Wide-Area Traffic Simulation based on Driving Behavior Model

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Abstract. Multiagent-based simulations are a key part of several research fields. Multiagent-based simulations yield multiagent societies that well reproduce human societies, and so are seen as an excellent tool for analyzing the real world. A multiagent-based simulation allows crowd behavior to emerge through interactions among agents where each agent is affected by the emerging crowd behavior. The interaction between microscopic and macroscopic behaviors has long been considered an important issue, termed the "micro-macro problem", in the field of sociology, but research on the issue is still premature in the engineering domain. We are focusing on citywide traffic as a target problem and are attempting to realize mega-scale multiagent-based traffic simulations. While macro-level simulations are popular in the traffic domain, it has been recognized that micro-level analysis is also beneficial. However, there is no software platform that can realize analyses based on both micro and macro viewpoints due to implementation difficulties. In this paper, we propose a traffic simulation platform that can execute citywide traffic simulations that include driving behavior models. Our simulation platform enables the introduction of individual behavior models while still retaining scalability.

1 Introduction

Simulation methodologies fall into two main categories; macro simulation and micro simulation. In macro simulations, the subjects are modeled from the macroscopic viewpoint and expressed using governing equations. The macro simulation methodology is suitable for the analysis of physical phenomena because there are obvious and uniform rules/mechanisms that well explain the subjects behaviors, *i.e.* physical laws. On the other hand, it is inadequate to replicate the social phenomena that emerge from human-human interactions because a human's decision-making mechanism is imprecise and diverse. For such phenomena, micro simulations are to be preferred. Micro simulations allow each entity to be distinctly represented so we can replicate societies consisting of humans in a natural way.

Multiagent-based simulation, one version of micro simulation, has been applied in various research fields [1–3]. Multiagent-based simulation yields multiagent societies that well reproduce human societies, and so are seen as an excellent tool for analyzing the real world. In a multiagent-based simulation, crowd behavior can emerge though interactions among agents while each agent can be impacted by the emerging behavior. The relation between individual behavior and crowd behavior is known to be an important problem, the "micro-macro problem", in the sociology domain. Current platforms, however, are not powerful enough to resolve this problem.

This paper has citywide traffic as its target problem. To understand citywide traffic, the analysis must combine two different viewpoints. The micro-level analysis (*e.g.* driving behavior) is achieved by considering the individual's viewpoint, while the macro-level analysis (*e.g.* congestion analysis) requires a consideration of the crowd viewpoint. No existing simulation platform can provide the power and sophistication needed. Additionally, almost all previous works on multiagent traffic simulations, which can represent a human driver as an agent, assumed that each agent has the same driving style [4–6]. For example, in [4], each agent chooses a driving route based on his/her own preferences. Unfortunately, there is no diversity in route choice mechanisms among the agents.

In this paper, we propose a traffic simulation platform that can execute citywide traffic simulations with individual driving behavior models. Our simulation platform realizes both scalability and the introduction of individual behavior models. Our platform can execute both micro and macro analyses and we can analyze the effect of micro-level behaviors on the macro-level traffic.

The reminder of this paper is as follows. Section 2 describes our approach to traffic analysis through multiagent-based simulations. We propose a simulation platform architecture and implementation in Sections 3 and 4 and demonstrate an application example in Section 5.

2 Overview of Mega-scale Traffic Simulations with Diverse Behavior Models

Figure 1 shows an overview of the challenges faced when trying to realize mega-scale multiagent-based traffic simulations with intimate driving behavior models. Following our participatory modeling perspectives [7], we have already developed a driver modeling methodology [8, 9] as explained in the next section. The next technical issue is how to run large-scale simulations with driving behavior models obtained from human subjects. We elaborate the design and implement the first prototype of the simulator.

