Extended Method to Alternate the Estimation of Global Purposes and Local Objectives in Multiple Human-Agent Interaction

Yoshimasa Ohmoto*, Takashi Suyama* and Toyoaki Nishida*
*Department of Intelligence Science
and Technology
Graduate School of Informatics
Kyoto University
Kyoto, Japan
Email: ohmoto@i.kyoto-u.ac.jp, suyama@ii.ist.i.kyoto-u.ac.jp, nishida@i.kyoto-u.ac.jp

Abstract—**We are interested in how to realize the natural interaction between human and agent in a virtual world the same way the human-human interaction occurs in real-world. The differences between virtual experiences and real-world experiences highlight the fact that the former are not equivalent to the latter. We focused on the mental stances to establish the social relationships between humans and agents. The purpose of this study was to investigate whether the extended method to alternate the estimation of local objectives and global purposes using a network-connected two-layer model in multiple human-agent interaction (eAEGL model) could induce the intentional stance in human participants. We conducted an experiment to evaluate the effect of the proposed method using two types of agents: an agent that implemented eAEGL model and a simple goal-oriented agent. The results suggest that the participants who interacted with the eAEGL agent considered the agent to be an interaction partner and they positively involved the agent in their virtual world experiences.**

Keywords–Multi-modal interaction; human-agent interaction; multi-user interaction; intentional stance.

I. Introduction

Many people use information technologies and devices to perform their everyday tasks. Virtual reality (VR) techniques and devices are developing rapidly and virtual reality technology will be widely applied to training games that are used in education, medical services, wellness, and fitness [1]. People can acquire various skills through game playing [2] or through games used for physical rehabilitation [3]. Additionally, software developers evaluate the user interface during the game usage [4]. In these applications, virtual agents are used as interaction partners, such as an instructor for the training, a rival character for giving motivation, or a crowd simulating a situation.

However, the differences between virtual experiences and real-world experiences highlight the fact that the former are not equivalent to the latter. For example, the character agents in the virtual world are not usually regarded as familiar friends but, more prosaically, as multi-modal interfaces that provide useful information. In such cases, once the user has learned the rules of social interaction in the virtual world, he or she may not be able to probe the true nature of those rules. As a result, the user either obeys the rules blindly or finds them impossible to follow. Therefore, we should consider how to establish the social relationships between humans and agents.

In previous studies [6][7], we focused on the mental stances that people took when interacting with their interaction partner using three categories: physical stance, design stance, and intentional stance [8]. The interaction partner can be both a human and an agent. We considered the intentional stance and the design stance as follows. The intentional stance is a mental state in which people assume unobservable inner state parameters for the interaction partner's behaviour estimation. Examples of the unobservable inner state parameters are a behaviour model, emotional aspects, and decision-making strategies of the interaction partner. Therefore, people who assume the intentional stance pay attention to various interaction parameters because they do not accurately identify the parameters that are important to obtain acceptable results in the interaction. The design stance is a mental state in which people believe they can estimate the interaction partner's behaviour by the observable interaction parameters. Therefore, people who assume the design stance pay attention to only the observable parameters that are clearly related to the interaction. The main difference between the intentional stance and the design stance is that people expect and accept that the results of the interaction are different when they provide the same interaction behaviour to their interaction partner.

In our previous studies [7][9], we proposed a method to alternately propagate estimates of human's objectives of the subordinate tasks (local objectives) and human's purposes of the entire task (global purposes) during a collaboration task through humna-agent interaction, using a network-connected two-layer model of emphasizing factors. An agent implementing this method estimates the human ' s local objectives from his/her behaviour, and the human ' s global purposes from the time series patterns of the local objectives. We believe that this method, which could provide consistency and coordination between local objectives and global purposes, could be useful to enhance factors that induce and maintain the intentional stance. For smooth interaction, it is important to understand the meta-rules to maintain the consistency and coordination, and the meta-rules are composed of some heuristics. By using this method, participants spontaneously speculate on the meta-rules through the interaction and pay attention to the unobservable inner state of the agent.

Recently, we applied the alternating estimation of human mental states in one-to-one human-agent interaction in a previous study [7]. However, multiple users often join a virtual world simulation and interact with an agent in different situations. Therefore, we should consider how to estimate and integrate the alternating estimations of multiple human mental states for an agent's decision making in human-agent interaction.

