-making by interacting with the group. The proposed model enabled robots to make decisions socially in order to adjust their behaviors to common sense not only in a large human society but also in partial human groups, e.g., local communities, because these robots can learn group norms when joining a group. Therefore, we presumed that these robots can join human society by adjusting their behaviors according to their interactions with group members.

4.6 Discussions

As a result of learning, we observed that if the standard deviation was comparatively lower at the first step, the participants did not feel the need to change their answers at the next step. However, it appeared that if the participants changed their answer at the next step, they felt the need to find a more suitable answer by considering the answers of the other group members. We also observed that the system’s answer affected the participants’ answers. For instance, compared to the answers at the first step, it appeared that the answers of Participant 2 were closer to those of the system at in second and third steps (Fig. 6(a)). We assumed that the participant felt that the system’s answer was as natural as a human’s answer because the participants in the group formed group norms considering the system’s answers. However, we cannot completely conclude that the system’s answers were as natural as a human’s when considering the fact that the third participant only obeyed the system because the system gave the same answers unnaturally in a row (Fig. 6(c)). Moreover, the third participant only obeyed the system and pretended to answer in a way similar to how humans answer. The other participants were unaware of this information. We cannot conclude that the system’s answer was as natural as a human’s answer solely by considering that the first and second participants knew that the third participant only obeyed the system.

From the results of these experiments, we concluded that the robot system made decisions in groups involving human members by considering the group norms. Moreover, we concluded that human participants in groups made decisions considering the robot system’s behaviors. The proposed model enabled robots to make decisions socially in order to adjust their behaviors to common sense not only in a large human society but also in partial human groups, e.g., local communities, because these robots can learn group norms when joining a group. Therefore, we presumed that these robots can join human society by adjusting their behaviors according to their interactions with group members.

Further studies are required to investigate whether using the proposed model, a real robot can adjust its behavior to be in line with human participants’ behaviors and whether participants could create a suitable criterion for decision-making by interacting with the group. The proposed model enabled robots to make decisions socially in order to adjust their behaviors to common sense not only in a large human society but also in partial human groups, e.g., local communities, because these robots can learn group norms when joining a group. Therefore, we presumed that these robots can join human society by adjusting their behaviors according to their interactions with group members.

5. Conclusion

In this study, we proposed a model to allow a robot to create a suitable criterion for decision-making by interacting with humans in a group in a multiparty quiz scenario wherein a system that obeys the model finds a suitable criterion based on the observation of the behaviors of other participants in a group.

Robots need to behave socially in multiparty scenarios to adapt themselves to a human society. All humans have unique personalities and use their choices to form criteria to govern their behavior. When people form a group, they influence each other’s decisions, resulting in the generation of a group norm. This norm is a thought or a behavioral pattern that we expect a robot in a group to obey. We investigated whether a robot system that uses our proposed model behaves socially in a group that includes humans.

Our results revealed that a system that adjusts itself to each group can generate group norms with human participants. The experimental results demonstrated that using the proposed model, the robot system adjusted own answers according to participants’ answers. Moreover, each member of the group adjusted their answers according to other members’ answers. Sherif reported similar results using groups involving only humans [13]. We assumed that the results indicated the system’s answer to be as natural as a human’s answer because the human participants formed group norms considering the system’s answers. However, we observed the system’s unnatural behaviors in experiments when considering that only the third participant obeyed the system. The proposed model enables robots to make decisions socially in order to adjust its behaviors to common sense not only in a large human society but also in partial human groups, e.g., local communities. From the results of these experiments, we concluded that the robot system made decisions in groups that include human members by considering the group norms. Moreover, we concluded that human participants in groups made decisions considering the robot system’s behavior.

This research aimed to investigate (1) whether using the proposed model, a real robot can adjust its own answers according to human participants’ answers and (2) whether the participants were affected by the robot’s answers. Further studies are required to reveal whether the robots’ answers affect people and whether participants create a suitable criterion considering the robot’s answer even in a situation wherein the participants recognize that they are interacting in a group that includes a robot.
References

[1] B.R. Duffy, “Anthropomorphism and the Social Robot,” Robotics and Autonomous Systems, vol.42, no.3-4, pp.177–190, March 2003.

