https://doi.org/10.20965/jaciii.2011.p0233

Paper:

Massive Multiagent-Based Urban Traffic Simulation with Fine-Grained Behavior Models

Hiromitsu Hattori, Yuu Nakajima, and Shohei Yamane

Graduate School of Informatics, Kyoto University
Yoshida-Honmachi, Sakyo-ku, Kyoto 606-8021, Japan
E-mail: {hatto, nkjm}@i.kyoto-u.ac.jp, yamane@ai.soc.i.kyoto-u.ac.jp
[Received August 9, 2010; accepted December 31, 2010]

As it is getting easier to obtain reams of data on human behavior via ubiquitous devices, it is becoming obvious that we must work on two conflicting research directions for realizing multiagent-based social simulations; creating large-scale simulations and elaborating fine-scale human behavior models. The challenge in this paper is to achieve massively urban traffic simulations with fine-grained levels of driving behavior. Toward our objective, we show the design and implementation of a multiagent-based simulation platform, that enables us to execute massive but sophisticated multiagent traffic simulations. We show the capability of the developed platform to reproduce the urban traffic with a social experiment scenario. We investigate its potential to analyze the traffic from both macroscopic and microscopic viewpoints.

Keywords: multiagent-based simulation, traffic simulation, human behavior modeling

1. Introduction

Social mechanism design is such an intractable task due to the complexity of human societies that effective heuristic technologies are being sought widely. Multiagent-based social simulations are increasingly seen as the most attractive approach to creating sophisticated social mechanisms [1, 2]. As fine-scale digital data can now be readily acquired via the latest personal devices, a vast quantity of data on human behavior is being accumulated. This situation suggests that there are two research directions for multiagent-based social simulations; that is, creating large-scale simulations and elaborating human behavior models against the backdrop of the huge amount of data. Although many studies have been conducted on both approaches, the vast majority of them seems to be strongly biased to one viewpoint. Yamamoto and Mizuta proposed a platform for massive agent-based simulations called ZASE [3]. While they showed ZASE can perform well with a large number of agents, they did not show great concern about the details of the behavior models. Murakami et al. proposed a modeling technology based on participatory simulations to construct behavior models that can reproduce human-like behaviors [4]. Although their proposed technology enables the construction of diverse behavior models, they did not execute large-scale simulations with the constructed models. This is because there is a trade-off between the scale of MultiAgent-based Simulations (MASim) and the granularity of behavior models in terms of the computation time. However, thanks to recent advances in computing power, it is becoming possible to conduct massive MASim with fine-grained behavior models. It is the time to combine scale-oriented MASim with model-oriented MASim, both of which have been studied in different threads up to now.

The challenge presented in this paper is to achieve massive urban traffic simulations with fine-grained levels of driving behavior. Traffic is an adequate target for our research because vehicular traffic is a phenomenon that emerges from interaction among a lot of human drivers with diverse driving styles. Toward our objective, we develop a multiagent-based simulation platform that enables us to execute massive MASim. Concretely, there are three issues to be achieved.

1. Development of a scalable MASim platform:
   We need to design and implement a scalable traffic simulation platform that can run citywide traffic simulations with agents controlled by individual driving behavior models.

2. The ability to reproduce "actual" urban traffic:
   To explain different traffic phenomena, we need to confirm that the developed platform can generate reasonable traffic flows.

3. Investigation of the potential to analyze the urban traffic based on both macroscopic/microscopic viewpoints:
   We need to ensure that the developed platform is useful in examining both the macroscopic and microscopic aspects of urban traffic.

2. Massive Traffic Simulation with Fine-Grained Models

2.1. Design of Traffic Simulator

The multiagent-based traffic simulation platform proposed in this paper is implemented as an extension of MATSim (MultiAgent Transport Simulation toolkit) [5].

