Learning from Humans: Agent Modeling with Individual Human Behaviors

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***Abstract*—Multiagent-based simulation (MABS) is a very active interdisciplinary area bridging multiagent research and social science. The key technology to conduct realistic MABS is agent modeling. In order to make agent models realistic, it seems natural to learn from human behavior in the real world. The challenge presented in this paper is to obtain an individual behavior model by using participatory modeling technology in the traffic domain. We show a methodology that can elicit prior knowledge for explaining human driving behavior in specific environments, and then construct a driving behavior model based on a set of prior knowledge. In the real world, human drivers often perform unintentional actions, and occasionally they have no logical reason for their actions. In these cases, we cannot elicit prior knowledge to explain them. We are forced to construct a behavior model with an insufficient amount of knowledge to reproduce driving behavior. To construct an individual driving behavior model with insufficient knowledge, we take the approach of using knowledge from others to complement the lack of knowledge from oneself. To clarify that the behavior model, which is filled out by knowledge from others, offers driving behavior individuality, we experimentally confirm that the driving behaviors reproduced by the hybrid model correlate reasonably well with human behavior.**

***Index Terms*—Multiagent simulation, modeling methodology, traffic simulation, participatory modeling**

I. INTRODUCTION

MANY STUDIES on Multiagent-based simulation (MABS) have been done in various fields [1], [2], [3]. MABS yields multi-agent societies that well reproduce human societies, and so are seen as an excellent tool for analyzing the real world. The key technology to implement MABS is agent modeling. This is because collective phenomena emerge from the local behaviors of many agents; that is, the simulation result depends on each agent's micro-level behavior. Most existing studies, however, use simple or abstract agent models [4], [5], [6]. In order to achieve realistic agent models, it seems natural to learn from human behavior in the real world. Our research focus is to develop a methodology for generating agent models from human behavior.

Participatory modeling is a promising technology with which to obtain individual behavior models based on actual human behavior. Participatory modeling allows us to elicit a human's behavior as well as the reason for the behavior in particular application domains. Such information can be used as prior knowledge to explain a human's individual behavior. For a sequence of human behaviors, we can construct an individual behavior model composed by a set of prior knowledge, each piece of which can explain one of the local behaviors in the sequence.

The challenge presented in this paper is to use participatory modeling technology to obtain a human-like behavior model in the traffic domain. A human driver controls his/her car based on his/her driving style. We want to construct a driver agent model that can reproduce diverse driving styles. Trying to achieve that with participatory modeling technology raises difficulties when trying to explain a sequence of driving behaviors. In the real world, a human driver occasionally performs unintentional actions (*i.e.*, actions with no logical reason). Additionally, there are cases where the driver cannot remember the reason for his/her actions. As a result, we cannot obtain sufficient prior knowledge to explain his/her driving behavior.

To permit a driver agent model to be created even though the knowledge is insufficient, we take the approach of using complimentary prior knowledge from other drivers. That is to say, if it is impossible to explain a driver's behavior using only the knowledge elicited from the driver, the knowledge acquired from other drivers is used to provide the explanation. This approach allows us to acquire a driving behavior model that is fleshed out (patched) by knowledge from others. In order to know whether the individuality of a driver's behavior is effectively preserved by the patched behavior model or not, we conduct an experiment on a driving behavior model to confirm that it well reproduces the individuality of driving behavior.

In section II, we first show some existing studies on agent modeling, then describe the process of participatory driver agent modeling methodology. In section III, we show how the proposed methodology works, and what behavior models can be constructed. In section IV, we introduce an investigation of the quality of the acquired models based on quantitative metrics. Finally, concluding remarks are given in section V.

II. DRIVER AGENT MODELING

A. Current Technologies and Limitations

In the multiagent research area, many researchers have focused on multiagent-based traffic simulations. To date, however, agent modeling with the goal of reproducing human driving behavior has not been the focus of most previous works. Balmer *et al.* [7], for example, constructed a multiagent traffic simulator where each agent iteratively revises his/her preferences on the route to be travelled. In this work, the agent model is considerably simplified since only route setting decisions are made. Halle and Chaib-draa [8] proposed an

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agent architecture for realizing collaborative driving by a convoy of cars. Their work, however, did not consider the individuality of driving style. In contrast, Paruchuri *et al.* [9] tried to reproduce a variety of driving styles. However, they did not consider the realization of human-like driving, but simply introduced three driving styles defined based on three fine-tuning parameters.