In the present study, we extended the method to alternate the estimation of participants' local objectives and global purposes using a network-connected two-layer model in one-to-one human-agent interaction to multiple human-agent interaction. We separately described the local objectives in local tasks and global purposes for the entire task for each human. Then, the agent decides which global purpose of the human is similar or conflicts with the agent's global purpose. Subsequently, the agent provides a goal-oriented behaviour related to the global purposes, to support the local objectives in the local tasks.

This paper is organized as follows: In Section 2, we briefly introduce the related works. Section 3 provides an outline of the proposed method. Section 4 contains a description of our experiment that compared experimental and control groups, and presents our results. In Section 5, we discuss the achievements of this research and some future work. We present our conclusion in Section 6.

II. Related work

The typical way to speculate about a human's intentions within human-agent interaction is human-agent communication through a dialogue. Kitamura et al. [10], for example, developed a system that matches users' queries with search targets by communicating with users throughout the interview. Most of the research considered that people had reliable demands and needs and they tried to uncover them. However, especially in collaborative tasks, people's demands and needs are ambiguous and they are interactively changed through the tasks in many cases. In human-human interaction, we do not think that we can precisely speculate people's intentions only through a dialogue.

Agents that collaboratively perform various tasks have been proposed in many studies, such as subordinate support agents when people perform tasks on their own initiative and automated attentive agents which automatically perform tasks in line with a human's wishes [11]. We assumed that the intentional stance was partially induced in the participants in the collaborative task because, if not, the engagement for the collaboration would have been low and they might have failed in the collaboration.

Some mutually directable methods and concepts affect task performance [12][13]. Mixed-initiative, for example, refers to a flexible interaction strategy wherein each agent can contribute to the task it does best. Furthermore, in general, the agents' roles are not determined in advance, but are opportunistically negotiated between them as the problem is being solved. In many cases, they merely provide a division of roles among interaction members; therefore, the consistency and coordination for performing the task are still managed by the main person.

Dindo et al. [14] proposed that humans use the intentional stance as a learning bias that sidesteps the (difficult) structure learning problem and bootstraps the acquisition of generative models for others' actions. They provided an example of how structure initialization can help in the learning of new parts of the model. In the example, they connected the action layer and intention layer by networks and identified the user's intentions from the sequence of the actions. This revealed that the network-connected layered model is effective for estimating the intentions of humans. They considered the intentional stance as a template of the structure generating the observed behaviour. In contrast, we consider the intentional stance itself as being an important factor to determine interaction behaviours.

Shirouzu et al. [15] investigated how collaboration leads to abstract and flexible problem solving. The results indicated that two factors, namely, individuals' activeness in choosing and confirming the initial strategies and the frequent role exchange between task-doing and monitoring in collaborative situations, interact in collaboration to generate various solutions differing in the degree of abstraction. These solutions are then reflected upon by the participants to lead them to abstraction. This shows that the observer's mental factors influence his/her evaluation of an observation target. In addition, in multiple human-agent interaction, a participant has an interaction-doing role whereas another has a monitoring role. Therefore, we should consider that the development of the human-agent relationships is different from that of one-to-one human-agent interaction.

III. Method to alternate estimation by representing global and local goal-oriented behaviour

Some methods induce the intentional stance, such as an agent resembling a human or an animal in appearance [16][17]. These methods mainly focus on inducing the intentional stance at the first impression. However, if the activities among the participants, including the agent, were not mutually influenced by them each other in collaborative long-term interaction, the participants would regard even human-human interactions as 'mechanical' because these interactions make people believe that they can estimate the interaction partner's behaviour by the observable interaction parameters.

In previous studies, we proposed a method to alternate estimation of local objectives and global purposes in a decision-making situation [9] and applied the method to a collaborative task for inducing and maintaining the intentional stance [7]. We called this Alternate Estimation by representing Global and Local goal-oriented behaviour (AEGL). AEGL separately describes an interaction partner's local objectives in local tasks and global purposes of the entire task. The agent implementing the method estimates the interaction partner's local objectives and global purposes based on the interaction responses. After the estimation, the agent updates its own local objectives depending on the estimated partner's global purposes. We expected that the interaction partner also estimates the agent's global purposes from its behaviour for the local tasks in one-to-one interaction. However, multiple users often join a collaboration task and interact with an agent in different situations. In addition, when the agent interacts with multiple users, the agent needs to prioritize the order of the interaction with the users and consider the user's global purposes. In this study, we extended the method used to alternate the estimation of local objectives and global purposes by a network-connected two-layer model in one-to-one human-agent interaction to multiple human-agent interaction. We called this extended method as eAEGL. Figure 1 shows the outline of this process.