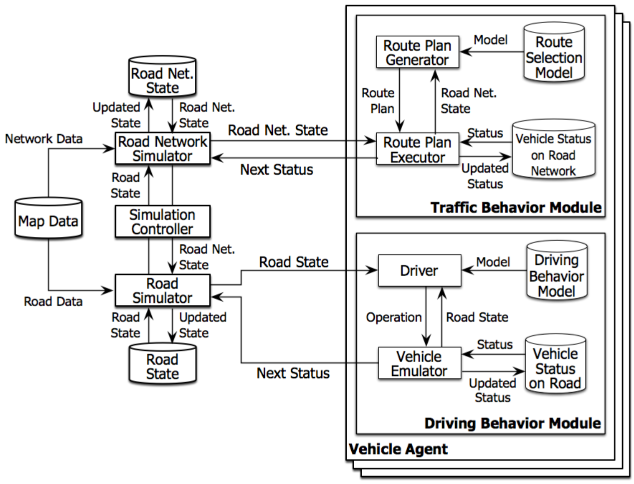


Fig. 1. Traffic simulation platform architecture.

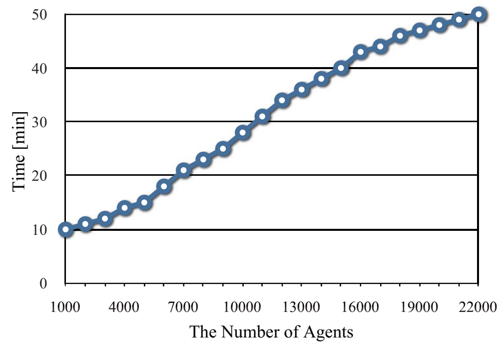


Fig. 2. Computation time.

Although MATSim enables to conduct queue-based massive traffic simulations, it fails to support realistic micro traffic simulations. This is because the details of road structures (e.g., the number of lanes) or surrounding environment including neighboring vehicles cannot be represented so that "driving behaviors" considering such locally available factors cannot be reflected in simulations. In order to achieve traffic simulations with the fine-grained driving behavior models, we designed and implemented a simulation platform shown in **Fig. 1**.

Our simulation platform includes two main simulation modules; *Road Network Simulator* and *Road Simulator*. Road Network Simulator plays the central role on controlling the transition of each vehicle on the extensive road network so that this simulator updates the location of each vehicle, i.e., the current road, on the road network. Road Simulator corresponds to one physical road and manipulates the vehicle agents on it; that is, the simulator requests each agent to execute the calculation required to carry out a simulation. Additionally, this simulator updates the status of each agent, such as its location on the road. During traffic simulations, these two simulators exchange state of vehicles and realize both global traffic phenomena and local traffic behaviors. On the simulation platform, an agent includes a traffic behavior module for route planning and driving behavior module for driving operation. Both modules are assigned models used to determine plans and operations. Currently, we use a common model for planning which calculates the shortest plan based on Dijkstra method. Road Simulator request each agent's driving behavior module to execute a driving operation every 100 msec, then *Driver* sub-module in each agent calculates the next operation based on the assigned driving behavior model. The next speed, velocity, and location are calculated in *Vehicle Emulator* based on the current status stored in *Vehicle Status on Road* DB.

As mentioned above, we extended established traffic simulator, MATSim. Although MATSim enables to represent each agent as a distinct entity, it is unable to explicitly represent the characteristics of agent behaviors. On the other hand, our platform enables to represent distinct unique behaviors of each agent. Thus, our simulator offers a more detailed view of complex traffic phenomena. AVENUE [6] is another traffic simulator which provides the detailed view of the urban traffic flow. AVENUE is based on hybrid block density method which can offer the future of both fluid model and discrete vehicle model. In AVENUE, micro behaviors are decided at the macro level. Namely, the movement of discrete vehicles are controlled by the parameter calculated by the fluid model. Therefore, traffic flows in AVENUE are not generated by the accumulation of diverse local behaviors of agents so that it is not based on pure bottom-up approach. On the contrary, our simulator generates traffic flows through bottom-up calculation based on two discrete models for route planning and reproducing driving behaviors. Thus, we are proposing pure micro traffic simulators with reasonable scalability (see Section 2.2).

