Investigation of Model for Initial Phase of Communication: Analysis of Humans Interaction by Robot

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We propose an agent model that determines its behavior from an internal state and a spatial relationship with a target to generate approaching and avoiding behaviors in encounter scenes. This model is based on the relationship with an opponent rather than with a scenario. The agent moves to increase the utility value obtained from the preferences for both aggressive and passive involvement. We analyzed the behavioral and utterance data of human–human interactions based only on two-dimensional position information by simple-shaped robots. The rate of participants' behavior following the model was significantly higher than that of a random walker. Based on this result, we estimated the internal state during the interactions from the behavior of the participants and analyzed it. The words uttered by one member of a pair correlated with the internal state estimated from the behavior of the other member of the pair. The frequency of the internal states observed from the participants who were recommended to interact with the partner was different from that observed from the participants who did not receive such recommendations. These results suggest that a model with two preferences can approximate a human's internal state in encounter scenes.

CCS Concepts: • **Human-centered computing** → **Interaction design**; *User models*;

Additional Key Words and Phrases: Initial phase of communication, spatial interaction, agent model

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1 INTRODUCTION

As robots that provide communication services continue to appear, people have increased opportunities to interact with robots in their daily lives. For social interactions between humans and robots, robots need to present readable social cues that are easy for humans to understand [Fong et al. 2003]. However, it remains unclear what internal robot state is appropriate to be expressed in an encounter and what kind of behavior is appropriate to express the internal state. In human communication, actions and reactions inevitably convey not only content aspects but also aspects of the adjustments of relationships [Watzlawick et al. 2011]. Therefore, we aim to

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design communication robots that can adjust their behavior based on their own internal states and their human partners like humans do. This study proposes a model of internal states and behaviors in human encounters that is applicable to both behavior evaluation and generation. In this article, we extend the model proposed in our previous study [Sakamoto and Takeuchi 2018], which generates approach and avoidance behaviors, and propose a method for estimating the internal states of humans and robots based on behaviors. We re-analyzed the experimental data from Sakamoto and Takeuchi [2015] and demonstrated the validity of applying the model to describe human and robot interaction in encounter scenes. This step increases scenes in which robots start conversation politely with people without causing unpleasantness.

During encounters between humans, interpersonal communication is started through physical-embodied interaction, which clarifies that one talks to the other before the actual conversation starts. Goffman proposed two communication steps with another person: unfocused interaction, in which little attention is paid to the other, and focused interaction, in which sufficient attention is mutually directed and shared [Goffman 1963]. As a transition from unfocused to focused interaction, the initial phase of communication is based on such body expressions as distance, body direction, gaze, and facial expressions [Mondada 2009; Mortensen and Hazel 2014]. The adjustment of distance [Hall 1966] and the construction of conversation space [Kendon 1990] have also been carried out in human-human communication. Psychological features such as intimacy and social dominance affect physical interaction [Argyle and Dean 1965; Burgoon et al. 2007]. To clarify the process of starting communication with others, the physical features of body expressions must be addressed.

According to dual process theories, the social cognitive process is based on the collaboration of two complementary processes: one direct and one reflective [Bohl and van den Bos 2012; Wiltshire et al. 2013]. In the initial phase of communication, it is desirable that behavior directly reveals internal states. Otherwise, it is impossible to select an agent who is aiming to communicate from all of the objects in the field of view. Thus, we assume that the process of perceiving internal states is directly expressed by previous behavior; this process triggers a reflective process in which the behavior's purpose is inferred based on its situation and context. Humans can attribute the motion of such objects as a geometric figure to internal states [Heider and Simmel 1944; Pantelis et al. 2016; Scholl and Tremoulet 2000; Tremoulet and Feldman 2006]. In addition to evaluations that observe motion, internal states must be considered object behavior through actual interaction (cf. Fukuda and Ueda [2010]). As a model's outset during the initial phase of communication, we must address the process in which an internal state is expressed directly by behavioral features, such as changes in distance and relative angles.

Communication robots need to adjust their relationships with humans through a physical interaction in the encounter just as humans do. Much research has focused on the design of spatial interactions between humans and robots (cf. Kruse et al. [2013] and Rios-Martinez et al. [2015]), including human subjective evaluation of robot spacing behavior. Humans feel comfort or discomfort with the robot depending on the physical distance between them, and the robot's body direction and approach and avoidance paths (e.g., Dautenhahn et al. [2006], Pacchierotti et al. [2006], and Walters et al. [2009]). In addition, human internal states, such as personal experience and character, affect the evaluation of robot spacing behavior [Mumm and Mutlu 2011; Takayama and Pantofaru 2009]. Therefore, robots need to adjust their behavior according to the human's reaction. By estimating the human's internal state from their behavior, robots can act with the appropriate timing. Models that describe the interaction in the encounter scene as a state transition have also been proposed. The internal state of the robot is often designed for the state transition of the interaction in an encounter (e.g., Gehle et al. [2017] and Holthaus et al. [2011]). In some studies, robots have estimated a human's state—the behaviors according to the estimated state are effective in starting a

conversation (e.g., Kato et al. [2015] and Shi et al. [2015]). These studies, however, designed robots based on a relationship with a scenario and constructed a model to reproduce pre-observed human behavior. Human–robot interaction design requires a model that can not only reproduce human behavior but can also describe interactions without limitation to any context or experimental tasks.

Methods have been proposed to generate robot behavior dynamically according to the situation of human and environment. For example, Sisbot et al. [2007] proposed a model to generate robot approaching and avoiding by changing the weighting variables of cost functions according to the tasks of robots. The cost value was calculated from the human position, posture, and visual field. Several studies have extended this model—approaching and avoidance paths are generated by combining modules that estimate formation of human groups and human intention (e.g., Svenstrup et al. [2011] and Truong and Ngo [2016]). In these studies, however, the descriptions of human behavior and robot behavior are expressed as different models. Models can be simplified if behavior and internal state can be described in the same way for both human and robot. Furthermore, robots' social behaviors are expected to be able to be described as an adjustment of the robot's internal state according to the human's internal state.

The design of the correspondence between internal states and behaviors provides two things: an estimation of internal states based on actions and the generation of actions based on internal states. A robot internal state is often modeled after a human internal state to generate behavior. The trajectory and velocity of the robot is designed by associating the model of the emotion to express the robot's internal state [Cauchard et al. 2016; Saerbeck and Bartneck 2010]. These behaviors encourage the human to understand the state of the robot. Designing a robot's internal state enables humans to understand a robot's behavior while enabling the robot to interpret its own behavior. The robot's intended behavior is not always fixed by a given role or task but should be changed through interactions. For example, it is not sufficient for a communication robot to wander around the field looking for a human to talk to. When the robot has other tasks to do, it should hold off on finding a communication partner. If the person in front of the robot is reluctant to communicate, the robot must be quiet to accommodate the person. We can adjust behavior according to the situation because we can control our own internal state, such as preference or desire. Implementing internal states in a robot is more accommodating than simply implementing behavioral patterns. However, there is no calculation model that can generate behavior in real time and describe the change in internal state through the interaction in the encounter scene.

Ideally, the goal of the design of human–robot interaction is to construct a computational model that is also applicable to human–human interaction, or to refine a human–human interaction model through the investigation of human–robot interaction. If such a calculation model can be constructed, it will be possible to generate the behavior of the robot, predict the behavior of the human, and estimate the internal state of the human. By constructing a calculation model, predicting the interactions that may occur before implementing the robot is possible. In the calculation model, differences in the design of the robot are expressed as differences of parameters and functions, which express the relation between variables. This makes it possible to distinguish between the general interaction property and the interaction property of a certain robot design. The validation of the calculation model contributes to the construction of a foundational model for HRI research.