Participatory technology has been used for multiagent-based simulations. Sempé *et al.* [10] proposed how to acquire information that could explain a subject's behavior through dialogue with the subject's own agent during simulations. Unlike our work, they did not show how to identify a subject's specific behavior and construct behavior models. Guyot *et al.* [11] aimed to design interaction models by observing the emergence of power-relations and coalitions during participatory simulations. Their research goal is different from ours which focuses on agents' internal mechanism.

Reinforcement learning (RL) seems a promising technology for obtaining driving behavior models [12], [13]. By agent modeling with RL technologies, we may be able to obtain a computational model to drive. But the acquired models can just run human driving log, so that we cannot know the individuality in driving style.

B. Participatory Driver Agent Modeling

1) Outline: During participatory driver agent modeling, we construct driving behavior models from human driving data by collaborating with the human subjects. Using the participatory modeling technique allows us to construct behavior models from not only our (modeler's) knowledge, but the actual behavior of the human subjects. The modeling process consists of the following five steps.

1) Collect human driving log data from trials performed on a 3D virtual driving simulator.
2) Together with domain experts, identify individual driving behaviors by the investigation of collected log data.
3) Collect prior knowledge constituting a driving behavior model by interviewing the subjects of the driving simulation
4) Select meaningful prior knowledge and represent it in formal expression
5) Construct a driving behavior model that can explain human subject's actions based on hypothetical reasoning [14]

We detail each step in the remainder of this section.

2) Collecting Driving Log on 3D Virtual Driving Simulator: In order to construct a driving behavior model, we need realistic driving data from humans. In the real world, however, it is hard to collect sufficient driving data in actual traffic environments due to the difficulties of setting up an experimental environment. Thus, we use a 3D virtual driving simulator that has a lifelike cockpit and a wide screen that can display a virtual environment (see Figure 1)[1]. Such simulations are often used to train drivers, and so our simulator is expected to yield realistic driving data. Figure 2 is one example of a chart made from driving log data. As shown, we can get information on transitions in running speed (the graph at the top), acceleration (graph second from the top), and the usage of accelerator/brake (graphs at the bottom).

Fig. 1. 3D Virtual Driving Simulator used for Collecting Driving Log Data

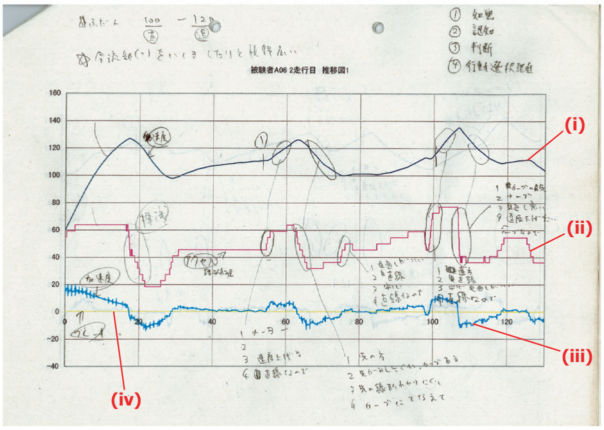

Fig. 2. An Example of a Chart made from Driving Log Data. Each graph (i), (ii), (iii), and (iv) denotes Speed, Acceleration, the Usage of Accelerator, and the Usage of Brake, respectively. Circles on the graph represent the subject's specific behaviors identified by traffic engineers.

3) Identifying individual behaviors with domain expert: We investigated the collected driving log data to identify each subject's individual driving behavior. For the investigation, we use the following data collected for each subject.

1) Mileage(km)	The mileage from the origin
2) Speed(km/h)	The speed of subject's car
3) Acceleration(m/s)	The acceleration of subject's car
4) Usage of Accel.(%)	The usage of accelerator, *i.e.,* accelerator pedal position[2]

We try to capture an individual's behavior by investigating his/her driving log data. In particular, the speed/acceleration transitions provide a lot of useful data. The experiment shown in Section III confirms that different drivers have different driving styles, even in identical conditions. Therefore, the sequence of each local driving behavior can be taken as an expression of driver individuality. Figure 2 shows some

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[1] This virtual driving simulator is located at Graduate School of Engineering Division of Global Architecture, Osaka Univ., JAPAN

[2] In this paper, when the pedal is not depressed, the rate is 0%, and the rate is 100% when the pedal is fully depressed.

transitions on graph (ii) in the figure (marked by circles); they represent the results of specific operations. Since, it was difficult for us to accurately identify key transitions from the log data, we elicited the help of domain experts (*i.e.*, traffic engineers).

