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Active adaptation in human-agent collaborative interaction

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Abstract When a human user interacts with an adaptive agent to achieve human-agent collaboration, active adaptation is considered to be one of the critical characteristics of the agent. In order to investigate the principal features of active adaptation, we developed a human-agent collaborative experimental environment called WAITER (waiter agent interactive training experimental restaurant) and conducted two types of experiments, a Wizard of OZ (WOZ) agent experiment and

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an autonomous agent experiment. The objective of these experiments is to observe how human users perceive the agents and change their instructions when interacting with adaptive agents. The results indicate that humans can recognize changes in the agent's actions and change their instruction methods accordingly. This implies that active adaptation of the agents may encourage the adaptation of the human users and help to build an adaptation loop between them. The experimental results also suggest that active adaptation may play an important role in a human-agent collaborative task.

Keywords Active adaptation · Human-agent collaboration · Wizard of OZ agent · Autonomous agent · Mutual adaptation

1 Introduction

Human-agent interaction (HAI) has been extensively studied in recent years. An active interface is considered to be one of the critical characteristics of agents that interact with human users in order to achieve human-agent collaboration. This characteristic is especially important when an ordinary human user begins to interact with an adaptive autonomous agent. Yamasaki and Anzai (1995) defined an *active interface* as a type of human-robot (agent) interface that not only waits for a user's explicit input but also tries to obtain information from a user's implicit input and external environment. Based on the obtained information, it acts spontaneously and keeps the system in a favorable condition for users. Silvia and Analia (2005) adopted an interface agent approach to personalize a user's interaction with a database. They argued that interface agents could help users by personalizing their information retrieval tasks. However, this method focuses more on an agent's adaptation to human users than on a human user's adaptation to agents. Maes (1994) argued that an adaptive autonomous agent needs to solve two problems: action selection and learning from experience. In order to enable an agent to make a rational decision, a Belief-Desire-Intention (BDI) model is popularly used (Wooldridge 2000). The BDI model supposes that an autonomous agent has its own intention and makes its own decision when interacting with its environment. In order to investigate how a human user interacts with an adaptive autonomous agent with an active interface, we designed a specific experimental task that involves an adaptive autonomous agent with various degrees of freedom. We implemented a human-agent collaborative experimental environment called WAITER (waiter agent interactive training experimental restaurant). Two types of agents, namely, a Wizard of OZ (WOZ) agent and an autonomous agent, are implemented. A WOZ agent has less degrees of

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freedom because a human WOZ operator partly controls its action selection policy. In contrast, an autonomous agent can choose all its actions by itself. Experiments are conducted to investigate how human users change their instructions when they interact with agents having different degrees of freedom.

The remainder of this paper is organized as follows. Section 2 explains the concepts of active interface, mutual adaptation, and hierarchical structure. Furthermore, some related works are also introduced. Section 3 describes the experimental design and procedure, and presents some obtained results. Section 4 summarizes the paper and provides some directions for future works.

2 Active interface and mutual adaptation

2.1 Definition

Because the goal of our research is to develop an adaptive autonomous agent with an active interface, it is first necessary to clarify the meaning of the phrase "adaptive autonomous." The word "autonomous" implies that the agent has a high degree of freedom in decision-making and the word "adaptive," a high degree of freedom in self-organizing. It is difficult to decide how much degree of freedom or initiative (leadership) an autonomous agent should be endowed with. Inadequate degrees of freedom might restrict the agent's adaptability to the environment; however, redundant degrees of freedom might produce unnecessary movements and instability. In addition to the issue of degree of freedom, people's adaptation is another issue. An adaptive interface is considered to be useful if it can (1) make people easily recognize changes in the agent, (2) help people easily adapt to the agent, and (3) facilitate the induction of the mutual adaptation phenomenon. In the field of HAI, because human factors make the environment more complicated, it is necessary to consider people's adaptability during HAI. Therefore, an agent with an active interface can not only adapt easily to human users but also help people adapt easily to the agent. In other words, *mutual adaptation* is considered to be one of the abilities that are useful for designing an active interface.

Suppose that there exist two agents A and B who need to accomplish a collaborative task. Neither A nor B has complete information about the task. Each agent can access different parts of partially available information about the task. In order to achieve a common purpose, each agent has to build a model for the other, try to adapt to the other by changing its action, predict the other's next action, and draw inferences about the other depending on various situations. In general, the two agents have to accomplish the task by gradually adapting to each other. In this paper, the abovementioned phenomenon is called *mutual adaptation*.

2.2 Related works

Many studies have focused on the areas of human-computer interaction (HCI), human-robot interaction (HRI), and human-agent interaction (HAI). Studies on HCI mainly focused on the design of effective user interfaces and the improvement of the usability of these interfaces. Studies on HRI mainly focused on the design of the appearances, functions, and behaviors of the interactive robot and the improvement of their efficiency. Studies on HAI mainly focused on the design of the interaction rather than the design of specific functions of the agents. Because human users inevitably adapt to the agent when they interact with it, it is necessary for the agents to actively adapt to humans so that they may take the initiative to affect the humans' adaptation and facilitate the interaction between the humans and the agents. Our study mainly focuses on the area of HAI.

