Can User-Centered Reinforcement Learning Allow a Robot to Attract Passersby without Causing Discomfort?*

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Abstract—The aim of our study was to develop a method by which a social robot can greet passersby and get their attention without causing them to suffer discomfort. A number of customer services have recently come to be provided by social robots rather than people, including, serving as receptionists, guides, and exhibitors. Robot exhibitors, for example, can explain products being promoted by the robot owners. However, a sudden greeting by a robot can startle passersby and cause discomfort to passersby. Social robots should thus adapt their mannerisms to the situation they face regarding passersby.

We developed a method for meeting this requirement on the basis of the results of related work. Our proposed method, user-centered reinforcement learning, enables robots to greet passersby and get their attention without causing them to suffer discomfort (p < 0.01). The results of an experiment in the field, an office entrance, demonstrated that our method meets this requirement.

I. INTRODUCTION

The working population in many developed countries is decreasing in proportion to the total population due to population aging, and this problem is expected to affect developing countries as well [1]. One approach to addressing this problem is to use social robots rather than people to provide customer services. Such robots, for example, are starting to be used as receptionists, guides, and exhibitors. Robot exhibitors are being used to provide, for example, exhibition services, such as explaining products being promoted by the robot owners. While robots can increase the chance of being able to provide a service by simply greeting passersby [2], passersby can suffer discomfort if they are suddenly greeted by a robot [3]. The robot may thus face a dilemma: whether to behave in a manner that benefits the owner or to behave in a manner that does not discomfort passersby.

Our goal was to develop a method that solves the robot dilemma described above. That is, a method by which a robot can greet passersby and get their attention without causing them to suffer discomfort. We call our proposed method user-centered reinforcement learning.

In the next section, we define the problem and describe how we found an approach to solving it by studying related work. In the Proposed Method section, we explain the method we developed for solving the problem. In the Experiment section, we explain the experiment we conducted in the field to test two working hypotheses created from the original hypothesis. The results show that our method can solve the problem. In the Discussion section, we examine the results from the viewpoints of physiology, psychology, and user experience. In the Conclusion section, we conclude that, by using user-centered Q-learning, a robot can increase the chance of being able to provide a service to a passerby without causing the passerby discomfort. We also mention future work to enhance the proposed method.

A. Related Works

Several researchers have addressed problems that are similar to the problem we addressed. These problems can be categorized in terms of the problem setting, the solution, and the goal.

In terms of the problem setting, the problem we addressed is similar to the problem of human-robot engagement, which is a complex problem. In accordance with human-robot interface studies [4], [5], we can interpret human-robot engagement as the process by which a robot interacts with people, from initial contact to the end of the interaction. Several researchers have analyzed human-robot engagement [6], [7] and have developed a method for maintaining human-robot engagement during the interaction [8]. We did not tackle the human-robot engagement problem directly; instead, we tackled the problem that precedes it, which is illustrated in Figure 2.

In terms of the solution, the problem we addressed is similar to machine learning, especially reinforcement learn-
Reinforcement learning in robotics is a technique used to find a policy \( \pi : O \rightarrow A \) [9] and is used for robotic control tasks. It is not used much for interaction tasks. Reinforcement learning has been applied to the learning of several complex aeronautic control tasks for radio-controlled helicopters [10] and to the learning of door opening tasks for robot arms [11]. The research on interaction tasks is less remarkable. Mitsunaga et al. showed that a social robot can adapt its behavior to humans for human-robot interaction by using reinforcement learning [12] if human-robot engagement has been established. Papaioannou et al. used reinforcement learning to extend the engagement time and enhance the dialogue quality [13].

The applicability of these methods to the situation before human-robot engagement is established is unclear. As shown in Figure 2, the problem we addressed occurs before engagement is established.

In terms of the goal, the problem we addressed is similar to increasing the number of human-robot engagements. Macharet et al. showed that, in a simulation environment, Gaussian process regression based on reinforcement learning can be used to increase the number of engagements [14]. Going further, we focused on increasing the number of engagements in a field environment.

**B. Problem Statement**

We use a problem framework commonly used for reinforcement learning in robotics, the partially observable Markov decision process (POMDP) to define the problem [9]. The robot is the agent, and the environment is the problem. The robot can observe the environment partially by using sensors.

We choose a exhibition service area in an entrance to a company as the environment. We assume the entrance consists of one automated exhibition system, one aisle and other space. In addition, the entrance is expressed as Euclidean space \( R^3 \), passersby can move freely around the exhibition system.