The main difference between the eAEGL in this study and the AEGL in the previous work is to estimate the purposes of multiple interaction partners and then to evaluate the effect of agent's interaction behavior towards each interaction partner based on the degree of influence on agent's purpose. The eAEGL had lists of local objectives and global purposes, and

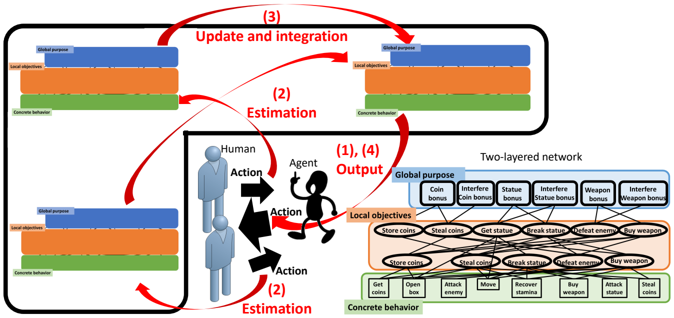

Figure 1. Outline of the alternating estimation process.

the relational networks for each user and its own depending on the task. The parameters of the network nodes were updated in a correspondent interaction behaviour of each user that included verbal and nonverbal responses. Subsequently, the parameters of the local objective nodes or global purpose nodes were speculated based on the parameters of the network-connected nodes. Based on the speculated parameters of global purpose nodes, eAEGL evaluated whether the user was collaborative or competitive, and how strongly influenced was the user's purpose on the agent's global purpose. This is an extended point. We briefly explain the interaction process below.

First, an agent with eAEGL determines its local objective based on weighted global purposes and provides appropriate behaviour to achieve the local objective. Subsequently, the agent estimates the local objectives of each user based on the behaviour and responses. From the estimation, the agent updates the weights of estimated global purposes of each user. Based on the updated global purposes, the agent evaluates whether each user is collaborative or competitive, and how strongly the user's purpose influences the agent's global purpose. The strength of the influence is the priority of the user. The agent calculates the cost when intervening with the higher priority user. If the cost is lower than a certain level, the agent increases the weights of the agent's global purpose related to the intervention. Finally, all parameters of the global purposes of each user and the agent are updated and integrated, then the agent modifies and determines its local objective based on the parameters.

The agent's representation to provide the goal-oriented behaviour for inducing and maintaining the intentional stance is different depending on whether the user is collaborative or competitive. When the user is collaborative, the agent tries to support the user's local objectives if possible, but the agent represents its global purposes through the local objective activities. When the user is competitive, the agent tries to interfere with the user's local objectives. The interference itself is a representation of the agent's global purposes. The agent's behaviour is modified through the interaction like a trial-and-error process. By repeatedly conducting the processes, the agent can represent the goals of the agent's activities towards the multiple users.

IV. Experiment

We conducted an experiment to investigate the effects of the proposed method on a user's impressions of the agent. In the experiment, participants played a "triangular field game" as a task. In this game, three players, an agent and two participants, competed for scores obtained in multiple ways. The participants could obtain scores regardless of other players and interfere with other players. The task and the relationships between the global purposes and the local objectives are more complex than those in the previous study. One of the reasons why we used the competitive task was that the participants usually ignored an agent's behaviour when multiple human players participated in a collaborative task. It was very hard to induce the participants' active interaction towards an agent when participants ignored the agent in a collaborative task.

In the task, we used two types of agents: an 'eAEGL agent' that provided interaction behaviour to the participants based on the eAEGL and a 'goal-oriented agent' that performed goal-oriented actions which took the game states of all participants into account, such as game scores and the positions in the game field. Both agents represented their goal to induce the intentional stance. The eAEGL agent controlled the representations based on the participants' inner state, such as collaborative or competitive. The goal-oriented agent prioritized its own global purposes. For example, in a situation in which a human participant interferes with an agent's purpose and another human participant very effectively obtain scores, the goal-oriented agent tries to confront with the interfering participants, but the eAEGL agent evaluates the effect of each participant's behavior and sometimes tries to interfere with the participant obtaining scores.

The reason we did not adopt the AEGL agent in our previous research was that, when the AEGL agent interacted with multiple participants, the agent's behaviour often changed owing to the influence of the participant who interacted immediately before. This means that it became rather difficult to estimate the agent's intentionality from its goal-oriented behaviour. We assumed that if the extended alternating estimation could influence the mental stance of the participants more than providing basic goal-oriented behaviour, the eAEGL agent could induce and maintain the intentional stance.

