Modeling Human Behavior for Virtual Training Systems

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Abstract

Constructing highly realistic agents is essential if agents are to be employed in virtual training systems. In training for collaboration based on face-to-face interaction, the generation of emotional expressions is one key. In training for guidance based on one-to-many interaction such as direction giving for evacuations, emotional expressions must be supplemented by diverse agent behaviors to make the training realistic. To reproduce diverse behavior, we characterize agents by using a various combinations of operation rules instantiated by the user operating the agent. To accomplish this goal, we introduce a user modeling method based on participatory simulations. These simulations enable us to acquire information observed by each user in the simulation and the operating history. Using these data and the domain knowledge including known operation rules, we can generate an explanation for each behavior. Moreover, the application of hypothetical reasoning, which offers consistent selection of hypotheses, to the generation of explanations allows us to use otherwise incompatible operation rules as domain knowledge. In order to validate the proposed modeling method, we apply it to the acquisition of an evacuee's model in a fire-drill experiment. We successfully acquire a subject's model corresponding to the results of an interview with the subject.

Introduction

Virtual training systems for individual tasks, such as the acquisition of flight techniques, are already in use, and are becoming popular for teamwork training, such as leadership development(Rickel & Johnson 1999; Traum & Rickel 2002). This is because several of the human participants necessary to conduct group training can be replaced by software agents. These agents, however, must offer highly realistic and compelling social interactions with humans because they have to interact with the trainee(Johnson, Rickel, & Lester 2000; Cavazza, Charles, & Mead 2002).

Agents that provide realistic interactions have been realized by adding human-like expressions to agents, such as speech and nonverbal and emotional behavior(Cassell *et al.* 2000; Marsella & Gratch 2002; Lester *et al.* 2000; Pelachaud *et al.* 2002), since these are needed for the face-to-face interactions that occur in collaborations. Moreover, in training for social navigation scenario based on one-to-many interaction, such as direction giving for evacuations, the evacuee agents must offer diverse behavior to make the training realistic(Wray & Laird 2003; Sukthankar *et al.* 2004). Reproducing the physical differences between agents, such as the speed of their movement, is an easy task, but realizing differences in personality has, up to now, not been possible.

Human behavior often depends on personality as implied by the proverbs "Fools rush in where angels fear to tread" and "Unless you enter the tiger's den, you cannot steal her cubs." Realizing diverse agent behavior is critical for making more realistic training events. As the first step in developing diverse agents, we set our goal as acquiring diverse user operation models from the logs of agents controlled by human subjects in participatory simulations. Models to decide agent behavior can be approximated by the operation models because the agents in the simulations are fully operated by the human subjects. In this paper, operation models are defined as sets of prioritized operation rules, which represent how the subjects operated their agents in the simulations. In order to accomplish our goal, we address the following two research issues.

Forming various consistent operation models

We must combine a wide variety of operation rules to realize the diversity of operation models. However, many of these rules will be inconsistent. When developing a operation model, we have to combine several operation rules while maintaining the consistency of the model.

Extracting operation models that offer personality

To ensure realism, the agent behavior must exhibit distinct personalities. Our approach is to extract personal operation models from the subjects' operation history and the logs of agents who participated in simulations.

This paper will first clarify what a participatory simulation is and the modeling process that it permits. Next, we define the technical terms used in this paper, and then formalize our target problem by using the terms for hypothetical reasoning. Finally, we validate our method in the evacuation domain by developing an operation model of a subject operating an evacuee agent.

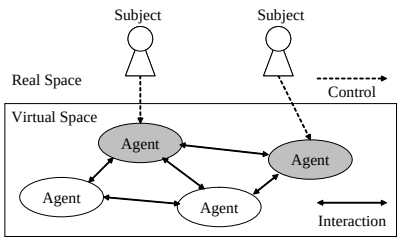

Figure 1: Participatory Simulation

Participatory Simulation

A participatory simulation is a multiagent simulation in which humans control some of the agents. The humans observe the virtual space from the view of their agents, and operate their agents by using controllers such as keyboards. The coexistence in virtual space of autonomous agents and agents controlled by humans can realize indirect interactions between agents and humans (Figure 1).