2.2. Computational Performance

We show that our simulator has sufficient scalability. In this experiment, we generated 100 ODs by pairing two randomly selected points from 25 main intersections within the heart of Kyoto city (2 km $\times$ 2 km square). For the simplicity, all agents used the same behavior model. The simulation time was 2 hours so some agents could not reach their destination due to congestion. We ran our experiments on a computer with a Core2Duo 2.53 GHz CPU and 3 GB of main memory. As we explained in the previous section, our simulator trades computation time off against an increase in simulation resolution. **Fig. 2** plots the computation time versus the number of agents. As you can recognize, the computation time is directional proportional to the number of agents. In fact, with the largest number of agents (22,000), the computation time is around 50 min. This result means our platform has sufficient scalability for urban traffic simulations with fine-grained behavior models. For example, Geroliminis and Daganzo executed traffic simulations in Yokohama, which is a major Japanese city of the Greater Tokyo Area, with

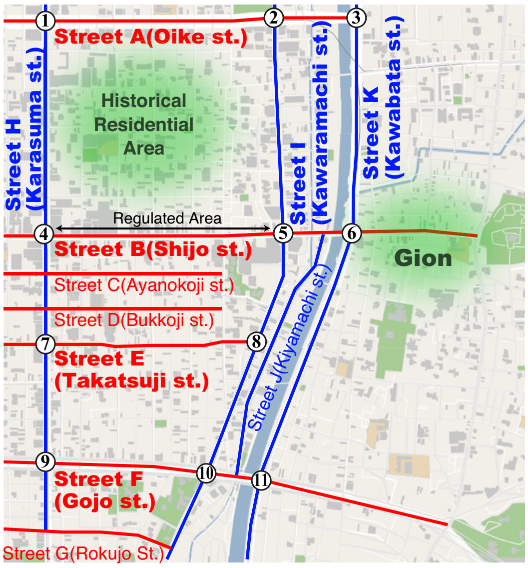


Fig. 3. Central part of the target area of the social experiment in the city of Kyoto.

12,000 vehicles [7]. Thus, our simulation framework is competent to conduct practical urban traffic simulations.

3. Simulations of Social Experiment

3.1. Experimental Scenario

In October 2007, Kyoto City's Traffic Policy, City Planning Bureau carried out a social experiment.[1] **Fig. 3** shows the central target area of the experiment. During the experiment, Street B, which is the busiest street in the city of Kyoto, was regulated and only buses and taxis were allowed to enter. Moreover, some narrow streets crossing St.B were closed. After the experiment, the following phenomena were reported:

- The amount of vehicular traffic on St.A and St.E, both of which run parallel with St.B, and St.I and St.K, both of which cross it, was clearly increased. For example, the total amount of traffic on both lanes of St.A was increased by 17% compared to the traffic at the same time one year prior. The logical reason was that vehicles used the parallel and cross streets to bypass the regulated streets.
- The traffic on St.F and St.H was, interestingly, not increased, but instead was decreased by 2% or 3%.
- Congestion was observed especially around the A-H junction and the B-K junction.

This social experiment was a good indication of the cost and complexity involved in real world experiments. For example, the experiment in Kyoto took one-year to prepare. Furthermore, it was impossible to observe all streets closely during the experiment so that there are limitations to investigate phenomena during the experiment leading to a lack of analysis clarity. These problems emphasize the importance of multiagent-based traffic simulations.

3.2. Virtual Experiment on our Platform

We conducted simulations with vehicle agents, each of which is assigned an OD (Origin-Destination) selected from 36 types of ODs. Both origin and destination mean start and goal of a trip, respectively. We prepared an OD set considering two types of traffic, i.e., traffic in the central part of the target area of the experiment and traffic through the central area. For the first type, we picked 6 intersections between the main streets (①, ②, ④, ⑤, ⑨, ⑩ in **Fig. 3**), and then made 30 directed-pairs from them; that is, one intersection was used as both an origin and a destination. For the second type, we also made 6 ODs between randomly selected intersections located just outside of the central part; northeast-southwest, northwest-southeast, west-east. The last OD was specifically set to represent the typical through-traffic in the entertainment district of the city. In the experiment, we split vehicle agents in two for each traffic type, and equally distributed them among the OD pairs. In this simulation, all agents had an identical driving behavior model; the model set the desired speed to 30 km/h and prioritized overtaking at speeds under this desired speed. The simulation period was set to 90 min and the simulation was iterated 50 times according to [8]. Furthermore, we applied the road network data, including all road links in Kyoto city.