2.1 Extracting Driver Model

The key factor in constructing multiagent-based simulations is agent modeling. This is because collective phenomena emerge from the local behaviors of many

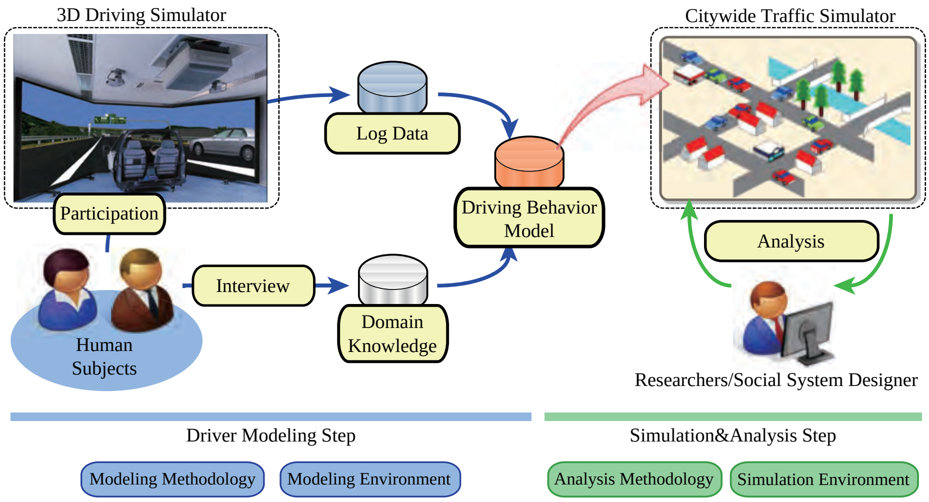


Fig. 1. Overview of analysis process of city traffic with multiagent based simulation

agents; that is, the simulation result depends on each agent's micro-level behavior. Most existing studies, however, use simple or abstract agent models [6, 10, 11].

For handling the diverse characteristics of drivers, we extract a driver model from each human subject. The process of this approach, called participatory driver modeling, is shown in the left part of Fig. 1.

During participatory driver 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. Use a 3D virtual driving simulator to collect realistic driving log data from human subjects. The 3D virtual driving simulator has a lifelike cockpit and a wide screen for displaying the virtual environment (see Figure 2).
2. Together with domain experts, identify individual driving behaviors by investigating collected log data. Figure 3 is one example of a chart made from log data. This example shows the transition in speed (the graph on the top), acceleration (graph second from the top), and the usage of accelerator/brake (graphs on the bottom) for a virtual road that includes curves and slopes. Because of the joint work with traffic engineers, we could access the extensive log data that they had accumulated.
3. Collect prior knowledge constituting a driving behavior model by interviewing the subjects of the driving simulation. We interview some subjects to collect driving rules, which contain domain knowledge. We used screen shots of the 3D simulator and charts showing speed, acceleration, and the usage

Fig. 2. A 3D virtual driving simulator used for collecting driving log data

of accelerator/brake in order to make it easy for the subjects to remember his/her behavior in the simulation. We then construct unique driving models, which can explain each driver's behavior, by the application of hypothetical reasoning.

4. Select meaningful prior knowledge and represent it in formal expressions.
5. Construct a driving behavior model that can explain the human subject's actions based on hypothetical reasoning [12]. The precise algorithm used is described in [13].

2.2 Execute Multiagent-based Simulations with Intricate Driver Agents

Multiagent simulations are a promising tool with which to analyze the effects of local driving behavior on the entire traffic pattern. We built a multiagent-based simulation platform that can execute citywide traffic simulations with intricate driver agent models (see the right part of Fig. 1).

Previous traffic simulation research consists of either local driving behavior on single roads or route selection on a road network. Research on local driving behavior has considered observations and actions about road geometry, signals, and surrounding cars. Research on route selection has lead to the modeling of decision processes and route utility functions.