The use of participatory simulations in the modeling process brings the following three benefits.

- It enables us to extract observations of each human subject and their operation history from the log data.
- It enables us to capture a subject's screen, which is then shown to the subject at the interview stage to acquire his/her operation rules effectively.
- It enables us to employ scenario-controlled agents in order to compensate for the lack of participants.

In this research, we acquire a subject's operation model, a set of operation rules, by explaining the subject's behavior observed in one or more participatory simulations. However, the operation rules so gained may exhibit some incompatibility. Therefore, we hypothesize whether each operation rule is employed by the target subject, and choose the assumptions that pass hypothetical reasoning, which offers the consistent selection of hypotheses. The result of hypothetical reasoning is a set of compatible operation rules employed by the target subject. We propose the following modeling process (Figure 2).

1. Conduct participatory simulations with agents controlled by human subjects.
2. Obtain a target subject's behavior from log data consisting of coordinate values and orientation of his/her agent, and describe the observations in predicate logic.
3. Collect operation rules constituting domain knowledge through interviews with some of the human subjects.
4. Generate explanations of the target subject's behavior by using the domain knowledge and the observations.
5. Winnow the explanations generated in the previous step by questioning the target subject. The hypotheses in the last explanation represent the subject's operation model.

In this paper, we focus on using hypothetical reasoning to acquire the operation models shown in the dotted frame.

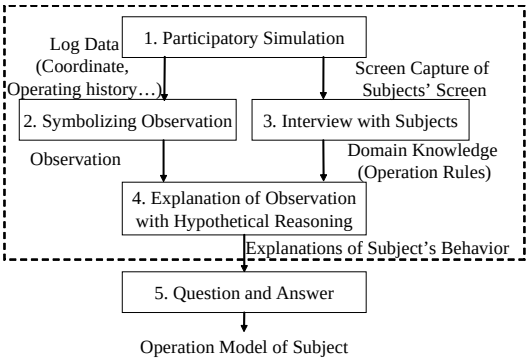

Figure 2: Modeling Process (This paper focuses on the area in the dotted frame)

Formalizing the Problem

In this section, to permit the application of hypothetical reasoning to the acquisition of subject operation models, we formally define the domain knowledge and observations.

Definition of Technical Terms

In this research, we assume that a subject decides his/her next operation based on the world as observed from the view of his/her agent, and his/her operation model. The world observed by the subject is indicated by S. S consists of conjunctions of literals about the world. We describe this piece of information at time t as S_t. Time is a discrete value incremented by one as the world observed by the subject changes. The operation model is a set of prioritized operation rules $\langle P, \preceq \rangle$. P is a set of operation rules that could be employed by the subject, and $\preceq$ represents the priorities of the elements of P. P is a subset of $Rules$, a set of operation rules obtained through interviews with subjects. $\preceq$ is a subset of the Cartesian product $Rules \times Rules$. If each operation rule in $Rules$ is indicated by $rule_i$ $(0 \leq i \leq j \leq |Rules|)$, $\langle rule_i, rule_j \rangle \in \preceq$ can be described as $rule_i \preceq rule_j$.

For applying hypothetical reasoning to the modeling of subjects, we define an operation selection mechanism and operation rules as domain knowledge Σ. Each element of domain knowledge is indicated by σ_k $(0 \leq k \leq |\Sigma|)$. We hypothesize which operation rules are employed by the target subject($rule_i \in P$), and which rules take priority($rule_i \preceq rule_j$). A set of these hypotheses, an inconsistent set of assumptions, is indicated by H. Moreover, we describe the subject's behavior from the beginning of the participatory simulation, 0, to the end of the simulation, end, as observation G. The solution h of hypothetical reasoning represents the an operation model of the subject. In addition, h is a subset of H.