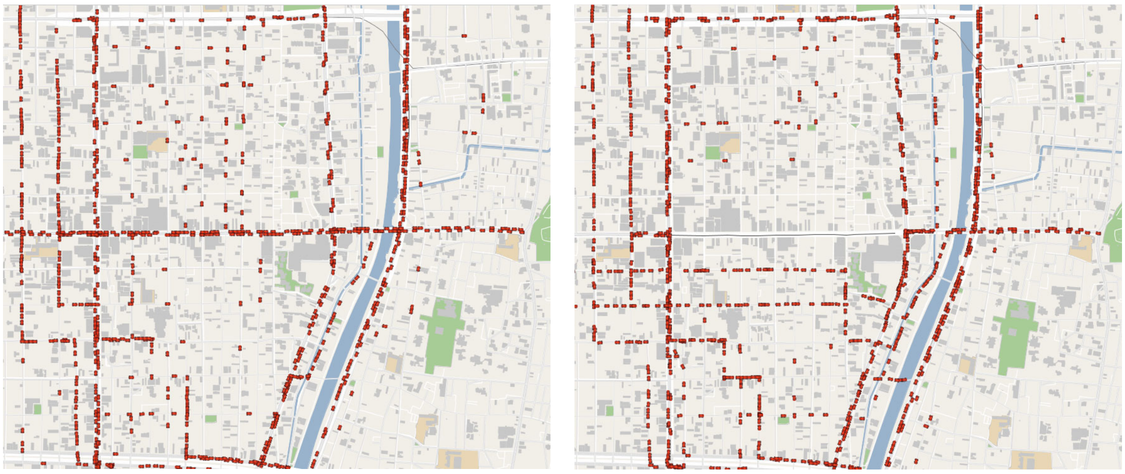
Figure 4(a)-(1) is a snapshot of the simulated traffic in the central target area without any regulation. The snapshot shows heavy traffic on Street B with some vehicles driving through the historical residential area from Street B to avoid congestion. Moreover, only a small number of vehicles drove on the streets to the south of St.B.

We turn now to the results of simulations with regulations executed in the social simulation. **Table 1** shows the change in the amount of the traffic on the main streets running north-south and east-west with and without the regulation. A "section" on the table corresponds to a link between two numbered intersections, see **Fig. 3**. As shown, the traffic on St.A, St.E, and St.I is clearly increased as it did in the actual social experiment. The traffic on St.F is almost same as that in the social experiment so that our simulations can obtain similar results on this street to the real world experiment. On the other hand, the traffic on St.H is also clearly increased and the traffic on St.K is increased slightly. Although these results show that we cannot reproduce the traffic flows exactly, our simulations achieved very reasonable results.

From **Fig. 4(a)-(2)** showing a snapshot of the simulated traffic under the same conditions as the social experiment, we can observe the following phenomena:

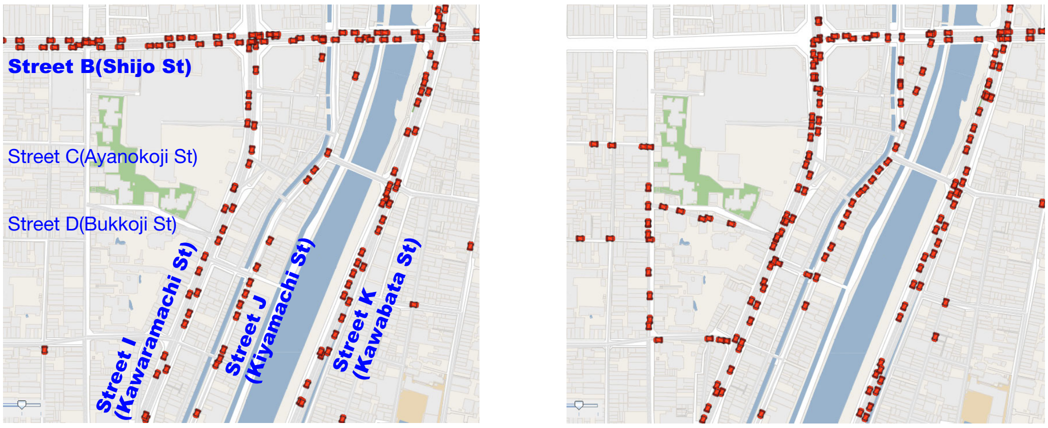
- Two streets to the south of St.B (St.C and St.D) become detours connecting St.H and St.I so that the traffic became heavy.