Both agents were controlled by the experimenter manually based on the predefined rules (Wizard of Oz). But, the behaviour planning of the agents were automatically determined based on the corresponding method; the eAEGL agent used the method to alternate estimation by representing global and local goal-oriented behaviour and the goal-oriented agent used the method to plan its own goal depending on the game states and situations. Each agent provided its next local objective and the experimenter controlled each agent based on the predefined rules. The expressions of the multimodal behaviour by the agents were also automatically produced.

To evaluate this, we analysed how frequently the participants spontaneously interfered with the agent's behaviour. Although the players competed for scores in the task, the players could not get scores by interfering with other players. Therefore, if the participants considered that the agent was not an interaction partner to perform the task excitingly, it would be more efficient to get a high score by not interfering with the other players. We assumed that, when the participants had an intentional stance toward the agent, they tried to interfere with the agent. In addition, we asked the participants to complete a questionnaire after the experiment.

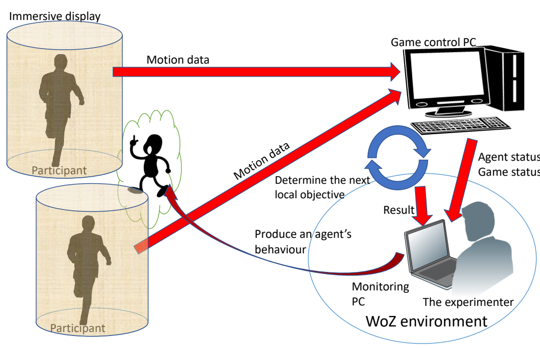

Figure 2. The experimental environment.

A. Task

An agent and two participants joined a triangular field game in which three players competed for scores obtained in multiple ways. In the game, each player had their own field in which each player stored treasures. The fields were placed in a triangular form. At the centre of the triangle, there was a neutral field where three resources existed: gold coins, artistic statues and weapons. When the players stored the resources in their own fields, they obtained a score. Each player could use the resources to get bonus scores, but the player needed to spend considerable resources and time. While the player spent time to get a bonus score, other players could interfere with the process to get a bonus score. The winner was the player with the highest score. One game session lasted for 20 min.

The agent's primary global purpose was to gather bonus scores. First, the agent tried to store statues. After the agent stored enough statues to get a bonus score, he immediately spent them to get the score. The agent evaluated the state of the game including other players' scores and the bonus process of other players at regular intervals. The goal-oriented agent selected a most efficient way to get scores or to keep the score different from the other players. The eAEGL agent estimates the global purposes of each participant and the priority. If the cost when interacting with the higher priority participant was low enough, the agent tried to interact with the participant. When the participant was collaborative (e.g., when the participant tried to interfere with another participant with whom the agent also tried to interfere), the agent tries to support the participant's local objectives. When the participant was competitive, the agent tries to interfere with the participant's local objectives.

B. Experimental setting

The experimental setting is shown in Figure 2. We used an Immersive Collaborative Interaction Environment (ICIE) [18] and Unity3D [19] to construct the virtual environment and the two agents. ICIE uses a cylindrical immersive display that is composed of eight portrait orientation liquid-crystal-displays (LCD) with a 65-inch screen size, arranged in an octagonal shape. In this environment, participants could look around in the virtual space with a low cognitive load, as in the real world. A participant's virtual avatar could be controlled by a game pad.

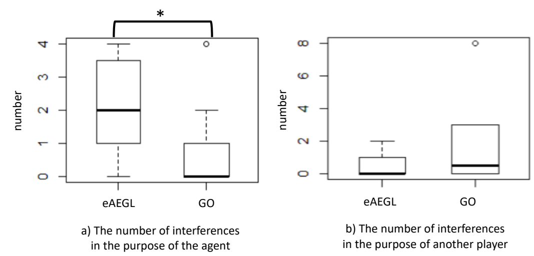

Figure 3. Results of the number of interferences in the purpose of other players.

C. Procedure

The interactive agent who joined the game was randomly selected. First, the participants were instructed regarding the experimental procedures. The experimenter provided the following instructions about the agent: 'The agent can recognize simple words. The agent has basic knowledge about the task. The agent changes its behaviour and strategies depending on your behaviour'. After the instructions were provided, the experimenter started the game. The participants first performed a practice session and then performed two game sessions. Each game session lasted for 20 min, with a 5-min rest interval between sessions. In the rest interval and at the end of the task, the participant completed questionnaires.