Domain Knowledge

Domain knowledge consists of operation rules obtained through interviews with subjects, the subjects' operation selection mechanisms, and constraints to prevent the inconsistency caused by the inappropriate combination of hypotheses.

We describe operation rules as condition-action rules. Subjects operate their agents following the action part of the rule whose conditions are satisfied. Example 1 shows a description of operation rules.

Example 1 (Description of operation rules).

$rule_1$:
if $Near(x, \text{self}), Noop(x), Noop(\text{self})$ then Initiate(walk)
$rule_2$:
if $Near(x, \text{self}), Walk(x), Noop(\text{self})$ then Initiate(walk)
$rule_3$:
if $Near(x, \text{self}), Noop(x), Noop(\text{self})$ then Initiate(turn)

$Rule_1$: the subject executing this rule makes his/her agent pass agent x if both are standing next to each other. $Rule_2$: the subject executing this rule makes his/her agent follow x if x walks by the standing agent. $Rule_3$: the subject executing this rule makes his/her agent look around if both are standing next to each other. In these examples, self *indicates the agent controlled by the target subject.*

Next, we define the operation selection mechanism.

Definition 1 (Operation selection σ_1).
$(\exists rule_i(rule_i \in P \wedge rule_i = \max_{\preceq}\{rule | Applicable(rule, S_t)\}))$
$\Rightarrow Do(action(rule_i))$

A subject employs $rule_i$ whose priority is the highest among all operation rules applicable in S_t, the world observed by the subject at time t. As a result, the subject starts the operation described in the action part of $rule_i$ at time t. $Applicable$ and Do are predicates meaning that the precondition of a rule is satisfied, and that the subject initiates an operation, respectively. In addition, function $action$ returns the agent's action initiated by the subject when executing the rule which is an argument of the function.

Definition 2 (Continuation of operation σ_2).
A subject can continue his/her current operation. This is represented by the predicate $Continue$.

Finally, we introduce the following constraint to prevent the inconsistency caused by the erroneous combination of hypotheses.

Definition 3 (Constraint: σ_3).

$$\forall rule_i, rule_j (rule_i, rule_j \in P \wedge (condition(rule_i) = condition(rule_j)) \Rightarrow (action(rule_i) = action(rule_j)))$$

P does not include operation rules whose preconditions are the same but whose actions are different. Function $condition$ returns the precondition of the operation rule which is an argument of the function.

Description of Observation

The number of observations increases every time S changes. We define G and G_t, observations at time t, as below.

Definition 4 (Observation G).

$$G \equiv (G_0 \wedge \ldots \wedge G_t \wedge \ldots \wedge G_{end})$$

Definition 5 (Observation G_t).

$$G_t \equiv (S_t \Rightarrow A_t)$$

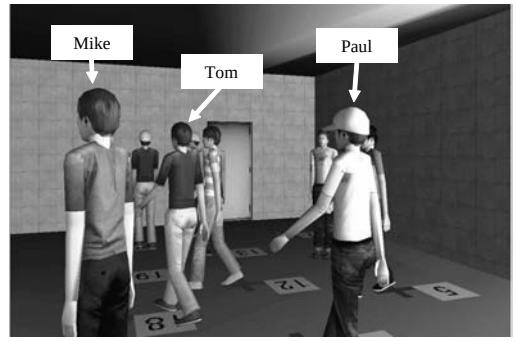

Figure 3: Agent John's View at T-1

Observation G_t describes what situation the target subject observes from his/her agent's view, and how the subject operates his/her agent. The subject's operation at time t is indicated by A_t. Specifically, A_t is either the literal represented by predicate Do, meaning the subject initiates an operation, or one represented by predicate $Continue$, meaning the subject continues an operation.

