# A Driver Modeling Methodology Using Hypothetical Reasoning for Multiagent Traffic Simulation

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**Abstract.** We propose how to acquire driver's individual operation models using the three-dimensional driving simulator in order to implement distinct personalities on each agent. In this paper, operation models are defined as sets of prioritized operation rules, each of which consists of the world as observed by a driver and his/her next operation according to the observation. Each driver might have different set of rules and their priorities. We apply a method to acquire individual operation models using hypothetical reasoning. Because of the method, we are able to obtain operation models which can explain driver's operation during driving simulation. We show some operation models acquired from aged/young human drivers, and then clarify the proposed method can catch each driver's characteristics.

## 1 Introduction

Multiagent-based traffic simulation has been considered as one of the promising approach to analyze traffic flow [1, 2]. In the multiagent traffic simulation, each human driver is modeled as an agent, which has common properties for driving. In the real world, there is a variety of drivers, such as aged drivers, novice drivers, and so on. In order to incorporate such variety of driver's properties into the traffic simulation, it is required to develop techniques to construct human driver's operation model [3–5].

We propose how to acquire driver's individual operation models using the three-dimensional driving simulator in order to implement distinct personalities on each agent. In this paper, we define an operation model as sets of prioritized operation rules, each of which consists of the world as observed by a driver and his/her next operation according to the observation. Each driver might have different set of rules and their priorities. In this paper, we address the following two research issues:

**1) Forming individual operation models from driving simulation log**
In order to acquire diverse driver models, we extract individual operation models from driving simulation log data.

**2) Efficient acquisition of individual operation models**
In order to form individual operation models, time-consuming tasks are required, such as recruitment of examinees, analysis of simulation log data. Therefore, we try to enable formation of operation models from little log data and operation rules, which are extracted through the interview with the small number of examinees.

For achieving these two issues, we apply a method using hypothetical reasoning for modeling driver's operation [6]. To put it concretely, driver's operation models are acquired according to the following process; 1) acquisition of examinees' behavior, 2) formal description of the observations in predicate logic, 3) extraction of operation rules through the interviews, and 4) construction of operation models from collected behavior and operation rules based on hypothetical reasoning.

From the viewpoint of traffic engineering, it is sometimes unclear what operation rules are used by an individual driver when he/she is driving a vehicle. In contrast, we can acquire operation models with only operation rules by using a method based on hypothetical reasoning.

The remainder of the paper is organized as follows. First, we describe the modeling process using hypothetical reasoning with log data resulting from driving simulation. Second, we define technical terms used in this paper, and then formalize our target problem by using the defined terms for hypothetical reasoning. Then, we apply a learning method using hypothetical reasoning to driving simulations for acquisition of operation models. Finally, concluding remarks are given in the final section and we also discuss possible future directions.

## 2 Modeling Process Using Driving Simulation Log

We explain an agent modeling process using hypothetical reasoning in our research. In the process, first, we conduct driving simulation on the three-dimensional driving simulator. Then, we acquire an examinee's operation model, a set of operation rules, by explaining the examinee's behavior observed in one or more driving simulations. However, the obtained operation rules may exhibit some incompatibility. Therefore, we hypothesize whether each operation rule is employed by the target examinee, 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 examinee. Some log data are not explained using operation rules, and then such data is removed. Details of an agent modeling process is as follows (also shown in Figure 1):

1) **Accumulation of driving log:** Conduct driving simulations where each examinee drives a virtual car on the driving simulator.
2) **Log data cleaning:** Eliminate operation log data which cannot be explained by operation rules.

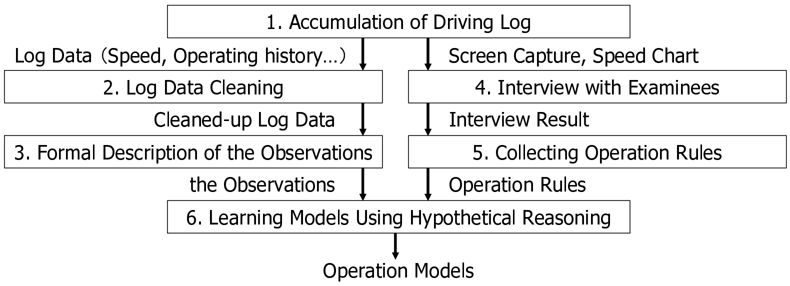


**Fig. 1.** Modeling Process

3) **Formal description of the observations:** Collect an observation from log data in driving simulations and describe the observations in predicate logic. In this paper, "observation" means the world (environment) which is observed by an examinee.
4) **Interview with examinees:** Interview with examinees using screen capture during driving simulation and kinds of charts.
5) **Collecting operation rules:** Collect operation rules constituting domain knowledge from the result of interview. In this paper, each operation rule represents what examinees observed and how they operated during simulations.
6) **Learning models using hypothetical reasoning:** Acquire candidate operation models using hypothetical reasoning with the domain knowledge and the observations. As we mentioned above, operation models are defined as sets of prioritized operation rules.