To the best of our knowledge, Yamada and Kakusho (2003) first proposed the concept of *mutual adaptation* in the research field of *HAI*. In early works, Yamada and Yamaguchi (2005) conducted an experiment called "mind reading game." In this experiment, a human user and an agent tried to infer the other's state of mind by recognizing the other's facial expression on the basis of figures of agents or pictures captured using a web camera. In another experiment (Yamada and Yamaguchi 2004), a human user was asked to train AIBO, a pet robot, using the classical conditioning method. His research confirmed that an agent's active adaptation did affect the humans' adaptive behavior in limited situation, however, it did not clarify if an active interface could help the humans and the agents adapt to each other and establish an adaptation loop.

In the context of HAI, there also exist some other related works. For example, Thomaz and Breazeal (2008) tried to build an easy-to-teach robot within a human-teacher and robot-learner framework. Kaplan et al. (2002) adopted an animal training method to teach a pet robot. Goldman et al. (1996) studied the adaptation between agents. However, these studies have not yet provided a solution to the problem of how a human user can finish a collaborative task with an adaptive autonomous agent.

The mutual adaptation phenomenon has been observed in a human-human interaction experiment (Xu et al. 2009b), the results of which indicate that mutual adaptation is helpful for establishing communication protocols and conveying intentions between human users in a collaborative task.

2.3 Hierarchical structure

The two-layered model proposed by Xu et al. (2008) indicates that mutually adaptive behaviors can exploit at least two levels of mutual adaptation protocols. This model is used to describe the common protocol space between two communicative partners (an instructor and an actor). The common protocol space is divided into two layers, the lower layer and upper layer, and includes at least three subspaces, the fundamental space, quantitative space, and structural space. The lower layer plays a fundamental role in the communicative system and the upper layer plays a role of adjusting and fine tuning. Both the instructor and the actor have a private learning space. However, in order to finish the collaborative task, they have to construct a common protocol space to achieve common communicative protocols. The primitive instructions and their response actions should be located in the fundamental space of the lower layer. In contrast, the abstract instructions and their response actions should be located in the learning space of the upper layer. In the WAITER environment, the former includes simple primitive instructions such as clicking a button to ask the agent to move to a location to carry out a specific task, such as "guide the customer," "let the customer take a seat," "place an order," "carry a dish," and "move to the kitchen." Furthermore, the latter includes a repetitive instruction such as clicking the same button consecutively or a sequence of primitive instructions such as issue the "let the customer take a seat" instruction by clicking a vacant seat after issuing the "guide the customer" instruction by clicking the entrance button. The fundamental elemental space consists of an establishment element, and its main function is to generate a fundamental protocol so that a consensus can be established between the instructor and the actor. The quantitative space consists of an adjustment element, and its main function is parameter adjustment, such as determining the acceptable duration between the instruction and the response action. The structural space consists of combining elements, and its main function is sequence generation and policy switching. By considering people to be advanced autonomous agents, we expect that the mutual adaptation phenomenon will also occur in HAI. Komatsu et al. (2005) developed a mutual adaptive speech interface. The interface adopts the cognitive features that humans use for communication by inducing and exploiting users' adaptation. This research mainly focused on the lower layer of the mutual adaptation model, and studied how human users acquire the meanings of voice instructions through paralanguage. This study extends Komatsu's research (Komatsu et al. 2005) to the upper layer and develops an experimental environment in which a human-agent collaborative task can be accomplished by a human user and an adaptive agent.

3 Experimentation

3.1 Objective

This research aims to investigate if an agent's actively adaptive behavior can cause the human users to change their instruction methods, and if this change can cause the agent to change its actions so that the mutual adaptation phenomenon can be observed. For this purpose, two experiments were conducted by considering a waiter training task.

3.2 Task

In order to provide a specific task, we designed a human-agent collaborative task. For the purpose of verification, a novel working platform of the experimental environment is developed. The task scenario used is the WAITER virtual restaurant world. In the task, a manager (human instructor) trains a waiter (agent) in the virtual restaurant to provide service to customers. The manager and the waiter have different evaluation functions. The manager aims to obtain more sales by trying to allow more customers to enter the restaurant. On the other hand, the agent aims to obtain more tips by placing more orders for customers who are waiting for order. However, neither of them knows what is the function on which the other's action depends. Therefore, both of them have to collaborate with each other so that they can accomplish the task together.

