Experimental Investigation of Human Adaptation to Change in Agent's Strategy through a Competitive Two-Player Game

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ABSTRACT
We conducted an experimental investigation on human adaptation to change in an agent's strategy through a competitive two-player game. Modeling the process of human adaptation to agents is important for designing intelligent interface agents and adaptive user interfaces that learn a user's preferences and behavior strategy. However, few studies on human adaptation to such an agent have been done. We propose a human adaptation model for a two-player game. We prepared an on-line experimental system in which a participant and an agent play a repeated penny-matching game with a bonus round. We then conducted experiments in which different opponent agents (human or robot) change their strategy during the game. The experimental results indicated that, as expected, there is an adaptation phase when a human is confronted with a change in the opponent agent's strategy, and adaptation is faster when a human is competing with robot than with another human.

Author Keywords
Human-Agent Interaction; human adaptation to an agent; two player game; appearance; intentional stance.

ACM Classification Keywords
H.5.2 [Information Interfaces And Presentation]: User Interfaces - Theory and methods;

General Terms
Experimentation; Human Factors.

INTRODUCTION
Human-Agent Interaction, Human-Robot Interaction and embodied conversational agents have been extensively studied in the HCI community. It is important to experimentally investigate the human adaptation process to construct an agent model to use when a user confronts an agent. Such a model enables us to adequately design an agent's appearance and behavior based on its influence on user adaptation [6, 8]. Although there have been many studies that have focused on the influence of an agent's appearance and behavior on humans [7, 5, 3], few have investigated human adaptation to an agent.

We believe human adaptation to change in an agent's behavior strategy is especially significant in various human adaptations. Because intelligent agents that learn a user's preference and behaviors have been developed, and most constantly change their behaviors through learning. To maintain successful interaction, a user needs to recognize and adapt to the agent's change in strategy.

We experimentally investigated human adaptation to change in an agent's behavior strategy through a simple two-player game. We prepared a modified matching-pennies game. A participant and an agent play the game through the on-line experimental system. The independent variable is the opponent agent's appearance including a bear-like robot and a human. The opponent agent changes its behavior strategy during the game. We carefully observed the behaviors of the participant to the change in the agent's strategy and investigated how different agent appearances influence human adaptation by using two different opponent agents.

Komatsu and Yamada proposed the *Adaptation Gap*[4], which describes the difference between an agent model and a user model before/after actual interaction, and conducted various experiments to understand human adaptation. Their focused sign $(+, 0, -)$ of adaptation gap's value AG, and made the following assumptions, "$AG < 0$: most people would be disappointed by the agent and would stop interacting with it and $AG > 0$: most users would continue interacting with it".

Gajos et al. [2] also studied human adaptability to an adaptive user interface. They prepared a simple adaptive user interface equipped with strategies, and conducted experiments to determine the relationship between a user's predictability on behaviors of the adaptive user interface and its accuracy in such an environment. They observed that improvement in the system's accuracy had a stronger effect on user's performance and satisfaction than the improvement in predictability.

MODEL OF HUMAN ADAPTATION TO AGENT

Model of human adaptation phase
We modeled the process of human adaptation to an agent's change in strategy in terms of exploitation and adaptation

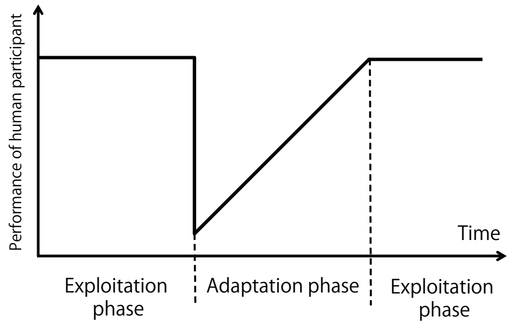

Figure 1. Player's performance in adaptation and exploitation phases.

phases. We focused on the adaptation phase in a competitive two-player game because adaptation to an agent's change in strategy is critical in a competitive situation. Figure 1 shows a simplified performance profile of a player in this two-phase framework. In a competitive two-player game, a player needs to identify the opponent's behavior strategy and decide his/her behavior strategy based on it. However, estimating the opponent's strategy based only on observed behavior is an ill-posed inverse problem because different strategies sometimes produce the same behavior. Therefore, probing an agent's strategy by actively changing player's strategy is more effective for quickly estimating than just waiting without changing strategy: the *adaptation phase*.

The player's performance in the adaptation phase increases according to improvement in estimation accuracy; therefore, performance in this phase can be approximately modeled as a linear function of time not as a step function. Once the player identified the opponent's strategy, he/she purely executes actions according to the current strategy and exploits the opponent as long as the opponent's strategy is stable in time: the *exploitation phase*. These two phases are repeated alternately.

