

The Effects of Extended Estimation on Affective Attitudes in an Interactional Series of Tasks

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Abstract—When engaged in long-term human-human interactions, we mutually estimate and construct a model of behavior. To achieve long-term, sustained human-agent interaction, the agent induces an active attitude within the human to demonstrate and share their common ground. This study aimed to investigate the effects of the agent’s estimation of a human’s preferences on the human’s affective impressions to induce an active attitude within a series of interactions. We conducted an experiment to evaluate the effect of the proposed method using two agents. The results showed that the proposed method could reduce the number of interactions in the decision-making process and improved some of the affective impressions related to the agent’s character. In addition, we found that the rate of participants’ acceptance of the proposals by the agent, which was implemented our proposed method, was significantly low. This was possible because the agent provided a consistent estimation of emphasizing points for each participant. The participants’ attitude indicates that they regarded the agent as being communicative.

Keywords—Multi-modal interaction; human-agent interaction; affective attitudes.

I. INTRODUCTION

In recent years, the development of conversational agents, such as robots and virtual agents, has rapidly expanded. However, many of these agents are regarded as multimodal interfaces that provide useful information rather than as social partners [1]. There are many issues to contend with in the production of a social partner agent. In this paper, we focus on methods for maintaining continuous interaction with such agents during long-term activities. During short-term interactions such as those occurring at front desks, shopping counters, and information offices, the quality of the interaction is “mechanical,” even between humans. Our aim is to develop an agent that could be regarded as a communicative social partner like human.

It is important that the mental state of people when they interact with the agents is the same as that when they interact with humans. The mental states that humans can be in with respect to an agent can be defined as physical stance, design stance and intentional stance [2]. When we take the physical stance, we pay attention to physical features such as the power of the motor, the spec of the display and so on. When we take the design stance, we expect that the agent works mechanically according to predefined rules. When we take the intentional stance, we consider that the agent has subjective thoughts and intentions. When a human interacts with another human, they usually take the intentional stance. In this case,

they and their communication partner respect each other. When a human interacts with a machine, they usually take the design stance. In this case, they usually interact with the machine from a self-centered perspective because they do not consider that the machine has its own intentions. To establish social relationships between a human and an artificial agent, the agent has to induce the intentional stance.

When engaged in long-term human-human interactions, we actively demonstrate and share our own preferences, mental attitudes, and inner states to facilitate smooth interaction. Through our interactions with each other, we mutually estimate and construct a model of behavior. However, in many human-agent interactions, it is difficult for the human to estimate the agent’s behavior model, because the agent and the human do not actively demonstrate and share a common ground. Consequently, the human is unable to apply a general human behavior model to the agent. To resolve this problem, previous researchers have attempted to approximate an agent’s behavior model to a generalized human behavior model. However, in the course of a long-term interaction, we expect that the behavior model will be personalized along with the interaction. Therefore, this approach is not considered suitable for developing an agent that can be regarded as a communicative social partner. To achieve long-term, sustained human-agent interaction, the agent induces an active attitude within the human to demonstrate and share their common ground..

To develop our social partner agent, we propose methods for dynamically estimating emphasizing points (DEEP) based on verbal reactions, body movements, and physiological indices. These methods aim to support interactive decision-making [3][4] and to induce an intentional stance for active interaction between a human and an agent [5]. However, these previous studies have demonstrated that it is not sufficient to investigate the effects of a model’s constructed inner state model on a human’s attitude toward the interaction within a series of such interactions. This study aimed to investigate the effects of the agent’s estimation of a human’s preferences on the human’s affective impressions within a series of interactions. We expected the provision of consistent estimation, using accumulated data on interactions, to induce a positive human attitude toward the agent and the interaction.

The paper is organized as follows. Section 2 briefly introduces previous works. Section 3 explains the outline of the proposed method which is partly described in previous works. Section 4 describes an experiment for comparing two types

of methods and then presents the results. Section 5 discusses the achievements and future work. We give our conclusion in Section 6.

II. RELATED WORK

Agents that collaboratively perform various tasks—such as subordinate support agents, when people perform tasks using their own initiative, and automated attentive agents, which automatically perform tasks in line with a human’s wishes, have been proposed previously. In addition, some researchers have developed systems that can provide proposals to satisfy a user’s demands. These systems gradually estimate user demand throughout the interaction.