The layout of the virtual restaurant is illustrated in Fig. 1. In total, there are 51 cells. The cells can be classified into three types: one "entrance" cell, one "kitchen" cell, and nine "seat" cells. The "entrance" cell has up to two states: "has no customer" and "has new customer (waiting for guide)." The "kitchen" cell has up to two

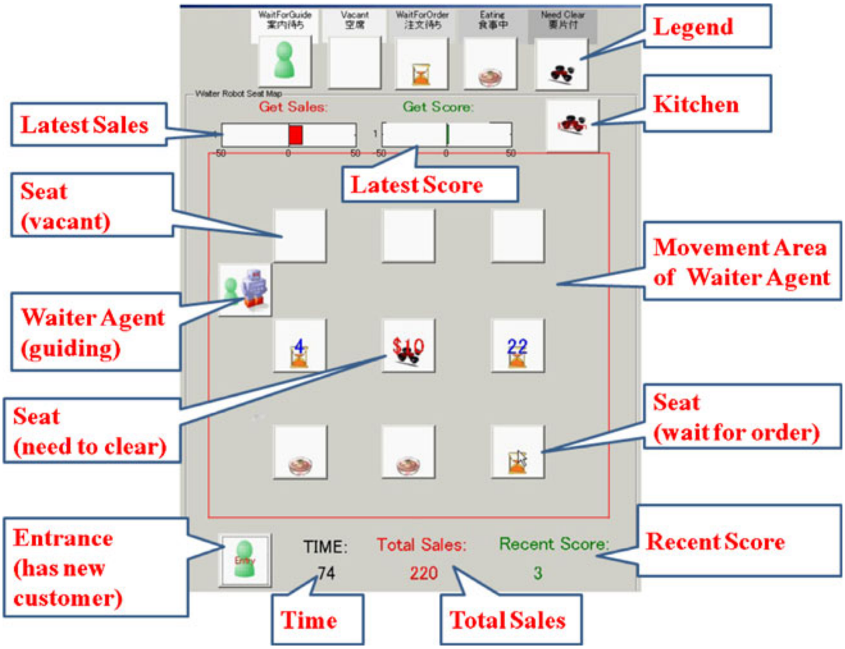

Fig. 1 Graphical user interface of WAITER (waiter agent interactive training experimental restaurant) system

states: "no dish" and "has dish." Each of the nine "seat" cells has up to four states: "vacant," "waiting for order," "eating," and "need to clear." The manager can issue an instruction by pressing one of eleven buttons (entrance, kitchen, and nine seats.) The waiter agent has up to three states: "free," "guiding (customer)," and "clearing (carrying dish)."

The human manager (instructor) is asked to issue instructions to the waiter agent (actor) whenever necessary by pressing a button. If the waiter agent changes its reactions according to the managers' instructions, this change may affect the managers' instruction method. On the other hand, if the manager changes his/her instruction methods by observing the waiter's responses, this change may affect the waiter's actions as well. In order to achieve a better score, both of them have to collaborate with each other. Therefore, mutual adaptation phenomena are expected to occur. A human participant always plays the role of a manager. An agent always plays the role of a waiter. The customers are automatically and randomly generated by the system.

In this manager-waiter (human-agent) collaborative task, if the waiter agent's active adaptation can cause the human manager's adaptation, that is, if the waiter agent actively changes its action to adapt to the human manager, it is expected that the manager will change his/her instruction methods accordingly. This is the first loop of the mutual adaptation circulation. If the agent can learn by improving its competence, it is hoped that the adaptation circulation will continue and long term human-agent interaction will be possible. In this paper, we focus on the first circulation of the mutual adaptation and try to investigate its relation to the active interface of an adaptive agent.

3.3 Implementation

The graphical user interface (GUI) of the WAITER system (Xu et al. 2009a) was developed in MATLAB 2007 using the GUIDE function (MathWorks 2010); a snapshot of the GUI is shown in Fig. 1. Generally, two types of modes, manual mode and autonomous mode, are designed for the waiter agent. In the manual mode (M-mode), the waiter agent follows every instruction from the manager. In contrast, in the autonomous mode, the agent can move autonomously and make its own decisions by either performing its own actions or following the manager's instructions.

A human participant who plays the role of a manager can instruct the waiter agent by pressing one among eleven buttons on the GUI of the WAITER system. The goal of the experiment is to investigate if active changes in the agent's behaviors can cause participants to change their instructional methods and induce mutual adaptation in HAI. First, we need to examine whether changes in an actively adaptive agent can be recognized by a human instructor. Second, we need investigate whether an actively adaptive agent can encourage the human instructors to change their instruction methods as well. Finally, if both are proved effective, the establishment of the first circulation loop of mutual adaptation can be confirmed. In other words, it can be confirmed that an agent waiter can adapt to a human manager by changing its action, and the human can adapt to the agent by changing his/her instructions accordingly.

Two types of WOZ agent experiments and three types of autonomous agent experiments were conducted. In the first type of WOZ agent experiment, the number of dishes that the agent can carry to the kitchen increases gradually in three stages. In the second type of WOZ experiment, the agent changes its action for six stages. In addition to the number of dishes the agent can carry to the kitchen each time, the capability of automatically finding a path to the kitchen is added. The stage-switching is controlled by a human WOZ operator or by a timer. If the WOZ operator does not give any command, the agent automatically switches its stage every one-third moment in the first WOZ experiment and every one-sixth moment in the second WOZ experiment.