The length of the adaptation phase differs depending on the complexity of the opponent's strategy. A more complex strategy requires a longer adaptation period because more probing steps are needed to identify the opponent's strategy. The gradient of the adaptation phase in Figure 1 indicates *adaptation speed*.

Different adaptation to different opponents

The appearance of an agent affects its modeling of cognitive ability and behavior. Dennett [1] proposed three stances, "intentional", "design", and "physical", as a criterion for an observer to model an object. Physical stance is the most concrete and concerned with the domain of physics. At this level, we are concerned with such things as mass, energy, and velocity. More abstract is the design stance, which is the domain of biology and engineering. At this level, we are concerned with such things as purpose, function, and design. Intentional stance is the most abstract and concerned with the domain of human/agent's minds. At this level, we recognize objects in terms of the belief, thinking, and intention.

With an artificial agent, we often recognize it as having intention (an intentional stance) as well as just being a machine (a design stance). Various factors, such as human-like appearance and life-like autonomy, lead a human to an intentional stance. Thus, we assigned a human opponent player and a robot player as independent variables for our experiments and investigated the change in human adaptation depending on whether the opponent is human or a robot. We expected a participant to construct a simpler and deterministic strategy model for a robot opponent and a more complicated and probabilistic model for a human one. Hence, we also expected human adaptation to a human opponent to be faster than to a robot opponent. As described in the next section, this expectation is hypothesized and verified by observing adaptation speed in an experiment with human participants.

EXPERIMENTS

The above-mentioned model of human adaptation to an agent leads to the following hypotheses:

H1: An adaptation phase exists when a human is confronted with a change in the opponent's strategy.

H2: Adaptation is faster when a human is competing with a robot than with a human.

The two hypotheses were tested through an experiment with human participants.

Penny-matching game with bonus round

A repeated penny-matching game with a bonus round was created for validating the hypotheses. The penny-matching game is a zero-sum game and is played between two players, players A and B. Each player has a penny and must secretly turn the penny to heads or tails. The players then reveal their own choices simultaneously. If the pennies match (both heads or both tails) player A keeps both pennies and gets to keep player B's penny (+1 for A, -1 for B). If the pennies do not match (one heads and one tails), player B keeps both pennies (-1 for A, +1 for B). While this game has no pure strategy Nash equilibrium, the unique Nash equilibrium of this game is in mixed strategies: each player chooses heads or tails with equal probability.

We modified the game rules so that players are able to use a deceptive strategy. The penny-matching game was played repeatedly. One game consists of six rounds, and ten games were played in the experiment. The payoff of the sixth round in every game is increased twenty times: the bonus round. A reasonable strategy for this game is to strive to win the bonus round and abandon the other five rounds because of the large payoff gap. A player is able to trap the opponent by making a series of choices during the normal five rounds so that the opponent's prediction of the player's sixth choice will be wrong. Note that the unique Nash equilibrium of the penny-matching game with a bonus round is still a mixed (random) one even though the bonus round is added.

The agents used as opponents in our experiment used only the two strategies (straightforward and deceptive) listed in Table 1. The two strategies are realized with two series of uniform and alternate choices. Uniform and alternate choices in the first five rounds were suggestive of the opponent; i.e., those exposed to the obvious trapping choices are forced to

round		1	2	3	4	5	6
payoff		1	1	1	1	1	20
straightforward	uniform	●	●	●	●	●	●
	alternate	●	○	●	○	●	○
deceptive	uniform	●	●	●	●	●	○
	alternate	●	○	●	○	●	●

Table 1. Two strategies (straightforward and deceptive) in penny-matching game with bonus round used in experiment. Black and white circles represent heads and tails, respectively. Only difference between straightforward and deceptive strategy is choice in sixth round.