Aydogan et al. [6] proposed an architecture in which both consumers and producers use a shared ontology to negotiate services. Through repetitive interactions, the provider accurately learns consumer needs to provide better-targeted offers. The system learns consumer needs through long-term interactions; however, it did not consider that user demands and needs could change during the process of the interaction. Azaria et al. [7] considered a two-player game in which an agent repeatedly supplies advice to a human user followed by an action taken by the user that influences both the agent’s and the user’s costs. That study consisted of a repeated setting that is analogous to choice-selection processes, in which a person is asked to choose a route to work from a set of possible candidates. In their study, they proposed an agent that models human behavior by combining principles from behavioral science with machine-learning techniques. In these studies, the researchers considered the effectiveness of task performance; however, they did not consider the influences on the affective attitude of the users. If a user could effectively perform a task but had poor affective impressions, the user would be hesitant to use the system or the agent. Papangelis et al. [8] argued that rapport, which is an affective attitude, had been identified as an important factor in human task.

Some studies have investigated how an agent’s advice is accepted by users. Goetz et al. [9] reported that an appropriate match between a robot’s social cues and its task improves people’s acceptance of and cooperation with the robot. Appearance is a factor that induces affective impressions. De Melo et al. [10] explored the interpersonal effect of emotions expressed by embodied agents on human decision-making. Their results show that participants are sensitive to differences in facial displays and cooperate significantly more with a cooperative agent. These results indicate that affective impressions influence human decision-making.

III. OVERVIEW OF FACILITATIVE DYNAMIC ESTIMATION OF EMPHASIZING POINTS WITH EXTENDED ESTIMATION

In an earlier study [3], we proposed DEEP method, based on verbal reactions, body movements, and physiological indices from an interaction. In Ohmoto et al. [4], we combined divergent and convergent processes with the DEEP method. We call this “facilitative DEEP” (fDEEP). In these studies, we tried to estimate “emphasizing points.” The emphasizing points are factors that we consider and emphasize to reach an appropriate decision. There are many factors which influence decision-making. We implicitly focus on some of the factors and make a decision based on the focused factors. We briefly explain the method and additionally propose “extended estimation,”

which is needed for maintaining emphasizing points in an interactional series of tasks.

A. Estimation of emphasizing points

The degree of emphasis is rated on a scale from zero to five. The rating is changed based on the following three factors in interaction between human and a system with DEEP. The system captures the factors by using cameras, microphones, motion capture systems and a measuring system for physiological indices.

1) *Verbal reactions*: Either of the following two reactions occurs.

- Listed words appear in answers or demands.
- The participant provides backchanneling phrases, which express acknowledgement, surprise, or understanding, such as “ah,” “oh,” “aha,” “I see,” and “I understand.”

2) *Body movements*: The participant repeatedly nods three times or more.

3) *Physiological indices*: Either of the following two responses occurs. (refer to [11], [12], [13]).

- Skin conductance response (SCR) increases more than 10% compared with resting levels.
- Low-frequency/high-frequency (LF/HF) value (electrocardiograph measurement) is more than 5.0.

Verbal reactions, body movements, and physiological indices, are used as criteria for determining when a new factor is discovered and should be emphasized, and for determining when a user’s degree of emphasis of a particular factor increases or decreases.

4) *Rules for changing estimated emphasizing points during interaction*: A DEEP system explains the proposals and the estimated emphasizing points change depending on the participant’s responses.

5) *Discovery of a new factor to be emphasized*: Verbal reactions, body movements, and physiological indices are the criteria for determining when a new factor is discovered and should be emphasized. When any one of the three criteria appears during interaction, the system decides that the factor should be slightly emphasized, and increases the degree of emphasis from zero to two. When any two or all three criteria are present, the system increases the emphasis from zero to three.

6) *Increasing or decreasing degree of emphasis*: Verbal reactions, body movements, and physiological indices are used as criteria for determining when a user’s degree of emphasis of a particular factor increases or decreases. When any one of the three criteria appears, the system decides that the factor should be emphasized, and increases the emphasis of the factor by one.

When there are physiological reactions, but no verbal reactions and body movements, the system decides that the factor should be emphasized less, and decreases the emphasis of the factor by one.

