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Personalizing Robot Behavior for Interruption in Social Human-Robot Interaction

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***Abstract*— People engaging in an activity usually has individual tolerance to be interrupted [1], [2]. Humans subconsciously adapt their behaviors to draw other one's attention and to get into a conversation based on their historical experiences, but robots often fail to be aware of humans' feeling and thus interrupt their users repeatedly. To endow service robots with such socially acceptable ability, we propose an online human-aware interactive learning framework in this paper, under which the robot personalizes its behaviors according to both observed user's attention and its conjecture about user's awareness of itself. To this purpose, the correlation between the robot's theory of awareness, user's attention and robot behavior are explored through reinforcement learning techniques. The conducted experiment shows that the robot can personalize its interruption strategy, and the optimal policies converged for at least 26 episodes.**

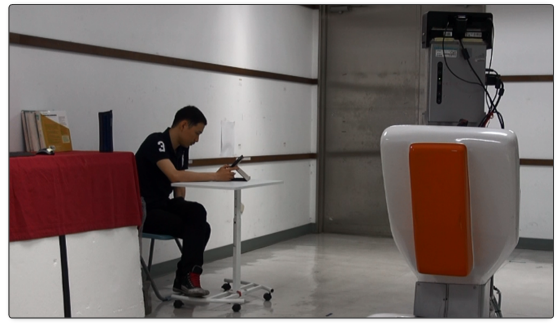

Fig. 1. The human partner engaging in the reading task is interrupted by our ARIO robot

I. INTRODUCTION

Recently, as robots are liberated from the constrained environment like factories, there has been wide interest in human-robot engagement. Robots have gradually become pervasive in our living environment, and human-robot engagement is expected to appear everyday, such as, a delivery robot working with staffs in a hospital [3]. Such migration causes robots to work beyond of the programmed routine schedule, *e.g.* in assembly lines, and to adopt the vague social conventions in human-human interaction. That is, to be merged into our human society, robots are required to behave in a *socially acceptable* way.

The kinds of socially acceptable behaviors really depend on the role of social robots. For example, a bartender robot wants to figure out whether the person sitting at the bar is a potential customer or not [11]. In such case, the social robot is demanded not only to predict the influence of its demeanor but also to estimate the current mental state of the person concurrently. This tough job can be easier if the social robots work in public places, where the interaction between the humans and the robot is structured (*e.g.*, a receptionist robot in a facility [10]). However, this interplay becomes mix-initiative when the social robots step into private places, such as homes, offices or senior centers. Modeling the human's communication dynamics is inevitable to enable social robots to achieve more natural human-robot interaction [4].

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According to [5], engagement is "the process by which interactors start, maintain and end their perceived connection to each other during an interaction." It is obvious that, besides social robots, humans also have the option of establishing or terminating the communication between them and the robot. People staying in private places, such as staff in an office, are often busy with their own activities. If a social robot initiates an interaction with its partner rashly, the person may feel interrupted, resulting in degraded performance results [6] despite that robots are expected to service a task proactively in many situation [7]. Otherwise, the tolerance that people can be interrupted depends on not only their individual differences [1], [2] but also their professional positions [3]. In the case of human-human interaction, we subconsciously adapt our behaviors so as to grab the partner's attention and to get into a conversation based on our own historical experiences. Therefore, our main question is: *Can the robot learn how to influence an individual's focus of attention by interrupting its partner and initiating an interaction in a socially acceptable manner?*

As social robots are deployed into humans' private place, the challenge concerning how a robot can personalize its behaviors to satisfy people's preferences have gradually received great attention. Most of the works about adapting the specification of robot task are focused on learning from the interaction with users. Mitsunaga *et al.* has proposed an adaptation mechanism based on policy gradient reinforcement learning (PGRL), which adjusts robot's behaviors according to users' subconscious body signals [13]. Likewise, the PGRL also has been utilized to match the user's personality to behaviors of socially assistive robots for post-stroke rehabilitation therapy [14]. Nejat *et al.* also proposes a robotic system which promotes bi-directional communication

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[15]. This system models the user's current affective states from body language and utilizes Q-learning to determine the effective response of the robot. However, these works all were based on a common assumption that all people intend to interact with the robot, which might not be true when social robots live together with a group of people everyday.