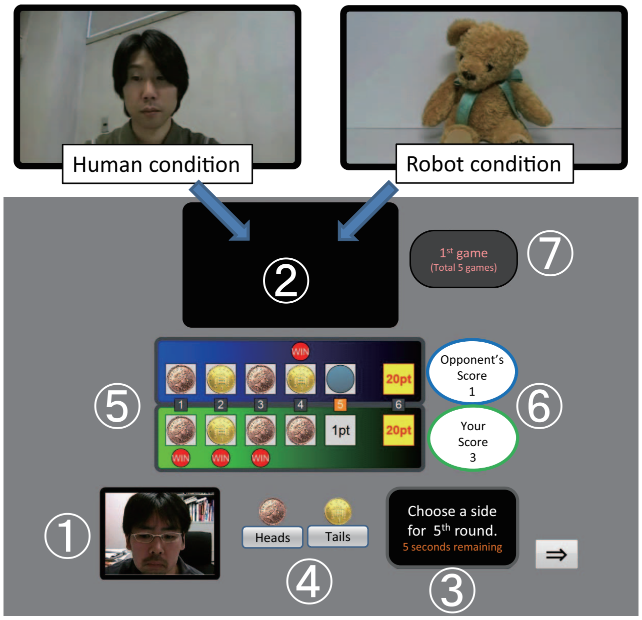

Figure 2. Interface of on-line experimental system: 1) participant's face, 2) opponent agent's appearance, 3) remaining time, 4) choice buttons, 5) histories of both players' choices, 6) scores for both players, and 7) game number.

anticipate that the opponent's sixth choice will be either deceptive (violating regularity) or straightforward (keeping regularity).

Experimental setup and measurement

The game was implemented with JavaScript and HTML and played in a Web browser (Firefox). Figure 2 shows the game interface. A Flash video of the opponent (robot or human) is displayed at the top of the interface. The bear-like robot moves its head and arms randomly in the video. The behavior of the human was recorded when he played the game in advance. The agents' behaviors, such as choosing a side of the coin, are automatically controlled by JavaScript program. Participants were told that the opponent is online. To make the participants believe the game is online, the participants' faces captured using a web camera mounted on the monitor were displayed at the bottom of the interface. Participants were instructed to click the button corresponding to his/her choice within 10 seconds for every round. Scores for both players are shown in the interface. The choices of both players remain displayed so that the participant is able to recognize the opponent's strategy. Before the main experiment, all participants played five games only for training.

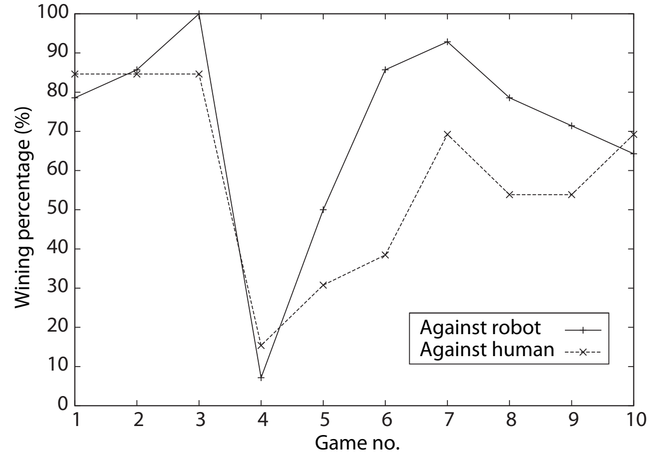

Figure 3. Percentage of participants who won sixth round of ten games.

A single-factor two-level between-subject experimental design was used. Twenty-eight graduate and undergraduate students participated in the study. Participants were randomly assigned to either a robot or human opponent condition and were seated in front of a desktop computer. Participants were informed that the point of the experiment was to access the usability of an online game system.

A total of eight series of choices including another four series beginning from tails equivalent to the four series shown in Table 1 were used. The agents used a straightforward strategy, one of the four series of straightforward strategy was randomly selected, in the first three games and a deceptive one for the rest. This is the change in agent's behavior strategy during the game, and observing human adaptation to it is our aim of the experiment.

The outcomes of the sixth round for all ten games were recorded because the participants' expectation of their opponents' strategies, i.e., which strategy, straightforward or deceptive, did they expect, was of interest. Winning the sixth round against an agent indicates that the participants expectation of the agent's strategy is correct.

RESULTS

The percentages of the participants who won the sixth round for all ten games are shown in Figure 3. Almost all the participants lost the fourth game because the agents changed their strategy from straightforward to deceptive. After the fourth game, the winning percentage with both opponent agents gradually recovered to the level of the third game. A chi-square test was conducted to investigate whether the winning percentages of the fourth to tenth games were different from that of third one (see Table 2). The results indicate that at least two games were required to adapt to the change in strategy of both agents. The gradual increase in the winning percentage after the opponent's strategy changed indicates the existence of the adaptation phase, confirming hypothesis **H1**.

The differences between recovery speeds of the winning percentage between those playing against the robot and those against the human agent (plotted on the graph in Figure 3)

Game no.	4	5	6	7	8	9	10
Against robot condition	**24.26, p<.01**	**19.33, p<.01**	2.15, n.s.	1.04, n.s.	3.36, n.s.	**4.67, p<.05**	**6.09, p<.05**
Against human condition	**14.29, p<.01**	**7.34, p<.01**	**5.60, p<.05**	0.85, n.s.	2.80, n.s.	2.80, n.s.	0.85, n.s.