7) *Rules for changing estimated emphasizing points from active demands*: The system asks whether or not a user has any demands. From the user’s response, the system determines what the user’s demands are and what changes there are to the emphasizing points. The system accepts keywords which are expected words in advance to express emphasizing points,

demands, and basic words necessary to capture demands in the user's responses. Words that are not expected to be included in answers are ignored.

8) *Discovery of new factors to be emphasized*: When the emphasis degree of the discovered factor is zero, the system increases the degree of emphasis from zero to three.

9) *Increasing or decreasing degree of emphasis*: When the emphasis of the discovered factor is greater than zero and the system decides that the factor should be increased, the system increases the degree by one. When the system decides that the emphasis of the factor should be decreased and the degree is greater than zero, the system decreases the degree by one.

B. Selecting the next step based on DEEP results

According to the criteria mentioned above, changes to a user's emphasizing points are estimated after the proposals are given and data are collected from the user's reactions and responses. After the estimation, the next two proposals are selected based on the estimation results.

The next proposals are selected using a table of orthogonal arrays prepared in advance. Orthogonal arrays are a special set of Latin squares, which can be used to estimate main effects using only a few experimental runs. Each proposal in the table has parameters of emphasizing points. From the table, the proposal that most satisfies the user's emphasizing points is selected. When many proposals in the table can satisfy a user's emphasizing points, a proposal is selected according to predefined rules. The rules are designed by hand. For example, the system selects a nearest proposal in convergent process because the system knows which factor is important for the user. The distances of the proposals are calculated by cosine similarity.

C. Method to control divergent and convergent processes in an interaction

The agent which supports the user's decision-making during the interaction needs to use social signals for active listening and teaming to control divergent and convergent processes based on the estimated emphasizing points in the interaction. For the facilitative interaction, we combined divergent and convergent processes with the DEEP method (fDEEP). The used signals are the frequency of providing a new proposal, recommendation from the agent, mimicry of nodding motions, and utterances.

1) *The agent's behavior in the divergent process*: The agent provides a small nod once in reaction to the user's utterance. The frequency of providing a new proposal is low. The agent provides a new proposal after the agent explains three emphasizing points. The furthest proposal from the previous one is selected as a new proposal. The degree of emphasis decreases if the emphasizing point is not explained in the previous proposal.

2) *The agent's behavior in the convergent process*: The agent provides two large nods in reaction to the user's utterance. The frequency of providing a new proposal is high. The agent provides a new proposal after the agent explains one emphasizing point, which is a recommendation. The nearest proposal to the previous one is selected as a new proposal. The degree of emphasis decreases only when the emphasizing point is clearly refused in the previous proposal.

3) *The rules to switch between the divergent process and convergent process*: The agent starts the interaction with a divergent process. The agent switches from the divergent process to a convergent process when the agent detects the following situations:

- There are more than three emphasizing points, with a degree of emphasis of more than one, and the degree of emphasis does not change during the interaction.
- The user offers a convergent opinion such as "I want to see like this one" and "I want to determine."

4) *The emphasizing points of the agent*: The agent has the same set of emphasizing points for the decision making. The emphasizing points and the degree of emphasis are the subjective opinions of the agent. The emphasizing points are set to the values of the recent proposal at the time when the agent switches from the divergent process to the convergent process. This means that the agent searches the neighbor of the last proposal of the divergent process during the convergent process. The degree of emphasis decreases when the emphasizing point is clearly refused by the user.

D. Extended estimation through maintenance of emphasizing points within a series of interactions

In this study, we used historical estimated emphasizing points within a series of tasks to estimate emphasizing points within a new but similar task. We have termed this "extended estimation," which is similar to near transfer. There are some previous studies about knowledge transfer [14][15]; however, we cannot apply the theory directly to our actual agent system. Figure 1 illustrates the concept of extended estimation. In this example, a person is coordinating their new living space. The person first selects furniture and electronics for the living space and then plans where to place them within this space. When selecting these items, their qualities are a primary consideration. During the planning phase, the person considers the relationship between the furniture and electronic items. Thus, while selection and planning are different tasks, they are correlated. Often, an adviser who helps plan the living space estimates emphasizing points during the planning phase based on the history of those involved in the selection. This individual then offers advice based on the extended estimation. One purpose of the extended estimation is to adjust the degree of each emphasizing point in the history of the previous tasks that is to be applied in the estimation of the emphasizing points of the next task. This adjustment is based on relationships that exist between these sequential tasks and it plays a role in converting the meaning of each emphasizing point within the previous and the next tasks.

