Model Analysis of Human Group Behavior Strategy using Cooperative Agents

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Abstract: Flexible and cooperative human group behavior are realized by changing our intentions and behaviors based on dynamic estimation of other participants' intention, and also adjustment of self and others' intention. We analyze human small group behavior using cooperative pattern task in 2D grid world to clarify an individual action selection process including inference of others' intention and adjustment of intention among participants. In previous research, we have constructed behavior strategy models based on the human behavioral experiments, implemented the models to cooperative agents, and confirmed the goal achievement in almost the same steps to humans in the agent simulations. In this research, we analyze combinations of human behavior strategies realizing group behavior by comparing agent behavior to subjects behavior.

1 INTRODUCTION

Understanding of flexible cooperative behavior in groups is important for construction of intelligent systems and social agents that cooperate with human. In cooperative behavior that we usually see in groups, it is considered that the top-down decision-making process is based on the shared intention of a group, and the bottom-up decision-making process is based on the dynamic estimation of each other's intentions based on each behavior and adjusting them according to a situation. In goal-type ball games such as handball, soccer or basketball, players interact with each other in dynamic situations and estimate each intention based on the nonverbal communication such as eye contact or body language, and change their behavior to deceive or deal with the opponents. Also in everyday lives, we understand the others' intentions through their behavior and decide to cooperate with them. The interaction of multi-person requires the participants not only estimate the one other person's intention, but also select whom to focus and estimate the shared intention of the group.

Purpose of this study is to clarify the behavioral decision-making process in intelligent interaction in such a group. We will conduct behavioral experiments using a cooperative task pattern task that focuses on the selection of others and the coordination of intentions between others and the self in group behavior, and analyze the results using an agent model.

2 RESEARCH BACKGROUND

We engage in complex interactions with others, such as competition and cooperation, in various situations in society, and several studies have clarified and modeled these processes. The BDI model of beliefs (B), desires (D), and intentions (I) based on Bratman's "Theory of Intentions"(Bratman, 1987)(Rao and Georgeff, 1991)(G.Weiss, 2013) and the Bayesian Theory of Mind by Baker, Tenenbaum, and colleagues(C. L. Baker, 2009)(C. L. Baker, 2014)(W. Yoshida, 2008) are examples of research that model interactions with others. In addition, Yokoyama et al. have studied meta-strategies in interpersonal interaction(T. Omori and Ishikawa, 2010).

In the BDI model(Bratman, 1987)(Rao and Georgeff, 1991)(G.Weiss, 2013), we set our own goals based on our beliefs about the surrounding environment and choose the means to achieve those goals. And we formulate intentions to carry out our goals and act in accordance with those intentions. When others intervene here, we set new goals based on our beliefs and the intentions of others, choose other means to achieve those goals, and form new intentions

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to carry them out.

Thus, our intentions are determined in part by the environment based on one's own beliefs. In addition, we estimate the intentions of others based on our own internal models, and make decisions by balancing . The ability of a person to estimate the intentions of others is important in theory of mind, and the model proposed by Baker, Tenenbaum, and others as the Bayesian Theory of Mind states that an estimation of human intentions behaves similar to a probabilistic model based on Markov decision processes. Furthermore, in the case of a group where there are multiple others, we are considered to have a "shared concept" to share our intentions and form a common behavior. If there are more than one other person, we can share the intention of each and have shared concept to form common action, and analyzing such structure of the multi-person interaction is also important for human robot interaction(R. Sato, 2014). For example, in soccer, which is an excellent cooperative behavior, even when each player acquires different environmental information, they can set a common goal, instantly set the means to achieve it, and formulate the intention to realize it. In this way we believe that it is important to model the choices of others involved in such shared concepts and the behaviors generated from them in order to understand interactions with others.