Table 2. Chi-Square values (df=1) and significance levels for the winning percentages of fourth to tenth games compared with that of the third one.

were statistically confirmed. Table 2 indicates that those who played against a human agent required one more game for adapting to their opponent's change in strategy than those who played against a robot. This implies that participant's adaptation speed against a human is significantly slower than against a robot, confirming hypothesis **H2**.

DISCUSSION

The participants did not equate the robot to the human in terms of adaptation speed against the opponent's change in strategy. While the strategy equally changed in the fourth game for both opponents, what caused the inequality in participant's adaptation speed is the difference in the video the participants watched. Slow adaptation of the participants who played against the human indicates that they were cautious but not optimistic against the opponent's strategies after the strategy change in the fourth game. This is because the human appearance made the participants anticipate another change in the human opponent's strategy, and the robot appearance gave the participants the impression that its strategy was stable. The behavior of the designed artifacts, including robots and computers, is governed by laws such as mechanical, algorithmic, or structural constraints; therefore, the input-output relations of the artifacts are stable. This prototypical concept of artifact's regulated behavior might make the participants expect the simpler and less complicated strategy of the robot.

There are two causes for the gradual increase in the winning percentage in the adaptation phase: 1) Each participant changed his/her strategy just once in the adaptation phase (during games 5 to 7) and the timings of the changes varied across the participants. 2) Each participant changed his/her strategy plural times to find the most suitable strategy. To investigate these causes, we compared the number of strategy changes in the adaptation phase in two conditions. The average number of strategy changes by the participants was 1.07 under an "against robot" condition and 1.57 under an "against human" condition was 1.57, so there was a marginally significant difference ($t(26) = 1.919$, $p = 0.066$). This suggests that strategy changes by the participants were one-shot deterministic under an "against robot" condition bat indecisive and exploratory under an "against human" condition.

We consider the drop of winning percentage in the eighth game could be accounted for by meta-adaptation. Our game design requires at least two levels to be adapted. The first is adaptation for regularity of the agent's choice in the first five rounds. The second is adaptation for strategy change in the fourth game. The third, which was beyond our expectations, is an adaptation for periodic change in an agent's strategy. Participants might think the agent's strategy changes once every three games and so expect to change again in the seventh game.

Not only the appearance but also the behavior of the agents differed between the two videos. We did not separate the appearance and motion factors in our experiment. Investigating which factor contributes to the change in human adaptation speed to an agent is for future work.

CONCLUSION

We theoretically modeled and experimentally investigated human adaptation to an agent. We conducted a penny-matching game with a bonus round in a web browser for investigating how humans adapt to an opponent agent's change in strategy. The experimental results indicated there is an adaptation phase when a human is confronted with a change in the opponent agent's strategy, and adaptation is faster when a human is competing with robot than with another human. Although this experiment might be just a preliminary stage, we strongly believe this work provided a significant case study and will be inspiration for practical design of an agent and its interaction with a human.

REFERENCES

1. Dennett, D. C. *The Intentional Stance*. Cambridge, Mass, Bradford Books/MIT Press, 1987.
2. Gajos, K. Z., Everitt, K., Tan, D. S., Czerwinski, M., and Weld, D. S. Predictability and accuracy in adaptive user interfaces. In *CHI'08* (2008), 1271–1274.
3. Kiesler, S. Fostering common ground in human-robot interaction. In *RO-MAN'05* (2005), 729–734.
4. Komatsu, T., Kurosawa, R., and Yamada, S. How does the difference between users' expectations and perceptions – about a robotic agent affect their behavior? *Int. Journal of Social Robotics* (2011), 1–8.
5. McQuiggan, S. W., Rowe, J. P., and Lester, J. C. The effects of empathetic virtual characters on presence in narrative-centered learning environments. In *CHI'08* (2008), 1511–1520.
6. Tinwell, A., and Grimshaw, M. Bridging the uncanny: an impossible traverse? In *Proceedings of the 13th International MindTrek Conference: Everyday Life in the Ubiquitous Era*, MindTrek '09 (2009), 66–73.
7. Vugt, H. C. V., Bailenson, J. N., Hoorn, J. F., and Konijn, E. A. Effects of facial similarity on user responses to embodied agents. *ACM Tran. on Computer-Human Interaction 17* (May 2008), 7:1–7:27.
8. Yee, N., Bailenson, J. N., and Rickertsen, K. A meta-analysis of the impact of the inclusion and realism of human-like faces on user experiences in interfaces. In *CHI'07* (2007), 1–10.