[2] F. Hegel, C. Muhl, W. Briede, M. Hielsher-Fastabend, and G. Sagerer, “Understanding Social Robots,” 2009 Second International Conferences on Advances in Computer-Human Interactions, pp.169–174, Feb. 2009.

[3] T. Fong, I. Nourbakhsh, and K. Dautenhahn, “A survey of socially interactive robots,” Robotics and Autonomous Systems, vol.42, no.3-4, pp.143–166, March 2003.

[4] C. Brozeal, Designing sociable robots, MIT Press, 2004.

[5] H. Salam, O. Celiktutan, I. Hupont, H. Gunes, and M. Chetouani, “Fully automatic analysis of engagement and its relationship to personality in human-robot interactions,” IEEE Access, vol.5, pp.705–721, Sept. 2016.

[6] M. Ficocelli, J. Terao, and G. Nejat, “Promoting interactions between humans and robots using robotic emotional behavior,” IEEE Trans. Cybernetics, vol.46, no.12, pp.2911–2923, Nov. 2015.

[7] W.Y.G. Louie and G. Nejat, “A learning from demonstration system architecture for robots learning social group recreational activities,” 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp.808–814, Oct. 2016.

[8] F.M. Carlucci, L. Nardi, L. Iocchi, and D. Nardi, “Explicit representation of social norms for social robots,” 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Sept. 2015.

[9] I. Shoji, H. Takenouchi, and M. Tokumaru, “Effectiveness of a sympathy expression model for the bystander robot,” Int. J. Affective Engineering, vol.15, no.3, pp.223–230, July 2016.

[10] R. Boyd, “The puzzle of human sociality,” Science, vol.314, no.5805, pp.1555–1556, Dec. 2006.

[11] D.J. Terry and M.A. Hogg, “Group norms and the attitude-behavior relationship: A role for group identification,” Personality and Social Psychology Bulletin, vol.22, no.8, pp.776–793, Aug. 1996.

[12] O.F. Kernberg, “What is personality?:,” J. Personality Disorders, vol.30, no.2, pp.145–156, April 2016.

[13] M. Sherif, “A study of some social factors in perception,” Archives of Psychology, vol.27, no.187, pp.5–16, Nov. 1934.

[14] Y. Fuse, H. Takenouchi, and M. Tokumaru, “A robot model in limited scenarios to create a suitable decision-making criterion by interacting with people in a group,” 2017 IEEE Symposium Series on Computational Intelligence (SSCI), pp.1–7, 2017.

[15] E.M. Aminoff, D. Clewett, S. Freeman, A. Frithsen, C. Tipper, A. Johnson, S.T. Grafton, and M.B. Miller, “Individual differences in shifting decision criterion: A recognition memory study,” Memory & Cognition, vol.40, no.7, pp.1016–1030, Oct. 2012.

[16] M. Deutsch and H.B. Gerard, “A study of normative and informational social influences upon individual judgment,” J. Abnormal and Social Psychology, vol.51, no.3, pp.629–636, Nov. 1955.

[17] L.S. Rashotte, “Social Influence,” In The Blackwell Encyclopedia of Sociology, Volume IX, pp.4426–4429, G. Ritzer, and J.M. Ryan (eds.), Oxford: Blackwell Publishing, 2007.

[18] N. Crichton, “Visual analogue scale (VAS),” J. Clinical Nursing, vol.10, no.5, pp.697–706, Sept. 2001.

[19] P. Kaelbling, M.L. Littman, and A.W. Moore, “Reinforcement learning: A survey,” J. Artificial Intelligence Research, vol.4, pp.237–285, May 1996.

[20] J. Kober, J.A. Bagnell, and J. Peters, “Reinforcement learning in robotics: A survey,” Int. J. Robotics Research, vol.32, no.11, pp.1238–1274, Aug. 2013.

[21] K. Arulkumaran, M.P. Deisenroth, M. Brundage, and A. Anthony Bharath, “A brief survey of deep reinforcement learning,” IEEE Signal Process. Mag., arXiv preprint arXiv:1705.05172, May 2017.

[22] T.M. Moerland, J. Broekens, and C.M. Jonker, “Emotion in reinforcement learning agents and robots: A survey,” arXiv preprint