4) Interview of Subjects: We interviewed the subjects after they participated in the driving simulation. The purpose of the interview was to gather information on their specific operations, identified in the previous step, for generating prior knowledge. We use screen shots of the simulation and charts like Figure 2 in order to make it easy for the subjects to remember the reasons for his/her actions in the simulation.

In the interview, we asked each subject about the following four points for each specific operation.

1) Reason/motivation for the operation
    Confirmation of the reason or motivation for the operation
2) Target of subject's gaze
    Confirming what the subject really gazed at
3) Recognized target
    Confirming what the subject recognized
4) Evaluation of the recognition
    Confirming how the subject evaluated the result of the recognition

Figure 2 shows some notes on several of the transitions. For example, the notes at the center of the figure show the following responses:

1) Getting ready for a curve
2) The road in front of me
3) The curve is close and I cannot see into the curve
4) The road forward is unclear

Our analyses of the interview log and charts yielded information on the subjects' operations under a range of conditions, *i.e.*, "sense-act" information. We use such information as prior knowledge and represent it as driving rules, each of which denotes a driving operation made under a certain condition.

5) Formal representation of collected knowledge: We first cleaned up the collected prior knowledge (*i.e.*, driving rules). For example, in the real example shown in Section III, we obtained knowledge such as "If I feel fine, I'll step on the accelerator." This kind of knowledge, which is related to feeling, is not suitable for use for modeling because we cannot observe the internal states of humans. Thus, we first eliminated such knowledge. The knowledge remaining is represented using formal expressions based on predicate logic. After a discussion with traffic engineers, we fixed some predicates to represent prior knowledge, see Table I.

These predicates are also used to formally describe the observations extracted from the driving log data. An observation describes what the subject noticed, and how he/she operated his/her car in the situation presented.

This formal description of prior knowledge and observations allows us to use them in the next step of model construction.

6) Construction of Driving Behavior Models:

a) Formalizing the Problem: In this paper, we assume that a subject decides his/her next operation based on the surrounding environment as observed from his/her viewpoint.

Predicate	Description
`Straight(X)`	`X` is a straight road.
`Curve(X)`	`X` is a curve.
`Uphill(X)`	`X` is an uphill.
`Downhill(X)`	`X` is a downhill.
`On(X,Y)`	`Y` is driving on `X`.
`InSight(X,Y)`	`Y` can see `X`.
`OverDesiredSpeed(X)`	The speed of a car `X` exceeds the desired speed.
`UnderDesiredSpeed(X)`	The speed of a car `X` is under the desired speed.
`OverCurveSpeed(X,Y)`	The speed of a car `Y` is too high in a curve `X`.
`SpeedUp(X)`	A car `X` is speeding up.
`SlowDown(X)`	A car `X` is slowing down.
`Accelerate(X)`	A car `X` is accelerating.
`Decelerate(X)`	A car `X` is decelerating.

TABLE I
PREDICATES TO REPRESENT ACTIONS

We denote the environment observed by the subject as E; it consists of conjunctions of literals about the environment; the environment at time t is tagged E_t. The driving model $\mathcal{M}$ is a set of prioritized driving rules $\langle P, \preceq \rangle$, which is a set of driving rules where $\preceq$ represents the priorities of each rule in P. P is a subset of $Rules$ which is the set of rules obtained from all subjects. Therefore, each driving model may be consist of prior knowledge obtained from several human subjects. $\preceq$ is a subset of the Cartesian product, *i.e.* $Rules \times Rules$. Each driving rule in $Rules$ is denoted as $rule_i (0 \leq i \leq j \leq |Rules|)$, so that $\langle rule_i, rule_j \rangle \in \preceq$ is described as $rule_i \preceq rule_j$.

In order to apply hypothetical reasoning [14] to the modeling of driving behaviors, we define driving rules and an operation selection mechanism as domain knowledge Σ. An element of domain knowledge is indicated by $\sigma_k (0 \leq k \leq |\Sigma|)$. We hypothesize which driving 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 is indicated by H. Additionally, we describe the subject's behavior from the beginning of the simulation on a 3D simulator, 0, to the end of the simulation, end, as observation G and the observation at time t is denoted as G_t.