In the WOZ agent experiment, the agent changes its behavior in a timely manner or by following the WOZ operator's command. In contrast, in the autonomous agent experiment, the agent changes its behavior according to the manager (participants who are ordinary user)'s instructions.

A typical scenario for the autonomous mode is as follows. When a new customer enters the restaurant, if a seat is vacant and the agent is idle (in the "free" state), the waiter agent will move to the entrance and guide the customer to a vacant seat. When the waiter is guiding a customer, its state will automatically change to "guiding customer." If there is neither an available vacant seat nor a customer who is waiting to place an order, the agent needs to find a "need to clear" seat, move there, clear the seat, and change its state to "carrying dish" while carrying dishes to the kitchen. However, if any customer is waiting to place an order, the agent will place the order. After the customer has been seated at a vacant seat, the seat state will be changed to "waiting for order." It will be kept unavailable for placing orders for a specific period (approximately 30 s). In order to prevent customers from leaving the restaurant after waiting for too long, which in turn reduces the sales and scores, the agent always tries to place an order as soon as possible when it works in the autonomous mode. When the agent finishes placing an order, it receives tips, and the restaurant's sales and scores are updated simultaneously.

In the beginning of the WOZ agent experiment, the agent is designed to purposefully ignore a "need to clear" seat with high probability. Because the agent's capability of carrying a dish is gradually increased by a timer or by the operation of a WOZ operator, the manager is expected to be aware of the agent's changes easily.

In the autonomous agent experiment, four types of switching modes of the agent, "linear prediction mode" (L-mode), "random mode" (R-mode), "Bayesian network mode" (B-mode), and "observation phase mode" (O-mode), are designed to switch its priority among three types of specific tasks, "guide a customer," "place an order," and "clear a seat." Because an autonomous agent always tries to adapt to the manager by changing its actions, the manager is expected to be aware of the adaptation from the agent.

In the L-mode, the agent calculates the recent frequency of three types of instructions ("guide a customer," "place an order," and "clear a seat.") and changes its priority according to the most frequently used instruction. In the R-mode, except to finish the current task automatically, the agent randomly switches its priority at fixed intervals. In the B-mode, a Bayesian network model generated from previous experiment results is used to choose the next action (Bishop 2007; Cooper 1995). In the O-mode, the manager is forced to stop providing instructions every 5 min.

The think-aloud method was utilized to facilitate the analysis of the intention of an instruction provided by the human manager (instructor). All participants were required to speak out the intentions of their instruction when issuing instructions.

As a result, three types of data were collected. Voice data were collected by using a digital voice recorder. The intermediate processing data of the WAITER system were recorded in log files. These data include the movements of the waiter, instructions (pressing button actions) of the manager, and values of sales and score. The screen output data of the WAITER system were captured by a screen recording software and recorded as video files. The behaviors and voices of participants were also videotaped using a video camera.

It is expected that the manager's instruction method will be affected by the agent's autonomous function. This in turn will enable the agent to learn and improve its performance and adapt to the manager by trying various actions. Therefore, it is desirable to induce the mutual adaptation phenomenon.

3.4 Participants and procedure

12 Japanese students (5 male and 7 female; age, 20–26 years; average age, 22.75 years) participated in the WOZ agent experiment. For convenience, we represented them as M1 through M12. All the participants are laymen and have no experience of using the WAITER environment.

25 people (16 male and 9 female, 23 Japanese and 2 Chinese; age, 18–37 years; average age, 21.68 years) participated in the autonomous agent experiment. For convenience, we represented them as N1 through N25. All participants completed the trials in the M-mode and R-mode, 24 completed the L-mode, 19 completed the trials in the B-mode, and 8 completed the O-mode.

In R-mode, the agent randomly switched its priority. In L-mode, the agent changed its priority by adapting to the human user's instruction. The B-mode was established on the basis of previous experimental results, and it was expected to predict the human instructor's instruction by learning from experience. The O-mode was expected to enforce the human managers to pause their instructions so that they had a chance to recognize the merit of the autonomous function of the agent. This was aimed to prevent the human instructor from constantly giving instructions.

3.5 Results and discussions

Table 1 shows the results of the WOZ agent and autonomous agent experiments. In the WOZ agent experiment, each participant participated in four to six trials within 90 min with an agent that works in four different modes: manual mode (M-mode), autonomous mode with timely stage-switching (TS-mode), autonomous mode with operator stage-switching (OS-mode), and autonomous mode with timely or operator stage-switching (T/OS-mode). Because of recording problems, two trials of the first participant were not recorded correctly, and therefore, an additional trial was added to the last participant. In total, 56 log files and 740 min of voice and videotaped data were recorded for the WOZ agent experiment.

