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Introduction to Applications of Swarm in Transportation Researches

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***Abstract*—The paper introduces applications of Swarm, an agent-based simulation platform, in transportation researches. A specific example is given, in which a traffic network is built, drivers are classified into three different groups based on learning abilities to route choices, and then a case study is conducted to illustrate the effect of individual's learning ability on spatial distribution of vehicles on the traffic network. Last, potential transportation researches based on Swarm are discussed, such as varieties of agents, topology structures of the traffic network, macroscopic fundamental diagram, etc.**

***Keywords*-Macroscopic phenomena; Urban traffic network; Mutli-agent; Swarm**

I. Introduction

The agent-based traffic simulation model as a bottom-up approach recently gain increasing attention. They are effective ways to study relationships between drivers, control and guidance devices in the microscopic level and phenomena in the traffic system level [1][2][3][4][5].

In the field of complex systems, Swarm [6] is an important multi-agent simulation platform, which is originally developed at the Santa Fe Institute; it offers advantages including a suite of standardized libraries of objects, schedules, and probes, hierarchical structures, etc[7].

This paper takes an urban traffic simulation model developed on Swarm as an example to explore applications of Swarm in transportation researches. In next section, we present the urban traffic simulation model on Swarm first. In this example, drivers are treated as agents and classified into three groups based learning ability; system performance in the macroscopic level are compared using different groups of drivers in a case study. Lastly, some potential traffic simulation models on Swarm are discussed.

II. Simulation Design based on Swarm

In this section, we will exhibit an urban traffic simulation model built on Swarm, which first introduced in a paper written in Chinese [8].

A. Network Design

Links and intersections are treated as agents, which are in charge of vehicles' entrance, exit and data collection. Then, we fix them on the $L \times L$ lattice, a container provided by Swarm, and number them from top to bottom as shown in Figure 1.

A unidirectional moving rule is introduced as vehicles are only allowed to enter a link or an intersection which ID is bigger than the one of the currently located link or intersection. Following the rule, a link points at a downstream intersection, while an intersection points at two downstream links. This unidirectional design simplifies the network and coding processes just by abandoning some routes between O-Ds.

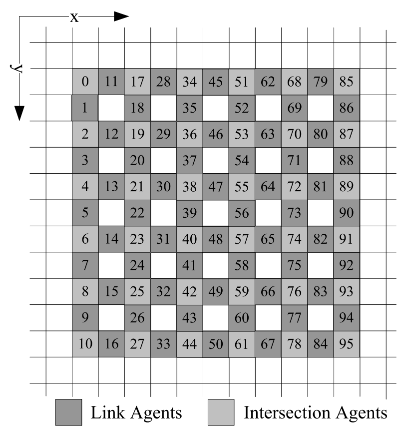

Figure 1. 2-D Traffic Network in Swarm

B. Travel Time in Links and Intersections

We implement a piecewise linear relationship between travel time and density on links. Let t_a and k_a be travel time and density at link $a \in A$, and t_a^{max}, t_a^{min}, k_a^{min} and k_a^{max} be corresponding thresholds. Consequently, the travel time is

$$t_a = \begin{cases} t_a^{min}, & k_a \le k_a^{min} \\ \frac{t_a^{max} - t_a^{min}}{k_a^{max} - k_a^{min}}(k_a - k_a^{min}) + t_a^{min}, & k_a^{min} < k_a \le k_a^{max} \end{cases}$$

We consider a constant travel time in intersections as $t_b = C$ and a maximum density k_b^{max}.

Vehicles are not allowed to enter the links or intersections in maximum density, which captures the spillback.

C. Microscopic Level: Travel Design

Vehicles are treated as agents and are classified into three groups based on drivers' learning ability to route choices.

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Type-I. Drivers without learning ability, who are not able to get information from travel experience and only make route choices by a distance shortest path. Hence, the expected travel time is $\tau_a = t_a^{min}$.

Type-II. Drivers learning from experience, who choose the route based on the accumulation of experience[5]: $\tau_a = (1/M)\sum_{m=1}^{M} t_a^m$, where t_a^m is the experienced travel time on link a in m^{th}, and M is the number of traveling on link a.

Type-III. Drivers learning from real-time information, which choose the route based on real-time travel information, i.e., taking a time shortest path: $\tau_a = t_a^*$ where t_a^* is current travel time on link a.

In the paper, we call the traffic system all consists of Type-I as no learning system, the one all consists of Type-II as experience system and the one all consists of Type-III as information system.

Three groups of drivers make their route choices by utility maximum. Let W be the set of all routes between O-Ds, A_w be the set of links related to the route $w \in W$, and B_w be the set of intersections. The expected travel time on the route w of three groups of drivers is $T_w = \sum_{a\in A_w}(\tau_a + \varepsilon_a) + \sum_{b\in B_w} t_b$, where ε_a is a random error of travelers' expectation of link a.

