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Evaluation of Traffic Management Strategies with Anticipatory Stigmergy

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Abstract: Traffic control/operation system based on probe vehicle data (i.e., vehicles' locations and trajectories, and past record of travel time) has been attracting attention. In this paper, we propose and evaluate a novel traffic management method to provide information using anticipatory stigmergy which can search an alternative route to avoid expected congestion by sharing the probe vehicles' locations in near-future. Because it might be ineffective if all drivers follow the fastest path searched by anticipatory stigmergy, we introduce new strategies for assigning a driver to a link based on the residual distance to his/her destination or the time involved in congestion from his/her departure. In addition, the impacts of driver's route choice behavior to follow the recommended link are examined as sensitivity analysis. The results of our numerical experiment show that our proposed anticipatory stigmergy with assignment strategy works better than conventional methods.

Keywords: traffic management, stigmergy, probe vehicle, intelligent transport systems

1. Introduction

Recently, there are several studies and practices for observing traffic flow and providing information on traffic condition. These are usually done by counting the vehicles that pass particular locations using sensing gates that are usually placed on the arterial roads. Such information is broadcast as current information to vehicles. It is rarely stored and cannot work as shared memory. More sophisticated coordination methods are becoming feasible by utilizing the current traffic information. More precise traffic information can be provided by probe vehicles data. Here probe vehicle (or floating car) is a car equipped with GPS (global positioning system) and other sensors, so they can measure directly travel time under various traffic conditions without installing a fixed traffic counter on all roadway. These probe vehicles data are stored in central servers as long-term memory that can provide stochastic travel time information to vehicles. Such information technologies have been already applied in the real world.

Research in the field of transportation and multi-agent system has been focusing on dynamic short-term memory. Vehicles share this dynamic information, and drivers can choose their routes more dynamically based on real-time information. This short-term traffic information is usually modeled as a stigmergy. Stigmergy has been used for indirect communication for cooperation among agents [1]. For example, ants' pheromone is a kind of stigmergy for cooperation among them. In this case, ants are modeled as agents in multi-agent models and also as vehicles in traffic situations. Vehicles can estimate their nearest future situation based these stigmergies.

One drawback of these long or short-term stigmergies approaches is that handling near-future congestion remains problematic because these stigmergies are basically past record of travel time (i.e., in order to avoid an expected traffic jam efficiently, we need not only historical and real-time information but also traffic conditions in near-future or drivers' intention). In this paper, we propose anticipatory stigmergy for sharing information on near-future traffic condition. In our model, each vehicle can automatically submit its near-future location based on the result of car-navigation as anticipatory stigmergy, and recalculates its shortest path based on predicted traffic volume that is summation of the submitted anticipatory stigmergies. And in order to avoid hunting or oscillation, that means different congestion occurs if all drivers follow the new recommended link, we introduce some strategies to assign a driver appropriately. In addition, we analyze impacts of driver's route choice behavior to follow the recommended link because it is difficult to control all vehicles systematically and automatically.

In this paper, we evaluate the following types of stigmergies with a custom simulator: combined long- and short-term stigmergy as a conventional method, and anticipatory stigmergy with assignment strategies. We conducted several experiments to compare the different kinds, and evaluate impacts of driver's route choice behavior as sensitivity analysis. Our results demonstrate that the anticipatory stigmergy works especially well by considering each driver's time loss in congestion, and that it is important to introduce incentive mechanisms for drivers to follow information.

2. Traffic Management Strategies with Stigmergy

We set the following five cases (Case0 – Case4) for traffic simulation, and explain how to collect and provide traffic

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information in each case to evaluate and compare the effect of stigmergies. And logit model is introduced to describe driver's decision-making of whether to follow route information.

2.1 How to collect and Provide Traffic Information

In this study, we assume that all vehicles are probe vehicles and a traffic control manager arranges sub-control managers at every intersection in road network so as to collect and provide traffic information. Each vehicle is modeled as an agent who can communicate with sub-control managers and search the shortest path from the current position to its destination based on the links' value (travel time) in each case. The information about a route travel time according to certain stigmergy is a sum of the travel time on links comprising this path.