In the autonomous agent experiment, 25 M-mode trials, 25 L-mode trials, 24 R-mode trials, 8 O-mode trials, and 19 B-mode trials were recorded.

In the WOZ agent experiment, there were significant differences in the instruction interval time between the first half and the second half of the same trial. In total, 40 out of 56 trials exhibited a longer time interval in the second half than in the first half ($p = 0.027$, one-tailed test). In the autonomous agent experiment, while there were no significant differences in the instruction interval time between the first half and the second half of the same trial (29 out of 51 trails, $p = 0.201$, one-tailed test), there was a significant difference in the B-mode (13 out of 19 trails, $p = 0.084$, one-tailed test).

Table 1 Experimental results

Exp. type	Participant no.	Trial no.	Mode	Time (min)	Inst. usage times	
					M	SD
WOZ agent	12	12	M	10	127.56	1.80
		12	TS	10	143.67	4.10
		12	OS	10	116.67	3.21
		8	T/OS	10	160.83	4.97
		6	OS	20	275.67	6.66
		6	OS	30	344.00	11.42
Auto agent	25	25	M	15	188.60	2.31
		25	L	15	329.28	10.96
		24	R	15	334.88	11.12
		19	B	15	323.11	10.49
		8	O	15	346.60	11.61

Exp. type: Experiment type, *Inst. usage times*: Instruction usage times. *M*: Manual mode, *TS*: Timely switching WOZ mode, *OS*: Operator switching WOZ mode, *T/OS*: Timely or operator switching WOZ mode, *L*: Linear prediction mode, *R*: Random mode, *B*: Bayesian network mode, *O*: Observation phase mode

The statistical analysis results indicate that for a WOZ agent, more degrees of freedom help improve the human participants' awareness of changes in the agent. With regard to the difference between the WOZ agent and the autonomous agent, the agent's behavior was controlled to change immediately to respond to the human user's instructions; however, the current version of the autonomous agent may have a time lag between the changes in the agent's action and the changes in the participant (manager)'s instruction, and this time lag may make it more difficult for the participants to recognize changes in the autonomous agent. Although a linear prediction function enables the agent to adapt to the user by switching its priority among "first guiding a customer," "first placing an order ," and "first clearing a seat." Because the B-mode was implemented on the basis of the results of the WOZ agent experiment, it appears to better encourage participants to change their instruction behaviors.

Figure 2 shows a typical example of the changing behaviors of one manager's instruction. It indicates that the same manager spends lesser time in the first half of the trial than in the second half for switching between consecutive instructions. This change in the instruction method suggests that the manager might adapt to the agent by observing its actions before giving instructions. As long as the agent takes a proper action, the manager prefers to observe and allow the agent to take initiative (leadership). Only when the manager finds that the agent performs some wrong or unexpected actions does he/she issue instructions to change the agent's actions.

Figure 3 illustrates the changing of the interval between the "guide" instruction and the "guide" action. The human manger (participant N18) uses the "guide" instruction to instruct the waiter agent to guide a customer who is waiting for

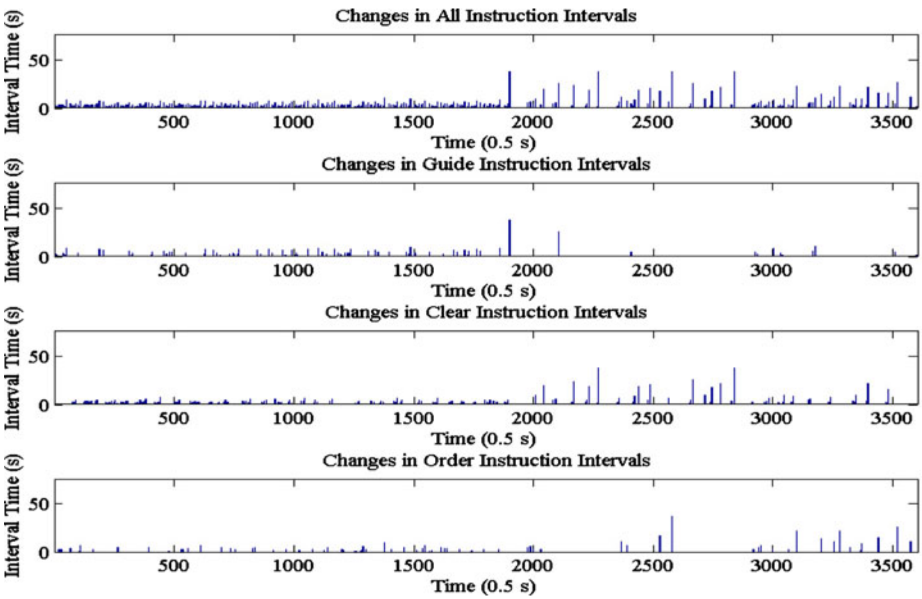

Fig. 2 Changes in instruction intervals, participant M10, 30 min, WOZ agent experiment, sample rate is 2