The operation selection mechanism is defined as follows:

Definition 1 (Driving operation selection: σ_1)
$$(\exists rule_i(rule_i \in P \wedge rule_i = \max_{\preceq}\{rule|\mathtt{Applicable}(rule, E_t)\})) \Rightarrow \mathtt{Do}(operation(rule_i))$$

Here, `Applicable` and `Do` are pseudo-predicates meaning that the condition part of a rule is satisfied, and that the subject initiates an operation, respectively. Function $operation$ returns the operation initiated by the subject when he/she executes $rule_i$. σ_1 means a subject employs $rule_i$, the rule that has the highest priority among all applicable operations at E_t.

Definition 2 (Continuation of operation: σ_2)
A subject can continue his/her current operation.

Definition 3 (Constraint: σ_3)
$$\forall rule_i, rule_j(rule_i, rule_j \in P \wedge (condition(rule_i) = condition(rule_j)) \Rightarrow (operation(rule_i) = operation(rule_j))$$

σ_3 means that P does not include driving rules that have identical condition parts but different operations. Here, the function *condition* returns the precondition of its argument.

We define G and G_t bellow:

Definition 4 (Observation G)

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

Definition 5 (Observation G_t)

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

A_t is the literal represented by predicate `Do`.

The observations, present in driving log data, are described using the predicates shown in Table I. We use road structure, driving speed, and acceleration pedal operation as observations. A typical description is as follows:

Example 1 (Description of observation)

$$\begin{aligned}&\texttt{Curve}(Curve_1) \wedge \texttt{InSight}(Curve_1, \text{self})\\&\wedge \texttt{Uphill}(Uphill_1) \wedge \texttt{On}(Uphill_1, \text{self})\\&\wedge \texttt{OverDesiredSpeed}(\text{self})\\&\Rightarrow \texttt{Do}(\texttt{ReleaseAccel}(\text{self}))\end{aligned}$$

This observation means that the subject released the accelerator when he/she sees $Curve_1$ (`InSight`), his/her car is driving $Uphill_1$(`On`), the speed of car exceeds the desired speed (`OverDesiredSpeed`), and he/she is decelerating (`ReleaseAccel`).

b) Model Acquisition Process: We applied a modeling method based on hypothetical reasoning [15] to acquire a driving behavior model of each human subject. The method should yield models that can explain G in association with Σ and H. As mentioned above, Σ is the operation selection mechanism and operation rules, and H indicates which driving rule is employed by the subject, *i.e.* which rule has priority.

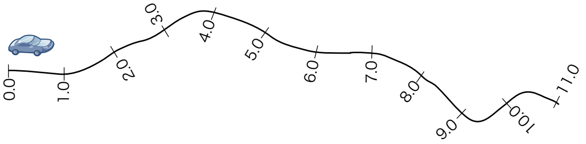
The major steps of the model acquisition algorithm are as follows:

1) The driving model at time $t-1$, $\mathcal{M} = \langle P, \preceq \rangle$, is input.
2) If the target subject continues the same driving operation as at time $t-1$, the algorithm just returns $\mathcal{M}$.
3) If the subject initiates a new operation at time t, a driving rule p, which is applicable to E_t and can explain A_t, is chosen from P. p is assigned higher priority than all other rules applicable to E_t in P ($\preceq$ is updated to $\preceq'$); finally, $\mathcal{M} = \langle P, \preceq' \rangle$ is returned. The goal of the algorithm is to obtain a minimal explanation. Therefore, the algorithm first tries to find an applicable rule in the current P to avoid adding another rule.
4) If there is no applicable driving rule in P, a driving rule p, which is applicable to E_t, is chosen from $Rules$. p is assigned higher priority than all other rules applicable to E_t in $Rules$ ($\preceq$ is updated to $\preceq'$); finally, $\mathcal{M} = (P \cup \{p\}, \preceq')$ is returned.

   If $P \cup \{p\}$ is inconsistent, the algorithm returns "$fail$".

For model acquisition, explanation-based learning (EBL) [16] is another potential technique. In EBL, an observation can be explained by using domain knowledge and training data without making a hypothesis. On the contrary, in hypothetical reasoning, an observation can be explained by using domain knowledge under a hypothesis and the hypothesis could be considered as true iff it is consistent with the domain knowledge. When we try to construct driving models, we do not know which rules are used by human subjects and which rule is prioritized. Thus, we are required to construct models based on hypothetical reasoning with hypothesis, such as "$rule_i$ was prioritized", "this subject had $rule_i$.