By using a simple-shaped robot for the interaction experiment, it is possible to focus on the relationship between the behavior of the robot and its internal state. Some studies focus on the behavioral variables of simple robots and investigate the effects on humans, such as the recognition of social engagement and helpful reflective information, intention attribution, and the promotion of joint action (e.g., Zaga et al. [2017], Terada et al. [2007], and Sirkin et al. [2015]). Mobile robots of the non-humanoid type are also used to investigate the effect of motion characteristics

Fig. 1. Internal state of model: Control represents positive or negative preference for aggressive involvement with target. Acceptance represents positive or negative preference for passive involvement from target.

and trajectory on human recognition and behavior (e.g., Knight et al. [2016], Fiore et al. [2013], and Saulnier et al. [2011]). These studies reveal the effects of behavioral variables on partners; however, no computational models have been constructed or validated to explain the process.

In this study, we propose an agent model for interaction that uses only position information as cues in encounters. This model is an expanded version of the previous model [Sakamoto and Takeuchi 2018]. The model describes the interaction only by behavior and internal states, regardless of the attribute of the agent. Thus, spacing behaviors of human and robot are equally described as the interaction of two agents. Two agents change variables of the environment, the relative distances between them, by approaching and avoiding behavior; the agents adjust the distance according to the value of its internal state. Since the initial phase of communication is a process in which agents consent that they are involved with each other, the internal state of the model is expressed by a preference for each other's involvement. In particular, the internal state of our model is represented by two variables: control as orientation to aggressive involvement with a target and acceptance as orientation to passive involvement with a target. Our model describes four internal states that consist of a combination of positive and negative for both control and acceptance (Figure 1). The utility function is defined as a representation through which the agent prefers a spatial relation based on its internal state. The model's agent chooses behavior to increase its utility by approaching or avoiding the target. The utility functions and calculation methods used in our research are simple. The difference in the utility value is evaluated for one frame of behavior. As for the classification of human trajectory, our calculation method is simpler than those of previous studies using machine learning such as support vector machine (e.g., Kanda et al. [2008] and Shi et al. [2015]), as the purpose of our model is to describe human-human and human-robot interaction, and this study focuses on the validation of the model.

In a previous study [Sakamoto and Takeuchi 2018], we generated approach and avoidance actions based on the proposed model and simulated the interaction of two agents based on a computer simulation. However, the proposed model is not evaluated based on actual human data. Therefore, we reanalyzed the experimental behavioral data in which human-human interaction was observed through simple-shaped robots [Sakamoto and Takeuchi 2015]. This experiment focuses on how a human spontaneously initiates an interaction in situations in which the information of the robot has not been previously given, such as an experimental task. In another study

[Sakamoto and Takeuchi 2016], we qualitatively analyzed the interaction based on the velocity and timing of utterances. This suggested that the synchronization of movement timing might trigger changes in interaction processes. However, the trajectory of movement and the content of utterances were not quantitatively analyzed. An analysis based on a model relating internal state and action was not carried out. In addition, our previous experiment observed not only participants who did not know that the robot represented the human position but also participants who were made aware of it through experimental suggestion [Sakamoto and Takeuchi 2015]. Fox et al. [2015] compared the effect of knowing that a partner is manipulated by a human (avatar) vs. that of knowing that the partner is an autonomous agent and showed that avatars are more effective for humans than agents. In our experiment, the behavior observed was expected to differ depending on the suggestion. Therefore, the following three questions were investigated in this study:

- Did the participant show identical approaching or avoiding behavior to the proposed agent model?
- What is the relationship between the estimated internal state based on the model and participant utterances during interaction?
- Was the internal state expressed by participant behavior affected by experimental suggestions to interact with the partner?

This article presents three new analyses distinct from previous studies ([Sakamoto and Takeuchi 2015, 2016, 2018]): model-based estimation of internal states, analysis of speech data, and comparison between experimental conditions. Based on the results of data analysis, we discussed the implementation of our model behavior and the robot's internal state estimation and further model expansion.

2 RELATED WORK

To be accepted by human society, communication robots need to have proper social interactions with humans. Concepts for social robots or social interaction have been proposed in many studies [Breazeal 2003; Dautenhahn 2007; Fong et al. 2003; Vinciarelli et al. 2011]. According to Dautenhahn [2007], the conceptual space of HRI approaches consists of three categories: robot-centered HRI, human-centered HRI, and robot cognition-centered HRI. To integrate studies on these categories, considering a model with high abstraction that describes not only human-robot interactions but also human-human interactions is necessary. In the following, related works on the initial phase of communication and spatial behavior are described.

2.1 Robot-centered HRI

In robot-centered HRI, a robot is designed as an entity that behaves autonomously with its internal state, such as its purpose, motivation, drive, and emotion. Research on social interactions have mainly verified the correspondence between the internal state and behavior. Some studies have designed the spatial behavior of robots based on emotion models, such as the circumplex model of affect [Saerbeck and Bartneck 2010] and Laban Effort system [Knight and Simmons 2014; Knight et al. 2016] and stereotypes of personality [Cauchard et al. 2016]. Evaluations have been carried out based on whether the targeted emotion could be perceived by humans based on the designed behavior. Some studies have not designed the internal states of the robot but verified the correspondence between the characteristics of behavior and the internal state sensed by humans [Harris and Sharlin 2011; Ju and Takayama 2009]; this is also related to the human-centered HRI approach.

Most studies have determined whether a robot needs to interact with humans or not as a task of the robot. These studies have treated two research problems separately: how the robot approaches

humans [Kato et al. 2015; Mead and Matarić 2017] and how the robot avoids humans [Dondrup et al. 2015; Shiomi et al. 2014; Trautman and Krause 2010]. An approach used to calculate social space via a cost function and generate trajectories has been used for both the approach and avoidance problems [Papadakis et al. 2014; Sisbot et al. 2007; Truong and Ngo 2016]. However, the parameters of the cost function were not treated as the internal state of the robot and did not change through interactions.

By assuming the internal state of the robot, values can be changed during the interaction; this is especially important for social interactions. For example, suppose a robot initially has a state in which it wants to interact with a human. Controlling the state for when humans show that they do not wish to interact with robots is necessary; this depends on the degree to which the human desires to interact with the robot. In some cases, it is necessary to tell the human why the robot itself would do a specific action. For example, the robot needs to mention its principles of behavior, such as “I refrained from starting conversation with you because you seemed busy.” This process is carried out through mutual behaviors. Behaviors are generated according to the internal state of themselves, and internal states are changed according to the partners’ behaviors.

2.2 Human-Centered HRI

In the human-centered HRI, robots are designed to ensure humans are comfortable and focus on the physical or psychological reactions of humans. Research has shown that humans feel comfortable or uncomfortable according to spatial relationships with robots [Walters et al. 2009]. Several studies have examined the factors that affect humans’ feelings or spatial reactions, such as the personal trail [Walters et al. 2005], experience with interactions [Takayama and Pantofaru 2009], and likeability [Mumm and Mutlu 2011]. Humans also feel comfort differently depending on the approach and avoidance trajectories of robots [Dautenhahn et al. 2006; Pacchierotti et al. 2006].