For social robots in private places, Das *at el.* investigates how a social robot uses just visual cues to grab human's attention and establishes a communication channel proactively [16]. The effect of nonverbal interruption is also explored in [17]. While noise of motors, generated by the movement of mobile robots, often distracts people in private places like homes or offices [17], we are interested in building an ability for mobile social robots to understand users' tolerance for interruption and initiate an interaction proactively. With that purpose, in this paper we describe an online human-aware learning framework, which enables a social robot to adapt its behaviors according to both partner's attention and its conjecture about partner's awareness of itself. The correlation between robot's theory of awareness, partner's attention and robot behavior are explored through the reinforcement learning technique.

The rest of paper is organized as follows: in Section II, we start with formulating our problem as a human-aware Markov decision problem, which contemplating the attention the attention of the user and the mental state of robots. Afterwards, Section III describes how the problem can be solved utilizing a Hidden Markov Model (HMM) and the reinforcement learning technique like Q-learning. The results of the experiment are reported in Section IV. Finally, Section V concludes the paper and discusses the future research directions.

II. Human-Aware Decision Problem

Since each trial when the robot tries to initiate an engagement can be seen as an episode, the problem is considered as a finite horizon decision problem. At each time step, from the person's point of view, the person may be aware of the robot's intention to interact, but he/she might decide to neglect it because of his/her on-going works. On the other hand, the robot is also required to maintain its own belief in the person's awareness of itself. The robot has to notice the state of the partner and takes the next action. This kind of problems, however, may not be reasonable for the typical representation of MDPs. Interruption in a polite way requires the robot to be aware of the state of the partner, which unfortunately cannot be observed directly using sensors mounted on the robot.

As a result, we propose a special form of MDPs suitable for modeling this kind of decision problems, which needs to be aware of the human's attention and to plan the robot's action simultaneously. A *Human-Aware Markov Decision Process* M_{ha} is defined as a tuple $M_{ha} = \langle S, A, T, Z, R, TK, U \rangle$, where

- S is the state space, where a state consists of both the robot's Theory of Awareness (ToA), denoted as S_{toa}, which borrowed the idea of Theory of Mind module [18] to represent the human's awareness of itself (meaning "robot"), and the intensity of Human Attention toward the Robot (HAR) S_{har}, namely, $\langle S_{toa}, S_{har} \rangle \in S$. For ease of later referencing, the state space S is regarded as a product of two sub-spaces, S_{toa} and S_{har}, so that for each element $s \in S$, $s = \langle s_{toa}, s_{har} \rangle$, we have $s_{toa} \in S_{toa}, s_{har} \in S_{har}$.
- A is a finite set of robot's primitive actions for catching human attention. It is clear that each robot's actions $a \in A$, like waving to the human partner, may affect the partner's attention toward the robot S_{har} and therefore update the robot's Theory of Awareness S_{toa} about the perceived partner.
- T specifies the state transition distributions of the two-tuple, $\langle T^p_{toa}, T^p_{har} \rangle = T$, where T^p_{toa} and T^p_{har} are the probability density function that $T^p_{toa} : S_{toa} \times A \times S_{toa} \to [0,1]$ and $T^p_{har} : S_{har} \times A \times S_{har} \to [0,1]$. The superscript p indicates that each persons' attention may have the different chance to be attracted by the robot action.
- Z is set of social signals observed from the human partner and utilized to infer the state of human attention S_{har}.

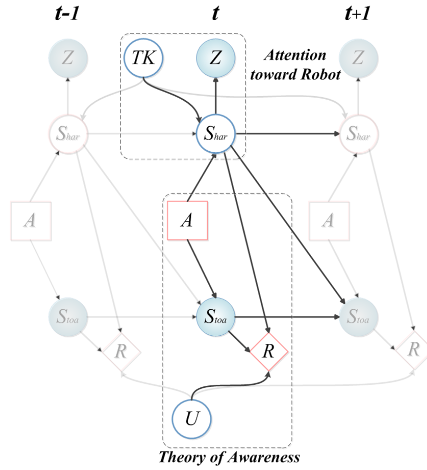


Fig. 2. The graphical model showing variables and dependencies in the human-aware Markov decision process. The social signal Z and robot's Theory of Awareness S_{toa} are fully observable and are represented as a shaded node.