The automated exhibition system consists of a tablet, a computer, a robot and a sensor system. The sensor system can sense a color image data \( I_t \) and a depth image data \( D_t \). We called these data Observation \( O_t \). The sensor system can also extract a partial passersby action from \( O_t \). The passersby’s action consists of the passersby’s position \( p_c = (x_t, y_t, z_t) \) and the head angle \( \theta_t = (\theta_t^{yaw}, \theta_t^{roll}, \theta_t^{pitch}) \). We define the times when the passersby enters the entrance \( t = 0 \) and when the passersby leaves from the entrance \( t = T_{end} \). We call the interval between \( t = 0 \) and \( t = T_{end} \) an episode. Let \( \Theta = (\theta_0, ..., \theta_{T_{end}}) \) be the passersby’s position in an episode, and let \( P = (p_0, ..., p_{T_{end}}) \) be the passersby’s head angle in the episode.

The proposed method takes an own their action from these passersby’s action.

Let \( N_u \) be a number of people that used the service. Let \( N_d \) be a number of people that used the discomfort. Then, we can declare this problem as "Find a robot’s policy \( \pi : O \rightarrow A \) such that \( \max(N_u) \) and \( \min(N_d) \)".

**C. Our Approach**

We solve this problem by controlling the robot on the basis of reinforcement learning, ordinarily Q-learning except for designing the reward function. The reward function is created by focusing on the user experience of stakeholders. We call this reinforcement learning including this reward function "user-centered reinforcement learning." We do not use deep reinforcement learning due to the difficulty at the present time of collecting the huge amount of data needed for learning.

**D. Contributions**

The contributions of this work are as follows,

1) We show that robots can learn abstract actions from a person’s non-verbal responses.
2) We present a method for increasing the number of human-robot engagements in the field without causing them to suffer discomfort.

**II. PROPOSED METHOD**

Proposed method, User-Centered Reinforcement Learning, is based on Reinforcement Learning. In this paper, We use Q-learning, one of reinforcement learning, as a base algorithm because it is easy to explain why the robot choose the past actions by Q-learning. We call this algorithm "User-Centered Q-Learning" (UCQL). UCQL is differ from original Q-learning [15] in an action set \( A \), a state set \( S \), Q-function \( Q(s,a) \) and reward function \( r(s_t,a_t,s_{t+1}) \). UCQL consists of three functions;

1) Select an action by a policy
2) Update the policy based on user’s actions
3) Design a reward function and a Q function as initial condition.

1) Selecting an action by a policy: Generally speaking, robot senses observation, and take an action including wait. Let \( t_a[sec] \) be the time when the robot acted. Let \( t_c[sec] \) be the time when the robot compute the algorithm. Let \( s_t \in S \) be the predicted user’s state on the time \( t \). Let \( a_t \in S \) be the robot’s action on the time \( t \). In UCQL, robot choose the action by Algorithm 1.

2) Update the policy based on user’s actions: In UCQL, robot update the policy by Algorithm 2.
Reward function by UCQL (r)

Algorithm 1 Select an action by UCQL (Action Selector)
Input: $t_c, s_{t_a}, Q(s,a), \pi(s,A,Q)$
Output: $a_t, t_a$

\begin{algorithmic}
    \State $a_t \leftarrow \pi(s_{t_a}, A, Q)$
    \State $t_a \leftarrow t_c$
    \State \textbf{return} $a_t, t_a$
\end{algorithmic}

Algorithm 2 Update the policy by UCQL (Policy Updater)
Input: $s_{t_{a}}$, $a_{t_{a}}$, $s_{t_{c}}$, $A, Q(s,a)$
Output: $Q(s,a)$

\begin{algorithmic}
    \If {$a_{t_{a}}$ is finished}
        \State $R \leftarrow r(s_{t_{a}}, a_{t_{a}}, s_{t_{c}})$
        \State $Q_{\text{old}} \leftarrow Q(s_{t_{a}}, a_{t_{a}})$
        \State $Q(s_{t_{a}}, a_{t_{a}}) \leftarrow (1-\alpha)Q_{\text{old}} + \alpha\left(R + \gamma \max_{a} Q(s_{t_{c}, a})\right)$
    \EndIf
    \State \textbf{return} $Q(s,a)$
\end{algorithmic}