In this paper, we focus on how to acquire operation models using hypothetical reasoning from log data resulting from driving simulations.

## 3 Formalization of the Problem in Driving Simulation

In this section, in order to apply hypothetical reasoning to the acquisition of operation models, we formally define operation rules, observations, and operation models.

### 3.1 Operation Rules

We describe an operation rule as a condition-action rule. The condition part of a rule describes an examinee's operation and the action part describes situation observed by an examinee. If and only if all conditions are satisfied, the action part of the rule could be executed. Example 1 shows a description of operation rules.

**Example 1: Description of operation rules**
$rule_1$: if $Curve(x)$,$InSight(x$,self) then $LoosenAccel$(self)
$rule_2$: if $Uphill(x)$,$InSight(x$,self) then $StrengthenAccel$(self)
$rule_3$: if $MoreThanDesiredSpeed$(self) then $LoosenAccel$(self)

$rule_1$: if an examinee(self) sees($InSight$) a curve $x$($Curve$), he/she releases the accelerator($LoosenAccel$). $rule_2$: if an examinee sees an uphill road $x$($Uphill$), he/she depresses the accelerator($StrengthenAccel$). $rule_3$: if the speed of examinee's vehicle is over his/her desired speed($MoreThanDesiredSpeed$), he/she releases the accelerator.

### 3.2 Observation

The observation, which is included in log data, is described in predicate logic according to the time line. We use road shape, driving speed, and acceleration pedal operation as observations. An example of the description of observation is as follows:

**Example 2: Description of observation**
$Curve(Curve_2) \wedge InSight(Curve_2, \text{self}) \wedge Uphill(Uphill_3) \wedge$
$On(Uphill_3, \text{self}) \wedge Accelerate(\text{self}) \wedge MoreThanDesiredSpeed(\text{self}) \wedge$
$StrengthenAccel(\text{self}) \Rightarrow Do(LoosenAccel(\text{self}))$

This observation means that an examinee releases the accelerator when the examinee sees $Curve_2$, his/her vehicle is running on $Uphill_3$($On$), he/she is increasing speed($Accelerate$), the speed of vehicle is over his/her desired speed, and he/she depresses the accelerator. In this example, $Do$ is a predicate meaning that he/she initiates an operation.

### 3.3 Operation Model

An operation model consists of sets of prioritized operation rules which are actually used by an examinee. If the condition part of an operation rule is satisfied, the rule is available to use. If there are many usable rules, the one which has the highest priority is chosen. Example 3 shows a description of an operation model.

**Example 3: Description of operation model**
$(rule_1, rule_2, rule_3, rule_2 \preceq rule_1)$

The meaning of this example is as follows. An examinee uses $rule_1$, $rule_2$, and $rule_3$. The priority of $rule_1$ is higher than that of $rule_2$, and thus when both of the condition part of $rule_1$ and $rule_2$ are satisfied at the same time, he/she uses $rule1$.

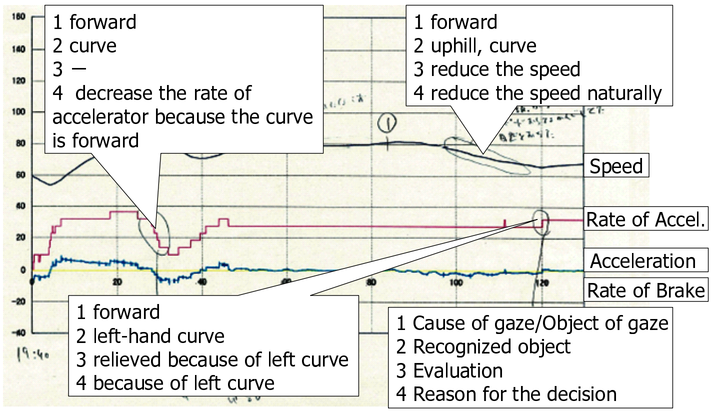


**Fig. 2.** Log data with the result of the Interviews

## 4 Detail of Driver Modeling

In this section, we are showing how to apply hypothetical reasoning to the acquisition of examinee's operation models in driving simulation.