In addition, the interruptibility of the human often depends on the current task in which he/she is engaged, while whether the robot should take a strong action to interrupt the partner relies on the urgency of the robot task. We further define the task context TK and urgency of message U to represent those two concepts:

- TK is the set of tasks people are engaged in currently. Each element in TK is the task label, say, $tk \in TK$. In contrast, U is the set of the urgent messages the robot want to deliver. For different urgency of the message $u \in U$, the robot may try different strategy to draw the attention of the human partner, and the specification of this will be defined in the reward function R.
- R is the reward function, where $R : S \times A \times U \to \mathbb{R}$,

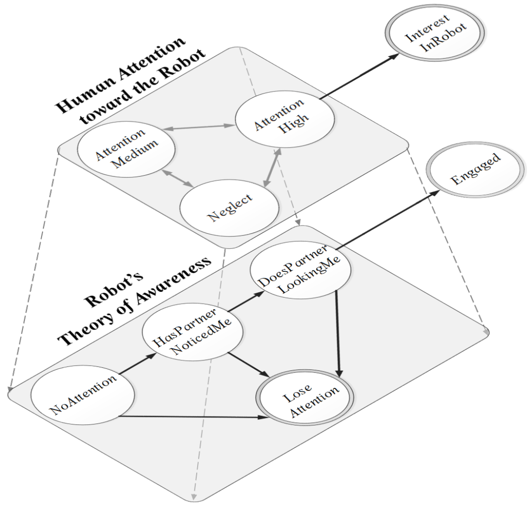


Fig. 3. State transition diagram of the S_{har} and S_{toa}. The transition of the S_{toa} depends on the current attention level S_{har} of the partner.

details how the robot gently interrupts the human to achieve its goal according to the urgency distribution U.

The overall proposed model are illustrated in Fig.2, and the detail of state spaces $\langle S_{toa}, S_{har} \rangle$ are explained in the following subsection:

A. Human Attention toward the Robot

The upper part of Fig. 3 shows the state transition diagram of the Human Attention level toward the Robot S_{har}. The states are divided into two parts: one is *not-engaged* and another is *engaged*. At the *not-engaged*, the three levels: *Neglect*, *Medium*, *High* are used to indicate the current intensity of the attention level to the robot. This attention level will be affected by the robot's interruption. On the other hand, when the partner shows the intention to interact, the state will change to the *InterestInRobot*. In addition, since the human often perform multiple tasks simultaneously in the domestic or working environment; for example, surfing the Internet and dialing the phone at the same time. Thus, the overall partner's attention level AL at any time steps might be considered as a union of an attention to the robot (ALR) and another attention to the human tasks (ALTs), where $ALT = \{ALT_1, ALT_2, \ldots\}$, *i.e.*, $AL = ALT \cup ALR$. Nevertheless, in our problem what the robot concerns is "*Has my partner noticed me?*". Only the ALR may be enough for the robot to infer whether the partner is focusing on his/her works or not; that is, the high value of ALR usually implies the low value of ALTs.

B. Robot's Theory of Awareness

Representing the environment only through the human attention states, however, might not satisfy the Markov property. The current level of attention toward the robot cannot summarize all the past events that have taken place. Hence, we borrow the idea of Theory of Mind module from [18], and enable the robot to further maintain its Theory of Awareness

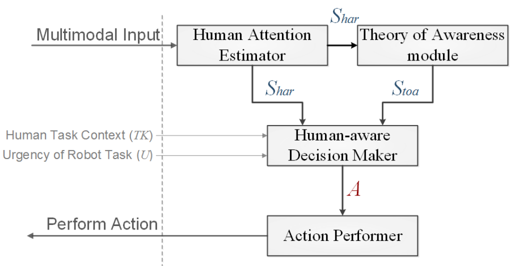


Fig. 4. The proposed system architecture

S_{toa} about the belief in the perceived partner's awareness of robot itself, as shown in the lower part of Fig. 3. This high-level representation abstracts the history of the partner's attention. For example, *HasPartnerNoticedMe* will be triggered when the the partner responds to the action of the robot through a verbal reply. After the partner starts to watch the robot, the robot ensures that *DoesPartnerLookingMe* is credible and tries to establish a communication channel. In contrast, if the partner does not pay any attention to the robot for long time or rejects the robot directly, the robot will know that it fails to attract the attention of the partner. Although these transitions are fired when the predefined condition is satisfied, the effect of each robot's action causing these activated transitions is unknown and might be different for different individual. In the next section, we will discuss how this problem can be solved through the model-free reinforcement learning technique.