Case0: No Information

No traffic information is gathered and provided. Each vehicle finds the best path by Dijkstra search before it departs. We assume several different starting and end points since drivers have different origins and destinations. The cost (or time) of link l can be shown in Eq. (1):

$$v_0 = t_0(l) = int\left(\frac{|l|}{v_{\max}(l)}\right) \tag{1}$$

where $t_0(l)$ defines a free flow travel time, and $v_{\max}(l)$ defines the maximum speed and $|l|$ is distance of link l.

Case1: Combined Long- and Short-Term Stigmergy

First we define historical travel time data as two stigmergy; long-term stigmergy and short-term stigmergy.

A road (link) stores and manages long-term stigmergy (historical) information forever. As long-term stigmergy information, each link stores the travel time from the vehicles equipped with GPS (i.e., probe cars), and provides them a long-term stigmergy value $v_l = ave + \rho \times sd$, where ave is the average, sd is the standard deviation of all stored data of each link, and ρ is the weight of standard deviation (in this paper, this value is set in 0.01). Each probe vehicle utilizes this long-term stigmergy information to make a new plan by Dijkstra search before its department. Long-term stigmergy value is updated every day (i.e., daily update).

As short-term stigmergy information, the each link keeps storing data about the travel time of probe cars for only the most recent a few minutes, and provides short-term stigmergy value v_s which is the average of the most recent ten minutes stored data in this study.

In this case, we consider the traffic information which combined long- and short-term stigmergies. As mentioned before, the long-term stigmergy information is the value of v_l that is updated daily, the short-term stigmergy information is the value of v_s that is updated every ten minutes. Each probe vehicle utilizes combined long- and short-term stigmergy information to make a new route plan by Dijkstra search every ten minutes. Equation (2) shows how to combine long- and short-term stigmergies, and v_{ls} is the combined stigmergy information:

$$v_{ls} = \omega \times v_l + (1 - \omega) \times v_s \tag{2}$$

where v_l is the long-term stigmergy value, v_s is the short-term stigmergy value, and ω is the weight of the long-term stigmergy ($0 \le \omega \le 1$). Each probe vehicle utilizes this combined stigmergy information to search new route by Dijkstra algorithm every ten minutes in this study.

Case2: Anticipatory Stigmergy without Assignment Strategy

Every ten minutes, all probe vehicles find the best route to their destination node based on long- and short-term stigmergy, as in Case1. Here, they submit (as a link) where they will be in the next ten minutes. This is how we define anticipatory stigmergy. Then they can confirm the traffic situation in future and search the best route based on the anticipatory stigmergies. Equation (3) shows the heuristic cost of link l by using anticipatory stigmergies, which are average travel time calculated by link performance function defined by the Bureau of Public Road (BPR) in U.S. [2]:

$$v_a = t_0(l) \cdot \left(1.0 + \alpha\left(\frac{Vol(l)}{Cap(l) \times 0.4}\right)^{\beta}\right) \tag{3}$$

$Vol(l)$ is the total number of probe vehicles in near-future on link l gathered as anticipatory stigmergy. Function $t_0(l)$ is a free flow travel time, and $Cap(l)$ is a capacity of link l that is adjusted adequately (in this study for the traffic simulation based on the cellular automaton model (see next subsection), the adjustment value is set in 0.4 because the condition to drive freely is a half of capacity). $\alpha = 0.48$, and $\beta = 2.48$. This cost function v_a is a heuristic; if there are many vehicles, v_a will be increased briefly.

In this Case2, there are concerns that it is efficient to navigate all probe vehicles to the path that is calculated based on information of anticipatory stigmergies (Eq. (3)). According to the results of sensitivity analysis [3], [4], we adopted 50% as a ratio of assigned drivers to the recommended link with anticipatory stigmergy. But in this case, there is no criterion of assignment (i.e., random assignment).