Next, in interaction with other people, it is necessary to self-observe how other people guess about themselves, thereby guessing what kind of influence can be given to others by themselves. Self-observation principle(T. Makino, 2003) estimates the behavior of others by adopting a model that looks at himself objectively to others. By the principle, it is possible for people to match with or withdraw others in the group and construct strategies mutually predicting of each mind. Furthermore, estimating internal states of each other also helps cooperative actions such as mutually coordinating behaviors and working jointly. In order to adjust their behavior, it is important to select one from the multiple sub-goals and estimate what the others intend. The problem is the recurrence of intention estimation between self and others. Omori et al. have proposed a model of meta-strategies such as active and passive in interpersonal interaction to construct social robots(T. Omori and Ishikawa, 2010). In addition to one-to-one estimation of mutual intentions, there is a strategy for estimating the intentions shared by multiple persons at the same time based on mutual estimation in group behavior. In other words, there is a process of coordinating intentions by dynamically considering one's own role in the group and selecting others to be involved in cooperative behavior from multiple others. We examine the effect of the difference between the two groups. Therefore, a cooperative task that abstracts the group behavior, we analyzed the subject's behavior using a pattern task as a cooperative task, and simulate the agent based on the results.

3 PATTERN TASK

3.1 Outline of Our Task

We propose the pattern task for analyzing human cooperative behavior. In this task, four subjects participate and cooperate in a grid world without verbal communication, and aim to realize the location goal pattern in as few steps as they can. Each subject behaves as an agent in the grid world and can take 5 actions (stop, go-left, go-right, go-up, go-down) (shown in Figure 1). Since the goal patterns are defined with relative distances of three points in grid without overlaps, each four agents ought to consider whom to cooperate with to achieve the pattern within minimal steps. That is, although the goal is achieved by whole four agents by positioning to form the goal pattern, each subject must estimate others' intention to prevent misunderstanding for achieving the goal in each steps, and tell others whether to participate forming the pattern or not, through only their behaviors.

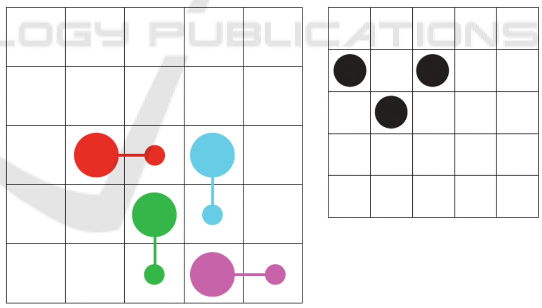

Figure 1: Pattern Task (Left) The grid world. The large round sprites in this figure represent the agents and their current locations and the small ones represent the location in the previous step. (Right) The goal pattern. Since the end condition of each trial is defined by the relative position of three points, the trial ends in this situation.

- **Phase1:** Select three coordinations where the subject realize the goal pattern at last, or the pattern will be realized by the other subjects.
- **Phase2:** Select other subjects whom to be focused to realize the goal pattern.
- **Phase3:** Select one of the five actions (stop, go-left, go-right, go-up, go-down).

Phase4: Select three coordinations where the subjects focused in Phase2 selected in Phase 1.

Phase5: Select the subjects who are considered to be selected in Phase2 by the subject.

The above whole five phases are repeated in each steps of a trial until the subjects achieve the goal pattern or the limit of maxi- mum steps. Then the initial locations of the agents are changed and after changing some different initial locations, the different goal pattern is applied and repeated each trials.

Several rules are set in this task:

- Subjects are not allowed to talk about their location or action which enables the other to specify the agent to the other subjects.
- The goal pattern can be realized by three out of four agents, and it is not necessary for whole four agents to locate in the goal locations.
- Since the task achievement is judged by the relative locations of the goal pattern, parallel shift of the coordinations is accepted but the rotation or reverse of the pattern is not accepted.
- The agents selected in Phase2 or 5 don't conclude the agent who is selecting in this phase himself. If the number of selected agents was more than three (for example, in the case the distance of the goal pattern was the same with few agents), the agent select the only three agents most possible to achieve the pattern.
- The goal coordinations selected in Phase 1 and 4 are the most realizable pattern to achieve.
- Agents are allowed to move to the same location of the other agents and they are able to move to the four neighboring cell of the grid world (left, right, up, down). The field is not torus grid world and the ends of the field are not connected (i.e., the agent cannot go right at the right edge and also the other edges).