III. Human-Aware Learning Framework

Due to the hidden states of the human-aware Markov decision process (HAMDP), its state space grows exponentially and requires a large computational time to be solved, as Karami reported in [12]. The conventional ways to solve partial observable Markov decision processes often require to specify transition probabilities clearly and solve offline, which is not suitable for our application. Therefore, we adopt combination of both the reinforcement learning (RL) and hidden Markov models (HMMs) to deal with the HAMDP. Our system architecture is outlined in Fig. 4. First, at each time step, the Human Attention Estimator (HAE) recognizes the human attention level toward the robot S_{har} from the multi-modal input, which are social signals extracted from the user. The resulting S_{har} will be forwarded into the Theory of Awareness Module (ToA), described in the previous section, to update the robot's belief in the perceived partner. Afterwards, both outcomes of HAE and ToA are utilized by Human-aware Decision-maker to determine an appropriate action to perform. The experience gained in the interaction will be stored and used for the next step action selection. In the following of this section, we will explain these two modules: Human Attention Estimator, Human-aware Decision-maker.

A. Human Attention Estimator

The Human Attention Estimator (HAE) is the perception component of our system that observes the partner's social

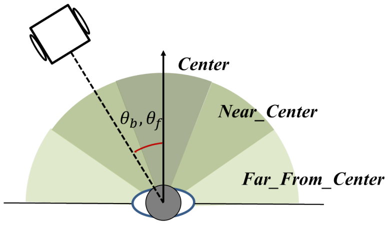


Fig. 5. The human's direction of attention observed by the robot. In this case, the face and body direction are facing in the same direction, and the included angle are shown as θ_f, θ_b. These angle are discretized to Near_Center by the robot.

signals and infers from those signals the level of attention toward the robot (ALR). Since the ALR cannot be observed directly from the conventional vision or audio sensors, ALR is represented as the hidden variable here and modeled through a Hidden Markov Model (HMM).

The HAE is a 5-tuple $\lambda = \langle S_{har}, Z, T_{hae}, O_{har}, b_0 \rangle$, where $S_{har} = \{Neglect, Medium, High, InterestInRobot\}$ is the set containing states illustrated in Fig. 3. Three types of social signals $Z = \{FaceDirection,\ BodyDirection,\ VoiceDetection\}$ based on the direction-of-attention detector proposed in [19] are selected to infer those hidden states. The face and body direction are defined here as the included angles made by both the partner's facial direction or body's heading direction and the robot's line of sight. These directions are used to determine whether the robot is in the partner's field of view and are discretized into four regions as shown in Fig. 5. The robot may be in the *center region*, *near center region* or *far from center region* within the partner's field of view. Besides face and body direction, the voice activity detection is also taken into account because talking activity is also an indicator of human non-interruptibility [20], except the situation where the partner is facing the robot and speaking to it. Such exception might be the case of interacting with the robot. The transition T_{hae} and observation function O_{har} are trained through the Baum-Welch algorithm, and b_0 is the initial belief distribution over the sub-space S_{har}. It is worth to note that the transition function T_{hae} may not be equal to T^p_{har} as described in the Section II since T_{hae} here does not consider the user preference. The T^p_{har} will be examined in the Human-aware Decision Maker described below. In addition, the estimated belief b_t is then passed into the Theory of Awareness module and Human-aware Decision Maker to determine the next probable action to attract the user attention.

B. Human-aware Decision Maker

In the interactive situation, predicting the potential events that will take place between humans and robots might not be realistic. Human-aware Decision Maker acts as the intellect component of the proposed architecture and makes a decision to select the appropriate action in next step. In this component, we apply the model-free reinforcement learning (RL) to integrate both Human Attention Estimator and Theory of Awareness module to learn the user preference from the robot's own experience about how its action affected the partner's attention. The model-free reinforcement learning is considered due to its model-free capability that the transition probability of T^p_{har} and T^p_{toa} is not required to be specific during the learning process.