Robots’ behaviors are interpreted by humans; a robot’s behavior changes a human’s behavior. Researches have verified not only internal states, such as emotions, but also the readability of behaviors according to robot tasks, such as interruption urgency [Saulnier et al. 2011] and approachability [Ju and Takayama 2009]. In addition, the influence of readable behaviors on human performance has been verified [Admoni et al. 2016].

These studies clarify human responses to robot behaviors. However, the process through which human reactions and actions change have not been studied via interactions. Robots behave according to their internal states. By observing and interpreting the behavior of a robot, the internal state of a human can be changed. In other words, this causes a behavioral change in the human. To describe these processes, modeling internal states and behavior generation of both robots and humans is necessary.

2.3 Robot Cognition-Centered HRI

Robot cognition-centered HRI focuses on the design of robot cognitive systems to handle tasks. The major tasks in determining the spatial interactions of social robots are starting communication or to avoid collisions. Some studies have shown that robots can detect a human’s condition based on body movements to regulate the timing and behavior of communication initiation [Gehle et al. 2017; Holthaus et al. 2011]. In designing robot collision avoidance, robots learn the passing behavior according to human spacing behavior [Kuderer et al. 2012]. Some studies have shown that robots generate behaviors based on the prediction of human behavior changes caused by the robot’s behaviors [Sadigh et al. 2016; Schmerling et al. 2018]. These robots can handle their own tasks in relation to humans. However, these robots do not consider how humans interpret interactions; this is different from human-centered HRI. Robots should be designed to realize how humans

interpret the robot's behaviors. This would encourage a correspondence between behavior and social cognition.

2.4 Comprehensive Approach

A comprehensive approach is needed to address these three perspectives. Research on social signal processing aims to bridge the social intelligence gap between humans and robots (c.f. Vinciarelli et al. [2011]). Methods for applying both the generation of social behavior and the recognition of social signals to robots have been investigated. Engineering human social cognition research is an extension of social signal processing that deals with the layer of higher order cognition [Wiltshire et al. 2017]. Our approach, as well as these studies, focuses on integrating human and robot social cognitive processes. We model interactions from the bottom up, especially from a few variables. By clearly defining internal states, connections to higher cognitive processes are expected in the future.

Considering not only cooperative behaviors of robots but also those of humans is necessary. Robots cannot take active behaviors in which only the robots adjust to humans. It is necessary to model the effects of robot behavior, including human cooperation, on humans [Trautman and Krause 2010]. Modeling interactions mathematically is important to cooperatively solve the problems between human and robot social interactions. Trautman and Krause modeled and verified the interactions through which a robot and human cooperatively avoided collision in a pedestrian group [Trautman and Krause 2010]. Kuderer et al. proposed a method to generate more human-like trajectories in cooperative crossings between a robot and a pedestrian [Kuderer et al. 2012]. For cooperative autonomous vehicles, Sadigh et al. described drivers' interactions as a dynamic system [Sadigh et al. 2016]. Changes in human driving behaviors are promoted by model predictive control: learn the parameters of human behavior and reward functions and generate the behaviors of an autonomous vehicle based on the prediction of changes in human behavior [Sadigh et al. 2016]. In these studies, physical features, such as position and velocity, were used as state variables, but psychological features were not sufficiently focused upon. The appropriateness of the behavior depends on the context of the task. In communication initiation, participants can change their psychological internal states, such as interest in others. Therefore, modeling the internal states of the participants is necessary.

Sakamoto and Takeuchi [2018] modeled the internal states of the agent in the initial phase of communication and generated spacing behavior. In this study, we extend upon this model. We assume that an agent in the model behaves according to the utility value determined by the spatial relationship and its internal state. Our model does not predict the behaviors of the other agent directly but estimates the preference of the other agent from the changes in utility value. The initial phase of communication can be described as the temporal change of preferences that occurs by assuming that both participants generate behaviors according to the utility value of the model. When this model is implemented in a robot, the robot moves according to its internal state, and the robot estimates the internal state of humans based on positional changes. This kind of processing will be necessary for robots to understand social interactions.

3 MODEL

In this section, we describe our agent model that represents spatial interaction with only the position information in encounters. The agent has an evaluation method for a situation based on an internal state and chooses a behavior to raise the evaluation value. The internal state of the agent and the physical features of interactions are based on a previous study [Sakamoto and Takeuchi 2018]. In this study, we newly define the calculation of the intensity of involvement and the utility function.

Fig. 2. Physical features that affect intensity of involvement between agents.

3.1 Internal States

The agent has a preference (expressed as an internal state) for a relationship with an object. This model takes account of two preferences of a relationship with a target: control and acceptance. Control represents a positive or a negative preference of aggressive involvement with the target. Acceptance represents a positive or a negative preference of passive involvement with it.

The agent in this study has one of four internal states, which are positive and negative combinations of these two preferences (Figure 1). Thus, internal state z of the agent takes one of the following values:

- $z = (+, -)$: assertive state in which an agent prefers aggressive involvement with a target;
- $z = (-, +)$: submissive state in which an agent prefers passive involvement with a target;
- $z = (+, +)$: reciprocal state in which an agent prefers mutual involvement with a target;
- $z = (-, -)$: avoidant state in which an agent prefers no involvement with a target.

In this study, the magnitudes of control and acceptance are not treated. Instead, only the sign is given, control (+ or -) and acceptance (+ or -), in that order, as shown in the parentheses in the list of values above.

3.2 Physical Feature and Involvement

The agents change their spatial relationships through their movement behavior. The agent's choice of behavior is determined by the preference represented by the internal state. We assume a utility function to evaluate whether the agent has moved to a more preferred spatial relationship. The intensity of involvement is determined by the spatial relationship between the agent and the target. The transactional segment at which humans become involved with a target is a short distance and has a front direction [Kendon 1990]. Since we only use position information in this model, the moving direction (just before reaching the current position) is regarded as a front direction. The intensity of involvement obtained from a relative position that consists of distance r and absolute value of relative angle θ is expressed as follows:

$$F(r, \theta) = f(r)g(\theta), \quad (1)$$

where $f(r)$ and $g(\theta)$ are monotonically decreasing functions. When agent P and target Q exist in the same place, the intensity of involvement from P to Q is obtained by r and θ_{PQ} , and the involvement from Q to P is obtained by r and θ_{QP} . Note that r is the distance between P and Q , θ_{PQ} is the relative angle from P to Q , and θ_{QP} is the relative angle from Q to P (Figure 2).

Fig. 3. Physical features when the agent and target move. The former moves to reduce or increase intensity of aggressive and passive involvement based on internal state.

3.3 Utility Function and Behavior

The agent's evaluation of the spatial relationship at a point in time is calculated by the utility function. P 's utility function is obtained by the sum of the involvement from P to Q weighted by P 's control value $c(z)$ and the involvement from Q to P is weighted by P 's acceptance value $a(z)$:

$$u(z, r, \theta_{PQ}, \theta_{QP}) = c(z)F(r, \theta_{PQ}) + a(z)F(r, \theta_{QP}). \quad (2)$$

We assume that the agent continuously evaluates the spatial relation and moves to increase the utility value each time. This model does not focus on the change in the utility value due to the behaviors of P and Q ; it simply focuses on the change in the utility due to P 's own behavior.