Eighteen Japanese college students (14 men and 4 women) participated in the experiment. They were undergraduate students aged 18 to 24 years (an average of 21.1 years). All of them interacted with one of the agents for approximately 40 min. Ten participants (8 men and 2 women) interacted with the goal-oriented agent (the 'GO group') and the rest interacted with the eAEGL agent (the 'eAEGL group').

D. Analysis of the number of interferences in the purpose of other players

We counted the number of the interferences in the bonus process of other players. The players could not get scores by interfering with other players. Therefore, it is more efficient to get a high score by not interfering with the other players. If the participants considered that the agent was an interaction partner who would make the task exciting, they tried to interact with the agent by interfering in the bonus process.

We compared the results from the eAEGL group with those from the GO group. These results are shown in Figure 3. A Mann-Whitney U test showed that the number of interferences with the agent in the eAEGL group was significantly more than that in the GO group ($Z = -2.03$, $p = 0.047$). On the other hand, there was no significant difference between the number of interferences with another participant in the eAEGL group than that in the GO group ($Z = 0.835$, $p = 0.41$). This result suggests that eAEGL was successful in inducing the intentional stance in multi-user interaction.

E. Analysis of the questionnaires

The purpose of this analysis was to investigate how the proposed method tested in the present study influenced the participants' subjective impressions. The participants rated the impressions of the agent on a seven-point scale, presented as ticks on a black line without numbers. The Q1 and Q2 were rated after the end of each session. The Q3 and Q4 were rated

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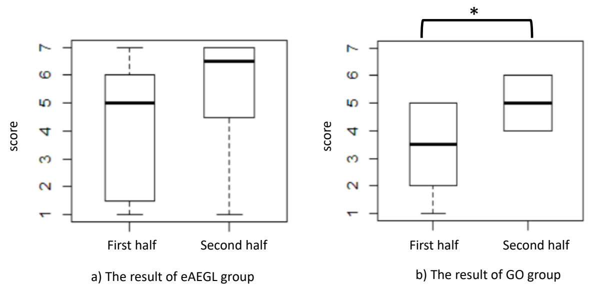

Figure 4. Q1: How carefully did the agent consider your intentions?

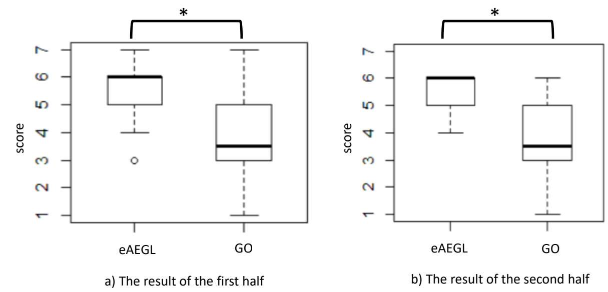

Figure 5. Q2: How strongly do you think that the agent considered its strategies based on players' intentions?

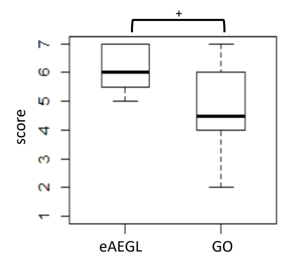

Figure 6. Q3: How strongly do you want to play the game with the agent again?

after the end of the experiment. We post-coded these scores from 1 to 7. We performed the Mann-Whitney U tests on the questionnaire data.

1) Q1: How carefully did the agent consider your intentions?: The eAEGL agent estimated the global purposes of each participant and the estimations were reflected on the changes of the agent's global purpose. The GO agent evaluated the states of the game including the results of the participants' behaviour and the results were reflected on the changes of the agent's global purpose. Therefore, the participants' intentions were more quickly reflected on the global purpose of the eAEGL agent than that of the GO agent. This question was asked to confirm whether the difference influenced the participants' feeling. This question was rated after the end of each session. The results have been shown in Figure 4. In the first and second sessions, there are no significant differences (first: Z = -0.808, p = 0.44; second: Z = -1.40, p = 0.18). On the other hand, we performed the Wilcoxon signed-rank test between the responses regarding the first and second half. Although there was no significant difference in the eAEGL group (Z=-1.56, p=0.16), the score for the second session was significantly higher than that for the first session in the GO group (Z = -2.38, p = 0.023). This indicates that the participants in the eAEGL group could quickly understand that the participants' intentions were reflected on the global purpose of the agent. The participants in the GO group firstly needed to understand the game structures and the strategies for identifying the relationships between the results of the participants' behaviour and the changes of the agent's behaviour.