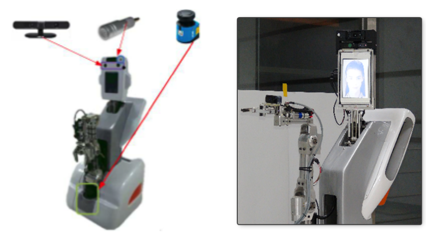
Q-learning is adopted to learn the optimal policy in the proposed *human-aware Markov decision process*. The algorithm aims to estimate the Q values, the expected discounted reward for executing action a at the state $\langle s_{toa}, s_{har} \rangle$ and following a policy π thereafter. In every time step n, the robot observes its current state $\langle s_{toa}, s_{har} \rangle$ from the result of Human Attention Estimator and updated Theory of Awareness. Afterwards, an action a is selected and performed based on the current Q values. The robot then observes the subsequent state $\langle s^{'}_{toa}, s^{'}_{har} \rangle$ and receives an immediate reward $r_n \in R$, adjusting its Q values according to:

$$Q_n(s,a) = (1-\alpha_n)Q_{n-1}(s,a) + \alpha_n[r_n + V_{n-1}(s^{'} \rangle)]$$

where $s = \langle s_{toa}, s_{har} \rangle$, α_n is a learning factor. The reward function R is defined as a function of current state S, which can be specified differently according to the urgency of the message robot delivering U, an example is shown in Eq. 1. After the Q values converges, the robot is able to obtain a optimal policy through finding the action a_r maximizing $Q_n(s, a_r)$ from all states S. Experiments used to verify the proposed architecture are reported in the next section.

IV. Experiments

For evaluating our human-aware interactive learning framework, the experiments are focusing on two parts: 1) Evaluation of Human Attention Estimator. 2) Experiment for Human-aware Decision Maker. We perform our experiment in an indoor environment at Ming-Da Building, National Taiwan University. For the experiment platform, we use our robot ARIO which is shown in Fig. 6(a).



(a) (b)

Fig. 6. The experimental platform — ARIO robot. (a) Sensors for human-robot interaction application include a laser range finder – SICK LMS 100, a RGB-D camera – ASUS Xtion Pro, and a Cardioid microphone (b) ARIO is performing the *ArmWave* action

A. Evaluation of Human Attention Estimator

To evaluate our model for human attention level toward the robot, 5 volunteers were recruited from National Taiwan University (NTU). These participants all came from engineering background and their ages ranged from 22 to 29. Each participants were asked to stand approximately 1.8 m apart in the robot's field of view and to engage in a reading task. The social signals Z of these participants were recorded to train our Human Attention Estimator. During the recording, ARIO was controlled using Wizard of Oz (WoZ) to perform some primitive actions, such as wave the arm or moving forward, to grab the participant's attention and thus record the change of social signals. To obtain the face heading direction, the frontal and profile face detection provided by OpenCV library are used to detect the partner's current face heading direction. The results of the frontal and profile face detection were labeled as *Center* and *Far_From_Center* shown in Fig. 5, respectively. The OpenNI library was also utilized to track the participant's body skeleton in order to compute the body heading direction. The voice from the subject was detected through a energy-based voice activity detection and represented as a boolean value. In addition, after the trial, participants were asked to label their attention level by themselves according to the video we recorded. The evaluation was conducted using leave-one-out cross validation. While the human behaviors are continuous in time, we chose to discretize the data at the rate of 750 ms. The accuracy of prediction was on average 87.21%, and the overall confusion matrix was shown in Table I.

TABLE I
THE CONFUSION MATRIX OF HUMAN ATTENTION ESTIMATOR

Test\Truth	*Neglect*	*Medium*	*High*
Neglect	93.1%	5.41%	1.48%
Medium	10.5%	80.35%	9.14%
High	0.9%	10.9%	88.2%

It should be noted that there are numbers of factors limiting the accuracy of the HMM: the states are sometimes ambiguous and do not allow precise labeling. These factors are inherent and difficult to be overcame by collecting more training data. Modeling these signals through Gaussian mixture models with continuous HMM might be a way to improve the accuracy.

B. Experiment for Human-aware Decision Maker

Here we reported our experiment for Human-aware Decision Maker. We evaluated how the robot's strategies for interruption had converged. The setting of this experiment was similar to the previous one, the same 5 participants were recruited again here and was asked to engage in a reading task except that the robot was standing approximately 2.1 m apart from the participant and was trying to inform the participant that there was a message left for you.