Accordingly, the chosen route is $w^* = \arg\min_{w\in W}\{T_w\}$

D. Simulation Operation

A driver chooses a route between randomly assigned O-D and runs along it on the network. Once the trip is finished, we assign another O-D randomly. To avoid the disturbance from that all vehicles are put on the network at the same time at the beginning of simulation, we set up an warm-up period, in which drivers don't accumulate experience and the simulation date are not be collected.

III. Case study: Macroscopic phenomena arisen from microscopic interaction

Here we will compare the spatial distributions of vehicle number on the network in different scenarios to illustrate the macroscopic phenomena arisen from interaction of vehicles at microscopic level.

We consider the following values in the simulation scenarios based on real urban traffic systems and simulate 2500 vehicles no learning system, experience system and information system:

Links: $k_a^{max} = 160$, $k_a^{min} = 20$, $t_a^{max} = 30$, $t_a^{min} = 3$, $\varepsilon_a = \{0, 1, 2\}$;

Intersection: $C = 1$, $k_b^{max} = 9$;

Network: $L = 11$, so the sum of links is $|A| = 60$, and the sum of intersection is $|B| = 36$ (see Figure 1);

Others: $I = 5$ and $\theta_1 = k_a^{min}$, $\theta_2 = 60$, $\theta_3 = 100$, $\theta_4 = 140$, $\theta_5 = k_a^{max}$.

To display the spatial distribution in the traffic network, we consider the variance of vehicle number in each links, which is a measurement of spatial inhomogeneity. Figure 2 illustrates the changes of variances in three systems composed of Type-I, II and III drivers. It is clear that the travel time information makes more homogeneity of the traffic network, and the drivers need a learning process to be familiar with the network in the learning system. Comparably, there is no improvement in the no learning system, because the drivers inside are not capable to learn or utilize information.

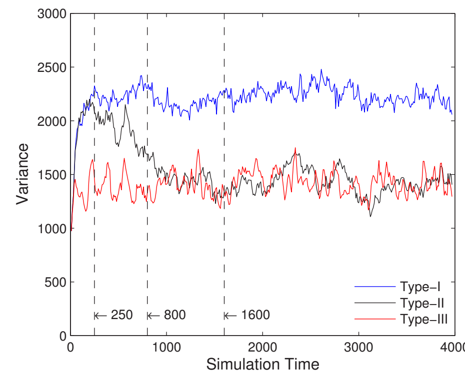
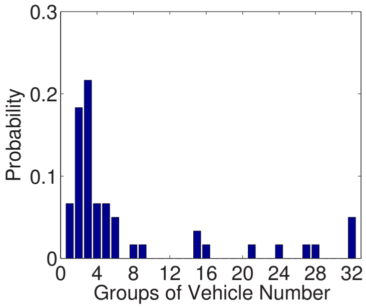


Figure 2. Variance changes of vehicle number in links

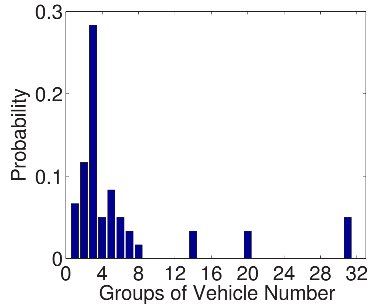
To present more details in the spatial distribution of the network, we employ the distribution of vehicle number in different groups at three time slices shown in Figure 2. The full range of vehicle number from 0 to k_a^{max} are discretized in 32 groups, and the histograms for each vehicle number group are plotted in Figure 3. Comparing with the variances at these time slices, Figure 3(a) to 3(d) have similar distributions, i.e., severly congested links still exist while most of links are not in congestion, which means the bearing capacity of the network is not fully used. The congested links are relaxed in Figure 3(f) to 3(i) by drivers' learning ability and guidance information. Figure 3(e) exhibit a transition. These figures present the details of the spatial distribution of vehicle number on the network, and demonstrate the different effects of drivers' learning ability and guidance information to the traffic system. The histograms are not very clear, however, to fit probability distributions, and the simulation model or the scenarios are still needed to be improved.