Agent P_t and target Q_t at time t change to P_{t+1} and Q_{t+1} at time $t+1$ (Figure 3). When the agent's internal state does not change, the agent behavior satisfies the following:

$$u(z, r_{P_t Q_t}, \theta_{P_t Q_t}, \theta_{Q_t P_t}) \leq u(z, r_{P_{t+1} Q_{t+1}}, \theta_{P_{t+1} Q_{t+1}}, \theta_{Q_{t+1} P_{t+1}}) \quad (3)$$

4 EXPERIMENT

To verify the proposed model, we re-analyzed a previous dataset [Sakamoto and Takeuchi 2015] and observed the interactions between humans just with position information. The position of the participants was mediated by the robots with each other. The dataset contains speaking data not for communicating with the partner but for observations about what they thought or felt during the interactions.

4.1 Setup

We used two rooms as the experimental environment (Figures 4 and 5). Both rooms were constructed with similar equipment. A three-meter diameter circle constituted the delimited field of the participant movements. In both rooms, the positions of the participants were mirrored by robots in another room. The robot position in one room mapped the participant position in the other room. In this way, each participant interacted with the other participant without any awareness of the other.

We used a robot that was covered with an outer case and had three omni wheels that could move in any direction (Figure 6) controlled by Bluetooth. The robot's position was calculated by encoders and corrected by image processing through a video camera. The experimental system was implemented in C++, and OpenCV was used for image processing.

The position coordinates of the participants on the two-dimensional plane were measured using a laser rangefinder (URG-04LX, Hokuyo Automatic Co.) set at a height of 1 m. The laser rangefinder measured the distance of the surrounding objects every 1 degree. The midpoint of the position

Fig. 4. Experimental setup: Two-dimensional positions of robots are synchronized with the position of participants in another room.

Fig. 5. Interaction scene.

3WD 100 mm Omni Wheel Mobile Robot
(Nexus Automation Limited)

- Dimensions: 305 mm x 305 mm x 126 mm
- Speed: 0.6 m/s

Fig. 6. Appearance and features of robot.

coordinates of the object detected in the field was made to be the position coordinate of the participant, because only the participant existed in the field at the height at which the laser rangefinder was set. The laser rangefinder communicated with the computer through an official driver via USB.

The position data of the participants and the robots were transmitted to and from the computer in another room by socket communication. These data were recorded as log data every 125 ms. The participants wore a headset and voice recorder to gather utterance data, which was transcribed after the experiment.

4.2 Procedure

We separately guided the participant pairs into the rooms without providing any knowledge of their respective partners. Before interacting with the robot, the participants practiced thinking aloud. They were instructed to talk about any of their feelings or thoughts as the experimental task (think-aloud protocol). They performed a 5-minute tangram puzzle to practice thinking aloud. The participants were instructed to think aloud as they did during practice and to move freely within the delimited field circle. The participants were given the following instructions and

information about the robot: the robot may move in the field, the participant is not allowed to kick or straddle the robot, the participant is not to hurt the robot or be broken by contact, the robot has no function to recognize voices, and the experimental task (think-around) does not affect the robot. In this phase, two types of instructions were given to the participants according to the experimental conditions.

Informed participants (IN). We gave the participants two pieces of information: the robot's movement mirrored the other participant's position, and their position was identically conveyed to their partner through a robot in another room. The participants were instructed to inform their partner of their existence.

Uninformed participants (UNIN). These participants were not told about the robot or the robot's behavior. They were simply instructed to move freely in the field.

The participants were guided to their initial standing position in the field. The initial position was at $x = 0$ mm, $y = 2,500$ mm in one room and $x = 0$ mm, $y = -2,500$ mm in the other room with respect to the center of the circle. After confirming that these instructions were completed in both rooms, the experimenter activated the experimental system. The participants were left alone in the room. They interacted with the robot for 7 minutes, and the start and end of the think-aloud protocol were signaled by beeps. Finally, the participants answered questionnaires.

4.3 Conditions

In this experiment, we set two types of pairs: IN-UNIN and UNIN-UNIN. The IN-UNIN pairs consisted of both informed and uninformed participants, and the UNIN-UNIN pairs consisted of only uninformed participants. Thus, the participants were assigned three conditions. In the IN-UNIN condition, the participants were IN and interacted with a UNIN participant. In the UNIN-IN condition, the participants were UNIN and interacted with an IN participant. In the UNIN-UNIN condition, the participants were UNIN and interacted with a UNIN participant.

IN-IN pairs were not constructed. In this combination, participants would know from the beginning that they could interact with each other, so we could not observe the initial phase of communication.

4.4 Participants

Our volunteer participants were Japanese informatics or engineering students ($N=38$, mean age=20.25, standard deviation of age =1.199, 22 males and 16 females). We randomly assigned 12 pairs to IN-UNIN and 7 pairs to UNIN-UNIN condition.

5 DATA ANALYSIS

5.1 Example of Interaction

Figure 7 shows examples of the trajectories of the participants in each internal, and the position and the direction at a certain time were represented by a triangle. The green triangles represent position of the robot. In the assertive state, the motion was toward the back of the partner. In the submissive state, the motion was toward the front of the partner. In the reciprocal and avoidant conditions, the distancing motion was dominant.

Figure 8 shows an example of an interaction's description in the experiment by the model. The top shows the time series of the utterances and the internal state estimated by the spacing behavior (see Section 5.3.1 for details of the estimation method) by colors. The bottom of Figure 8 shows the trajectories of the participants, and the position and the direction of the participant at a certain time were represented by a triangle. The estimated internal state values were expressed in color.

Fig. 7. Examples of trajectory and estimated internal states (see Section 5.3.1 for details of the estimation method).

Fig. 8. Example of spacing behavior, change of estimated internal states, and utterance data (IN-UNIN pair). Color plots and triangle colors represent estimated internal states (see Section 5.3.1 for details of the estimation method). Triangles represent position of participant pair of each frame. t is the duration time, and it represents the start time and end time of UNIN and IN movement, respectively.

It was expected that the temporal change in internal state estimated from the behavior would represent the process of initiating communication. The informed participant IN_1 tried to involve the partner from the beginning of the experiment because of the instructions. Therefore, internal state $\hat{z}$, which was estimated from the behavior, is more frequently observed as a reciprocal state than the other states. IN_1 showed both approaching and revolving behavior around the partner. Since the uninformed participant UNIN_1 did not know about the robot's behavior before the interaction, they avoided the approaching robot at the beginning of the interaction. At the same time, UNIN_1 talked about the robot's approaching behavior. At 80 seconds, UNIN_1 conversely started approaching the robot. This change was indicated by the transition of UNIN_1's internal state from the avoidant to the reciprocal state. In response, IN_1 moves away from its partner. IN_1's internal state estimated the avoidant and assertive states to move away from the partner's front because of this response.

As shown in this example, we expect that the model will improve the descriptions of spatial interaction by changing the internal states during interaction. In the following, we did three analyses to show the model's validity for describing the spacing behavior of humans.

5.2 Evaluation of Behavior by Utility Function

To validate the model, we investigated whether participants showed behavior that matched the model. We evaluated whether the participant behavior increased the utility value calculated by the model. We estimated the internal states of the participants by their behavior and examined how long they increased the utility value. We compared the rates of the participant behaviors to increase the utility value with a random walker.