These observations, in time-series form, are obtained from the log data of participatory simulations, and are described in predicate logic. Given the nature of the virtual space used, the log data consists of agent coordinate values and orientation, and subject's operation history. For example, we use observation $G_{\mathrm{T}-1}$ to indicate that the subject's operation at time $\mathrm{T}-1$ results in John, see Figure 3, starting to walk at time T after standing at time $\mathrm{T}-1$, as below.

Example 2 (Description of observation $G_{\mathrm{T}-1}$).
$Near(\text{Mike}, \text{John}) \wedge Near(\text{Paul}, \text{John}) \wedge Far(\text{Tom}, \text{John}) \wedge Noop(\text{Mike}) \wedge Walk(\text{Paul}) \wedge Walk(\text{Tom}) \wedge ToLeft(\text{Paul}) \wedge ToLeft(\text{Mike}) \wedge Forward(\text{Tom}) \wedge InFrontOf(\text{Paul}, \text{John}) \wedge InFrontOf(\text{Mike}, \text{John}) \wedge InFrontOf(\text{Tom}, \text{John}) \wedge \ldots \wedge Noop(\text{John}) \Rightarrow Do(\text{walk})$

The predicates constituting the above observation are classified into the following four types.

Distance $Near(x, y), Far(x, y)$: Agent x is near/far from agent y.

Positional relation $InFrontOf(x, y)$: Agent x is in front of agent y from the target subject's view.

Orientation $Forward(x), ToLeft(x)$: Agent x faces the same direction as the agent controlled by the target subject/Agent x faces to the left from the target subject's view.

Action $Noop(x), Walk(x)$: Agent x is standing/walking.

Acquisition of Behavior Model

In this section, we explain how to acquire operation models through the use of hypothetical reasoning(Poole 1987). Specifically, we generate an explanation of G, behavior of the target subject, with Σ, which consists of operation rules and an operation selection mechanism, and H, whether each operation rule is executed by the agent and which rule has priority. The solution h fulfills the following three conditions and is the behavior model of the agent.

1. $h \cup \Sigma \vdash G$
2. $\Sigma \cup h$ is consistent.
3. A subset of h does not fulfill the above conditions.

First, the condition is transformed into $h \cup \Sigma \vdash G_0, \ldots, h \cup \Sigma \vdash G_t, \ldots, h \cup \Sigma \vdash G_{end}$ by applying "Rule T", transitive law of provability, since G consists of conjunctions of G_t as indicated by definition 4. Additionally, $h \cup \Sigma \vdash G_t$ is transformed into $h \cup \Sigma \cup \{S_t\} \vdash A_t$ by applying the deduction theorem to the condition since G_t is equivalent to $S_t \Rightarrow A_t$ as indicated by definition 5. For example, the proof of $G_{\mathrm{T}-1}$, the observation shown in Example 2, is transformed into $h_{\mathrm{T}-2} \cup \Sigma \cup \{S_{\mathrm{T}-1}\} \vdash Do(\mathrm{walk})$. This proof is illustrated by the proof tree in Figure 4. Note that we assume $Rules$ to be $\{rule1, rule2, rule3\}$, which are illustrated in Example 1, and $h_{\mathrm{T}-2}$, the operation model acquired from $G_0, \ldots, G_{\mathrm{T}-2}$, to be $\{rule_3 \in P\}$. $G_{\mathrm{T}-1}$ is proved in the following process.

1. According to σ_1, the proof of $Do(\mathrm{walk})$ needs to prove $action(rule_i) = \mathrm{walk}$, $rule_i \in P$, and $rule_i = \max_{\preceq}\{rule \mid Applicable(rule, S_{\mathrm{T}-1})\}$ to be true.
2. $Rule_1$ and $rule_2$ can satisfy the first condition, $action(rule_i) = \mathrm{walk}$, since their consequents are $\mathrm{Initiate(walk)}$.
3. Substitute $rule_1$ for $rule_i$
   (a) Choose the assumption, $rule_1 \in P$, from H to prove $rule_1 \in P$ true. However, $rule_3$ and $rule_1$ in P are incompatible according to σ_3, and thus we are forced into back-tracking.