IV. Potential researches on Swarm

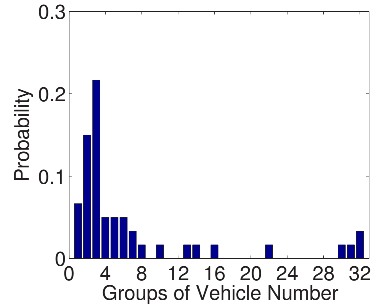
In this section, we will discuss some potential researches about the traffic system based on Swarm. As a multi-agent based simulation platform, Swarm allowed us to import variety of agents. Naturally, studies on the relationships between agents and between agents and system are the best way to take the advantages of Swarm. Lots of elements in the traffic system can be considered as agents and be modeled in



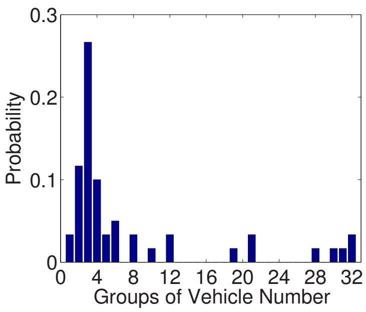
(a) Time 230 at no learning system



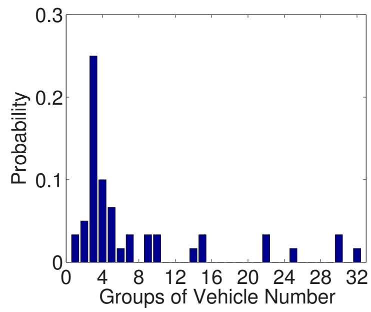
(b) Time 800 at no learning system



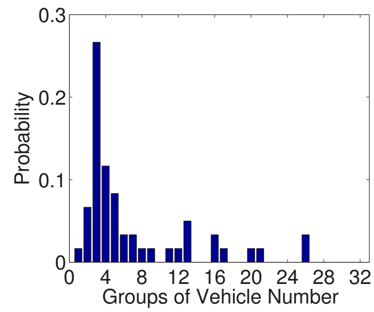
(c) Time 1600 at no learning system



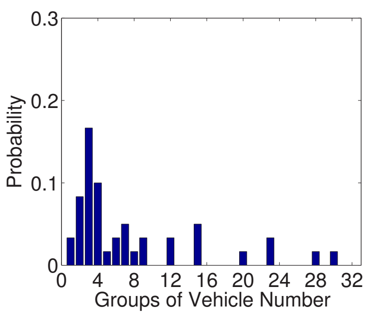
(d) Time 230 at learning system



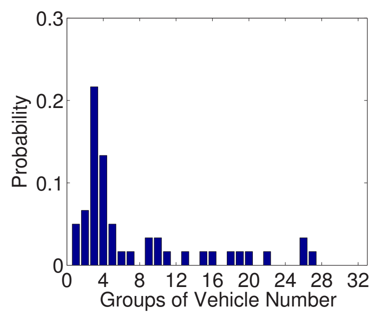
(e) Time 800 at learning system



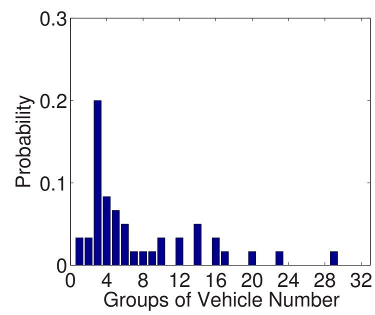
(f) Time 1600 at learning system



(g) Time 230 at information system



(h) Time 800 at information system



(i) Time 1600 at information system

Figure 3. Histograms for different values of vehicle number at different time slices

Swarm, such as traffic lights, types of vehicles and drivers, guidance equipments.

Route choice is a behavior determined by the relationship between deliberation and habit, for example the stronger determinant habit is, the weaker determinant intension is, and vice versa[9][10][11]. Weighted average of measured travel times, average return model and the reinforcement learning model, etc. are the typical dynamic route choice models in deliberation. We could study macroscopic phenomena from simulating aggregation by constructing traveler agents with these route choice models (see Figure.4).

Another interesting topics are the influence of topology structures of traffic network to the traffic system. The 2-D lattice provided by Swarm is able to reproduce types of

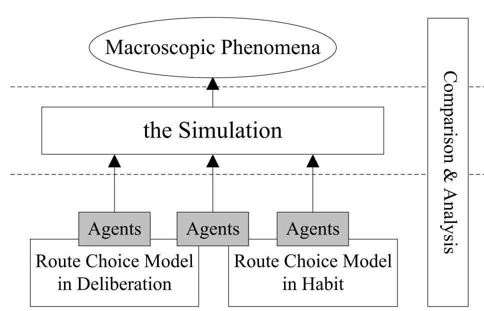
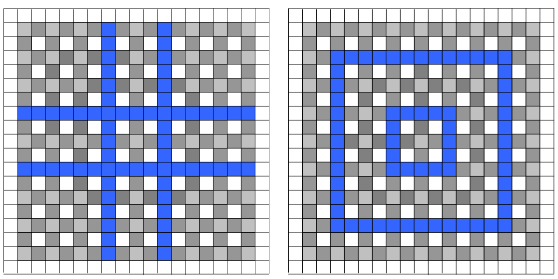


Figure 4. Bottom-up Study to Route Choice Model and its Macro Phenomena

network structures (see Figure5). Travelers' distribution, the places that traffic jams always occur, the maximum capacity of network can be thereby studied by comparing the simulation results on different structure networks. If the evolution of the traffic network is considered, the interaction between travelers and traffic network can be modeled properly.