We assume that there is some interaction between local driving behavior and route selection. What we need is analyze how local driving behavior affects

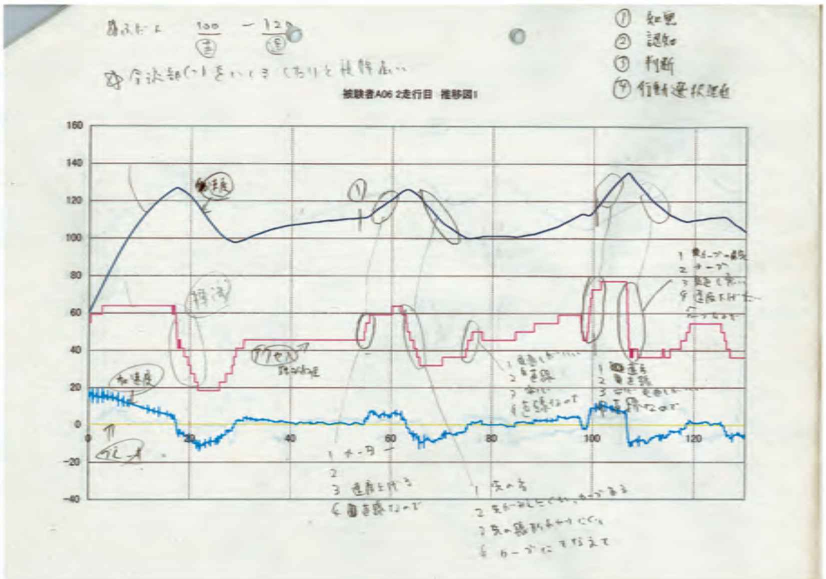


Fig. 3. An example of a chart made from driving log data. Circles on the graph represent the subject's specific behaviors identified by traffic engineers.

citywide traffic patterns. Therefore, the simulation platform is must be able to incorporate both driving behavior models and route selection models.

For example, we want to analyze the traffic environment created by aged drivers because driver behavior changes with age and the number of aged drivers is increasing in Japan. We extract driver models for several age groups and execute large-scale multiagent-based simulations for estimating the traffic patterns yielded by large numbers of aged people.

It is difficult to execute driving behavior simulation in the whole traffic environment because the calculation cost becomes enormous. Therefore, the driving simulations in this paper examine only a major road; other simulations consider a simple road network.

3 Architecture

Our proposed platform can deal with intricate driving behavior when analyzing the relation between personal driving behavior and crowd behavior. The architecture of our platform is shown in Fig. 4. This platform has three layers.

- **Mental layer**
  Mental layer receives road network data and OD (Origin-Destination) data. Road network data describes road status and OD data consists of tuples of

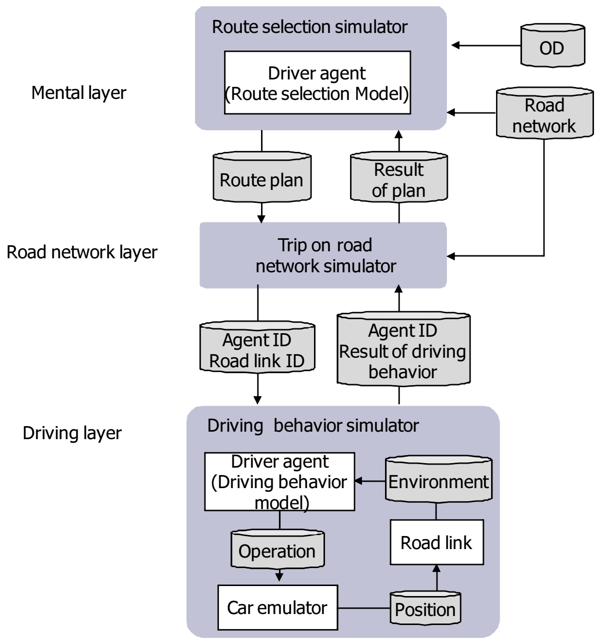


Fig. 4. Platform Achitecture

starting point and destination point of agents. In the mental layer, an agent is regarded as the entity performing route selection. The agent sets the route that has minimum cost considering map information and previous simulation results. A route plan consists of paths, mode choice, daily activity and so on.

– **Road network layer**
  Road network layer receives a route plan from each driver agent on the mental layer. In the road network layer, the agent is regarded as the plan executor. A road network is abstracted as a network consists of nodes and links. The agent acquires location information on node and link basis. The agent moves along road network so as not to violate road network constraints.