1. Press Release on the social experiment from the Kyoto City Government: http://www.city.kyoto.jp/koho/news/newspaper/2007/19KS1001.pdf



(1) Without Regulations (2) With Regulations

(a) Traffic Flows in the Central Area of the Social Experiment



(1) Without Regulations (2) With Regulations

(b) Traffic Flows around the Intersection between Shijo st. and Kawaramachi st.

Fig. 4. Simulations of the traffic in the heart of Kyoto city with or without regulations executed in the social experiment.

Table 1. The rate between the amount of traffic on main streets without and with regulations.

(a) The results on streets running north-south

Direction	**Street A**		**Street E**		**Street F**	
	West to East	East to West	West to East	East to West	West to East	East to West
Section	1-3	3-1	7-8	8-7	9-11	11-9
Ratio[%]	296%	168%	194%	223%	100%	107%
Average[%]	232%		209%		104%	

(b) The results on streets running east and west

Direction	**Street K**				**Street I**				**Street H**			
	South to North		North to South		South to North		North to South		South to North		North to South	
Section	11-6	6-3	3-6	6-11	10-5	5-2	2-5	5-10	9-4	4-1	1-4	4-9
Ratio[%]	113%	108%	93%	106%	141%	150%	154%	118%	125%	174%	108%	189%
Average[%]	116%		100%		146%		136%		150%		149%	

- Vehicles did not drive through the historical residential area from South to North (or opposite direction) due to the traffic restriction.

- The traffic around the intersection of St.I and St.B became heavy. **Fig. 4(b)** shows a magnified image around the intersection. Because traffic flows arrived from / going to St.C and St.D, St.I became busy. In **Fig. 4(b)-(2)**, it seems that the traffic on St.I backed up to point that a new short flow emerged on St.J. Consequently, the area becomes crowded.

4. Analyzing Urban Traffic with Numbers of Fine-Grained Agents

4.1. Setup of Experiment

This experiment used almost the same setup of the previous simulations, i.e., 36 ODs, 8000 vehicles, 50 iterations, and 90 minute simulation period. The difference is the driving behavior models used by the agents. We prepared four types of behavior models unlike previous simulations, which used just one model. We picked two factors to distinguish driving behaviors; the desired speed (fast or slow) and the attitude for overtaking (aggressive or cautious). These two factors yield, in combination, 4 behaviors: fast&aggressive, fast&cautious, slow&aggressive, and slow&cautious. Fast and slow desired speeds were set to 30 km/h and 15 km/h, respectively. An aggressive vehicle agent tries to overtake when the vehicle in front of him/her is slower while a cautious vehicle agent overtakes the vehicle in front only if it is driving under 4 km/h. For example, a fast&aggressive agent makes positive efforts to drive at the relatively high speed and to overtake slower vehicles whenever possible.[2]

To show the experimental results, we selected 7 ODs from the 36 ODs set in Section 3.2; 4 ODs from the central part and 3 ODs for through traffic as shown below (please refer to the intersection numbers in **Fig. 3**):

- OD-1: From intersection No.2 to No.10
- OD-2: From intersection No.10 to No.9
- OD-3: From intersection No.9 to No.1
- OD-4: From intersection No.1 to No.2
- OD-5: From S.W. of intersection No.9 to N.E. of No.3
- OD-6: From S.E. of intersection No.11 to N.W. of No.1
- OD-7: From the west of intersection No.4 to the east of No.6

For each OD, vehicle agents were assigned one of the four behavior types with equal probability.

4.2. Evaluation

First, we show how outcomes are affected by the type of driving behavior. **Fig. 5** provides a scatter diagram representing the distribution of agents for OD-6 by the travel time and the travel distance. Additionally, **Table 2** lists statistical data related to each driving behavior model. These results indicate several interesting trends and phenomena as follows:

- The difference between fast vehicles and slow vehicles in terms of travel time is quite clear. Almost all fast vehicles reached their destination ahead of the fastest slow vehicle. In particular, as indicated in **Table 2**, fast&aggressive vehicles had shorter average travel times than fast&cautious vehicles. Additionally, fast&aggressive vehicles had smaller standard deviations than fast&cautious ones. We note that some fast&cautious vehicles were very slow in reaching their destination. This is because they were occasionally blocked by slow vehicles, drove steadily at around 15 km/h.