Case3: Anticipatory Stigmergy with Assignment Strategy considering Residual Distance

Every ten minutes, all probe vehicles search the best route to their destination node based on a link travel time with anticipatory stigmergy (Eq. (3)). In Case2, the route that a driver assigned actually is set randomly, so it might not be efficient. In this Case3, we introduce a strategy to assign vehicles reasonably into the two routes, that one is a route searched with historical information (i.e., combined long- and short-term stigmergy in Case1) and the other is a route searched with near-future information (i.e., anticipatory stigmergy in Case2). Although there are various criteria of assignment, in this study, a rest of straight-line distance to his/her destination is adopted. A concrete procedure to assign vehicles into two routes is as follows.

- If the number of vehicles on the link searched with the traffic information of anticipatory stigmergy is larger than the congestion level, which is a half of capacity (i.e., $Cap(l) \times 0.5$) to drive freely in the cellular automaton model, vehicles are sorted in descending order by a straight-line distance from the current cell to his/her destination.
- In the concentrated situation, the upper 50% vehicles are assigned to the link that is recommended as the best route with anticipatory stigmergy as shown in Case2, and the rest of

vehicles are assigned to the link that is searched with combined long- and short-term stigmergy as shown in Case1. Otherwise, all vehicles choose the link on a route calculated in Case1.

In this study, we set two situation considering driver's travel behavior; one is deterministic case that all drivers follow travel information perfectly, another is stochastic case that drivers can choose a link by themselves because there is no penalty and incentive to obey this rule.

Case4: Anticipatory Stigmergy with Assignment Strategy considering Lost Time of Traffic Congestion

In this Case4, we adopt an assignment by a time involved in congestion so for. Although there are some definitions of traffic congestion [5], we regard an extra time from a free flow time as a congestion time in this study. A concrete procedure to assign vehicles into two routes is as follows.

- First, the time stayed in congestion from departure is calculated for each driver base on Eq. (4),

$$t_{congestion} = \sum (t_{travel}(l) - t_0(l)) \tag{4}$$

where $t_{congestion}$ is a time involved in congestion from departure, $t_{travel}(l)$ is the vehicle's travel time on link l, and $t_0(l)$ is a free flow travel time calculated in Eq. (1).

- If the number of drivers on the link searched with the traffic information of anticipatory stigmergy is larger than the congestion level, vehicles are sorted in ascending order by his/her time stayed in congestion ($t_{congestion}$) and then the upper 50% drivers are assigned to the link that is recommended as the best route with anticipatory stigmergy in the same way of Case3.

2.2 Driver's Route Choice Behavior

Logit Model

Logit model is one of a discrete choice model, and this model has been widely used in transportation planning field. In this study, logit model is introduced to describe each driver's decision-making of whether to follow travel information because it is not realistic that all drivers follow the provided information.

We assume that a driver is a rational individual and a driver's route choice behavior is expressed as logit model. According to famous textbooks [6], [7], logit model is formulated as follows; The utility that the decision-maker obtains from alternative j is decomposed into (a) a part labeled V_j that is known by the researcher up to some parameters, and (b) an unknown part ε_j that is treated by the researcher as random: $U_j = V_j + \varepsilon_j, \forall j$. The logit model is obtained by assuming that each ε_j is distributed independently, identically extreme value. The distribution is also called Gumbel. Then representative utility is usually specified to be linear in parameters: $V_j = \boldsymbol{\beta} \boldsymbol{x_j}$ where $\boldsymbol{x_j}$ is a vector of observed variables relating to alternative j and $\boldsymbol{\beta}$ is a vector of parameter. With this specification, the logit probabilities become:

$$P_i = \frac{\exp(\beta x_i)}{\sum_j \exp(\beta x_j)} \tag{5}$$

Route Choice Model

All drivers have a chance to make a decision whether to follow the travel information or not. Most of drivers believe that it is efficient to obey the result of route search by car-navigation, but a few drivers would change a route by one's own judgment. In order to represent these drivers' route choice behavior, we develop a link choice model, which is expressed as logit model.