To implement the extended estimation, we have added two components to DEEP. The first is for maintaining the history of the estimated emphasizing points within a series of interactions related to sequential tasks. The second adjusts the degree of each emphasizing point to a new task. We termed this enhanced version "facilitative DEEP with extended estimation" (feeDEEP). When applied to a new task, feeDEEP converts the degree of estimated emphasizing points in previous tasks to those in the new task using predefined rules, such as a pre-designed relational network. For this study, we constructed predefined rules from the observations performed during preliminary experiments. In the preliminary experiment, we listed candidates of emphasizing points and the relationships among them. We interviewed the participants to select and determine

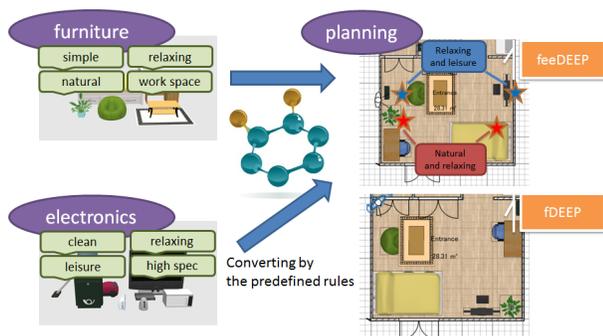


Figure 1. Example of extended estimation.

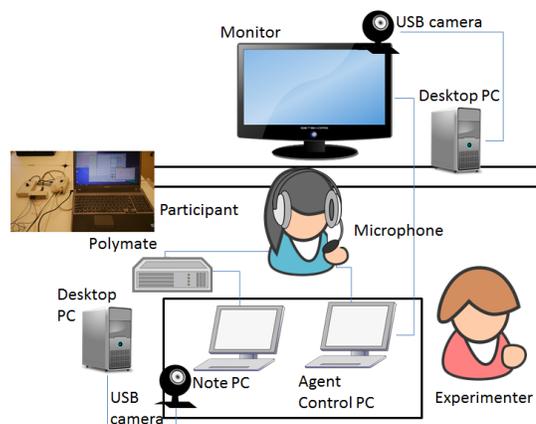


Figure 2. The experimental setting.

the emphasizing points and the weight of the relationships after the preliminary experiment. In addition, when the extended estimation achieved a degree entailing a sufficient number of emphasizing points, an agent implemented feeDEEP by initiating the interaction through a convergent process.

We expected that feeDEEP can estimate the degree of emphasizing points effectively because their initial values could be set based on user preference. The agent implementing feeDEEP could also provide affective impressions that conveyed an impression of the agent's consistent individuality to the user. These affective impressions are important for motivating users to engage in continuous interaction with the agent.

IV. EXPERIMENT

The purpose of our experiment was to investigate how feeDEEP affects the efficiency of the decision-making process and impressions related to agent behavior in an interactional series of tasks. We expected that the extended estimation will reduce cognitive load on decision-making by effective support; thus, participants would notice agent proposals that were personalized for them. We used two types of agents to evaluate the effects of the proposed method. One was an agent that implemented feeDEEP and the other was an agent that implemented fDEEP. The feeDEEP agent maintained the participant's emphasizing points; however, the fDEEP agent did not. The inputs for the agents were captured automatically, with the exception of data related to verbal meanings, such as the verbal negative feedback and the questions by the participants, because we could not robustly determine them automatically in real time, such as whether a user's utterance was positive or negative and whether the user's utterance was a question. We refer to the agent control method using manual inputs as a Wizard of Oz (WOZ) method. After the experiment, we analyzed the interaction behavior of participants and questionnaire responses.

A. Task

The participants were asked to coordinate a new living space. The primary task included three tasks, i.e., furniture selection, electronics selection, and living space planning. They first selected furniture and electronic items for the living space, and then planned where to place these items within the space. The participants interacted with the agent about the selection of items and the planning. We identified 16 factors of emphasizing points, such as relaxing, natural, for work, clean,

leisure, high spec and so on, that the participants considered when they performed each task. The factors in each task were partially the same; however, some differed. In addition, between the selection tasks and the planning task, the meanings of the same factors differed.