5.2.1 Method. We evaluated the rate of frames that increased the utility value as an indicator of how the participants conformed to the model. To obtain the utility values, four functions must be set: $a(z)$, $c(z)$, $f(r)$, and $g(\theta)$. Since $c(z)$ and $a(z)$ are functions for obtaining weights from an internal state, they were set to the following values:

$$c(z) = \begin{cases} 1 & (z = (+, -), z = (+, +)) \\ -1 & (z = (-, +), z = (-, -)) \end{cases}, \quad (4)$$

$$a(z) = \begin{cases} 1 & (z = (-, +), z = (+, +)) \\ -1 & (z = (+, -), z = (-, -)) \end{cases}. \quad (5)$$

We set $f(r)$ and $g(\theta)$ as follows as a monotonically decreasing function:

$$f(r) = \frac{r_{\max} - r}{r_{\max}}, \quad (6)$$

$$g(\theta) = \frac{\pi - \theta}{\pi}, \quad (7)$$

where $r_{\max}$ is the maximum interaction distance of the field's diameter (600 pixels).

In this study, since the field was limited, the above equation was used as a monotonic decreasing function. In other situations, however, the inverse of distance can be used as the function.

We obtained the distance r and absolute value of relative angle θ from the position coordinates of the participants and the robot. The distance r_{PQ} between the participant and the robot was determined as follows

$$r_{PQ} = \sqrt{(x_Q - x_P)^2 + (y_Q - y_P)^2}, \quad (8)$$

Fig. 9. Division of behavioral data into sequences.

where (x_P, y_P) and (x_Q, y_Q) are coordinates of the participants and the robot, respectively. The absolute value of relative angle θ_{PQ} was determined as follows:

$$\theta_{PQ} = \left| \arctan \frac{y_Q - y_P}{x_Q - x_P} - \arctan \frac{y_P - y_{P_{t-1}}}{x_P - x_{P_{t-1}}} \right|, \quad (9)$$

where $(x_{P_{t-1}}, y_{P_{t-1}})$ are the previous coordinates of the participants. The absolute value of relative angle θ_{QP} was determined as follows:

$$\theta_{QP} = \left| \arctan \frac{y_P - y_Q}{x_P - x_Q} - \arctan \frac{y_Q - y_{Q_{t-1}}}{x_Q - x_{Q_{t-1}}} \right|, \quad (10)$$

where $(x_{Q_{t-1}}, y_{Q_{t-1}})$ are the previous coordinates of the robot.

The following is the utility function of Equation (2):

$$u(z, r_{PQ}, \theta_{PQ}, \theta_{QP}) = c(z) \frac{(r_{\max} - r_{PQ})(\pi - \theta_{PQ})}{r_{\max}\pi} + a(z) \frac{(r_{\max} - r_{PQ})(\pi - \theta_{QP})}{r_{\max}\pi}. \quad (11)$$

The absolute of the first term increases when P approaches Q 's position, and the absolute decreases when P moves away from Q 's position. The absolute of the second term increases when P is located in the Q 's moving direction and near Q 's position, and the absolute decreases when P is located in the opposite of Q 's moving direction and Q 's far position. Therefore, the behaviors that cause P to increase the utility value is as follows: when P 's control $c(z)$ is positive, P approaches Q 's position; when P 's control $c(z)$ is negative, P moves away from Q 's position; when P 's acceptance $a(z)$ is positive, P moves toward Q 's moving direction; when P 's acceptance $a(z)$ is negative, P moves away from Q 's moving direction. Figure 7 illustrates examples of the trajectories estimated for each internal state.

Although the participant's internal state changes based on the situation, the same internal state is maintained within a certain number of frames. Thus, the time series of the behavioral data was cut and divided into sequences consisting of frames, as shown in Figure 9. The sequences were delimited in the following two cases: cases in which the participants greatly changed their moving direction and cases in which they stopped moving. In particular, the behavioral data were specifically cut and divided into sequences at the frames in cases in which the movement angles exceeded $\pi/3$ or the movement velocity was zero. We excluded from analysis the sequences in which participants stopped because the model was addressing movement. Sequences of fewer than four frames were also excluded because such movements were too small.

Fig. 10. Calculation of $\hat{z}_0^i$.

When the participant's behavior satisfies Equation (3), it is defined as a behavior by the proposed model. To apply Equation (3), it is necessary to assume the participant's internal state. If the participant moved based on Equation (3), a frame's internal state can be estimated from the difference between the utility values of the frame and the next frame. Assuming that the internal state did not change within the sequence, the participant's internal state was estimated from the sequence's first frame, as shown in Figure 10. Equation (3) specifies only the increase of utility. Therefore, the estimation value of the internal state by using differences in utility is not always determined by only one value. However, only one of the four states has positive values in both the first and second terms of Equation (11). Therefore, we obtained estimated internal state $\hat{z}_0^i$ of the first frame of sequence i :

$$\hat{z}_0^i = \underset{z}{\operatorname{argmax}} \left\{ u \left(z, r_{P_1^i Q_0^i}, \theta_{P_1^i Q_0^i}, \theta_{Q_0^i P_1^i} \right) - u \left(z, r_{P_0^i Q_0^i}, \theta_{P_0^i Q_0^i}, \theta_{Q_0^i P_0^i} \right) \right\} \quad (12)$$

Assuming that the internal state did not change within the sequence, the participant's internal state was estimated from the sequence's first frame. Assuming that the internal state of sequence i was $\hat{z}_0^i$, we calculated the proportion of participants who are acting by the model. From Equation (3), evaluation value v_j^i of frame j of sequence i is defined as the amount of the change of the utility value and is obtained:

$$v_j^i = u \left(\hat{z}_0^i, r_{P_{j+1}^i Q_j^i}, \theta_{P_{j+1}^i Q_j^i}, \theta_{Q_j^i P_{j+1}^i} \right) - u \left(\hat{z}_0^i, r_{P_j^i Q_j^i}, \theta_{P_j^i Q_j^i}, \theta_{Q_j^i P_j^i} \right) \quad (13)$$

Rate α is obtained at which the participant showed behavior conforming to the mode:

$$\alpha = \frac{|\{v_j^i | v_j^i > 0\}|}{|\{v_j^i\}|} \quad (14)$$

We calculated α for each internal state and compared α between the participant and a random walker. To generate a random walk, we set the initial position of each sequence by the participant's position in its first frame. The next position of the random walker is a random position with a movement angle within $\pi/3$ and a movement distance within 15 pixels. We calculated the random walkers' frame rate with increased utility by the average values of 100 trials in each sequence. The chi-square test was used to test for the difference between α of participants and α of a random walker.

To verify the internal state and utility functions, we compared the proposed model with the distance and exclusive two involvement models. The distance model agent increased (or decreased)

Table 1. Rate of Frame with Increased Utility

	Rate α		χ^2	Cohen's h
	Participants	Random walker		
Assertive	0.663 (6,811/10,931)	0.486 (5,309/10,931)	417.2***	0.277
Submissive	0.600 (4,205/7,010)	0.489 (3,426/7,010)	174.1***	0.224
Reciprocal	0.638 (9,291/14,559)	0.487 (7,089/14,559)	676.1***	0.306
Avoidant	0.702 (9,014/12,843)	0.488 (6,261/12,843)	1223.3***	0.441

*** $p < 0.001$.

Table 2. Comparison of Rate of Frame with Increased Utility between Models

	Proposed model	Distance model	Exclusive two involvement model
Rate α	0.647 (29,321/45,343)	0.622 (28,216/45,343)	0.628 (28,473/45,343)
χ^2 with proposed model	—	57.95***	34.22***
Cohen's h	—	0.051	0.039

*** $p < 0.001$.

the distance and relative angles simultaneously. Only two sets of internal states exist in the distance model: the reciprocal state $z = (+, +)$ and the avoidant state $z = (-, -)$. The distance model is one in which the internal state variables are integrated into one variable. The exclusive two involvement model uses only one of the two terms of Equation (11). Our model does not assume that the values of control or acceptance are zero. In contrast, the internal state of the exclusive two involvement model assumes that the control and acceptance values are independent, so one takes the value of zero. Therefore, the internal states of the alternative model differ from the four internal states (assertive/etc.). In other words, there are four sets of internal states in the exclusive two involvement model: $z = (+, 0)$, $z = (-, 0)$, $z = (0, +)$, and $z = (0, -)$. Here, $a(z)$ is assumed to be 0 for $z = (+, 0)$, and $z = (-, 0)$; $c(z)$ is assumed to be 0 for $z = (0, +)$ and $z = (0, -)$. Although an agent in this model has preferences for two involvement, the agents do not consider both together. The agent takes behavior exclusively by considering only one involvement.