3.2 Human Behavioral Analysis

A total of 77 trials of the coordination task were conducted with 20 subjects using one to three different goal patterns. As a result, each subject assumed a novel pattern at the beginning of the task, and the relationship between the pattern assumed by the subject and the pattern assumed by others. After that, some subjects changed their own goal patterns when the intentions of all the subjects became consistent, and finally all the subjects continued to estimate their own patterns in a consistent manner. Specifically, the following three relationships were found between the patterns selected by the subjects and the patterns selected by others.

(a) Select the same pattern as Phase 1 in the previous step.

(b) Select the same pattern as the pattern selected by Phase 1 by another agent.

(c) Select a new pattern different from every pattern selected in the previous step.

Based on these 3 choices, we analyzed the pattern selection process of subjects. In the early part of task, subjects selected a new pattern of choice (c). After that, one of subjects showed a change in strategy, matching a pattern selected by other subjects. Such a change in strategy can be divided into cases where subjects reach a common agreement in the first half of trial and cases where they agree in the second half. Based on these results, in this pattern task, which encourages everyone to cooperate, we present each other's intentions to others in a form that is as easy to understand as possible, and select the goal pattern that shortens the total number of steps to be taken in each situation. In the pattern task, we present our intentions to others in a way that is as clear as possible, and select a goal pattern that shortens the overall arrival time in each situation. In order to see the tendency of pattern selection within subjects, we checked self-priority of goal pattern selected by subjects at each step. In Phase 1, 86/113 (76%) of the subjects' choices were included in the shortest goal set, and 86/132 (65%) of the subjects' choices were included the case where Phase 1 was not included in the shortest goal set. Based on these results, we construct an agent model based on the behavioral strategies of the group.

4 AGENT MODEL

Based on the results of previous chapter, we construct an agent model and conduct simulations. In this simulation, we clarify the action decision process including estimation of intended goal patterns of others in Phases 1 to 5. We compare the set of goal patterns that can be reached in shortest time at each step with set of goal patterns estimated based on the actions of others after initial step, and implement the process of narrowing down goal by majority vote.

In the initial step, each agent's action is determined from the tree structure of the shortest goal pattern (Phase 1), the set of interested others (Phase 2) which determines the three agents that make up the pattern, and the action of agent corresponding to each goal point (Phase 3). Next, the goal patterns of the others corresponding to Phase4 and Phase5 and the others of interest are inferred based on the tree structure from the numbers of the other agents and their actions. Action decisions after the initial step are determined by goal patterns estimated based on this method and the own goal patterns determined in the same way as in the initial step. In addition, it is determined by using its own goal pattern in the previous step (see (K. Itoda, 2017) for details of each algorithm). The agent action selection algorithm is presented in Algorithm 1.

Algorithm 1: Agent Action Selection.

Require: Action Decision Tree, Current State Set$X_t \in \mathbb{Z}^{4\times2}$, Target Pattern$g* \in \mathbb{Z}^{3\times2}$
Ensure: Action Set $\mathbf{A}_t \in \mathbb{Z}^4$
 Extract nearest pattern set G_t realizing target pattern $g*$ from current state set X_t
 for $i = 1$ to 4 **do**
  if t >0 **then**
   Extract the intersectional set between the set of the target pattern $\mathbf{g}^i_{t-1}$ and the target patterns of others $\{\mathbf{g}^j_{t-1}(i)\}_{j=1\ldots|\mathbf{f}^i_{\mathbf{g}^i_{t-1}}|} = \mathbf{G}_{t-1}(i)$ estimated by the agent i at the time $t-1$, and the target pattern set G_t and get the target pattern candidate set $\mathbf{G}^i_c = \{\mathbf{g}^i_{t-1}, \{\mathbf{g}^j_{t-1}(i)\}\} \cap G_t$
   if $|\mathbf{G}^i_c| = 0$ **then**
    $\mathbf{G}^i_c \leftarrow G_t$
   end if
  else
   $\mathbf{G}^i_c \leftarrow G_t$
  end if
  if Random Selection **then**
   Randomly select the target patterns $\mathbf{g}^n_t \in \mathbf{G}^i_c (n = 1\ldots|\mathbf{G}^i_c|)$ and get $\mathbf{g}^i_t$ ... Phase1
   Randomly select the focused agent $f^m_{\mathbf{g}^i_t} \in F_{\mathbf{g}^i_t} (m = 1\ldots|F_{\mathbf{g}^i_t}|)$ belongs to the selected target pattern and get $\mathbf{f}^i_{\mathbf{g}^i_t}$ ... Phase2
   Decide the action $\mathbf{a}^i_t$ and the corresponding agent i by tracing the action decision tree forward ... Phase3
  else if Self-priority Selection **then**
   Extract the target pattern set from the target candidate set $\mathbf{G}^i_c$ including the agent i in the focused agent set $f^m_{\mathbf{g}^n_t}$ and get the target pattern set $\mathbf{G}^i_{c'}$
   Randomly select the target patterns $\mathbf{g}^l_t \in \mathbf{G}^i_{c'} (l = 1\ldots|\mathbf{G}^i_{c'}|)$ and get $\mathbf{g}^i_t$ ... Phase 1
   Randomly select the focused agent $f^m_{\mathbf{g}^i_t} \in F_{\mathbf{g}^i_t} (m = 1\ldots|F_{\mathbf{g}^i_t}|)$ and get $\mathbf{f}^i_{\mathbf{g}^i_t}$ ... Phase 2
   Decide the action $\mathbf{a}^i_t$ and the corresponding agent i by tracing the action decision tree forward ... Phase3
  end if
 end for