$$S_{\mathrm{T}-1} = \left\{ \begin{array}{l} Near(\mathrm{Mike}, \mathrm{John}) \wedge Near(\mathrm{Paul}, \mathrm{John}) \wedge \cdots \wedge \\ Noop(\mathrm{Mike}) \wedge Walk(\mathrm{Paul}) \wedge \cdots \wedge Noop(\mathrm{John}) \end{array} \right\}$$

$$A_{\mathrm{T}-1} = Do(walk),\ h_{\mathrm{T}-2} = \{rule_3 \in P\}$$

$$Rules = \left\{ \begin{array}{l} rule_1 : \text{if } Near(x, \mathrm{self}), Noop(x), Noop(\mathrm{self}) \text{ then Initiate(walk)} \\ rule_2 : \text{if } Near(x, \mathrm{self}), Walk(x), Noop(\mathrm{self}) \text{ then Initiate(walk)} \\ rule_3 : \text{if } Near(x, \mathrm{self}), Noop(x), Noop(\mathrm{self}) \text{ then Initiate(turn)} \end{array} \right\}$$

$$H = \{rule_1 \in P, rule_2 \in P, \ldots, rule_1 \preceq rule_2, rule_2 \preceq rule_1, rule_3 \preceq rule_2, \ldots\}$$

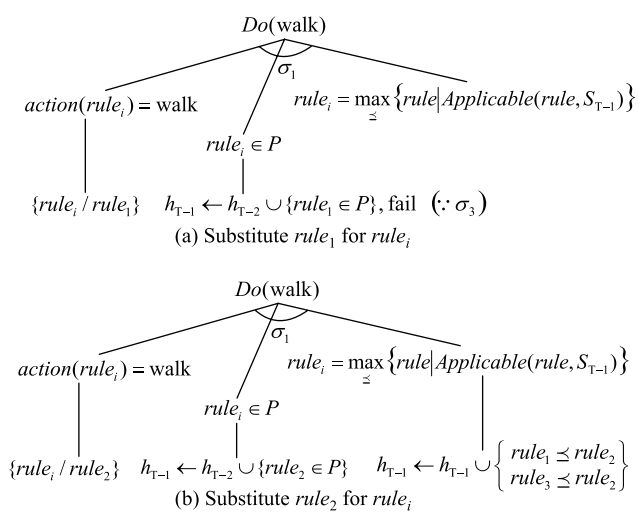

Figure 4: Proof Tree of $h_{\mathrm{T}-2} \cup \Sigma \cup \{S_{\mathrm{T}-1}\} \vdash Do(\mathrm{walk})$

Algorithm 1 OperationModel(t) **return** (P,$\preceq$)

```
t  /* time */
P  /* A set of operation rules employed by the target subject
      (P ⊆ Rules) */
⪯  /* Priorities among the elements in P */
S_t  /* The world observed by the target subject at time t */
A_t  /* The target subject's operation at time t */
if t < 0 then
   return ({}, {})
end if
(P, ⪯) ←OperationModel(t − 1)
/* If the subject continues the same operation as time t − 1 */
if A_t = Continue then
   return (P, ⪯)
end if
/* If the subject initiates a new operation at time t */
/* Choose an operation rule from P */
if choose p ∈ {rule | Applicable(rule, S_t),
                      A_t = Do(action(rule))} ∩ P then
   Update ⪯
      s.t. ∀r(r ∈ {rule | Applicable(rule, S_t)} ⇒ r ⪯ p)
   return (P, ⪯)
end if
/* Choose a new operation rule not in P */
if choose p ∈ {rule | Applicable(rule, S_t),
                      A_t = Do(action(rule))} \ P then
   P ← P ∪ {p}
   if Inconsistent?(P) then
      fail
   end if
   Update ⪯
      s.t. ∀r(r ∈ {rule | Applicable(rule, S_t)} ⇒ r ⪯ p)
   return (P, ⪯)
end if
fail
```