B. Experimental setup

The experimental setting is shown in Figure 2. A participant sat in front of a 60-inch monitor displaying the agent and the proposal. The experimenter sat out of view of the participant and entered the stimuli via a WOZ interface. Two video cameras recorded participant behavior, i.e., one was placed on the monitor to record the participant's behavior and another was placed behind the participant to record the agent's behavior. The participant's voice was recorded using microphones placed under the monitor. Polymate was used to measure SCR and an electrocardiogram. The experimenter instructed the participants to keep their left arm on an armrest.

C. Procedure

After brief instruction about the experimental procedures, the experimenter showed a video of typical interaction with the agent in a preliminary experiment in which participants performed a different task. Then, electrodes were attached to the participant to measure SCR and LF/HF values. After a 2-min relaxation period, the experimenter began the first task. The participant repeatedly asked questions about the proposal and considered the proposals provided by the agent until one of the proposals satisfied the participant. The participants rested between each task. At the conclusion of the experiment, the participants completed a questionnaire.

The participants in this experiment were 21 Japanese college students (16 males and 5 females) aged between 19 and 31 years (average age was 22.9). Eleven participants (8 males and 3 females) interacted with the feeDEEP agent (feeDEEP group) and the rest interacted with the fDEEP agent (fDEEP group).

D. Results of the analysis of the number of proposals

To investigate whether the extended estimation contributed to effective decision-making, we counted the number of proposals from the agent in the second selection task and the

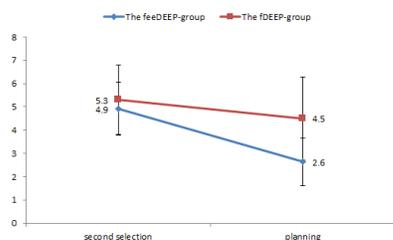


Figure 3. The number of proposals in the second selection task and in the planning task.

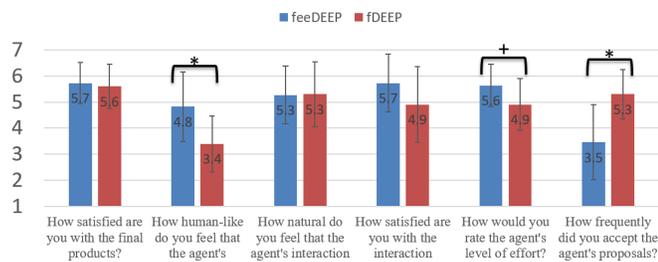


Figure 4. Questionnaire results.

planning task. We performed a paired t-test on the data of each group to compare the interaction efficiency in the tasks. Figure 3 shows a significant difference in the feeDEEP group ($p = 0.00034$); however, there was no significant difference in the fDEEP group ($p = 0.26$). In addition, we performed an unpaired t-test on the data in the planning task between each task. As a result, the value for the feeDEEP group was significantly less than that for the fDEEP group ($p = 0.0078$). These results indicate that the feeDEEP agent achieved more effective decision-making support in the planning task than the fDEEP agent.

E. Results of questionnaire analysis

The purpose of this analysis was to investigate how the extended estimation influenced the participants' subjective impressions relative to the agent's behavior. The participants answered six questions using a seven-point scale. The scale was presented as seven ticks on a black line without numbers (scored from 1 to 7). The results are shown in Figure 4. We performed a Mann-Whitney U test on the data from the questionnaire.

1) *How satisfied are you with the final products?:* There was no significant difference between the groups ($p = 0.53$). The average scores were higher than the midpoint of the scale; thus, the participants accepted the final products provided by the agents. This indicates that the algorithms that controlled the human-agent interaction and provided candidates were accepted by the participants.

2) *How human-like do you feel that the agent's behavior was?:* The participants in the feeDEEP group felt that the agent was significantly more human-like than the participants in the fDEEP group ($p = 0.035$). We believe that one reason

for this is that the feeDEEP agent was consistent in terms of suggestions and candidates. Consistency by the extended estimation affected the participants' impressions of a human-like agent.

3) *How natural do you feel that the agent's interaction was?:* There was no significant difference between the groups ($p = 0.57$). The average scores were higher than the midpoint of the scale; thus, the agents achieved natural interaction to some degree. However, the extended estimation did not affect the participants' impressions.

4) *How satisfied are you with the interaction process?:* There was no significant difference between the groups ($p = 0.54$). The average scores were higher than the midpoint of the scale; thus, the participants felt relatively good about the agents' estimations. However, the extended estimation did not affect the participants' impressions.