We calculated the α for each model and carried out chi-squared tests to compare these two models with the proposed model.

Note that analyses in this study were coded and run using RStudio version 1.2.1335 with R version 3.6.0.

5.2.2 Results and Considerations. Table 1 compares the rate α of frames in which the utility value of the participant increased with the α of the random walker. The results showed that the α value of the participants was larger than that of the random walker in all four conditions (assertive state: $\chi^2 = 417.2$, $h = 0.277$, $p < 0.001$; submissive state: $\chi^2 = 174.1$, $h = 0.224$, $p < 0.001$; reciprocal state: $\chi^2 = 676.1$, $h = 0.306$, $p < 0.001$; avoidant state: $\chi^2 = 1223.3$, $h = 0.441$, $p < 0.001$)

This result indicates that participants showed more behavior that conformed to the model than random motion. Our model appropriately represents approaching and avoiding behaviors when assuming four states. We only consider the internal state of the participants at this stage. The participants changed their behavior based on the robot behavior, which described the internal state. By focusing on this point, it is necessary to verify the relationship between the internal state of the participant and the robot as future work.

Table 2 shows the alpha comparison between the proposed model versus the distance and exclusive two involvement models. As a result, the alpha value of the proposed model was significantly larger than the other models (the distance model: $\chi^2 = 57.95$, $h = 0.051$, $p < 0.001$; the exclusive

two involvement model: $\chi^2 = 34.22$, $h = 0.039$, $p < 0.001$). From this fact, the validity for using two variables of the internal state and the calculation of the utility function of Equation (11) can be verified.

5.3 Relationship between Internal State and Utterances

In this section, we examine whether the internal state of the model is consistent with the human recognition of behavior. This section analyzes the relationship between the content of the speech being interacted with and the internal state estimated from the partner's behavior. If the utterance's content conforms to the internal state estimated by the partner's motion, the participants are focusing on the motion based on the model.

5.3.1 Method. The internal state, which was exposed by the robot behavior (it was actually performed by other pairs of participants), was estimated using the model's utility function. The behavioral data were divided into sequences in the same way as in Section 5.2. From Equation (3), the internal state of each sequence was presumed to be the state in which the utility value most increased among the four internal states. We obtained internal state $\hat{z}^i$ exposed by the interaction partner by the motion of sequence i :

$$\hat{z}^i = \underset{z}{\operatorname{argmax}} \left\{ \sum_j u \left(z, r_{P_{j+1}Q_j^i}, \theta_{P_{j+1}Q_j^i}, \theta_{Q_j^i P_{j+1}^i} \right) - u \left(z, r_{P_j Q_j^i}, \theta_{P_j Q_j^i}, \theta_{Q_j^i P_j^i} \right) \right\} \quad (15)$$

Utterance data were transcribed by the first author using ELAN (EUDICO Linguistic Annotator) timeline-based annotation software. Requests to third-party transcription companies in Japan (Voitex, ASCA21 Inc.) were made for audio files only. The concordance rate of the segmented points of the utterances was 0.715 ($m/[m+d]$), where m is the number of utterances with matched split points and d is the number of discrepancies). The segmented points were adjusted to match the more detailed segmented points. The concordance rate of utterance was 0.932 ($c/[c+i]$), where c is the number of congruent utterances and i is the number of incongruent utterances). Because the concordance rate was high, the analysis was conducted using the first author's transcription data. The total number of participant utterances was 2,243. Based on the duration time of the experiment, the utterance data and the internal state estimated from the behavior of the partner participant in the opposite room were associated. Specifically, the utterance was associated according to the internal state of the partner at the beginning of the utterance. If the utterance was started at the time the partner stopped, the utterance data were excluded from the analysis. This association between speech and behavioral data and the exclusion of utterance data was conducted mechanically based on the timestamp of the log data. The utterances were associated with 228 Assertive, 99 Submissive, 175 Reciprocal, and 179 Avoidant states. It should be noted that the utterance data included comments on the participant's own actions and comments unrelated to the robot. However, it can be said that they were mainly utterances related to the robot, because the utterances that started while the robot moved were excluded, as described above.

Words were extracted from the utterance data by morphological analysis using RMeCab, a library for Japanese text mining of the R language. A total of 704 words were extracted. Among them, words of grammatical parts of utterances other than nouns, verbs, and adjectives and words with a frequency of less than 10 were excluded from the analysis. Finally, 17 words were tabulated for each internal state of the partner's behavior. All of the utterances were observed in Japanese and translated into English after word extraction and aggregation. The relation between each state and extracted words was verified by the chi-square test and the residual analysis. We calculated the standardized residuals of each word. If the standardized residual is regarded as the z score in a

Table 3. Frequency and Standardized Residual of Words in Each Internal State Estimated from Robot Motion

Word	Japanese	Assertive	Submissive	Reciprocal	Avoidant
move	(動く)	18 -0.391	11 1.443	13 -0.961	18 0.285
do	(する)	13 -1.459	10 1.335	18 1.081	14 -0.532
come	(来る)	17 2.024	3 -0.812	11 0.543	5 -2.031
stop	(止まる)	9 -0.390	2 -1.077	9 0.301	11 0.901
approach	(近づく)	4 -2.200	3 -0.384	11 1.414	11 1.172
avoid	(逃げる)	3 -2.023	2 -0.584	5 -0.557	13 3.070
chase	(追いかける)	11 2.241	2 -0.362	0 -2.771	7 0.664
no	(ない)	3 -1.566	6 2.548	5 -0.042	5 -0.213
great/awesome	(すごい)	14 3.967	0 -1.697	3 -1.104	2 -1.775
motion	(動き)	4 -0.925	0 -1.650	8 1.737	6 0.468
afraid	(怖い)	2 -1.841	7 3.622	7 1.375	1 -2.108
out	(出る)	13 4.287	0 -1.551	2 -1.313	1 -2.009
crash	(ぶつかる)	4 -0.466	1 -0.708	6 1.183	4 -0.157
become	(なる)	6 0.661	2 0.084	1 -1.790	6 1.009
go around	(回る)	4 0.301	0 -1.278	6 2.113	1 -1.444
leave	(離れる)	4 0.536	1 -0.253	0 -1.934	5 1.528
understand	(分かる)	1 -1.520	1 -0.253	3 0.236	5 1.528

standard normal distribution, ± 1.96 is the threshold of 5% significance. Therefore, we regarded a cell with a standardized residual of over 1.96 as highly frequently observed.

5.3.2 Results and Considerations. Table 3 shows the words and standardized residuals that were observed 10 or more times in descending order in each internal state exposed by the interaction partner. As a result, the frequency of these words was significantly different for each internal state (chi-square test with simulated p-values for small sample size: $\chi^2 = 119.26$, Cramer's $V = 0.298$, $p = 0.005$).