### 4.1 Driving Simulation

In our research, we try to acquire log data from aged examinees and young examinees, and then investigate their decision making process to determine their operation. During driving simulation, each examinee drives 11km road including diverse road alignments. In order to focus on the relationship between each examinee's operations and road conditions, we choose solo driving scenario. Through the investigation, we analyze the relationship between each examinee's operations and road conditions.

Figure 2[1] shows an example of log data with answers at post simulation interview. The horizontal axis denotes the elapsed time, and the vertical axis denotes speed (km/h), acceleration (m/ss), the rate of acceleration/brake(%).

### 4.2 Collecting and Cleaning-up Log Data

In this research, we use the following data to construct operation models.

1) **Time(s)** The elapsed time from the beginning of driving simulation.
2) **Mileage(km)** The mileage from the start point.
3) **Speed(km/h)** The speed of examinee's vehicle
4) **Rate of Accel./Brake(%)** The rate of acceleration/braking, *i.e.,* accelerator/brake pedal position. When an examinee does not step on the pedal, the rate is 0%, and he/she fully steps on the pedal, the rate is 100%.

[1] The log data is offered by Iida Lab., Osaka University

During driving simulation, there is a possibility of examinee's unintentional/meaningless operation. For example, an examinee sometimes increases the speed without any explicit reasons. Currently, we only have a method to acquire models from examinee's intentional operation. This is because an operation rule consists of intentional operation and surrounding environment, so that it is impossible to explain an unintentional operation by using operation rules. Therefore, we eliminate unintentional operation log before the step for acquiring operation models. Currently, we take the following two policies for the elimination.

1) **Elimination of unintentional operations**
   In general, it is practically difficult to execute intentional operations in short time. Thus, we eliminate such operations from log data. We empirically eliminate operations which are subsequently executed within 2 seconds (shown in Figure 3).
2) **Elimination of operations unrelated to surrounding environment**
   An examinee sometimes continuously executes operations until he/she can recognize the change of surrounding environment. For example, when an examinee wants to reduce the speed, he/she steps on the brake several times. This is because it takes time to get to the desired speed. In such case, there are many moves in log data due to the continuous operations. Therefore, we use only the first operation and eliminate subsequent operations. Empirically, we eliminate operations subsequently executed within 3.5 seconds (also shown in Figure 3).

### 4.3 Description of Observation

We describe observations, extracted from log data, based on predicate logic. In this paper, we pick up observations which could affect examinees' operations, and define the following predicates.

$\boldsymbol{Straight(x)}$, $\boldsymbol{Curve(x)}$, $\boldsymbol{Uphill(x)}$, $\boldsymbol{Downhill(x)}$**:** $x$ is straight/curve/uphill/downhill
$\boldsymbol{On(x, y)}$**:** $y$ is running on $x$
$\boldsymbol{Finish(x, y)}$**:** $y$ is running at the end of curve $x$
$\boldsymbol{InSight(x, y)}$**:** $y$ can see $x$
$\boldsymbol{Sharp(x)}$, $\boldsymbol{Slow(x)}$**:** $x$(*e.g.* curve, slope) is sharp or slow
$\boldsymbol{MoreThanDesiredSpeed(x)}$, $\boldsymbol{LessThanDesiredSpeed(x)}$**:** the speed of vehicle $x$ is over the desired speed
$\boldsymbol{MoreThanCurveSpeed(x, y)}$**:** the speed of vehicle $y$ is too high to safely drive in curve $x$
$\boldsymbol{Accelerate(x)}$, $\boldsymbol{Decelerate(x)}$**:** the vehicle $x$ is accelerating/decelerating
$\boldsymbol{KeepAccel(x)}$**:** $x$ keeps the rate of acceleration
$\boldsymbol{StrengthenAccel(x)}$**:** $x$ is increasing the rate of acceleration
$\boldsymbol{LoosenAccel(x)}$**:** $x$ is decreasing the rate of acceleration
$\boldsymbol{ReleaseAccel(x)}$**:** $x$ is releasing the accelerator
$\boldsymbol{Brake(x)}$**:** $x$ is stepping on the brake