5) *How would you rate the agent's level of effort?:* This question was asked because we want to know whether the participants regarded the agent as an independent-minded partner. The participants felt that the feeDEEP agent tried harder than the fDEEP agent ($p = 0.087$, marginally significant difference). Only one participant in the feeDEEP group scored lower than the midpoint of the scale, and this participant indicated that the agent's voice did not express hard work. This reason did not relate to the agent's interaction behavior. On the other hand, four participants in the fDEEP group scored higher than the midpoint of the scale. We suggest that the extended estimation affected the participants' impressions of the agent's character.

6) *How frequently did you accept the agent's proposals?:* The participants in the feeDEEP group accepted significantly fewer proposals than the participants in the fDEEP group ($p = 0.013$). In the interviews, most participants from the feeDEEP group said that they could express their opinions. In contrast, most of the participants in the fDEEP group said that they compromised due to the agent's ability. The ability of the agents was the same, with the exception of the extended estimation of the feeDEEP agent; therefore, we suggest that extended estimation can induce participant opinions.

V. DISCUSSION

We conducted an experiment to investigate whether extended estimation influences the efficiency of decision making and the affective impressions of the implementing agent. The experimental results indicate that extended estimation reduced the number of interactions in the decision-making process. This reduction was not attributed to the tediousness of the interaction with the agent because the extended estimation also provided positive affective impressions related to the agent's character. In addition, we did not obtain high scores for impressions related to the interaction process (naturalness and confidence). One of the reasons for this was that the agent only provided proposals for the decision-making task. Naturalness and reliability are important for motivating sustained interaction; therefore, we will consider how to gain user confidence in future research.

A particularly important finding emerged from our analysis of the data obtained from the questionnaire used in the experiment, i.e., the rate of participant acceptance of the feeDEEP agent's proposals within these interactions was significantly

low despite a decrease in the number of interactions. Intuitively, one of the reasons why the number of interactions may have decreased was that the agent was able to provide proposals that matched participant preference, thereby leading to quick acceptance of a proposal. However, this contradicts the results of the previous questionnaire. In addition, there was no significant difference in the number of interactions during the selection sessions. However, participants chose their top three emphasizing points out of a total of 15 at the end of the experiment. The average number of matched emphasizing points was 1.67, and all of the participants' emphasizing points had at least one match. This indicates that the agents were, to some extent, able to estimate participants' preferences accurately. Based on these results, we suggest that the feeDEEP agent induced an active attitude toward the decision-making interaction, which reflected the participants' desires due to the extended estimation. However, participants who interacted with the fDEEP agent demonstrated a passive attitude by selecting an agent's proposal that relatively matched their preferences. We further suggest that the reason for an active attitude among participants was that they were able to construct an estimation behavior model for the agent. This was possible because the agent provided a consistent estimation of emphasizing points for each participant. The participants' attitudes indicate that they regarded the agent as communicative. To create a system that is user-centric, it is necessary for the user to maintain an active attitude toward the decision-making interaction in order to accomplish their goals. This study has demonstrated one method that can be applied to induce an active attitude.

In our previous work [16][17], we analyzed physiological indices (SCR and LF/HF values) that were obtained experimentally. However, we could not include an analysis of these indices in this paper. In the near future, we will analyze these data in detail to investigate the underlying reasons for these experimental results.

VI. CONCLUSIONS

In this study, we investigated the effects of the consistent estimation of a human's preferences on the human's affective impressions within a series of human-agent interactions. For this purpose, we proposed the estimation model with extended estimation based on DEEP. We conducted an experiment to evaluate the effect of the method using two agents; a feeDEEP agent, which was proposed in this study, and a fDEEP agent, which was proposed in our previous work. The results showed that feeDEEP agent could reduce the number of interactions in the decision-making process and improved some of the affective impressions related to the agent's character. In addition, we found that the rate of participants' acceptance of the feeDEEP agent's proposals was significantly low. This was possible because the agent provided a consistent estimation of emphasizing points for each participant. The participants' attitude indicates that they regarded the agent as being communicative.

In this study, we constructed predefined rules from observations, which is one of the most important point of extended estimation. We will develop the automated construction method of the rules based on the obtained data of actual interaction in future.

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