

Performance of Pheromone Model for Predicting Traffic Congestion

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ABSTRACT

Social insects perform complex tasks without top-down-style control, by sensing and depositing chemical markers called “pheromone”. We have examined applications of this pheromone paradigm towards realizing intelligent transportation systems (ITS). Many of the current traffic management approaches require central processing with the usual risks of overload, bottlenecks and delay. Our work points towards a more decentralized approach that may overcome those risks. We use new category of the ITS infrastructure called the probe-car system. The probe-car system is an emerging data collection method, in which a number of vehicles are used as moving sensors to detect actual traffic situations. In this paper, a car is regarded as a social insect that deposits multi-semantics of (digital) pheromone on the basis of sensed traffic information. We have developed a basic model for predicting traffic congestion in the immediate future using pheromone. In the course of our experimentation, we have identified the need to properly tune the model to achieve acceptable performance. Therefore, we refined the model for practical use. We evaluate our method using real-world traffic data and results indicate applicability to prediction. Furthermore, we describe the practical implications of this method in the real world.

Categories and Subject Descriptors

I.6.3 [Simulation and Modeling]: Applications

General Terms

Algorithms, Performance, Experimentation

Keywords

pheromone, traffic congestion prediction

1. INTRODUCTION

Many social insect species such as ants, bees, and wasps coordinate the activities of individuals in the colony without direct communication or complex reasoning. Instead, they deposit and sense chemical markers called “pheromone” in a shared physical environment (pheromone potential field) that participates actively in the system's dynamics. We will examine applications of this pheromone paradigm towards realizing intelligent transportation systems (ITS).

ITS have spread widely recently. Beyond car navigation systems and traffic information systems [22], various types of sensors and communication devices are being introduced for various kinds of applications. Solving traffic congestion is a serious problem among such applications.

One of the key technologies for solving this problem is traffic prediction. There are traffic information systems which are now operational in many countries. Drivers can easily grasp the current surrounding traffic situations through traffic information systems. However, the problem of traffic information system is that traffic information may be delayed due to communication between the road and data center or due to processing time at the data center. This leads to a driver often receiving traffic congestion data that are different from the actual traffic situation.

Another problem in solving traffic congestion is that current traffic data will become useless after a while on a given route. Traffic prediction techniques can solve this problem by predicting appropriate data for each stage of traffic data on the route. Traffic prediction techniques are widely studied in many institutions [4] and have already been introduced in commercial car navigation systems [23]. Some of such techniques deal with long-term predictions, such as predictions spanning 1 hour to 1 day based on statistical analysis of past data. However, long-term predictions cannot be applied to driving in a small area and cannot predict the innately sharp fluctuation of traffic. Short-term prediction is suitable for driving in a small area and for improving prediction accuracy.

Short-term prediction methods have also been studied [24, 26]. However, most of the studies use statistical data of the past. As such, it does not work sufficiently with sharp or irregular fluctuations in traffic.

We propose a short-term traffic prediction method using the pheromone model, which has a relatively simple mechanism that

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does not require statistical data. In our method, a car is regarded as an agent or an ant. Each car would deposit some pheromone into a virtual space with its amount based on their sensing of traffic situations.

To implement our idea as an actual service, we use new categories of the ITS infrastructure called the probe-car system (it is also called the floating car system) [19]. The probe-car system is an emerging data collection method, in which a number of vehicles are used as moving sensors to detect actual traffic situations. Our new method realizes traffic prediction by employing a pheromone mechanism and the probe-car information system without resorting to the use of a traffic control center.

We experimented with the pheromone prediction method the basis of real-world traffic data to evaluate its performance. The results indicate its applicability to the prediction of traffic congestion in the immediate future. Furthermore, we describe the relationship between model type and prediction accuracy.