(a) horizontal alignment



(b) vertical alignment

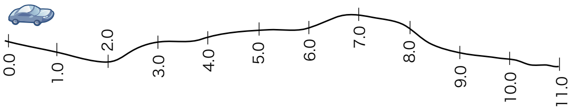


Fig. 3. Road Structure in 3D Driving Simulator

RuleID	Description of a rule
$\mathbf{rule}_{01}$	If a subject is driving a curve, he/she releases the accelerator.
$\mathbf{rule}_{02}$	If a subject is driving a straight, he/she steps the accelerator.
$\mathbf{rule}_{03}$	If a subject is driving uphill, he/she steps on the accelerator.
$\mathbf{rule}_{04}$	If a subject is driving downhill, he/she releases the accelerator.
$\mathbf{rule}_{05}$	If a subject sees a curve ahead, he/she releases the accelerator.
$\mathbf{rule}_{06}$	If a subject sees a straight ahead, he/she steps the accelerator.
$\mathbf{rule}_{07}$	If a subject sees an uphill ahead, he/she steps on the accelerator.
$\mathbf{rule}_{08}$	If a subject sees a downhill ahead, he/she releases the accelerator.
$\mathbf{rule}_{09}$	If the speed exceeds the desired speed, a subject releases the accelerator.
$\mathbf{rule}_{10}$	If a subject is driving under the desired speed, he/she steps on the accelerator.
$\mathbf{rule}_{11}$	If a vehicle slow down, he/she steps on the accelerator.
$\mathbf{rule}_{12}$	If a vehicle speed up, he/she release the accelerator.

TABLE II
OBTAINED KNOWLEDGE FROM HUMAN SUBJECTS

III. A REAL EXAMPLE OF DRIVER AGENT MODELING

We conducted an experiment to construct drvier agent models based on the modeling methodlogy we mentioned above. In this section, we show how the proposed methodology works, and what models were constructed in the experiment.

A. Setting and Modeling Process

First, we describe the setting of the driving simulation used to collect driving log data. In this experiment, we used an 11km virtual highway whose layout is shown in Figure 3. For simplicity, in this experiment, each human subject drove alone, so that we could elicit prior knowledge representing just the driving operations. There were 36 subjects, each of them had experience in using the 3D simulator. We could successfully obtain prior knowledge (*i.e.*, driving rules) from all subjects through a collaboration with traffic engineers, but some subjects provided only one or two rules. The set of obtained prior knowledge is shown in Table II. Because the experiment was held on a virtual highway with no other cars, all subjects used just the accelerator. In a few cases, the subject used the brake, but had no logical reason for doing so. Prior knowledge indicated how the human subject might decide to use the accelerator considering surrounding road structure, current velocity, and own desired speed.

We then formally expressed the obtained prior knowledge by using the predicates we defined to describe observations. Example 2 shows a description of prior knowledge.

Example 2 (Description of prior knowledge)
rule₅:
if $\texttt{Curve}(x) \wedge \texttt{InSight}(x,\text{self})$ **then** $\texttt{ReleaseAccel}(\text{self})$
rule₇:
if $\texttt{Uphill}(x) \wedge \texttt{InSight}(x,\text{self})$ **then** $\texttt{Accelerate}(\text{self})$

For instance, $rule_5$ means that if there is an upcoming curve x ($\texttt{Curve}(x)$) and if the subject ("self") sees the curve x ($\texttt{InSight}(x,\text{self})$), he/she releases the accelerator ($\texttt{ReleaseAccel}(\text{self})$). $rule_7$ means that if hill is to be climbed x ($\texttt{Uphill}(x)$) and the subject sees that, he/she steps on the accelerator ($\texttt{Accelerate}(\text{self})$).

Finally, we used the obtained knowledge and observations to construct driving behavior models using the algorithm shown in II-B6b. We show here an example of the modeling process using the rules and observation in Example 1 and 2. This example shows how $\texttt{Do}(\texttt{ReleaseAccel}(\text{self}))$ is derived. Here, we assume $rule_{12} \in P$.