Algorithm 3 Reward function by UCQL (r)
Input: $s_{t_{a}}, s_{t_{c}}, a_{t_{a}}$
Output: $r$

\begin{algorithmic}
    \State $r \leftarrow 0$
    \If {$a_{t_{a}}$ is not wait}
        \State $r \leftarrow r + V_u(a_t)$
        \State \textbf{(intrinsic motivation)}
    \EndIf
    \If {$s_{t_{a}}$ is discomfort for users than $s_{t_{a}}$}
        \State $r \leftarrow r - V_u(s_{t_{c}}, s_{t_{a}})$
        \State \textbf{(extrinsic motivation)}
    \EndIf
    \If {$s_{t_{c}}$ is better than $s_{t_{a}}$ to achieve the goal}
        \State $r \leftarrow r + V_g(s_{t_{c}}, s_{t_{a}})$
    \EndIf
    \State \textbf{return} $r$
\end{algorithmic}

III. Experiment

In this chapter, we aim at showing the hypothesis that "by using user-centered Q-learning, a robot can increase the chance of being able to provide a service to a passerby without causing the passerby discomfort".

A. Concrete Goal

At first, we convert the hypothesis into another working hypothesis by operationalization because we cannot evaluate the hypothesis quantitatively.

In Introduction, we define this problem as "Find a robot's policy $\pi : O \rightarrow A$ such that $\max(N_u)$ and $\min(N_d)$". We give shape to $N_u$ and $N_d$ for this experiment. According to Ozaki's study [3], This knowledge has two important points. Firstly, passerby is not suffer a negative effect by robot’s call if passerby don’t use a robot service. Secondly, passerby is suffer a negative effect by robot’s call if passerby use the robot service. Thus, this is a binary classification problem that passerby who is called by robot uses the robot service or do not use it. we can define a confusion matrix for evaluation of the method. We infer that $N_u$ and TP, TN have a positive correlation. We also infer that $N_d$ and FP have a positive correlation. We also infer that $N_d$ and FP have a positive correlation. On the other hand, we infer that $N_d$ and TN have a negative correlation. Therefore, we can use Accuracy = $(TP + TN)/(TP + FP + TN + FN)$ as a index for evaluation because $\max$(Accuracy) is one of another representation of $\max(N_u)$ and $\min(N_d)$.

From the above discussion, we define the working hypothesis $W H$ as "The accuracy after a learning by UCQL is better than the accuracy before a learning by UCQL".

In this experiment, we test $W H$ in order to show that the hypotheses is sound.

B. Method

In this section, we explain how to conduct the experiment in a field environment. We can divide the method for this experiment into five steps.

1) Create an experimental equipment
2) Construct an experimental environment
3) Define an experimental procedure
4) Evaluate the working hypotheses by statistical hypothesis testing
5) Visualize the effect of UCQL

1) Create an experimental equipment: Firstly, we create an equipment including UCQL. The equipment can be explained in the aspect of the physical structure and the logical structure.

Figure 3 is a diagram of the equipment in the view of the physical structure. According to Figure 3 the experimental equipment consists of a table, a sensor, a robot, a tablet PC, a router and servers. The components are connected with Ethernet cable or Wireless LAN. We use Sota [1], a palm-sized social humanoid robot, as a robot. Sota has a speaker to output voices, a LED to represent lip motions, a SoC

https://sota.vstone.co.jp/home/
Equipment

**Figure 3:** The physical structure of the experimental equipment (Real line: Wired, Dashed line: Wireless)

Sensors

**Figure 4:** The logical structure of the experimental equipment

Effectors

Environment

Pedestrian

Motion Capture

State Estimator

Action Decoder

Action Selector

Policy Updater

Algorithm 4 Select an action by the experimental system including UCQL

**Input:** $t, O_t$

**Output:** $E_t$

if the system is NOT initialized then

$Q \leftarrow Q_0$

$\Theta \leftarrow$ a empty list

$P \leftarrow$ a empty list

end if

$I_t, D_t \leftarrow$ sense($O_t$)

$\theta_t, p_t \leftarrow$ extract ($I_t, D_t$)

Push $\theta_t$ into $\Theta$.

Push $p_t$ into $P$.

$s_t \leftarrow$ estimate($\Theta$, $P$)

$a_t \leftarrow$ selectAction($t, s_t, Q, \pi$)

Push ($t, a_t, s_t$) into $X$.