  Road network layer sends agent ID and road ID to driving layer, when the agent enters the road that the social system designer is focused on.
– **Driving layer**
  Driving layer receives agent ID and road ID from road network layer. In the driving layer, the agent is regard as a virtual driver and vehicle. They move over a 2D space rather than an abstract road network.

  If the simulator was forced to calculate the driving behavior on all roads, the computational cost would be too high. Therefore, in our architecture, driving behaviors are only simulated on certain roads which an social system

designer pays attention to, for example, which are applied the new rule of traffic law.
The execution process is summarized as follows. When an agent enters the area of interest, the wide area traffic simulator invokes the driving behavior simulator and sends agent ID to it. The driving behavior simulator orders the corresponding driver agent to initiate the decision making cycle. Driver agent decides the operation commands for acceleration/braking/steering based on his/her driving model and road condition. Driver agent sends its decisions to the vehicle module. Vehicle module transforms acceleration/brake/steering operations into an acceleration vector according to the vehicle's specification.

4 Implementation

We implement a platform using the proposed architecture. We combined the traffic simulation tool kit MATSim [1], which is a large-scale multiagent-based traffic simulation platform, with our driving behavior simulator. MATSim has been applied to estimate the traffic of real cities such as Zurich [4] and Berlin [14].

MATSim manages mental layer and road network layer. We combined driving layer to MATSim. These three layer is described precisely in following section.

4.1 Route Selection Simulator

The route selection simulator calculates the average trip time of each road based on the traffic information of the previous day. The agents decide the best route considering the trip time and their activity plan.

The route selection simulator receives road network and the execution result of previous plan from the road network simulator.

4.2 Road Network Simulator

We use QueueSimulation in MATSim as the road network simulator. In QueueSimulation, the road network consists of road links and road nodes. Each road link is associated with a running queue and a waiting queue. Road link parameters imply the physical form of the road.

Figure 5 describes the execution process of road link and road node.

- **Process of road link**
  Road link put driver agents who enter the road into the running queue. Road link assumes that the driver agents can drive at any speed up to some limit which is decided by the road's physical form and speed limits. When the driver agent arrives at the end of the road link, it is popped from the running and pushed into the waiting queue.

[1] http://www.matsim.org/

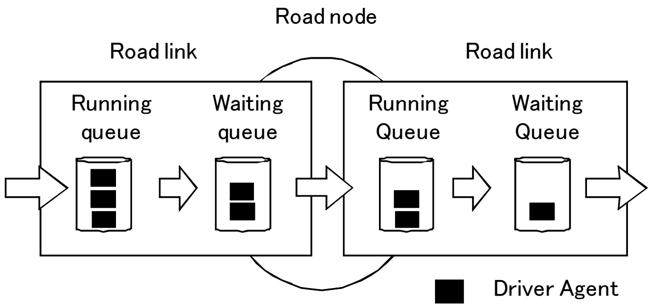


Fig. 5. Road link and road node

– **Process of road node**
  Road node pops a driver agent from the waiting queue and pushes it onto the running queue of the next road link, if the running queue on the next road link has enough space.

The road network simulator abstracts the driver agents as homogeneous grains on abstracted road networks, not two dimensional spaces.

4.3 Driving Behavior Simulator

The driving behavior simulator calculates vehicle behavior with each driver model. On the driving behavior simulator, the driver agents are assumed as heterogeneous grains. The driver agents are mapped on two dimensional spaces.

Figure 6 shows the architecture that combines the driving layer with the road network layer. The main components of the driving layer are driver agent and vehicle module. The driver agents decide their operations through the following steps.

1. **Ovservation**
   Driver agent observes surrounding environment. He observes state of own car, surrounding cars, and the roads in the immediate vicinity.
2. **Recognision**
   Drivers may not be able to recognize all observed information. This step filters the observed information based on the driver's characteristic. For example, an aged driver is unable to mentally map the surrounding traffic situation as quickly as a young driver.
3. **Decision**
   Driver agents decide their acceleration/brake/steering operations according to the recognized information.
4. **Execution**
   The driver agents execute the acceleration/brake/steering operations. This involves not only setting the accelerator/brake/steering values directly but also execute sequential acts such as changing lane.