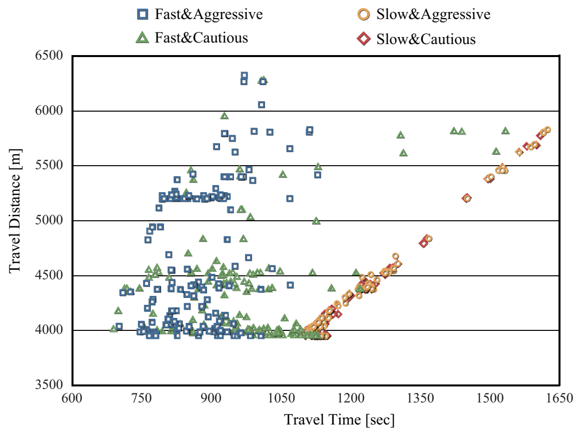


Fig. 5. Distribution of agents by travel time and travel distance.

Table 2. Average and standard deviation of travel time.

	Fast&Agg.	Fast&Caut.	Slow&Agg.	Slow&Caut.
AVE.	878.5	969.9	1197.3	1185.9
STDEV.	85.6	145.8	131.1	119.2

- Although fast vehicles can reach their destination in shorter times, they traveled further, on average, than the others. This result suggests that the fast vehicles choose long detours where they could better exploit their own features.
- There is little difference between slow&aggressive and slow&cautious vehicles. It seems that slow vehicles took diverse driving routes of various lengths, but almost all of them drove at around their desired speed as you can see in the diagram. The cause of traffic congestion was the slow vehicles themselves so that they could drive steadily without any obstructions. Additionally, slow vehicles had shorter average travel distance than fast vehicles as shown in the table. We suppose that slow vehicles tended to choose nearly the shortest routes because it was not beneficial for them to detour due to their slow desired speed. Therefore, they are prone to sticking to the shortest routes.

Next, we investigate other ODs. **Fig. 6** shows averages of the travel distance, the travel time, and the driving speed for each behavior type in each OD.

- As demonstrated in **Fig. 5** and **Table 2**, fast vehi-

2. Overtaking can only occur if the vehicle in front is within 30 meters ahead and the next lane (overtaking space) is available.

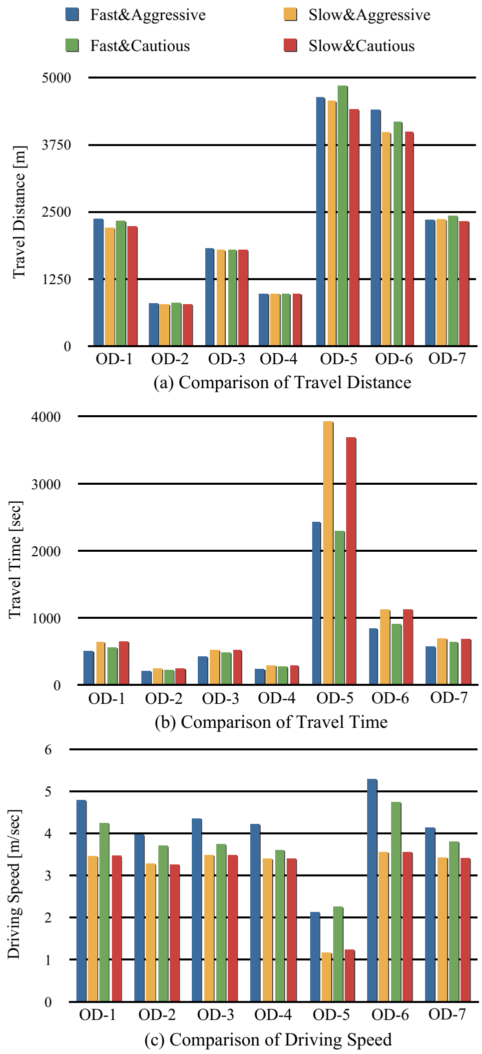


Fig. 6. Average of travel distance, travel time, and driving speed.

cles are much faster than slow vehicles (see **Fig. 6(c)**) and fast vehicles had longer average travel distance than slow ones despite all vehicles use common route planning model, Dijkstra method (see **Fig. 6(a)**). This is because fast vehicles tend to detour and drive at high-speed on empty routes through iterations.