$E_t \leftarrow$ decode ($a_t, \theta_t, p_t$)

return $E_t$

**TABLE I: Action set in this experiment**

| Symbol | Detail |
|--------|--------|
| $a_0$  | Robot waits for 5 secs until somebody comes. |
| $a_1$  | Robot calls a passerby with a greeting. |
| $a_2$  | Robot looks at a passerby. |
| $a_3$  | Robot represents joy by the robot’s motion. |
| $a_4$  | Robot blinks the robot’s eyes. |
| $a_5$  | Robot says ‘I’m sorry.’ in Japanese. |
| $a_6$  | Robot says ‘Excuse me.’ in Japanese. |
| $a_7$  | Robot says ‘It’s rainy today.’ in Japanese. |
| $a_8$  | Robot says how to start their own service. |
| $a_9$  | Robot says goodbye. |

**TABLE II: State set in this experiment**

| Symbol | Detail |
|--------|--------|
| $s_{00}$ | The passerby’s state changes ‘Not Found’ into ‘Not Found’. |
| $s_{10}$ | The passerby’s state changes ‘Not Found’ into ‘Passing By’. |
| $s_2$   | The passerby’s state changes ‘Looking’ into ‘Passing By’. |
| $s_3$   | The passerby’s state changes ‘Passing By’ into ‘Leaving’. |
| $s_4$   | The passerby’s state changes ‘Leaving’ into ‘Established’. |
| $s_5$   | The passerby’s state changes ‘Leaving’ into ‘Leaving’. |

\[ T_0(s) = 1 \]

\[ T_{n+1}(s) = \begin{cases} T_n(s) & \text{if } T_n(s) < T_{\text{min}} \\ k_T \times T_n(s) & \text{otherwise} \end{cases} \]

\[ p(s, a) = \frac{\exp (Q(s, a)/T_n(s))}{\sum_{a \in A} \exp (Q(s, a)/T_n(s))} \]

2) Construct an experimental environment: At first, we have to define how to construct an environment for the experiment. Figure 5 shows a overhead view of the environment. The environment consists of a exhibition space, a parameter. $T_n(s)$ means a thermometer when it is updated $n$ times on $s$. $T_n(s)$ depends on the states because $s_{00}$ occur many times. We utilize $k_T = 0.98$ and $T_{\text{min}} = 0.01$ as learning parameters.
Algorithm 5 Create initial Q-function for the experiment \((Q_B)\)

Input: (void)
Output: \(Q(s, a)\)
\[
q_C \leftarrow 1 \\
q_H \leftarrow 5 \\
Q \leftarrow \text{a } |S| \times |A| \text{ zero 2D-array}
\]
for \(i = 0\) to \(|A| - 1\) do
    for \(j = 0\) to \(|A| - 1\) do
        \(Q(s_{ij}, a_0) \leftarrow 0\)
    end for
end for
for \(j = 1\) to \(5\) do
    \(Q(s_{0j}, a_1) \leftarrow q_C\)
end for
for \(i = 1\) to \(4\) do
    \(Q(s_{i5}, a_8) \leftarrow q_H\)
end for
\(Q(s_{56}, a_9) \leftarrow q_H\)
\(Q(s_{59}, a_9) \leftarrow q_H\)
return \(Q(s, a)\)

Fig. 5: The overhead view of the experimental environment.

Fig. 6: An example Q-function represented by heat map. The columns mean the state symbols of agent and the rows mean the action symbols of agent. For example, \(Q(s_{01}, a_1)\) is 0. That means the robot call a passerby that is passing by it will get no value.

We constructed a experiment environment described on Method in the entrance of our buildings. Figure 1 shows a picture of the equipment in the environment. The experimenter was the corresponding author. The participants were a lot of employees and visitors of our company. The learning interval is three days. As a result, we measured a lot of data. We clean the data by the following step because the data interval is three days. As a result, we measured a lot of data.

We calculate the the accuracy before the learning and the accuracy after the learning in order to test \(WH\) hypothesis. We use the one-sided Test of Proportion because we want to test the hypotheses. The robot do not learn during the test.

We start collect data for the evaluation by rosbag\(^5\) Each data is recorded by rosbag. We can recode all of values in ROS by rosbag during the procedure.

4) Evaluate by statistical hypothesis testing: We evaluate the working hypothesis \(WH\) by statistical hypothesis testing. We calculate the the accuracy before the learning and the accuracy after the learning in order to test \(WH\). Finally, we use the one-sided Test of Proportion because we want to evaluate statistical difference between the accuracy before the learning and the accuracy after the learning.

5) Visualize the effect of UCQL: We visualize the Q-function before the learning and the Q-function after the learning by heat map in order to analyze the effect of UCQL. UCQL can change the action by updating Q-function. Therefore, we can know how robot learn the action by visualizing Q-function. Figure 6 is an example Q-function to explain a visualization on this paper.