From the experiment, it was found that subjects' behavioral decision making process includes In order to reach each other's goal as quickly as possible within the shortest step in each step, majority-based decisions are taken. In addition, in Phases 4 and 5, subjects' attention is focused on intentions of others. The agent intention estimation algorithm is presented in Algorithm 2.

Algorithm 2: Intention Estimation of Other agents.

Require: Action Set $\mathbf{A}_t \in \mathbb{Z}^4$, Focused Others Set$\mathbf{F}_{\mathbf{G}_t}$
 Initialize the candidate of others' target patterns and others focused $D[g^n_t, f^m_{g^n_t}]$
 for $i = 1$ to 4 **do**
  Estimate the focused agent $f^m_{g^n_t}$ and the target pattern g^n_t from the agent number i and its aciton $\mathbf{a}^i_t$ by tracing the action decision tree backward, and vote them as the candidates of the target pattern and the focused agent of others
 end for
 for $i = 1$ to 4 **do**
  Filter the candidates by the focused agent $\mathbf{f}^i_{\mathbf{g}^i_t}$ of the agent i and get $D^i[g^n_t, f^m_{g^n_t}]$ $(f^m_{g^n_t} = \mathbf{f}^i_{\mathbf{g}^i_t})$
  for $j \in \mathbf{f}^i_{\mathbf{g}^i_t}$ **do**
   Filter the candidates $D^i[g^n_t, f^m_{g^n_t}]$ additionally by the agent j and get $D^i_j[g^n_t, f^m_{g^n_t}]$ $(j \in f^m_{g^n_t})$
   The most majority candidates are assumed to be the target pattern $\mathbf{g}^j_t(i)$ and the focused agent $\mathbf{f}^j_{\mathbf{g}^j_t}(i)$ of the agent j estimated by the agent i (the candidates of the same number of votes are selected randomly) ... Phase 4, 5
  end for
 end for

In addition, when selecting a pattern from a set of goal patterns that can be reached in the shortest possible time, it is thought that subjects will preferentially select a pattern that includes themselves, or will randomly select a pattern regardless of whether it includes themselves or not, and will then estimate and adjust the goal patterns of others. Therefore, we set the following conditions for the simulation. The following five strategies are used to determine agent's behavior.

Strategy A: Self-priority Selection x Intention Estimation of Other Agents
It estimates goal patterns from previous steps of other agents and matches them with the goals that can be reached by current shortest path. After that, it extracts a set of patterns that include itself among them, and randomly selects a goal among them to go to that goal.

Strategy B: Self-priority Selection x No Intention Estimation of Other Agents
Estimate the goal that can be reached by current shortest path, extract the pattern set that includes own from the goal, and randomly selects a goal from pattern set.

Strategy C: Random Selection x Intention Estimation of Other Agents
Estimate the goal pattern from previous steps of

other agents and match it with the goal to be reached by the current shortest path. After that, randomly select a goal among them and go to that goal.