1) In order to derive $\texttt{Do}(\texttt{ReleaseAccel}(\text{self}))$, due to σ_1, it is required to prove that $action(rule_i)$ = $\texttt{Release Accel}(\text{self})$, $rule_i \in P$, and that $rule_i = \max_{\preceq}\{rule|\texttt{Applicable}(rule, E_{t-1})\}$ are true.
2) Because the consequences of $rule_5$ is $\texttt{Initiate}(\texttt{ReleaseAccel}(\text{self}))$, they validate $action$ $(rule_i)$ = $\texttt{ReleaseAccel}(\text{self})$.
3) Substitute $rule_5$ for $rule_i$
    a) Choose an assumption, $rule_5 \in P$, from H to prove $rule_5 \in P$ is true.
    b) Choose an assumption, $rule_7 \preceq rule_5$ from H to prove $rule_5 = \max_{\preceq}\{rule|\texttt{Applicable}(rule, E_{t-1})\}$ is true.
    c) $h_{t-1} = \{\{rule_{12}, rule_5\}, \{\{rule_7 \preceq rule_5\}\}\}$ is acquired.

This process is iterated until G_{end} can be explained; the result is a driving model.

B. Acquired Driving Behavior Models

In the experiment, we could construct driving behavior models for all subjects. In this section, we show some examples of the driving behavior models so acquired. Table III shows a set of driving rules and their priorities. Figure 4 shows transitions in running speed and acceleration of the subjects and their corresponding driver agents. In Figure 4, the vertical axis and horizontal axis represent speed (km/h) and mileage (km), respectively. The bold blue line and bold green line plot subject's running speed and acceleration, respectively. The thin red line and thin orange line represent driver agent's running speed and acceleration, respectively.

Case 1 for S_1: The driving behavior model of subject S_1 consists of 6 driving rules and the relationships defining their priorities. The road section of 1km - 7km is a gentle ascending slope with some curves, as shown in Figure 3. S_1 drove under his/her desired speed (120km/h) in this zone (see Figure 4(A-1)). S_1's behavior model can reproduce his/her driving log by the application of three rules, $rule_{03}$, $rule_{07}$, and $rule_{10}$. The running speed is increased by these rules. After the 7km point, the road curves downhill. Because S_1's model does not include a rule to release the accelerator, at first, the running speed is continuously increased. However, once the speed exceeds the desired speed, $rule_{09}$ is fired, and the accelerator pedal is released. If the speed becomes too slow, this model can recover because $rule_{11}$, which is used to speed-up when car speed becomes too slow, is prioritized over $rule_{01}$ and $rule_{05}$ which are used to release the accelerator in a curve.

ID	**Driving behavior model**
S_1	$P = \{rule_{01}, rule_{03}, rule_{05}, rule_{09}, rule_{10}, rule_{11}\}$ $\preceq = \{rule_{10} \preceq rule_{01}, rule_{01} \preceq rule_{05}, rule_{10} \preceq rule_{05},$ $rule_{05} \preceq rule_{10}, rule_{01} \preceq rule_{10}, rule_{01} \preceq rule_{03},$ $rule_{05} \preceq rule_{03}, rule_{03} \preceq rule_{01}, rule_{03} \preceq rule_{09},$ $rule_{09} \preceq rule_{03}, rule_{09} \preceq rule_{05}, rule_{01} \preceq rule_{11},$ $rule_{05} \preceq rule_{11}, rule_{09} \preceq rule_{11}\}$
S_2	$P = \{rule_{01}, rule_{02}, rule_{04}, rule_{05}, rule_{06}, rule_{09}, rule_{10},$ $rule_{11}\}$ $\preceq = \{rule_{01} \preceq rule_{04}, rule_{09} \preceq rule_{01}, rule_{01} \preceq rule_{11},$ $rule_{09} \preceq rule_{11}, rule_{11} \preceq rule_{09}, rule_{09} \preceq rule_{02},$ $rule_{02} \preceq rule_{06}, rule_{09} \preceq rule_{06}, rule_{02} \preceq rule_{09},$ $rule_{11} \preceq rule_{05}, rule_{05} \preceq rule_{11}\}$
S_3	$P = \{rule_{01}, rule_{02}, rule_{03}, rule_{04}, rule_{05}, rule_{06}, rule_{11}\}$ $\preceq = \{rule_{04} \preceq rule_{02}, rule_{11} \preceq rule_{04}, rule_{04} \preceq rule_{11},$ $rule_{04} \preceq rule_{01}, rule_{11} \preceq rule_{01}, rule_{01} \preceq rule_{11},$ $rule_{06} \preceq rule_{05}, rule_{01} \preceq rule_{06}, rule_{11} \preceq rule_{06},$ $rule_{02} \preceq rule_{01}, rule_{02} \preceq rule_{06}, rule_{01} \preceq rule_{03},$ $rule_{05} \preceq rule_{03}, rule_{03} \preceq rule_{01}, rule_{03} \preceq rule_{11},$ $rule_{05} \preceq rule_{11}, rule_{11} \preceq rule_{03}, rule_{03} \preceq rule_{06},$ $rule_{02} \preceq rule_{03}, rule_{06} \preceq rule_{03}, rule_{03} \preceq rule_{05}\}$