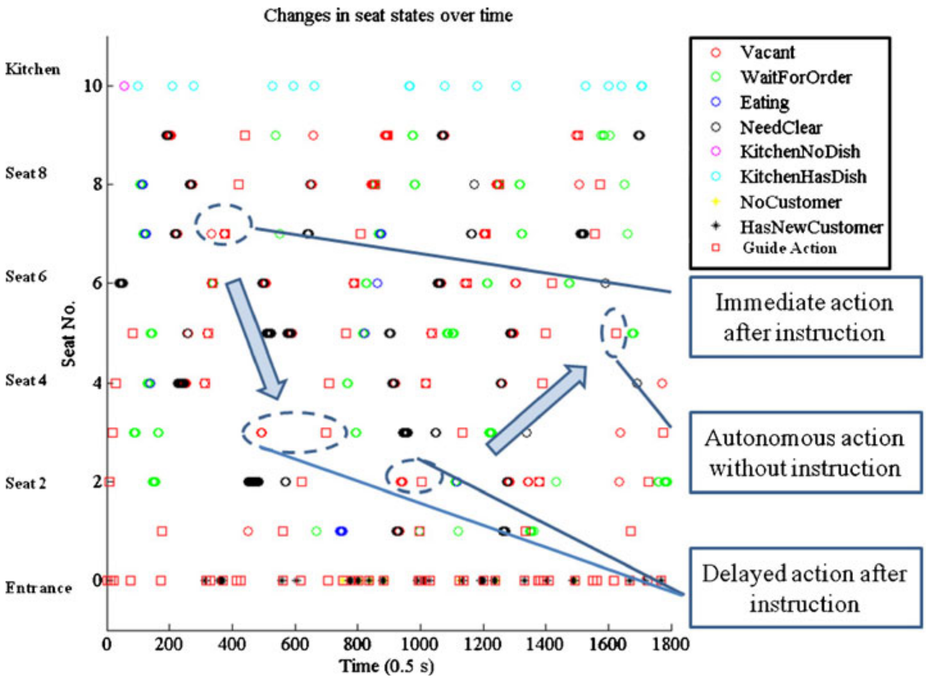

Fig. 3 Changes in seat states over time (participant N18, 30 min, B-mode, autonomous agent experiment, *Y-axis* indicates seat No: 0, Entrance; 1–9, seat 1–9; 10, Kitchen; *X-axis* indicates Time, time unit is 0.5 s, sample rate is 2 times per second)

guide at the entrance. The waiter agent can decide to perform the "guide" action immediately or to perform some other actions first according to its own criteria. From the figure, we can find that the agent performs some autonomous "guide" action at the beginning. However, the human instructor might not care about this action and continue to issue the "guide" instruction. After watching the agent perform the "guide" task immediately, as indicated in the upper-left corner by a dashed circle, the manager issues the guide instruction in advance when the waiter agent is still quite far from the target seat. The changed instruction method causes a delayed action of the agent after the manager issues the "guide" instruction. Finally, when the manager is satisfied with the response actions of the agent, he/she simply allows the agent to perform the "guide" action without issuing any instruction, as indicated by the middle-right dashed circle in the figure. In summary, the human instructor changed his instruction method to adapt to the waiter agent.

Figure 4 shows that the usage times of three types of instructions, "guide" instruction, "order" instruction, and "clear" instruction, all decrease over time. The trend that all usage times of instructions decrease over time is similar, as mentioned above.

Figure 5 shows another example in which the manager adopts a different method of instruction. In this case, the manager observed the agent's autonomous movements without issuing any "guide" instruction at the beginning. Because the agent's actions were not satisfactory, the manager began giving instructions, causing two

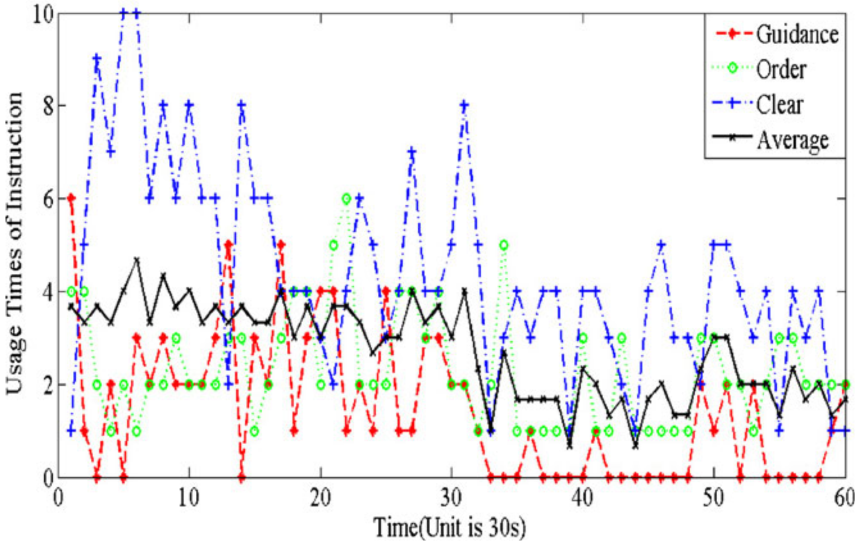

Fig. 4 Usage times of instruction (participant M10, 30 min, WOZ agent experiment, width of time window is 30 s)

long instruction intervals at the beginning and reduced values later. Similar trends were repeatedly observed with a gradual reduction in instruction intervals later. With regard to changes in the instruction intervals for the "clear" instruction, the values were relatively small at the beginning, and they reached a maximum at around