Fig. 11. Examples of the trajectories of participant and robot when the participant uttered the high-appearance frequency word.

The residual analysis results show that words with a high appearance frequency are different for each internal state estimated from the partner's motion. In particular, when the partner's $\hat{z}^i$ was in the assertive state, "come," "great/awesome," "out," and "chase" were uttered at a high frequency. When the partner's $\hat{z}^i$ was in the submissive state, "afraid" and "no" were uttered at a high frequency. When the partner's $\hat{z}^i$ was in the reciprocal state, "go around" was said at a high frequency. When the partner's $\hat{z}^i$ was in the avoidant state, "avoid" was said at a high frequency.

Figure 11 shows examples of a participant's and robot's trajectories when the participant uttered frequent words. When the internal state was assertive, an agent of the model approached the target from behind the target's moving direction. The participants described that the robot came from behind; the words "come" and "chase" correspond to the assertive state. The agent of the model is assumed to have a region of involvement in the forward direction. An agent moving to behind a partner is regarded as preferring involvement to itself but not from the partner; such agents are considered to have an assertive state. The correspondence between "great/awesome" or "out" and the assertive state seems to depend on the experimental settings. The participants—especially those who did not know about the robot—were likely to be surprised when they realized they were being recognized by the robot. In the experimental situation, the opportunity for participants to notice the robot's recognition seemed to be limited to the robot's chasing behavior. When the robot nearly went out of the field, the participant made utterances, including "out." This is likely to occur when both the participant and the robot rotate around the interaction field of the experiment (see Figure 11). The relation between "out" and the assertive state is assumed to be caused by the setting of the experiment field.

When the internal state is submissive, an agent of the model approaches the target from the front of the target's moving direction. As shown in Figure 11, when a robot shows a movement to overtake, the participant makes an utterance, such as "afraid." The word "no" was said when the robot took no response to the participant's behavior. When the robot moved in front of participants, these participants seemed to regard the robot as unresponsive. It may be unnatural to

Table 4. Observation Ration of the Internal State Estimated from the Participants Motion in Each Condition

	Assertive state	Submissive state	Reciprocal state	Avoidant state
IN-UNIN	21.3%	15.2%	33.5%	29.9%
UNIN-IN	31.3%	11.7%	24.9%	32.1%
UNIN-UNIN	29.5%	16.2%	23.2%	31.1%

regard these movements as submissive. These actions are considered to be the result of replacing the body direction with the moving direction.

When the internal state is reciprocal, an agent of the model approaches the front of the target. The participant described the robot as having moved in the direction of the participant in advance; the phrase “go around” corresponds to the reciprocal state. This could be regarded as reciprocal because they were close to each other.

When the internal state was avoidant, an agent of the model chose to distance themselves from the target. The participant directly described the robot as having chosen distance; the word “avoid” corresponds to the avoidant state.

Regarding the motion of the internal states (especially assertive, avoidant, and reciprocal), the participants directly described robot motions using different words. The participants used different words depending on the robot’s approach trajectory. This corresponds to the internal states of the model. These results suggest that the internal states of the model coincide with the human recognition of spatial behaviors.

5.4 Relationship between Internal States and Suggestions

In this section, we validate the correspondence between the recognition of the partner and the internal state of the model. Our analysis shows the relationship between the suggestions given before the interaction and the internal state estimated from the participant’s motions. If the suggestion influences the observed frequency of the internal state of the model, it means that the model can describe the human’s recognition of the partner.

5.4.1 Method. The behavioral data were divided into sequences in the same way as in the previous sections. We obtained internal state $\hat{z}^i$ of the participants estimated from the motion of each sequence by Equation (15). For each experimental condition, the number of the sequences of each internal state was summed up and the ratio of each internal state was calculated. We carried out chi-squared tests on the experimental conditions and the estimated internal states of the participants. After that, we carried out multiple comparisons via pairwise Mann-Whitney U tests with Holm’s correction method. We compare the median frequency of the internal states exhibited by each participant’s behavior. The number of sequences for each internal state were summed up for each participant. The frames for each sequence were summed and converted into seconds.

5.4.2 Results and Considerations. Table 4 shows the ratio of the internal states estimated from the behavior of the participants. From chi-squared test results, the frequency of the internal states estimated from the participant’s motion was significantly different depending on the experimental condition ($\chi^2 = 796.97$, $df = 6$, Cramer’s $V = 0.094$, $p < 0.001$).

Figure 12 shows the total time of the internal states estimated from the behavior of participants. In the assertive state, there were no significant differences between IN-UNIN ($Mdn = 33.00$) and UNIN-IN ($Mdn = 31.56$, $p = 1.00$), between IN-UNIN and UNIN-UNIN ($Mdn = 38.56$, $p = 1.00$), and between UNIN-IN and UNIN-UNIN ($p = 1.00$). In the submissive state, the results revealed

Fig. 12. Total time of the internal state estimated from the participants' motions in each condition. The colored bars indicate medians and asterisks indicate p-values of pairwise comparisons using Mann-Whitney U tests with Holm's correction method; * $p < 0.05$, ** $p < 0.01$.

significant differences between IN-UNIN ($Mdn = 22.75$) and UNIN-IN ($Mdn = 12.00$, $p = 0.04$) with no significant differences between IN-UNIN and UNIN-UNIN ($Mdn = 13.06$, $p = 0.13$), and between UNIN-IN and UNIN-UNIN ($p = 0.61$). In the reciprocal state, the results revealed significant differences between IN-UNIN ($Mdn = 61.44$) and UNIN-IN ($Mdn = 25.94$, $p = 0.003$), and between IN-UNIN and UNIN-UNIN ($Mdn = 24.75$, $p = 0.04$) with no significant differences between UNIN-IN and UNIN-UNIN ($p = 0.82$). In the avoidant state, there were no significant differences between IN-UNIN ($Mdn = 47.56$) and UNIN-IN ($Mdn = 29.94$, $p = 0.30$), between IN-UNIN and UNIN-UNIN ($Mdn = 34.88$, $p = 0.30$), and between UNIN-IN and UNIN-UNIN ($p = 0.60$).

Under the IN-UNIN condition, the participants, who received suggestions about interacting with the robot and knew that its movement mirrored the other participant's movement, frequently chose behaviors of reciprocal states. Due to the effect of the suggestions, the participants tried to get involved with their partner and to accept involvement with that person at the beginning of encounters. The participants tended to choose acceptance values that were more positive than other conditions. However, the tendencies of the internal states under UNIN-IN and UNIN-UNIN participants who were not given suggestions about the robot seem similar. The participants under the IN-UNIN could influence under UNIN-IN behavior. However, participants took various responses. Therefore, this effect is considered to be small as a tendency. These results suggest that the internal state of the model estimated from the behavior can describe the difference of the recognition of the partner.

6 DISCUSSION

6.1 Summary and Future Works

In our first analysis, we verified that participants showed approaching and avoiding behaviors to the robot following our proposed model. The rate of participants' behavior to raise the utility value of the model significantly exceeded 0.50 and was also greater than the random walker rate. This result suggests that humans show behavior based on our proposed model in the interactions just using position.

Our second analysis tested the validity of four internal states, assertive, submissive, reciprocal, and avoidant, where the proposed model was represented by a combination of two types of involvement. The frequency of each word uttered by the participants during the interaction was significantly different for each internal state that was estimated from the behavior of the interaction partner. In particular, the partner's behaviors to reduce the distance were classified as assertive, reciprocal, or submissive, but the frequencies of the words used to describe these behaviors were different between each state. The participants used different words for their partner's behavior of each state because they recognized that these behaviors were different. These results indicate that internal states in the encounters consist of two types of involvement.