As a systematic component in a driver's utility function, three variables are considered; a) reliability to traffic information (x_1), b) regret based on his/her own past experience (x_2), and c) short-sighted present situation (x_3). We define each variable as follows;

$$x_1 = \begin{cases} 1 & \text{if link is on a shortest path (provide information)} \\ -1 & \text{if otherwise} \end{cases},$$

$$x_2 = \frac{\left(t_{travel}^{yesterday}(l) - t_0(l) \right)}{t_0(l)},$$

$$x_3 = \frac{Vol^{now}(l)}{Cap(l)},$$

where $t_{travel}^{yesterday}(l)$ is a past link travel time that each driver uses yesterday, $t_0(l)$ is a a free flow travel time calculated in Eq. (1), $Vol^{now}(l)$ is current link traffic volumes, and $Cap(l)$ is a capacity. So x_2 means a delay from a free flow travel time, and x_3 means congestion rate that each driver can visually judge.

Then the probability of choosing the link i is expressed by the following logit model;

$$P_i = \frac{\exp(\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3})}{\sum_j \exp(\beta_1 x_{j1} + \beta_2 x_{j2} + \beta_3 x_{j3})} \tag{6}$$

Unfortunately, these parameters cannot be estimated from real data, so we examine the effect of each parameter on the results of driver's link choice as sensitivity analysis.

3. Traffic Simulator

3.1 Cellular Automaton Model

In order to treat each vehicle as a discrete one (not continuous), our developed traffic simulation model is one of a cellular automaton model. A vehicle can move from a current cell $cell_{current}$ to next cell $cell_{next}$ at time $t + 1$ if there is no other vehicle at cell $cell_{next}$ at current time t. If there is a vehicle at cell $cell_{next}$ at current time t, then it stops at current cell $cell_{current}$. This simple rule is famous as a "Rule 184" [8].

3.2 Road Network

We model a road network as a graph. Let directed graph $G = (N, E, Cap, t_0)$ serve as a model of the road network, where N is a finite set of nodes that model intersections, and E is a set of links that model one-way roads among intersections. Link $l = (n, n')$ in E if and only if there is a link that permits traffic to flow from intersections n to n'. Function $Cap(l)$ defines the capacity on link l. Function $t_0(l)$ defines a free flow travel time of link l. Each vehicle i has origin node n_i^o and destination node n_i^d. $|l|$ is the length of link l.

We assume two road classifications: arterial and ordinary. Arterial roads have two lanes while ordinary roads have one lane. The following is the procedure to determine the characteristic values for each link in this paper.

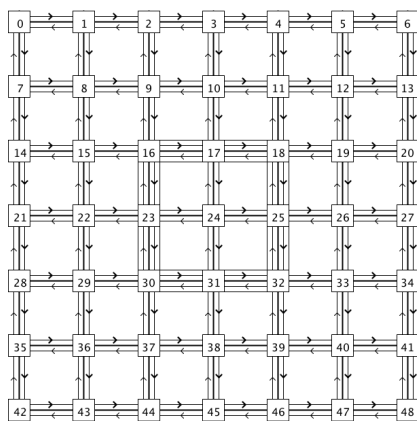- The links in road network are classified into an arterial road or an ordinary road.

Fig. 1 Road network.

Fig. 2 Total travel time.

- If a link is an arterial road, the number of lanes of link l is two. Otherwise, it is one.
- If a link is an arterial road, the maximum speed of link l, $v_{max}(l)$, is sampled from $Uniform(20, 30)$ km/h. Otherwise, it is sampled from $Uniform(15, 25)$ km/h.
- Every link is divided into some cells. The number of cells for one lane in l is defined by $int(|l|/v_{max}(l))$.
- We call one unit-time for passing one cell. The number of cells equals to a free flow travel time $t_0(l)$. One unit-time is supposed one minute in this paper.
- The capacity $Cap(l)$ is calculated from the number of cells and lanes.

In this study, we use a simple road network (see **Fig. 1**), where 16<->17, 17<->18, 16<->23, 18<->25, 23<->30, 25<->32, 30<->31, and 31<->32 are set arterial roads (the number of lane is two), and the others are the ordinary roads (the number of lane is one).

3.3 Origin-Destination Traffic Volume

OD (origin-destination) traffic volumes are 800 vehicles. The 200 vehicles start from nodes 0 to 48 (i.e., OD is 0->48). Another 200 vehicles start from nodes 2 to 45 (i.e., OD is 2->45), and start from nodes 4 to 45 (i.e., OD is 4->45). The Last 200 vehicles start from nodes 6 to 42 (i.e., OD is 6->42). Every minute, each vehicle starts from origin node. Also, we assume that all vehicles in each OD pair have a device to send and receive information (i.e., probe car like car-navigation systems that can handle stigmergies).