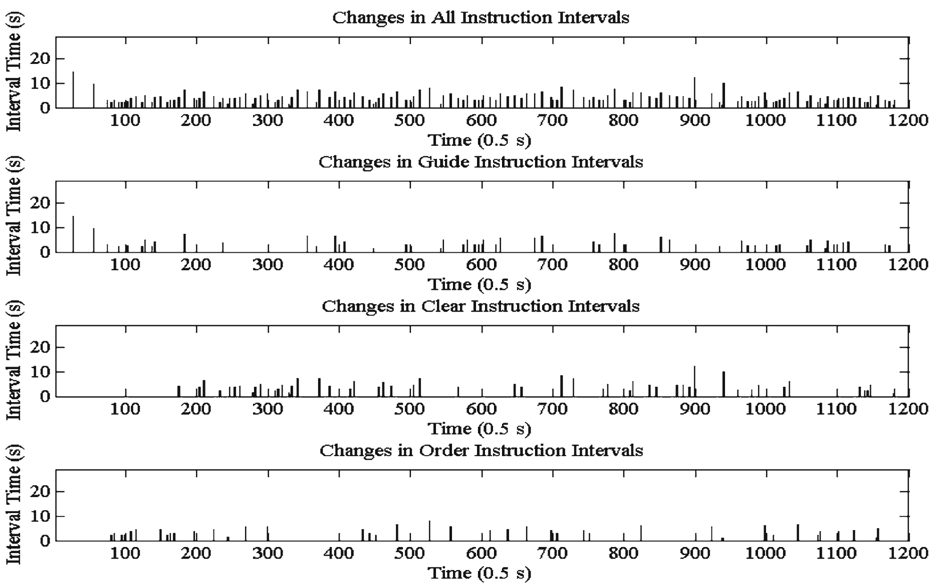

Fig. 5 Changes in instruction intervals (participant M8, 10 min, WOZ agent mode, sample rate is 2)

moment 900 to 950. This implies that the manager issued the "clear" instruction relatively frequently but waited for much longer after issuing this instruction, that is, the intervals increased later. This might be because the manager realized that the agent could perform the "clear" task well and did not feel the need to issue instructions too frequently. With regard to the interval of the "order" instruction, no obvious changes were observed. This implies that the manager might build a model for the agent after observing its autonomous actions at the beginning of the first trial.

Figure 6 shows the comparison results of the usage times of the "guide" instruction for the four modes of the autonomous agent. Although the agent was designed to respond immediately to the human users' instructions, there is a time lag between the changes in the agent's action and the changes in the participant's instruction; this time lag may make it difficult for the participants to recognize changes in the autonomous agent. In the L-mode, the linear prediction function enables the agent to trace the user's intention by switching its priority among "guiding a customer first," "placing an order first," and "clearing a seat first"; however, the participants appeared to be unsatisfied by the agent's reaction. The B-mode was implemented based on previous experimental results; it did not exhibit a significant difference from the results of other modes. Because there is no statistical difference between the four autonomous modes, namely, the L-mode, R-mode, B-mode, and O-mode, it implies that the mutual adaptation phenomenon may not depend on a specific adaptive algorithm.

Although pressing the "eat" button in the current task serves no purpose, some participants continued to use this instruction with the intention of "staying at this place." Furthermore, some accidentally pressed the "eat" button immediately after