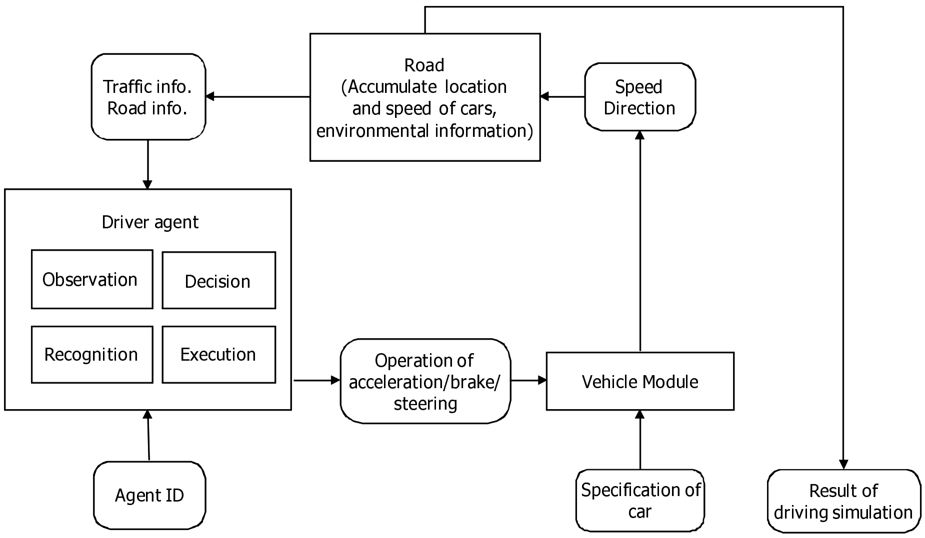


Fig. 6. Construction of driving layer

Each vehicle module holds car specifications, such as size, maximum speed, fuel consumption, car type, type of fuel, etc. Vehicle module and driver agent are separated. Vehicle module converts the operations set by the driver agent into acceleration/deceleration.

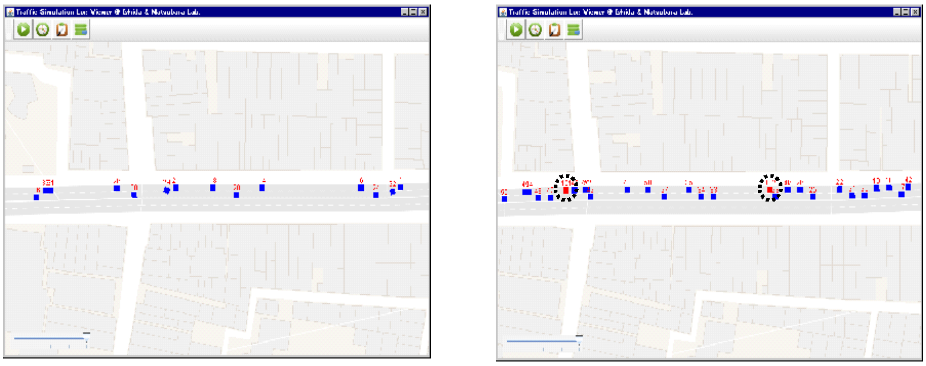
When a driver agent enters the especial road, the driver agents send agent ID to the driving layer, and then the driving layer calculates driving behavior of the corresponding driver agent. Driver agents observe the simulated road environment, recognize the observed information, decide car operation, and execute the operation.

5 Application Example

Street parking in urban areas is a major cause of traffic jams. If many cars try to use a road link with a lot of parked cars, the capacity of the link becomes small. Drivers do not like links with small capacity, and will thus change their routes.

To see the micro-macro link effect in the case of street parking, two sample scenarios were run on Kyoto City's road network using our simulator. The wide-area simulation is queue based, and only the street indicated by arrow in Fig. 8 was simulated about driving behavior in detail.