Algorithm 2 Inconsistent?(P) **return** $boolean\ value$

```
if ∃p_i, p_j(p_i, p_j ∈ P ∧ (condition(p_i) = condition(p_j))∧
   ¬(action(p_i) = action(p_j))) then
   return true
end if
return false
```

4. Substitute $rule_2$ for $rule_i$
   (a) Choose the assumption, $rule_2 \in P$, from H to prove $rule_2 \in P$ true.
   (b) Choose the assumptions, $rule_1 \preceq rule_2$ and $rule_3 \preceq rule_2$, from H to prove $rule_2 = max_{\preceq}\{rule \mid Applicable(rule, S_{\mathrm{T}-1})\}$ true.
   (c) $h_{\mathrm{T}-1} = \{rule_2 \in P, rule_3 \in P, rule_1 \preceq rule_2, rule_3 \preceq rule_2\}$ is acquired.

By repeating the above process until G_{end} can be explained, we can acquire the operation model of the subject operating John. Algorithm 1 illustrates the algorithm used to acquire the operation model.

The goal of function OperationModel is to acquire operation model h such that $h \cup \Sigma \vdash G$, $\Sigma \cup h$ is consistent, and h is a minimal explanation. Consistency means that P does not include rules that have the same preconditions but

different consequents. Therefore, we have only to confirm whether P is consistent by using Algorithm 2 every time P is updated (step18 and step 19). P is updated by adding an operation rule non-deterministically chosen by the choose function. If an inconsistency occurs, another rule is chosen from the remaining rules. If there are no other candidates, the choose function returns false.

To acquire a minimal explanation, function Operation-Model tries to explain G_t using P acquired by the explanation of G_{t-1} (step 13-16). If it fails, it chooses a new operation rule not in P (step 17-24). If no candidate can explain G_t, the function restarts the explanation of G_{t-1} to acquire another P.

Application

To validate our method, we used it to model a subject operating an evacuee agent in an evacuation drill.

Evacuation Domain

We used our modeling method to create the evacuee agents needed to carry out virtual training for developing evacuation methods. Specifically, we used a controlled experiment conducted in the real world(Sugiman & Misumi 1988). The experiment was held in a basement that was roughly ten meters wide and nine meters long; there were three exits, one of which was not obvious to the evacuees as shown in Figure 6. The ground plan of the basement and the initial position of subjects are also shown in the figure. Exit C was closed after all evacuees and leaders entered the room. At the beginning of the evacuation, Exit A and Exit B were opened. Exit A was visible to all evacuees, while Exit B, the goal of the evacuation, was initially known only by the leaders. All evacuees were guided to Exit B by the leaders.

At first, we reproduced the same situation in FreeWalk(Nakanishi 2004), 3D virtual space platform. Next, we conducted a participatory simulation by replacing 12 scenario-controlled agents with agents controlled by human subjects (Figure 5). The remaining agents were controlled by their scenarios described in scenario description language *Q*(Ishida 2002; Murakami *et al.* 2003).

Figure 5: Participatory Simulation by FreeWalk

Table 1: Operation Models of Subject Operating Agent 11

h	Operation models
h_1	$P = \{$Rule2, Rule6, Rule12, Rule17, Rule18, Rule21$\}$ Rule2 = Rule6 = Rule12 = Rule17 = Rule21
h_2	$P = \{$Rule2, Rule6, Rule12, Rule17, Rule19, Rule21$\}$ Rule2 = Rule6 = Rule12 = Rule17 = Rule21
h_3	$P = \{$Rule2, Rule6, Rule17, Rule18, Rule21, Rule22$\}$ Rule2 = Rule6 = Rule17 = Rule21 = Rule22
h_4	$P = \{$Rule2, Rule6, Rule17, Rule19, Rule21, Rule22$\}$ Rule2 = Rule6 = Rule17 = Rule21 = Rule22