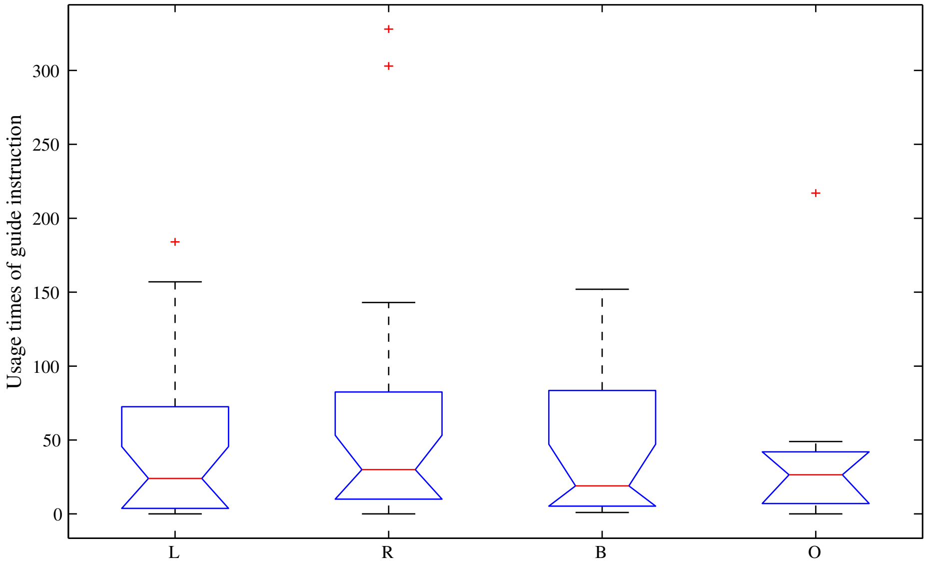

Fig. 6 Usage times of guide instruction for four autonomous agent modes (*Y-axis* indicates usage times of an instruction, *X-axis* indicates *L*, linear mode; *R*, random mode; *B*, Bayesian network mode; and *O*, observation phase mode)

the seat changed its state. This type of instruction should be currently classified as noise. Currently, these two types of instructions cannot be distinguished. Further study may be required in the future to solve this problem.

The agent's adaptation ability was subjectively evaluated by requiring the participants to fill questionnaires before and after the experiment, along with one specific questionnaire after each section. For the WOZ agent experiment, the answers to the question "How intelligent do you expect/feel the robot is/was in this experiment?" indicated that 67% (8 out of 12) participants gave a positive evaluation by rating the same or higher score after the experiment than before the experiment.

Table 2 lists the results of the participants' subjective evaluation of the changes in the agent's behavior and the participant's instructions during the breaks between different trails. For the questions Q1:"How much do you think the agent changes its behavior?" and Q2:"How differently did you instruct the waiter at the beginning and at the end?", the participants of the WOZ agent experiment gave relatively higher scores (mean = 5.3, std = 1.23, 7-point evaluation score with lowest evaluation 1 to highest evaluation 7) for Q1 and a slightly high score (mean = 4.6, std = 1.5, 7-point evaluation score) for Q2. This result suggests that many participants recognized the changes in the agent's behavior and also changed their instructions method by themselves. With regard to the reason for which they changed their instruction method, 9 out of 12 participants in the WOZ agent experiment chose the answer "because the agent changes its actions." The remaining participants chose the answer "because I could not predict the agent's action." In the autonomous agent experiment, for the same questions, 44% (11 out of 25) of the participants chose the first answer and 6 other participants chose the second answer.

Although all three utilities of the adaptive interface have not been completely achieved in the current experiment, at least some part of them was achieved effectively. The experimental results indicate that the current system can (1) make most human users recognize the change in the agent with a relatively high degree of freedom, (2) cause some human users to change their instruction method to adapt to the agent, and (3) probably realize at least the first circulation loop of the mutual adaptation phenomenon. Mutual adaptation is considered as a very general phenomenon that occurs when human users face any adaptive artifacts. Although the current environment uses a specific waiter training task, it can be considered to be an effective platform to study this topic. By the implementation of various

Table 2 Subjective evaluation of the behavioral changes in experiment

Rank item	Experiment type	Rank score	
		M	SD
Change in agent's behavior (Q1)	WOZ agent	5.08	1.24
	Auto agent	5.3	1.23
Change in instruction behavior (Q2)	WOZ agent	4.96	1.40
	Auto agent	4.6	1.50

Q1: "How much do you think the agent changes its behavior?"
Q2: "How differently did you instruct the waiter at the beginning and at the end?" (7-point scale, 1-low, 7-high)

machine learning algorithms, this environment can potentially be used to elucidate the fundamental concepts of interactive learning.

4 Conclusions

Research in Xu et al. (2010) clarified the induction conditions of mutual adaptation phenomenon that are necessary for realizing agents with competence of mutual adaptation and obtained related findings by conducting an autonomous adaptive agent experiment and a WOZ agent experiment.

In this paper, we studied the method of realizing an actively adaptive agent and further discussed the influence of adaptive function of an agent's degrees of freedom on adaptive behaviors of a human user. In order to investigate the principal characteristics of an active interface, we develop a human-agent collaborative experimental environment called WAITER. Two types of experiments, a WOZ agent experiment and an autonomous agent experiment, were conducted. The objective of these experiments is to disclose how human users change their instructions when interacting with adaptive agents with different degrees of freedom. As a result, some adaptive behaviors were observed. Experimental results indicate that human participants can recognize changes in the agent's actions and change their instruction methods accordingly. This implies that changes in the instruction method depend not only on the agent's reactions but also on the human user's cognitive models of the agent. A further analysis of the obtained results is required to extract participants' instruction patterns and to improve the agent's capability. The experimental results also suggest that active adaptation may play an important role in a human-agent collaborative task.

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