- For other ODs, the difference in driving speed between fast vehicles and slow vehicles is distinct. Moreover, excepting OD-5, the speed of fast&aggressive vehicles is always faster than that of fast&cautious vehicles since fast&aggressive vehicles secure more opportunity for high-speed driving by overtaking more often. However, in **Fig. 6(b)**, we cannot see any clear difference in the travel time. This is because the distance of the OD-1,2,3,4,7 route is not long enough for the differences to emerge (see **Fig. 6(a)**).
- The histogram for OD-5 shows some interesting results. First, the difference in travel time between fast vehicles and slow vehicles was quite large. Second, all vehicles had much lower driving speeds on OD-5 than the others. This is because OD-5 was heavily congested that overtaking was rarely possible.

From the above experimental results, we can see that agents demonstrated various behaviors depending on the behavior model assigned and these behaviors yielded different outcomes. For instance, fast vehicles can have shorter travel times than slow vehicles especially for OD-5,6,7. However, as we showed in **Fig. 5**, some fast&cautious vehicles can be negatively impacted by slow vehicles due to their infrequent overtaking.

Additionally, we can see the interaction between traffic flows and each agent's driving behavior. As mentioned above, fast vehicles tended to travel further than the others, and in contrast, slow vehicles traveled nearer, on average, than others. We can explain these phenomena as follows: fast vehicles are more likely to encounter slow vehicles on the short route while the long route is relatively free. Hence, fast vehicles preferably select the long route. On the other hand, since slow vehicles are less likely to encounter slower vehicles on the short route so that it is common for them to select the short route. Resultingly, the mass behaviors of slow vehicles (routing to short routes) probably causes fast vehicles' routing to long routes. The essential point is that an agent makes a decision to obtain better outcomes with each behavior model and his/her decision is affected by traffic flows that emerges from the accumulation of microscopic behaviors. This indicates that we are able to observe the dynamic interrelationship between macroscopic phenomena (traffic flows) and microscopic driving behavior in our simulator.

5. Conclusion

In this paper, we have developed a multiagent-based urban traffic simulation platform, so that it can represent local maneuvers in driving. On our platform, we conduct traffic simulations with the scenario of a social experiment held in Kyoto city. The results confirmed that our simulator can provide sufficient statistical and qualitative information on changes to traffic flows. We also show the potential of investigating the relationship between traffic flows (macro-aspect) and agents' driving behaviors (micro-aspect).

Although the driving behavior models in this paper consist of just two factors, it is clear that human drivers have far more diverse driving behaviors with complicated decision making processes. We are going to implement more human-like driving behavior models by using human behavior modeling methodologies [9].

Acknowledgements

This work was supported by a Grant-in-Aid for Young Scientists (B) (21700161, 2009-2011) from Japan Society for the Promotion of Science (JSPS) and Panasonic Corp. / Kyoto University Joint Research: Regional EMS based on Multiagent technologies.

References:

[1] J. Epsterin and R. Axtell, "Growing Artificial Societies: Social Science from the Bottom Up," MIT Press, 1996.

[2] D. Scerri, S. Hickmotthas, A. Drogoul, and L. Padgham, "An Architecture for Modular Distributed Simulation with Agent-Based Models," Proc. of AAMAS-2010, pp. 541-548, 2010.

[3] G. Yamamoto, H. Tai, and H. Mizuta, "A Platform for Massive Agent-based Simulation and its Evaluation," Lecture Notes in Computer Science, Vol.5043, pp. 1-12, Springer, 2008.

[4] Y. Murakami, Y. Sugimoto, and T. Ishida, "Modeling Human Behavior for Virtual Training Systems," Proc. of AAAI-2005, pp. 127-132, 2005.

[5] J. Illenberger, G. Flotterod, and K. Nagel, "Enhancing MATSim with Capabilities of Within-Day Re-Planning," Proc. of the IEEE Intelligent Transportation Systems Conference, pp. 94-99, 2007.

[6] J. Bhattacharya and R. Horiguchi, "Implementation of Transportation Management Strategies using AVENUE for developing countries," Proc. of 7th Asia-Pacific ITS Folum, 2005.