4. Experimental Results

4.1 Results of Total Travel Time

Figure 2 compares total travel times in all cases (Case1 – Case4 and with/without driver's route choice behavior). The following summarizes the strategies for managing traffic congestion.

- Case0: No information
- Case1: Combined Long- and Short-Term Stigmergy
- Case2: Anticipatory Stigmergy without Assignment Strategy
- Case3: Anticipatory Stigmergy with Assignment Strategy considering Residual Distance
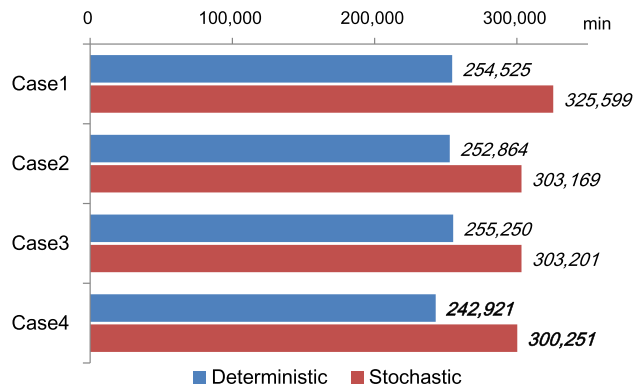- Case4: Anticipatory Stigmergy with Assignment Strategy

considering Lost Time of Traffic Congestion

- [Deterministic]: Without driver's route choice model
- [Stochastic]: With driver's route choice model

In Case0 [deterministic], total travel time is 484,306 minutes, which is the worst results because all vehicles in each OD pair use the same route and do not share any traffic information. The result of Case1 [deterministic] (i.e., long- and short-term stigmergy is combined) is one under the condition that the weight of the long-term stigmergy ω in Eq. (2) is 0.7. The total travel time in Case1 is almost half of one in Case0 since both characteristics are harnessed by integrating long- and short-term stigmergy. Similarly from the result of Case2 [deterministic], we can confirm that anticipatory stigmergy (i.e., near-future traffic information) is effective. As one of a management to assign drivers to network, we proposed in Case3 to judge by the level of the rest of straight-line distance to his/her destination, and in Case4 to judge by the level of the time involved in congestion after departure. From Fig. 2, the result of Case4 [deterministic] is better than Case1 and Case2, but the total travel time in Case3 [deterministic] is not improved. In this study, the assignment ratio to the link which is recommended as the best route with anticipatory stigmergy is simply fixed 50%, it would be desirable to explore an optimal assignment ratio with learning day-to-day results. From the comparison of the results of the total travel time in each deterministic case, a car-navigation services, which have been introduced already in real world and utilize the historical traffic information maximally as in Case1, is one of the effective traffic management policy. In order to increase efficiency more, it is better to gather the near-future traffic information as anticipatory stigmergy and to assign drivers appropriately.

In more realistic situation, it can be generally assumed that all drivers do not follow the travel information, so we consider a driver's route choice behavior (see Section 2.2). "Stochastic" in Fig. 2 (red bar) shows the results of each cases introduced the link choice model, in which parameters (β_1, β_2, β_3) are set in 1.0 respectively[*1]. From Fig. 2, the result of Case4 [stochastic] is best one, and a provision of information based on anticipatory stigmergy (Case2 – Case4) reduces total travel time compared with only historical travel data (Case1). However the results of case that all drivers follow the recommended link are better than

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[*1] If the number of alternative is three, this is a situation where 80% drivers follow the recommended link, and the other 20% drivers will choose the others.

Table 1 Average of each driver's time loss in congestion.