2. PHEROMONE

2.1 Basic Mechanisms

The term “pheromone” (Greek for “carrier of excitement”) was named by P. Karlson and M. Luscher in the 1950s [11]. Pheromone is defined as a communication chemical that possesses certain meanings that are mutually understood by individuals of the same species. Pheromones have various kinds of functions (flavors). For example, ants use trail pheromone (attractive sign) to guide other ants to food, and bees use alert pheromone (repulsive sign) to inform of disturbance to other bees.

The trail pheromone mechanism has already been applied to certain areas to efficiently solve problems such as the traveling salesman problem [6]. The mechanism works as follows: Ants find food and transport it to their nest, depositing trails of pheromone on their return path. The pheromone diffuses into the surrounding environment and its intensity weakens over time. However, the density of pheromone left on the path where ants have passed most frequently increases. Eventually, pheromone on the shortest path to the food becomes most dense (see Figure 1).

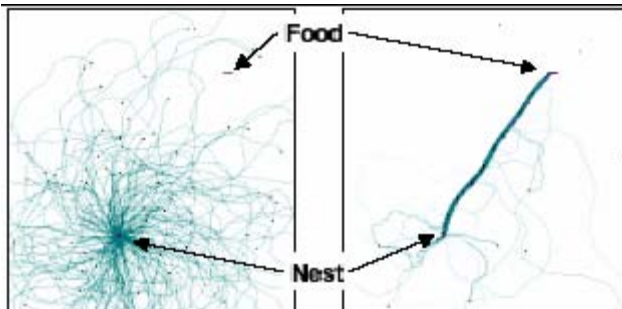


Figure 1: Action pattern of ants which used trail pheromone [20].

On the other hand, bees use alarm pheromone. A leading bee would inform of any danger using alarm pheromone and other bees that follow would avoid the alarm pheromone. This simple mechanism has also been applied to some technologies [16].

2.2 Characteristics

Pheromone is a simple chemical media for delivering information. Although each individual ant or bee possesses just a simple and local behavior rule, they are capable of enabling complex functions. This is largely related with the characteristics of “evaporation” and “propagation” [5]. “Evaporation” represents old information disappearing as time passes due to the volatile nature of pheromone. This enables other ants to receive the most recent information. “Propagation” represents the characteristic of pheromone spreading out towards the surrounding environment. This allows other ants in different places to receive this information.

3. MODEL FOR TRAFFIC

In this paper, we discuss the use of this dynamism to predict traffic. The model used here will regard cars as ants or bees and will deposit pheromone on the pheromone potential field. Cars equipped with some kind of sensors would deposit multiple pheromone on the basis of sensed traffic information. Other cars that follow their route would avoid traffic congestion by checking the intensity of pheromone.

3.1 Digital Pheromone

We propose a traffic prediction method based on digital pheromone [21]. Digital pheromone is modeled on the pheromone fields that many social insects use to coordinate their behavior. A formal model of the essential components of these fields has been developed and applied to a variety of problems. Digital pheromone is defined as having the following characteristics:

1. Pheromone is information deposited on a certain place by agents when an event occurs (Information aggregation)
2. Deposits of a certain flavor are added to the current amount of that flavor of pheromone located at that place. Total amount represents the information potential of each location (Information fusion)
3. Pheromone evaporates over time thus decreasing its value (Truth maintenance)
4. Pheromone propagates towards the surrounding environment (Information diffusion and dissemination)
5. Each agent is affected by pheromone. (Decision making)

Following the above this definition of digital pheromone, we define traffic prediction pheromone as follows.

- 1'. Pheromone is information deposited by cars on the basis of the surrounding traffic situation.
- 2'. Deposits of a certain flavor (certain sensing traffic data) are added to the current amount of that flavor of pheromone located on the road. Total amount represents the traffic situation at each location.
- 3'. Pheromone evaporates over time. This corresponds to traffic moving towards another location over time.
- 4'. Pheromone is propagated towards nearby roads. This corresponds to traffic movement along the flow.
- 5'. Each driver is then affected by the traffic prediction based on pheromone.