Application of Modeling Process

We applied our method to model the subject operating agent 11, circled in Figure 6. The set of operation rules in domain knowledge consisted of 22 operation rules obtained through interviews with 6 human subjects. As a result, we acquired 4 types of operation models as shown in Table 1. Note that we applied the transitive law of priorities and transformed the priorities between RuleX and RuleY from RuleX $\preceq$ RuleY and RuleY $\preceq$ RuleX to RuleX = RuleY. In Table 1, all rules except for Rule18 and Rule19 have equal priority. Rule18 and Rule19 have no order relation with the other rules. This means that Rule18 and Rule19 can have any priority. Whatever priorities they have, these operation models can explain the subject's behavior. The operation rules constituting these operation models are given below.

Rule2: If the evacuee cannot see a leader, he looks for them by looking around and stepping backward.

Rule6: If the evacuee cannot see the exit, he looks for it by looking around and stepping backward.

Rule12: The evacuee moves in the same direction as the leader

Rule17: The evacuee follows someone in front of him.

Rule18: If the evacuee encounters congestion, he walks through it.

Rule19: If someone in front of the evacuee walks slowly, he passes him/her.

Rule21: If the evacuee sees the exit, he goes toward it.

Rule22: The evacuee looks around before going to the exit.

Only h_1 can explain the same execution sequence of operation rules as that obtained in an interview with the subject controlling agent 11. Specifically, the operations at times t_a, t_b, t_c, t_d, t_e, and t_f in the behavior path are explained by Rule2, Rule12, Rule6, Rule17, Rule21, and Rule18, respectively.

Conclusion

To render virtual training systems more realistic, a diversity of agent models must be realized, as well as agents that offer human-like expressions. In this research, we addressed the following two issues in realizing the needed diversity of operation models.

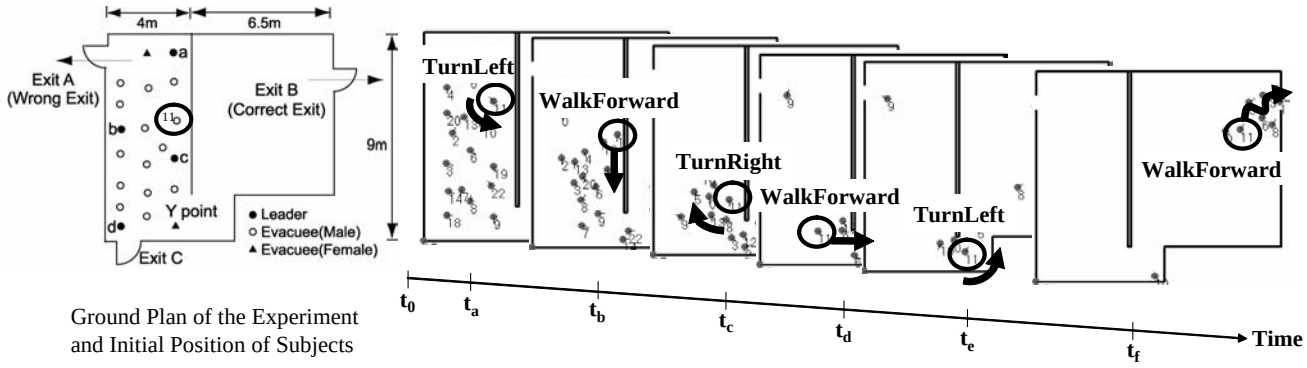

Figure 6: Operation History of the Subject Operating Agent 11

Forming various consistent behavior models

We established a modeling process, based on hypothetical reasoning, that offers the consistent selection of assumptions. This allows us to combine operation rules in various ways while avoiding incompatibilities.

Extracting behavior models that offer personality

We extracted a personal operation model from log data by generating explanations of each subject's operation. This enables us to characterize each subject as combinations of operation rules constituting the explanation.

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