		Time Loss in Congestion [min]
Case1	Deterministic	48.7
	Stochastic	36.4
Case2	Deterministic	54.2
	Stochastic	31.9
Case3	Deterministic	56.0
	Stochastic	33.7
Case4	Deterministic	47.6
	Stochastic	28.5
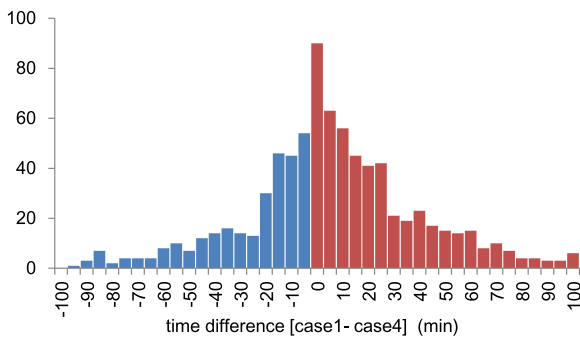
Fig. 3 Histogram of time difference in congestion [Case1–Case4].

Fig. 4 Sensitivity analysis ($\beta_2 = \beta_3 = 1.0$).

Fig. 5 Sensitivity analysis ($\beta_1 = 1.0$).

the results of cases with drivers' choice model, therefore, it is important to consider how to follow the specified route as travel information.

4.2 Results of Time Loss in Congestion

Time loss in congestion is compared as another index of total travel time which is calculated for each driver from Eq. (4). We consider that this index is one of a driver's levels of frustration with the danger of bringing about a traffic accident. The results of average of each driver's time loss in congestion are shown in **Table 1**. Table 1 demonstrates that Case4 is the best result as well as the total travel time (see Section 4.1), and that the stochastic way is better than the deterministic way in all cases. From a viewpoint of efficiency, which is better if the total travel time is smaller, it is significant to obey the navigation's instructions (recommended route), but from a viewpoint of driver's frustration, it would be necessary to allow driver's deviation from the instructions.

Figure 3 is the histogram of lost time difference of Case1 [stochastic] and Case4 [stochastic]. The number of drivers in red part, in which time loss in Case1 is bigger than Case4, is 506, and the blue part is 294 drivers. We can confirm that time loss is increased for 37% of drivers (= 294/800), although the average of time loss in traffic congestion is improved by introduction of the provision of anticipatory information with assignment strategy considering lost time of traffic congestion. So it is necessary to consider another strategy as future tasks.

4.3 Results of Sensitivity Analysis of Logit Model

In this paper, logit model is adopted to express driver's route choice behavior, but the parameters in this model are not estimated due to lack of real observed data of driver's behavior or psychological factors. Therefore we do sensitivity analysis of
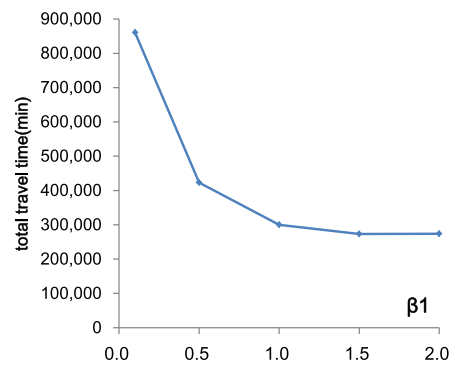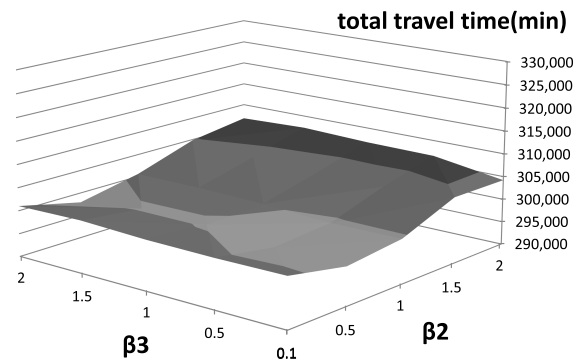
parameters in driver's route choice model to understand the impacts on total travel time.

Figures 4 and **5** show the results of sensitivity analysis in Case4 [stochastic] (i.e., anticipatory stigmergy with assignment strategy considering lost time of traffic congestion). Parameters (β_1, β_2 and β_3) in the link choice model are coefficient of reliability to traffic information (x_1), regret based on his own past experience (x_2), and short-sighted present situation (x_3), respectively (see Section 2.2).