IV. Result

We wants to attract the passersby in the second scenario mainly. We do not wants to attract the passersby in the first scenario because the visitor wants to go to W.C.. Therefore, because we wants the robot to learn the rules, we let the robot learn the rules on the environment by UCQL for several days. Then, we can get learned Q-funcion \(Q_A(s, a)\)

After the learning, we let the robot attract passersby under two condition. We define two condition: Before Learning and After Learning because we want to test the hypotheses. The robot do not learn during the test.

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TABLE III: Items of the result after the data cleansing.

| items    | Before | After | Total |
|----------|--------|-------|-------|
| episodes | 87     | 122   | 209   |
| time[h]  | 13.7   | 26.7  | 40.4  |
| days[d]  | 3      | 6     | 9     |

Fig. 7: The accuracy of the experiment on each condition (**: p < 0.01)

have a lot of noise on the field such as detection errors by Motion Capture and so on.

- We drop episodes that interval is less than 1 [sec] because it takes a 3 [sec] to walk across the detection area of Motion Capture.

- We drop episodes that is from \( s_{00} \) to \( s_{00} \) only because nobody was in the detection area of Motion Capture.

We got 209 total episodes in the experiment after the data cleansing. Table III shows number of episodes and time on each condition. We calculated the accuracy from the confusion matrix on each condition. The confusion matrices for the before condition and the after condition were respectively \((TP,FP,FN,TN) = (11,59,0,17)\) and \((TP,FP,FN,TN) = (7,23,0,92)\). Therefore, the accuracy of the baseline and proposed methods were respectively 0.322 and 0.811. In testing \( WH \) by the one-sided Test of Proportion, we found a significant difference in accuracy between the before and after condition \((p = 4.46 \times 10^{-13} < 0.01)\).

V. DISCUSSION

We discuss the original hypothesis, "The robot can attract passersby without users’ discomfort by User-Centered Reinforcement Learning.", in the point of following views.

1) Can we accept the original hypothesis?
2) Why the robot attract passersby without discomfort by the proposed method?
3) What is the limitations of the method and the experiment?

A. Can we accept the original hypothesis?

We explain why we can accept the original hypothesis by using the result of the experiment and another study.

At first, we show that the we can accept \( WH \), "The accuracy after a learning by UCQL is better than the accuracy before a learning by UCQL". According to Capture IV, we found a significant difference in precision between the before and after condition. Thus, we accept \( WH \). Therefore, we can infer \( WH \) as true.

The result of the experiment supports the original hypothesis though the above-mentioned discussion because the working hypothesis is true. Therefore, we can accept the original hypothesis.

B. Why the robot attract passersby without discomfort by the proposed method?

We can explain why the robot attract passersby without discomfort in view of the learning process with Figure. 8.

Why the robot reduce FN by UCQL? We compare the row of \( s_{01} \) in Figure. 8(a) and the row of \( s_{01} \) in Figure, 8(b). The robot before learning selected a action \( a_4 \) because \( \arg\max Q_B(s_{01},a) = a_4 \). The robot after learning selected a action \( a_0 \) because \( \arg\max Q_A(s_{01},a) = a_0 \). That means robot do not calls if passerby don’t use a robot service. Therefore, the robot reduce FN by UCQL.

C. What is the limitations of the method and the experiment?

In this experiment, we supposed that a passerby do not walk with others. In other words, we do not consider a group of passersby. Thus, we need to expand the method in order to process a group of them.

The data in this study are sampled from biased population. We need to take further experiments on other environments if we want more soundness about the working hypotheses.

In this experiment, we create the reward function based on other studies. However, it is hard to create reward functions on each case. Therefore, we have to create a easy method in order to design reward function and Q function.

VI. CONCLUSION

We investigated the hypothesis that "by using user-centered Q-learning, a robot can increase the chance of being able to provide a service to a passerby without causing the passerby discomfort." We proposed a method based on reinforcement learning in robotics and focused on the reward function and the Q-function because we wanted the robot to perform actions in view of user experience? To investigate our hypothesis, we made a working hypothesis and tested it experimentally. From the results, we accepted the working hypothesis and the original hypothesis.

Future work includes generalizing the method for creating the reward function to make it applicable to different tasks and developing a distributed reinforcement learning method that enhances time-efficiency.

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Fig. 8: The changing process of Q-function by UCQL.

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