The limited time for each episode was set to 3 minutes. If the participant did not give any responds during the time interval, the timeout event would be triggered and ARIO would know that she lost the attention of the participant. Furthermore, the urgency level of the message we considered here was set to *Normal*; that is, the effect of the robot succeeded or failed to initiate the engagement is the same. So, based on the states of Theory of Awareness (ToA), the reward function R was defined as:

$$R(S^n) = \begin{cases} 20 & \text{if } S^n_{toa} = Engaged \\ 5 & \text{if } S^n_{toa} = HasPartnerNoticedMe \\ -20 & \text{if } S^n_{toa} = LoseAttention \\ -5 & \text{if received reject signal} \\ -1 & \text{Otherwise} \end{cases} \quad (1)$$

where n is the current step in the episode. In different urgency situation, we could define different reward function to shape the robot's behavior.

Considering to generalize the behavior of robots, which is the robot action set A contained the primitive actions that the robot can perform to draw the partner's attention, we decomposed the A into three types of actions: *Gestures*, *Locomotion*, *Audio*.

- *Gestures*: Gestures consist of movements of the robot head or arm, $\{HeadShake, ArmWave\} \in Gestures$. The head shake let the head of the robot to turn left and right along the transverse plane repeatedly during a small time interval. The arm wave commends the robot to wave its arm up and down, as shown in 6(b). In addition, the robot would consistently turn its head to face the partner when it was trying to initiate an interruption. There are the evidences that people will feel the robot's intention to interact when it is facing us [17], [21].
- *Locomotion*: Locomotion is the action subset that approachs to the partner in a constant speed. $\{Approach, MoveAround\} \in Locomotion$. The robot would go straight to the partner when the $Approach$ was executed. Besides going straight to the partner, the action, *MoveAround*, would try to move the robot into the partner's field of view. The robot will stop approaching when it enters the intimate space of the partner according to the Hall's proxemics [22].
- *Audio*: The audio signal of the robot we concerned here has two aspect. One is to make a small sound to catch the partner's attention; another one is to call the partner's name directly to interrupt the partner. Thus, $\{MakingSound, CallName\} \in Audio$.

Those six primitive actions are used by the robot to interrupt the partner, and their influence will be learned through the Human-aware Decision Maker. For all of the 5 subjects, the optimal policy was converged after about 2 hours of interaction, or approximately 30 episodes of the interaction. Their cumulative rewards are shown in Fig. 7. From this figure, we can observe that the slope of these line become constant after the 26 episodes, which indicates that the policy has converged.

The optimal policy for each subject are reported as follows: For subject 1, the resulted policy was approaching to the participant first and then calling his name continuously. Another example is the optimal policy of the subject 2, which the robot called the participant's name first and then approached to wave its arm endlessly. The optimal policy for subject 3 involves only the locomotion of the robot, the robot approached first and then moved to the front of the

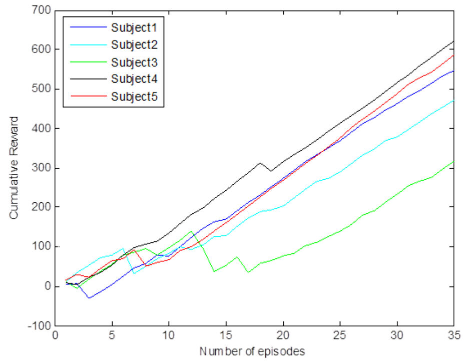


Fig. 7. The results of cumulative reward collected from the experiment

subject. Subject 4 reported that it is annoying for him when the robot called his name. His optimal policy was making a small sound to inform the interruption and then approached him to wait for his response. The optimal policy for subject 5 is similar to the subject 2, the robot called the participant first then waving its arm to inform the interruption. In the future work, we would like to involve more participants in a field experiment to evaluate how the robot personalized its behavior.

V. Conclusion

In this paper, we proposed an online interactive learning framework for social robots to initiate an interruption of its user in a socially acceptable manner. A human-aware Markov decision process was presented to consider both user's attention and robot's mental states concurrently. The correlation between robot's theory of awareness, user's attention, and robot's behavior were explored through the Q-learning scheme. Our preliminary experiments showed that the robot was able to personalize its behavior to subjects at least 26 episodes. In the future, we are interested in involving more participants in a field experiment, such as in a senior center, to evaluate how the robot personalized its behavior to initiate an engagement.

The framework provides service robots with the ability to perform living aids or assistance in private place seamlessly. However, numerous challenges remain. The task people were engaged in may involve more than just one person, like group meeting. In such case, besides user's attention, the timing for robots to interrupt people will also be a factor to concern. In addition, techniques like policy shaping [23] provides an opportunity to integrate the user feedback into our framework and to speed up the rate of convergence.

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