The third analysis tested whether the actual internal states of the participants set by suggestions appeared as behavior during interactions. The observed times of the reciprocal state of the participants who were encouraged to interact with their partners exceeded the observed times without any suggested condition. This result shows that a change of the internal state of the participants appears in the behavior; this change can be described by our model. These results suggest that our scheme is valid and can model human internal states and behaviors in interaction between encounters only with position information.

Based on the model, we can generate the robot's own behavior and estimate the internal state of human partners. The robot can choose a behavior to increase the value of the utility by changing its relative position with the partner. Similar to our analysis, we can also let the robot estimate the internal state of a partner by assuming that she acts to increase the model's utility function. By setting a combination of control and acceptance as an internal state, we represented the elements that revolve around the object in approaching or avoiding trajectories.

Humans generally prefer a robot that approaches from the side rather than from the front [Dautenhahn et al. 2006]. They also tend to approach by moving around objects and avoiding the front of them when approaching to open a conversation due to the internal state of objects [Yoshioka et al. 2018]. Based on our model, these trends are influenced by the internal state that is expressed by approaching behavior. This point must be verified in the future using a robot with an apparent body direction.

6.2 Limitations

In this study, modeling and verification were carried out with as few elements as possible for simplification purposes. Verifying whether the model can describe interactions similarly for robots with more complicated shapes is necessary. The appearance of the robot gives expectations during communications with humans. For example, the shapes of the face and body indicate which direction the robot is facing. The size and height of the robot can also affect the prediction of behavioral characteristics, such as moving speed. How these features affect the intensity of involvement should be examined. For example, Walters et al. [2009] proposed to adjust the settings of robots' proxemics according to the robot's appearance and context. Such adjustments may be used to calculate the utility values in our model. Physical features such as the height could be incorporated into the utility function as parameters. However, the relation between distance or body angle and intensity seems to be universal—intensity is represented by a monotonically decreasing function of distance and body angle. By experimenting with the use of different appearances in the robot, the relationship between appearance and intensity can be verified.

We treated only three variables: physical properties, distance, and relative angles. To implement communications robots, it is necessary to extend the model by increasing variables of physical features. What variables are used depends on the form of the robot. When we focus new variables, we need to newly define functions that represent correspondence with the intensities of involvement. This means expanding the channels of communication within the model. At first, it is necessary

to carry out verifications by the robot with explicit body directions instead of moving directions. Other extensions include handling body orientation and gaze direction separately and some gestures. In some studies, gaze and head nodding are used as social signals in robots to represent engagement during interactions (e.g., Hall et al. [2014]). The correspondence of these actions with the control and acceptance of internal conditions will be examined in future work. For example, high acceptance could cause a nod, and the nod could express positive acceptance. For that purpose, experiments will have to be carried out using various types of robots.

This study mainly analyzed spontaneous interactions without an experimental task or a purpose in the participants. There was only one condition that set the purpose in this study. Under the condition of the given instruction, the frequency of behavior estimated as the reciprocal state increased compared to spontaneous interactions. To clarify the relation between internal states and behaviors, it is necessary to observe interactions when given corresponding suggestions or experimental tasks that coincide with the other three internal states: assertive, submissive, and avoidant. For example, a situation where a participant hands an object to a robot is considered to be a situation that occurs in the assertive condition, a situation where a robot hands an object to a participant is considered to occur in a submissive condition, and a situation where a participant does other tasks and does not want to be involved with the robot is considered to occur in the avoidant condition. Internal states could be estimated based on the trajectory of human spatial behaviors in these situations. The validity of the model will be supported if the observation frequency of internal states estimated from behaviors increase according to the situation.

The experiments in previous studies ([Sakamoto and Takeuchi 2015]) were not designed for the current analysis. The instructions given to the participants contained two types of information: (1) whether they know the robot is mimicking a person's movement and (2) whether they are told to actively attempt to inform their partner of their presence. It is necessary to separate the effects of the experimental task from knowing whether the robot's movements mimic a person's movement. Distinguishing between these effects requires experimental conditions in which participants simply know that the robot is performing mimicry.

At this stage, although our model clarifies the internal state expressed by a behavior during an interaction using position information, it does not represent how internal states are changed through the interaction. Humans change their internal states according to the behavior presented by others. Assuming an interaction between agents that conform to the same model, the behavior of another directly expresses the internal state. We can improve the model by incorporating a structure that changes the internal state when an agent observes the behavior of another agent. This result responds to the opponent's behavior that can be represented by the model.

The analysis of the relational aspects in conversation encodes the relational control included in utterances and specifies patterns of codes [Rogers et al. 2014; Rogers and Farace 1975]. In both studies, the codes of responses were tabulated based on previous codes, and the tendency of the observed frequency is regarded as a characteristic of the relationship between the speakers. In conformity with this analysis method, the interaction tendency can be analyzed by aggregating the internal state expressed by the previous partner's behavior and the internal state that responds to it. However, in the initial communication phase, unlike a conversation, a turn's composition is vague. The reaction time can affect the estimation of the internal state of the behavior. Regarding this point, the influence of the robot's reaction speed is addressed in this experimental environment. Further research is needed to extend the model so that robots can anticipate and generate behaviors based on human behavior.

For estimating the internal states of other agents in more real situations, the model needs to consider how to associate with the reflective process. At this stage, estimation of the internal state in the model is directly obtained only from the observable behavior of the other agent. When

the agent is placed in a complicated situation, the internal state expressed by the behavior may differ from the actual internal state of the other agent. For example, when an agent approaches a destination from behind the other agent, the estimation of the direct process is evaluated by the agent's internal state to the other agent as high values of control and acceptance. Estimating the internal state, which is directly expressed from the behavior of the other agent, is required, but the reflective process of estimation is also required in which the agent uses the environmental features and the interaction context. To solve this problem, a previous method estimates the internal state by Bayesian inference, assuming that the agent's behavior is optimized for the goal [Baker et al. 2009, 2011]. We need to consider how control and acceptance values that are used in the direct process can be used for the reflective process. By doing this, we can verify future models where the robot can reproduce such complicated behaviors as those based on human partners.

7 CONCLUSION

We proposed an agent model for interaction just using position information as cues in encounters. Our model uses four internal states that consist of a combination of positive and negative for all the preferences for both aggressive and passive involvement. The agent's evaluation of the spatial relationship at a point in time is calculated by the utility function and uses behavior to increase the utility value.

To verify the proposed model, we analyzed human-human interaction that just depends on position information through simple-shaped robots. In our first analysis, we calculated the rate of the frames in which the participants increased their utility value and compared the rate with random walkers. Since the rate of the participants significantly exceeded the rate of the random walkers, the model seems to appropriately represent approaching and avoiding behaviors in the experimental situation. Based on this result, we analyzed the internal state during interactions predicted from the behavior of participants. In our second analysis, we tested the validity of four internal states by showing a correlation between the words of utterances and the internal states estimated from the behavior of interaction partners. In the third analysis, we tested whether the internal states of the participants who were influenced by suggestions appeared as behavior during interactions. The observed time of the internal state of the participants who received suggestions about interaction with their partner differed from the time of the participants who did not receive such suggestions. These results indicate that the model clarified the internal states expressed by behaviors during interactions using position information.

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