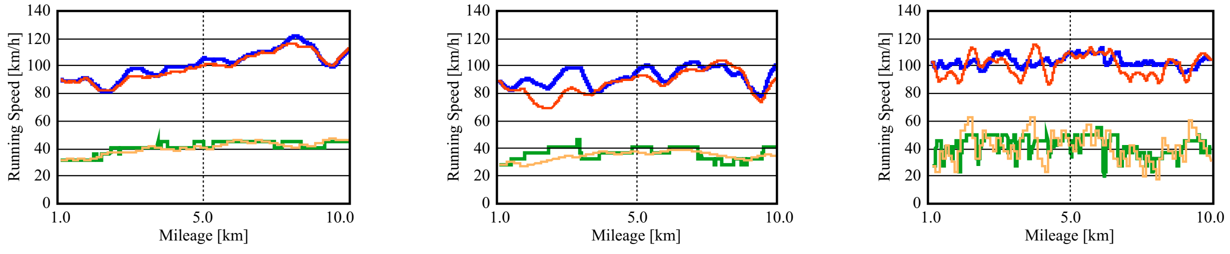
TABLE III
EXAMPLES OF ACQUIRED DRIVING BEHAVIOR MODELS

Case 2 for S_2: The driving behavior model of subject S_2 includes 8 driving rules. In Figure 4 (A-1) and (A-2), S_2's behavior looks similar to S_1. The difference is apparent around 7km - 9km region. S_2 drove at around 100km/h while S_1 exceeded 100km/h. S_2's model can reproduce this difference in driving behavior. It includes $rule_4$, representing "if the subject sees a downhill ahead, he/she releases the accelerator." Therefore, S_2's model lowers the speed. This is one example of realizing individuality in driving style.

Case 3 for S_3: S_3 was a driver whose driving style was hard to explain and reproduce. The frequency of acceleration is relatively high. This is because he/she seems keen to maintain his/her desired speed exactly (100km/h). As shown in Figure 4 (A-3), S_3 speeds up little by little to just over 100km/h. The model of S_3 can reproduce this driving style by including both $rule_{10}$ ("If the car speed up, he/she release the accelerator") and $rule_{12}$ ("If the subject is driving under the desired speed, he/she steps on the accelerator"). A comparison of the transitions in acceleration makes it clear that S_3's model yields behavior different from those of the other two models.

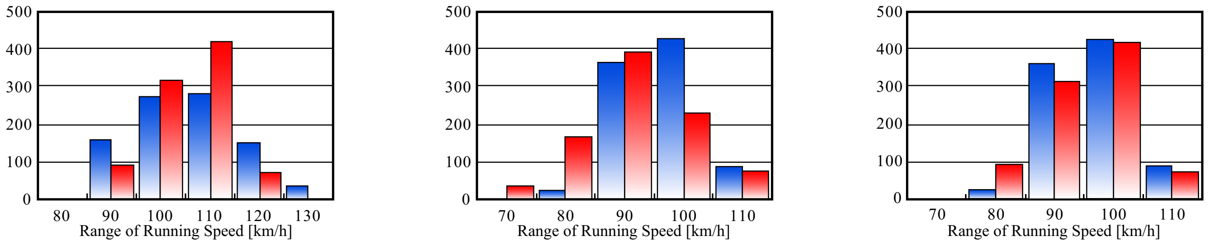
IV. EVALUATION AND DISCUSSION

The previous section claimed that our behavior models can reasonably reproduce individual behaviors. In this section, we investigate the quality of the acquired behavior models through quantitative metrics. First, we evaluate whether the acquired models can well reproduce the transitions in running speed. To do that, we calculated the correlation value between the running speed of the human subject and that of his/her behavior model. Such correlation value is a time-tested and



(A-1) (A-2) (A-3)