- **First scenario**
  There are 500 driver agents. All agents leave Kyoto Station at 6:30 and their goal is Yasaka Shrine. Boxes are cars and there are no parked cars in the street as shown in Fig. 7 (a). This street is indicated by arrow in Fig. 8 (a).



(a) (b)

Fig. 7. Local area view: simulation area which simulates precice driving behaviour

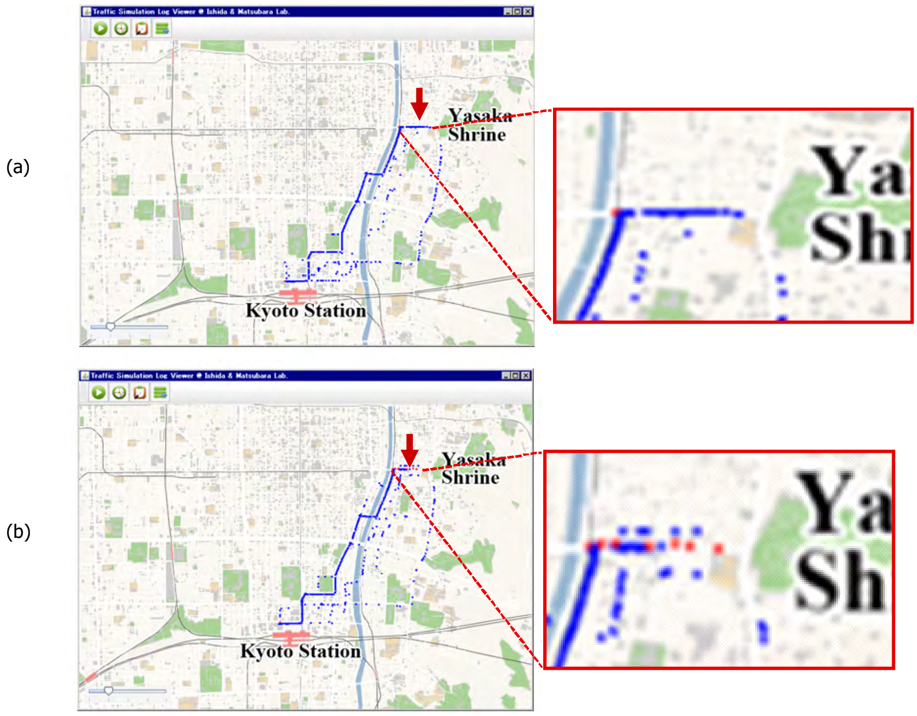


Fig. 8. Wide area view: simulation of street parking in urban streets

– **Second scenario**
  There are 500 driver agents. All agents leave Kyoto Station at 6:30 and their goal is Yasaka Shrine. Circled boxes are parked cars and there are parked cars in the street as shown in Fig. 7 (b). This street is indicated by arrow in Fig. 8 (b).

Fig. 7 (a) shows the first scenario at the micro level: with no parked cars, the driver agents proceeded smoothly. Fig. 7 (b) shows the second scenario: the same street with some parked cars, the driver agents tried to move around stopped cars and the traffic flow became jam.

Figure 8 (a) shows the first scenario at the macro level: driver agents found several routes and chose one as they like, and (b) shows the second scenario: a few agents changed their routes to the north street or the south street to avoid the jam caused by the parked cars.

6 Conclusion

Multiagent-based simulations yield multiagent societies that well reproduce human societies, and so are seen as an excellent tool for analyzing the real world. In a multiagent-based simulation, agents interact with each other and generate crowd behavior. Moreover, crowd behavior can influence agents. The relation between personal behavior and crowd behavior is taken to be an important problem in the domain of sociology, unlike the domain of engineering.

The platform proposed in this paper enables us to analyze how micro driving behavior affects to large area traffic patterns in a city. We demonstrate the effect of street parking in urban streets as an example.

In future work, we will extract driver models of several age groups and execute large-scale multiagent-based simulations for estimating the traffic patterns created by many aged people.

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