Strategy D: Random Selection x No Intention Estimation of Other Agents
Estimate the goals that can be reached by current shortest path. It randomly selects one of the goals and goes to that goal.

Strategy E: Random Behavior Agents
At each step, randomly select and execute an action from the action set, regardless of the current state.

5 ANALYSIS OF SUBJECT STRATEGIES

In order to clarify subject's behavioral strategy by comparing the combination of each strategy and the behavior, we implement the model strategies A to E from the previous section on each of four agents. In this experiment, we first simulate a random initial state to verify how quickly each strategy combination itself accomplishes the task. To compare the results with subject's behavior, we simulated the initial state of the subject's behavior experiment and compared final positions.

5.1 Combination of Strategies and Number of Steps to Reach the Goal

First, we check how easy it is to accomplish the task for each combination of strategies. We randomly prepared 100 initial positions and 100 initial goal patterns, and simulated them. The average number of steps required to reach the goal for each combination of strategies is shown in Figure 2.

Figure 2 shows that the average number of steps required to reach the goal increased in a stepwise pattern according to the number of agents in strategy E that randomly selected actions among four agents. This suggests that randomly acting agents have a large impact as noise in the group. On the other hand, there was not much difference in the average number of steps among combinations of strategies with the same number of agents of strategy E in the group.

In particular, (A, A, A, A) and (A, A, A, B), which have many agents with self-priority strategy A and estimates the intentions of others, are able to accomplish a task in a shorter number of steps. On the other hand, the combination with not only a large number of strategy A but also a large number of strategy B, which is self-priority but does not perform estimation of others' intentions, comes out on top. Strategy A can reduce the number of steps to reach a goal, because it can limit the goal of the group by considering self-priority and the intentions of others. Strategy B, which does not estimate the intentions of others, achieves a task at an early stage. Even if there are many strategies that only pursue their own goals without considering others, it is possible to achieve the task faster. In particular, strategies such as (B, B, B, B) are fifth from the bottom among the combinations of strategies that do not include strategy E. In the case of a self-priority strategy, a coordinator such as strategy A or strategy C, which randomly selects the shortest goal but estimates the intention, may be able to accomplish the task quickly.

5.2 Comparison of Each Strategy Combination and Subject Behavior

Next, based on the initial conditions used in subject behavioral experiments, 100 agent simulations were conducted for each. We analyzed the subjects' behavioral strategies by comparing their final arrival positions with the final arrival positions of agents. It is important to compare the selection of the goal pattern in Phase 1, the selection of others of interest in Phase 2 in the action sequence of each steps. However, the agent's selection is bounded by conditions such as self-priority, and randomness occurs. For this reason, in this simulation, we compared the final positions of the subjects and agents when they completed a task in order to compare their tendencies as a whole group. We used the initial state of 15 trials among all 77 trials of subject data, in which subjects finally reached the goal and there were no erroneous inputs in steps of the trials in all phases.

In a preliminary experiment, we found that when there is little ambiguity in the initial state and the final goal is uniquely determined, agents without randomly selected strategy E reach the same location as subject's final destination. In this paper, we will examine how to resolve ambiguity when the ambiguity of the goal is high. We focus on trials in which minimum number of shortest goals that can be reached from the initial state is two or more and distance from initial position to initial goal is two or more steps.

Table 1 shows top ten strategy combinations with the largest number of final arrival position matches. As a result, except for strategy E, which is a random action selection strategy, the strategies that include a large number of strategies A, which are self-priority and estimate the intentions of others, have a large number of matches between subjects and agents. This