(A) The transition of running speed and acceleration



(B-1) (B-2) (B-3)

(B) The distribution of running speed

Fig. 4. Transitions in running speed and acceleration of human subjects and corresponding driver agent

an academically accepted index to quantitatively measure the performance of simulations, especially traffic simulations [17]. Table IV(a) shows correlation values for the running speed of human subjects S_1, S_2, and S_3 and their agents. Bold values in the table shows the correlation value between human subjects' log data and the corresponding agents' log data. This data confirms that the first two models for S_1 and S_2 reasonably reproduce the transitions in running speed. Although the correlation value of the model for S_3 is not as high, it still exceeds 0.60. The average correlation value for all human subjects was 0.72. While this is not an outstanding value, we think the quality of the acquired behavior models is acceptable given that the behavior models were created using intermingled knowledge. Additionally, from the data shown in this table, we can acquire models that can reproduce individual driving styles. For example, the model for S_1 is best at reproducing subject S_1's driving style, it does not well reproduce those of others. The correlation values between S_1's model and S_2 (S_3) are 0.62 and 0.21. In particular, as we can sense from Figure 4(A), the model for S_3 is highly uncorrelated. The correlation values for S_1 and S_2 are 0.05 and 0.1, respectively. Accordingly, we have succeeded in acquiring individual driving behavior models, each of which can reproduce the characteristic driving style of a different human subject.

		S_1		S_2		S_3	
		Human	Agent	Human	Agent	Human	Agent
S_1	Human	1	*	*	*	*	*
	Agent	**0.95**	1	*	*	*	*
S_2	Human	0.66	0.62	1	*	*	*
	Agent	0.90	0.87	**0.72**	1	*	*
S_3	Human	0.30	0.21	0.59	0.34	1	*
	Agent	0.05	-0.03	0.1	-0.03	**0.61**	1

(a) Correlation value for the running speed of humans and agents

ID	Entity	Average	Standard Dev.
S_1	Human	100.9	10.6
	Agent	95.8	9.1
S_2	Human	91.6	7.18
	Agent	86.8	9.5
S_3	Human	102.9	5.32
	Agent	100.2	8.22

(b) Average and Standard deviation of the running speed

TABLE IV
COMPARISON BETWEEN HUMAN SUBJECTS' LOG DATA AND AGENTS' LOG DATA

The above evaluation assessed the agreement of transitions in running speed, but the actual speeds are equally important. Thus, we assessed whether the speeds were similar or not. Figure 4 (B) shows the distribution of running speeds. This figure plots the number of opportunities to drive at each speed. In this figure, the blue bar is for the human subjects and the red bar is the result of the behavior models. In Table IV(b), we also plot the average and the standard deviation of the running speed of three examples. We can confirm that there is no crucial misfit in the standard deviation for all cases, so that the acquired models can well reproduce driving at the approximate speed with human subjects. In particular, for S_1, both of transitions in running speed and value of the speed are approximate. Also, for S_3, both human subject and his/her behavior model can drive at the approximate running speed and the characteristic driving style using the accelerator at highly frequent rates. As a result, we can acquire driving behavior models which can reasonably well reproduce individual driving styles of human subjects.

V. CONCLUSION

The agent modeling methodology proposed in this paper represents another direction in agent modeling for realizing human-like individual agent behavior. Our method does not rely on the modeler's knowledge or ability, but learns from actual human responses by applying the participatory modeling technique. We can explicitly obtain information on humans' characteristic behavior, *i.e.*, prior knowledge, through the modeling process, and then construct diverse and individual agent behavior models from the obtained knowledge.

We focused on the traffic domain and encountered several difficulties in constructing agent models due to the lack of prior knowledge. Driving demonstrates many actions whose motivation is hard to explain. If we want a lot of detailed knowledge, we have to spend a lot of time interviewing many human subjects. This represents a bottleneck in knowledge acquisition for agent modeling. In this paper, we took the approach of using complimentary knowledge from other humans in the same situation. As shown in the evaluation conducted here, we can obtain reasonably well correlated driving behavior from agents. Although we will continue to enhance our methodology, our approach to overcome the lack of knowledge for agent modeling represent a highly attractive first step.

In summary, the contributions of this paper are to (1) propose a novel agent modeling methodology for realizing individuality in agent behavior, (2) introduce an approach that can offset knowledge shortfalls for agent modeling, and (3) provide a hint for constructing driver agents for realistic traffic simulations.

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