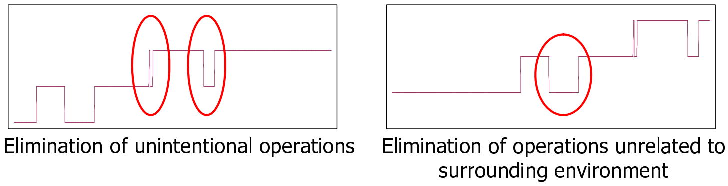


**Fig. 3.** Types of Elimination

### 4.4 Interview

We interview an examinee with a chart which shows speed/acceleration/rate of accelerator and brake. Additionally, we use screen capture of an examinee's screen in order to help him/her to remember his/her behavior during simulation. In the interview, we ask about the following four points:

1) **Cause of gaze/Object of gaze:** The reason why an examinee gazes something or the thing what an examinee gazes.
2) **Recognized object:** The thing what an examinee recognizes
3) **Evaluation:** The feeling that an examinee has
4) **Reason for the decision:** The reason of examinee's decision making

In this paper, we have an interview on some points where the speed/acceleration is drastically changed (5km/h, 5m/ss) or his/her rate of acceleration is drastically changed (10%). Examples of answers to above four points are shown in Figure 2.

### 4.5 Extraction of Operation Rules

We analyze the result of interview and log data, then we generate an operation rule which can denote an examinee's generic operation. We extract the condition part of a rule by analyzing the result of interview (cause of gaze, recognized object). We extract the action part of a rule by analyzing examinee's operations for the condition. In this paper, we extract operation rules from aged and young examinees. As a result, the following operation rules are extracted.

$\boldsymbol{rule_1}$**:** if an examinee sees a curve ahead, he/she releases the accelerator
$\boldsymbol{rule_2}$**:** if an examinee sees a curve ahead and the speed of vehicle is too high to drive the curve, he/she releases the accelerator
$\boldsymbol{rule_3}$**:** if an examinee sees a sharp curve ahead and the speed of vehicle is too high to drive the curve, he/she releases the accelerator
$\boldsymbol{rule_4}$**:** if an examinee is driving at the end of a curve, he/she depresses the accelerator
$\boldsymbol{rule_5}$**:** if an examinee sees an uphill ahead, he/she depresses the accelerator

$\boldsymbol{rule_6}$**:** if an examinee sees a downhill ahead, he/she releases the accelerator
$\boldsymbol{rule_7}$**:** if an examinee is driving on an uphill, he/she depresses the accelerator
$\boldsymbol{rule_8}$**:** if an examinee is driving on a downhill, he/she releases the accelerator
$\boldsymbol{rule_9}$**:** if the speed is over the desired speed, an examinee releases the accelerator
$\boldsymbol{rule_{10}}$**:** if an examinee is driving on a straight road and the speed is under the desired speed, he/she depresses the accelerator
$\boldsymbol{rule_{11}}$**:** if an examinee depresses the accelerator and then the vehicle is accelerating, he/she keeps the rate of the accelerator
$\boldsymbol{rule_{12}}$**:** if an examinee releases the accelerator and then the vehicle is decelerating, he/she keeps the rate of the accelerator

### 4.6 Operation Models

In this section, we show operation models acquired by our proposed method.

**Example 1: Operation model acquired from the aged examinee A04**
$(\{rule_7, rule_8, rule_{11}, rule_{12}\}, rule_7 = rule_8 \preceq rule_{11}, rule_7 = rule_8 \preceq rule_{12})$

This model means that the aged examinee A04 used four operation rules ($rule_7$, $rule_8$, $rule_{11}$, $rule_{12}$). Figure 4(a) shows the order of priorities of these rules. In this figure, the direction of an arrow describes the order of priority between rules. An rule with an arrow-head has the higher priority. For example, the priority of $rule_{11}$ is higher than that of $rule_7$ and $rule_8$. $rule_7 = rule_8$ means that $rule_7 \preceq rule_8$ and $rule_8 \preceq rule_7$ are approved. In the figure, an arrow in both direction shows that the priorities of both rules are same.