[7] N. Geroliminis and C. Daganzo, "Existence of Urban-scale Macroscopic Fundamental Diagrams: Some Experimental Findings," J. of Transportation Research Part B: Methodological, Vol.42, No.9, pp. 759-770, 2008.

[8] B. Raney and K. Nagel, "Iterative Route Planning for Large-scale Modular Transportation Simulations," Future Generation Computer Systems, Vol.20, No.7, pp. 1101-1118, 2004.

[9] H. Hattori, Y. Nakajima, and T. Ishida, "Learning from Humans: Agent Modeling with Individual Human Behaviors," IEEE Trans. on Systems, Man, and Cybernetics-Part A: Systems and Humans, 2010.

Name:
Hiromitsu Hattori

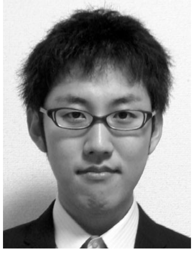
Affiliation:
Graduate School of Informatics, Kyoto University

Address:
Yoshida-Honmachi, Sakyo-ku, Kyoto 606-8021, Japan

Brief Biographical History:
2004 Received Ph.D. (Doctor of Engineering) from Nagoya Institute of Technology
2004-2007 Research Fellow, the Japan Society for the Promotion of Science (PD)
2004-2005 Honorary Research Assistant, University of Liverpool
2006 Visiting Scholar, Massachusetts Institute of Technology
2007- Assistant Professor, Graduate School of Informatics, Kyoto University

Main Works:
• "Learning from Humans: Agent Modeling with Individual Human Behaviors," IEEE Trans. on Systems, Man, and Cybernetics Part A: Systems and Humans, Vol.41, No.1, pp. 1-9, 2011.
• "Multi-issue Negotiation Protocol for Agents: Exploring Nonlinear Utility Spaces," in Proc. of the 20th Int. Joint Conf. on Artificial Intelligence (IJCAI-2007), pp. 1347-1352, 2007.

Membership in Academic Societies:
• Japanese Society for Artificial Intelligence (JSAI)
• Information Processing Society of Japan (IPSJ)
• The Institute of Electronics, Information and Communication Engineers (IEICE)



Name:
Yuu Nakajima

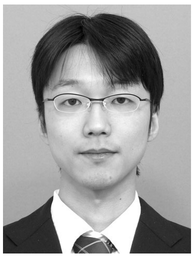
Affiliation:
Graduate School of Informatics, Kyoto University

Address:
Yoshida-Honmachi, Sakyo-ku, Kyoto 606-8021, Japan

Brief Biographical History:
2009 Received Ph.D. (Informatics) from Kyoto University
2009-2010 Researcher, Graduate School of Informatics, Kyoto University
2010- Assistant Professor, Graduate School of Informatics, Kyoto University

Main Works:
• "Disaster Evacuation Guide Using a Massively Multiagent Server and GPS Mobile Phones," in Proc. of the 7th Int. Symposium on Applications and the Internet (SAINT-2007), Vol.2, 2007.
• "Augmented Experiment: Participatory Design with Multiagent Simulation," in Proc. of the 20th Int. Joint Conf. on Artificial Intelligence (IJCAI-07), pp. 1341-1346, 2007.

Membership in Academic Societies:
• Japanese Society for Artificial Intelligence (JSAI)
• The Institute of Electronics, Information and Communication Engineers (IEICE)



Name:
Shohei Yamane

Affiliation:
Graduate School of Informatics, Kyoto University

Address:
Yoshida-Honmachi, Sakyo-ku, Kyoto 606-8021, Japan

Brief Biographical History:
2007 Received Master of Informatics from Kyoto University
2007- Ph.D. Candidate, Graduate School of Informatics, Kyoto University
2007-2010 Research Fellow, the Japan Society for the Promotion of Science (DC1)

Main Works:
• "Participatory Simulation Environment gumonji/Q: A Network Game Empowered by Agents," Int. Conf. on Principles of Practice in Multi-Agent Systems (PRIMA-09), 2009.
• "Meta-level Control Architecture for Massively Multiagent Simulations," Winter Simulation Conf. (WSC-06), pp. 889-896, 2006.