From Fig. 4, we can understand that the reliability to traffic information (x_1) has a significant impact on total travel time, and that it is again important to enhance a belief in travel information. On the other hand, although the impacts of regret based on his own past experience (x_2) and short-sighted present situation (x_3) are limited as shown in Fig. 5, the total travel time is relatively good when the parameter of the regret to his/her past behavior is small ($\beta_2 = 0.5$).

4.4 Discussion

Now we discuss an incentive for drivers to follow the travel information. First we introduce a point system, in which drivers can collect a point by choosing the link on a route of travel information and the criterion of assignment strategy in Case4 is also converted to driver's cumulative points. In this point system, drivers have incentive to follow the recommended route because a driver who has more points could be assigned preferentially. The total travel time with this point system introduced is 302,458 minutes, which is about the same results of Case3 (303,201 minutes) and worse than the results of Case4 (300,251 minutes), because the maximum of collected points in one trip is proportional to the OD pair distance.

Traffic congestion is one of external diseconomy, therefore it is efficient to implement the road pricing which has been introduced in Singapore or London (e.g., Ref. [9]). If road pricing is introduced, the point system is usable as "Credit Based Congestion Pricing" in which a point-based mechanism is adopted for exchanging the rights to pass a congested road during peak demand [10]. Moreover the scoring rule (e.g., Ref. [11]) could be introduced as considered in electricity market [12].

5. Related Work

Chen and Cheng [13] review comprehensively some examples to which Agent Technology is applied as traffic management, and they show that provision of dynamic route information is an important research area.

There are much research on travel information, but most of them are intended for a use of historical travel time data. Narzt et al. [14] deal with the link travel time of each vehicle as stigmergy, and Ando et al. [15] deals with velocity passing through link as stigmergy. Moreover these papers validate how to provide the real-time traffic information. Similar to our study, Claes et al. [16] define the route information based on the traffic condition in near-future as anticipatory stigmergy, and introduce a reservation system as an assignment strategy for a usage of link in a few minutes. However if driver's route is changed, his reservation is only left not canceled in a moment, their strategy has much room of improvement. Recently Dallmeyer et al. [17] uses an inverse ant colony optimization. It is inversed in the sense that a strong pheromone trace will influence following cars not to follow their predecessors but instead to avoid this road, taking a different route to their goals. De Weerdt et al. [18] propose intention-aware routing system which is similar to our proposed management strategy with anticipatory stigmergy. Although they calculate the optimal path by Markov Decision Process analytically, our approach is more realistic way by using only the Dijkstra algorithm (i.e., sequential optimization). As assignment strategy, a reservation system is adopted to controlling a traffic signal [19], or the auction system to treat tradable permits to pass bottleneck, such as a bridge, is proposed [20].

On the other hand, Morikawa et al. [21] provide knowledge on drivers' dynamic route choice behavior using probe-vehicle data. Modeling route choice from real probe-vehicle data is essential because real route choices could be biased by habitual activities. There are some researches related to drivers' dynamic routing modeling [22], [23].

6. Conclusion

We proposed some provisions of travel information based on anticipatory stigmergy and evaluated the effect of anticipatory stigmergy with assignment strategy. Our preliminary results demonstrated that the anticipatory stigmergy with assignment strategy considering lost time in congestion works better than a conventional way with only historical and real time travel time data. Furthermore, in order to describe a driver's route choice behavior, logit model, in which the reliability to traffic information, the regret based on driver's own past experience, and the short-sighted present traffic situation are considered as explanatory variables, is introduced. After taking into account of drivers' travel behavior, it is also most effective method to provide information based on anticipatory stigmergy with assignment strategy considering lost time of traffic congestion. In addition, the same method is the best result in average of lost time in congestion.

From the results of sensitivity analysis of parameters in logit model, it is important to raise the reliability to traffic information for an improvement of efficiency. And we have a little discussion about an incentive for drivers to follow the travel information.

Future work will examine more types of stigmergies, larger maps, and dynamic environments including accidents and road construction. All of our analysis was based on the particular network we showed in this study. We have to investigate the effect on both of the different shape of test networks and road networks in real world.

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