Noticeable, a new concept of network, the macroscopic fundamental diagram (MFD)[12][13][14], are released. MFD indicates a relation between average flow and average density on the macroscopic level of urban traffic system. The influences from lots of microscopic individuals are still unclear, such as the travelers' learning ability, information guidance, traffic lights, etc. Swarm could be made used to study the complex relationships between bottom level and MFD.



(a) Radiation Network (b) Ring Network

Figure 5. Two Possible Networks (where blue grids represent corridors)

Moreover, the Swarm-based simulations also can be considered in the studies about the effect of applications of Advanced Transportation Information System and the determination of proportion of the floating cars.

V. Conclusions

Swarm, as a multi-agent simulation platform, has many advantages in modeling agent-based system. The paper discussed the potential applications of Swarm in the transportation researches. A specific study based on Swarm were exemplified, in which a traffic system with network and driver agents were modeled, and case studies were conducted to show the influence of individual's learning ability and information on the traffic system. After the illustration, potential researches based on Swarm were further discussed, which can be taken as the idea of future works.

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References

[1] H. Dia, "An agent-based approach to modelling driver route choice behaviour under the influence of real-time information," *Tramsportation Research Part C: Emerging Technologies*, vol. 10, no. 5-6, pp. 331–349, 2002.

[2] R. J. F. Rossetti, R. H. Bordini, A. L. C. Bazzan, S. Bampi, R. Liu, and D. V. Vliet, "Using BDI agents to improve driver modelling in a commuter scenario," *Tramsportation Research Part C: Emerging Technologies*, vol. 10, no. 5-6, pp. 373–398, 2002.

[3] N. Cetin, K. Nagel, and B. Raney, "Large-Scale Multi-Agent Simulations for Transportation Applications," *Computer Physics Communications*, vol. 147, no. 4, pp. 559–564, 2002.

[4] M. Balmer, N. Cetin, K. Nagel, and B. Raney, "Towards truly agent-based traffic and mobility simulations," in *Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent SystemsVolume 1*, vol. 1pp. IEEE Computer Society Washington, DC, USA, 2004, pp. 60–67.

[5] H. Huang, H.J, Liu, T.L, Yang, "Modeling the Evolutions of Day-to-day Route Choice and Year-to-year ATIS Adoption with Stochastic User Equilibrium," *Journal of Advanced Transportation*, vol. 42, no. l, pp. 111–127, 2008.

[6] "Swarm," 2010. [Online]. Available: http://www.swarm.org

[7] M. Savage, Melissa; Askenazi, "Arborscapes: A Swarm-based Multi-agent Ecological Disturbance Model," 1999. [Online]. Available: http://www.santafe.edu/

[8] Z. He, S. Ma, and G. He, "Experimental Macroscopic Phenomena in Urban Transportation System," *Acta Physica Sinica*, 2010.

[9] G. E. Cantarella and E. Cascetta, "Dynamic Processes and Equilibrium in Transportation Networks Towards a Unifying Theory," *Transportation Science*, vol. 29, no. 4, pp. 305–329, 1995.

[10] T. Gärling, R. Gillholm, and A. Gärling, "Reintroducing attitude theory in travel behavior research. The validity of an interactive interview procedure to predict car use." *Transportation*, vol. 25, no. 2, pp. 129–146, 1998.

[11] T. Gärling and K. Axhausen, "Introduction: Habitual travel choice," *Transportation*, vol. 30, no. 1, pp. 1–11, 2003.

[12] C. F. Daganzo, "Urban gridlock: Macroscopic modeling and mitigation approaches," *Transportation Research Part B: Methodological*, vol. 41, no. 1, pp. 49–62, 2007. [Online]. Available: http://linkinghub.elsevier.com/retrieve/pii/S0191261506000282

[13] C. F. Daganzo and N. Geroliminis, "An analytical approximation for the macroscopic fundamental diagram of urban traffic," *Transportation Research Part B: Methodological*, vol. 42, no. 9, pp. 771–781, 2008. [Online]. Available: http://linkinghub.elsevier.com/retrieve/pii/S0191261508000799

[14] N. Geroliminis and C. F. Daganzo, "Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings," *Transportation Research Part B: Methodological*, vol. 42, no. 9, pp. 759–770, 2008. [Online]. Available: http://linkinghub.elsevier.com/retrieve/pii/S0191261508000180