**Example 2: Operation model acquired from the aged examinee A20**
$(\{rule_5, rule_7, rule_9, rule_{11}, rule_{12}\}, rule_5 = rule_7 = rule_9 \preceq rule_{11}$, $rule_5{=}rule_7{=}rule_9{\preceq}rule_{12})$

This model means that the aged examinee A20 used five operation rules ($rule_5$, $rule_7$, $rule_9$, $rule_{11}$, $rule_{12}$). Figure 4(b) shows the order of priorities of rules. Because the order of priorities of three rules ($rule_5$, $rule_7$, $rule_9$) are same, this model represents that the examinee depressed or released the pedal when he/she saw an uphill and the speed of his/her vehicle was over the desired speed. Therefore, it would appear that he/she could not always sense an uphill and the driving speed was over his/her desired speed.

**Example 3: Operation model acquired from the young examinee Y01**
$(\{rule_7, rule_{11}\})$

This simple model (Figure 4(c)) means that the young examinee Y01 drove based on only two operation rules ($rule_7$, $rule_{11}$). Because the condition part of these rules could not be satisfied at the same time, the order of priorities of these rules are not fixed.

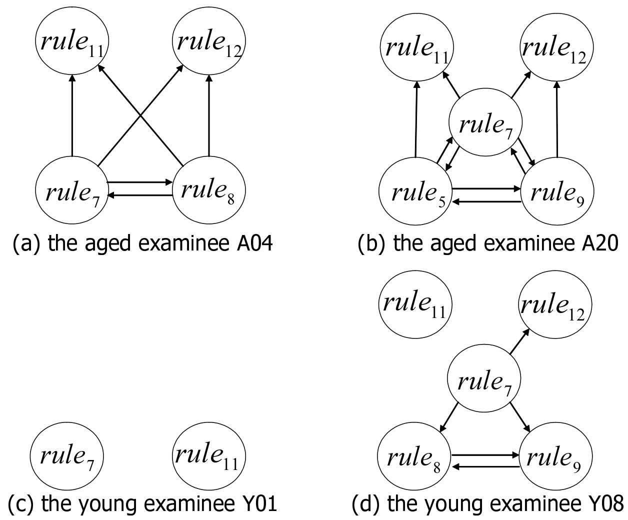


**Fig. 4.** The order of priorities of operation rules

**Example 4: Operation model acquired from the young examinee Y08**
$(\{rule_7, rule_8, rule_9, rule_{11}, rule_{12}\}, rule_7 \preceq rule_8 = rule_9, rule_7 \preceq rule_{12})$

This model (Figure 4(d)) means that the young examinee Y08 used five operation rules ($rule_7$, $rule_8$, $rule_9$, $rule_{11}$, $rule_{12}$). Figure 4 shows the order of priorities of these rules. Because the priority of $rule_9$ is higher than that of $rule_7$, it would appear that the examinee wanted to keep his/her desired speed instead of keeping up the speed on an uphill.

In this research, operation models of a young examinee usually consists of less numbers of operation rules. On the other hand, the models of an aged examinee consists of more numbers of rules. That is to say, an young examinee tends to drive a vehicle based on simple driving model and an aged one tends to drive a vehicle based on relatively complex model.

## 5 Conclusion

For conducting multiagent-based traffic simulation, one of the central issue is how to model an agent including diverse characteristics of a human driver. For achieving this issue, we proposed a method to acquire operation models using hypothetical reasoning, and then showed acquired operation models from aged/young human drivers. The main contributions of this paper are the following two points:

**1) A method to acquire operation models from log data in driving simulation**

We have proposed a method to acquire operation models of an individual examinee using log data in driving simulation. In the proposed method, first the interview is conducted to catch the reasons of behaviors during driving simulation, and operation rules are described using predefined predicates. Then, we use hypothetical reasoning to acquire characteristic operation models. The acquired model is sets of prioritized operation rules.

**2) Reduction of modeling cost**

Actually, having the interview and log data analysis are time-consuming task. However, in our method, firstly operation rules are acquired from some examinees. Then, all acquired rules are usable for explaining any examinee's log data. We do not need to interview all examinees and analyze all log data, so thus we could cut out troublesome modeling cost.

In the proposed method, it is possible to acquire promising operation models if an examinee takes simple "intentional" operations. That is to say, when we use straightforward log data, the proposed modeling process using hypothetical reasoning could work well. If there is noise data, *i.e.* "unintentional" operations, it becomes difficult to accurately acquire operation model. Our possible future work includes: improving noise-canceling method in order to acquire more sophisticated operation model; incorporating more information (condition) into operation rules; implementation of the models, operating on traffic simulation, based on the acquired operation models; analyzing the validity of the models for practical traffic simulation by making evaluation experiments.

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