2) Q2: How strongly do you think that the agent considered its strategies based on players' intentions?: Although both agents changed their global purposes and their behaviour depending on the participants' behaviour, there is a difference in the causal relationship between the global purpose of the agent and the intentions of the participant. This question was asked to confirm whether the participants were aware of the rules to determine the agent's strategies. This question was rated after the end of each session. The results are shown in Figure 5. In both the first and second sessions, the score for the eAEGL group was significantly higher than that for the GO group (first: Z = -2.13, p = 0.030; second: Z = -2.40, p = 0.015). In addition, there are no obvious differences between the first session and the second session. This indicates that the participants were aware of the effect of the influence of factors that determined the agent's behaviour early in the task.

3) Q3: How strongly do you want to play the game with the agent again?: This question was asked to confirm whether the agent's behaviour based on the eAEGL influenced the subjective feeling of the participants. The result is shown in Figure 6. There was a marginally significant difference between the groups (Z = -1.96, p = 0.058), which suggests that the participants preferred the eAEGL agent.

4) Q4: How actively did you involve this task?: This question was asked to confirm whether the agent's behaviour based on the eAEGL influenced the evaluation of the whole of the task. The result is shown in Figure 7. The score for the eAEGL group was significantly higher than that for the GO group (Z = -2.12, p = 0.042). The human-agent interaction which was not needed to efficiently achieve the task goal influenced the positive impression about the whole of the task.

V. DISCUSSION

The main contribution of this study is that the eAEGL model is useful to induce the intentional stance of the participant in complex multiple human-agent interaction. An analysis of the number of interferences in the purposes of other players helped us confirm that the eAEGL group spontaneously interacted with the agent to perform the task excitingly. In addition, in Q3 and Q4 of the questionnaires, the scores for the eAEGL group were relatively high. From these results, we suggest that the participants who interacted with the eAEGL agent considered that the agent was an interaction partner (i.e., the participants took the intentional stance) and they positively involved the agent in their virtual world experiences. The suggestion is in agreement with our previous research [7], and it can be said that we can extend the method to alternate the estimation of local objectives and global purposes in one-to-one human-agent interaction to multiple human-agent interaction.

The Q1 and Q2 of the questionnaires were similar but the results were different. The Q1 asked the impression of the agent's attitude towards the participant. The Q2 asked the

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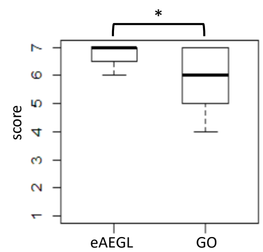

Figure 7. Q4: How actively did you involve this task?

impression of the agent's attitude towards all participants. In this study, we applied the eAEGL to multiple-user interaction, so that a participant could observe the interaction between another participant and the agent. We expect that the observation is important to estimate the agent's behaviour model. Multi-user interaction requires a complex decision-making process to estimate multiple participants' intentions and decide their actions. By providing the opportunity to observe interactions made by others, there is an advantage that it becomes easier to estimate the behaviour model of the agent relatively. Although it becomes easier to estimate the behavioural model of the agent, we should be careful that participants are more likely to take a design stance. It is important to continuously and mutually change the inner state, such as through eAEGL, in natural long-term interactions.

In this study, we could confirm that the agent could induce active interaction from the participants. This is one of the limitations in our previous study. In addition, we could apply the eAEGL to relatively long-term interactions. On the other hand, we had to hand-code the two-layered relational networks depending on the task. In the future, we will apply the machine learning techniques to reconstruct the relational networks through the human-agent interaction.

VI. Conclusion

The purpose of this study was to investigate whether the extended method to alternate the estimation of local objectives and global purposes using a network-connected two-layer model in multiple human-agent interaction could induce the intentional stance in human participants. To evaluate the method, we implemented two types of agents: an eAEGL agent (that mutually estimates and changes global purposes based on the priority and relationship with each participant), and a goal-oriented agent (that performed goal-oriented actions which took the game states of all participants into account). We conducted an experiment to evaluate the effect of the proposed method. The results suggest that the participants who interacted with the eAEGL agent considered the agent to be an interaction partner and they positively involved the agent in their virtual world experiences. In future work, we will attempt to update the relational two-layer network, which is determined by the agent's basic strategies and behaviour, during the human-agent interaction.

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