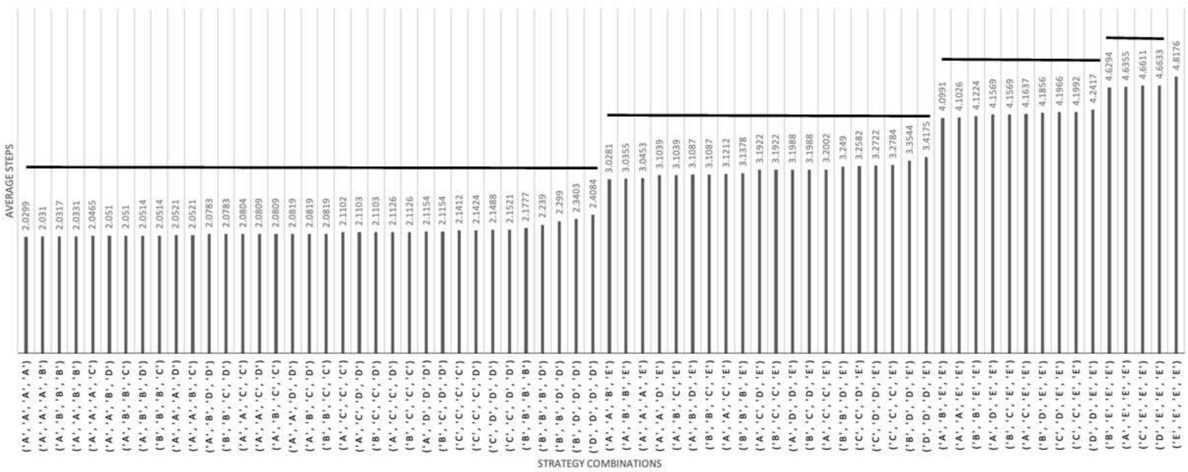

Figure 2: Combination of strategies and average number of steps reached in goal pattern. As the number of randomly acting agents in strategy E increases, steps increase in a stepwise. Randomly acting agents have a large impact on the noise in the group.

Table 1: Comparison of each strategy combination and the subject's final position of arrival in the case of high ambiguity.

initial distance	initial shortest goal number	A A A A	A A A A	A A A A	A A A A	A B B B	A B B B	A B C B	A B D B	B B B B	B B C B	total
2	5	10	7	8	10	11	8	22	21	17	18	132
2	3	51	49	58	60	49	51	51	59	57	46	531
2	2	44	23	41	29	37	43	35	45	42	44	383
2	2	79	74	75	75	82	78	72	68	75	68	746
2	2	45	55	41	45	47	40	46	43	46	44	452
2	5	53	59	46	58	46	50	42	47	45	50	496
	total	282	267	269	277	272	270	268	283	282	270	

means that when there is a high degree of ambiguity in goals of subjects' behavior, they choose self-priority goals so that their own goals are easily perceived by others. It is also possible that subjects will behave more like strategy A, which is to execute the task while estimating goals of others. In addition, since a task can be accomplished by three of the four agents, there will be more agreement on final destination positions when there are three agents with strategy A.

On the other hand, when the number of initial shortest goals is large, such as three or five, the number of matches is larger for strategy combinations such as (A, B, C, C), (A, B, D, D), and (B, B, C, D) than for combinations that include a large number of strategies A. This means that rather than all subjects choosing a goal in a self-priority pattern and acting while estimating the intentions of others, some subjects choose a goal randomly among the shortest goals, or think of a goal without estimating the intentions of others, which at first glance may seem to be a bad choice, but they reach the same place. If the ambiguity is too large, there is a high probability that goals of both subjects will be divided when they make self-priority choices. In addition, by ignoring the intentions of others, we may reduce the number of possible goals in each situation. Therefore, by making these adjustments within the group, it is thought that subjects perform the task when there is high ambiguity.

6 CONCLUSIONS

In this study, we conducted agent simulations based on behavioral experiments of a cooperative task pattern task in order to clarify the decision-making process in cooperative group behavior. By simulating a group of agents with each strategy combination, we verified the characteristics of each strategy from average number of steps reached in accomplishing the task. We also simulated each strategy combination using initial conditions of subjects' behavioral experiments, and compared final positions of subjects and agents in achieving a task when ambiguity of goals is high. We found that when ambiguity is very high, the strategy combination with shortest number of steps is not always close to subjects in the case of agent simulation alone.

In order to analyze the differences between conditions in more detail, we control the ambiguity in each condition and increase the number of trials in each case. In addition to ambiguity in goals, there may be ambiguity in subjects, such as who subjects in the same goal, and subjects may take actions to explicitly reduce ambiguity by their actions as well as their estimation strategies. By incorporating these factors into the model, we can perform more detailed simulations.

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