3.2 Pheromone Vocabulary

Several “flavors” of pheromone are used to improve system performance. For example, in this study [17], multiple flavors of pheromone such as target, nest and threat pheromone are used to find the optimal path to a target.

We have explored several basic mechanisms essential to the engineering deployment of pheromone mechanisms. In our traffic scenario, there also exist various kinds of factors that affect near-future traffic. We will present three kinds of traffic pheromones and explore the performance of the system for various combinations of these three pheromones. The three pheromone flavors are as follows:

3.2.1 Basic Traffic Pheromone

This is a pheromone of repulsion which informs other cars about the possibility of an increase in traffic congestion. Each car, equipped with a speed sensor and a communication device, deposits basic traffic pheromone according to congestion rate. Generally, speed is used to represent congestion rate, so a car agent will deposit some amount of pheromone depending on its speed.

Let the external deposit of basic traffic pheromone of pheromone flavor *traffic* at time t and location p be $d(\Phi_{traffic}, t, p)$. $v_i(t, p)$ is the speed corresponding car ID i and $C(t, p)$ is the set of car IDs within the interval $(t-1, t]$ at location p . Location p represents a road link or some span of a road between intersections. This function is represented as follows.

$$d(\Phi_{traffic}, t, p) = \frac{1}{|C(t, p)|} \sum_{i \in C(t, p)} \frac{1}{v_i(t, p)} \quad (1)$$

Equation (1) implies the following:

- The deposit increases with decreasing speed (Figure 2 (a)).
- The deposit decreases with increasing speed (Figure 2 (b)).

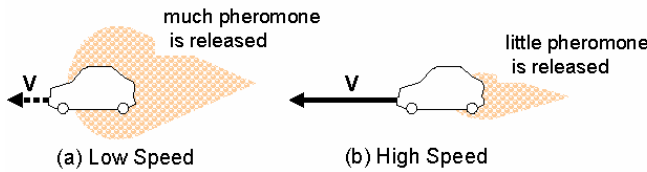


Figure 2: Image of car agents depositing basic traffic pheromone

3.2.2 Braking Pheromone

This is also a pheromone of repulsion which informs other cars about the possibility of an increase in traffic congestion. Each car, equipped with a brake sensor, deposits this repulsive pheromone. Generally, stepping on brakes causes traffic congestion; thus, a car agent will deposit some amount of pheromone depending on the number of times its brakes are applied.

Let the external deposit of braking pheromone of pheromone flavor *braking* at time t and location p be $d(\Phi_{braking}, t, p)$. $braking_i(t, p)$ is the number of times stepping on the brakes is performed corresponding to car ID i and $C(t, p)$ is the set of Car IDs within the interval $(t-1, t]$ at location p .

$$d(\Phi_{brake}, t, p) = \frac{1}{|C(t, p)|} \sum_{i \in C(t, p)} braking_i(t, p) \quad (2)$$

3.2.3 Distance Pheromone

Different from above two pheromones, this is the pheromone of attraction which informs other cars about the possibility of a decrease in traffic congestion.

A car equipped with a millimeter-wave radar deposits this pheromone. Generally, the distance between cars increases with decreasing congestion level. Thus, a car agent will deposit some amount of pheromone depending on its distance between cars.

Let the external deposit of distance-between-cars pheromone of pheromone flavor *distance* at time t and location p be $d(\Phi_{distance}, t, p)$. $dis_i(t, p)$ is the intercar distance corresponding to car ID i and $C(t, p)$ is the set of Car IDs within the interval $(t-1, t]$ at location p . $T_{distance}$ represents the threshold below which $dis_i(t, p)$ is set to zero.

$$d(\Phi_{distance}, t, p) = \frac{1}{|C(t, p)|} \sum_{i \in C(t, p)} dis_i(t, p) \quad (dis_i(t, p) > T_{distance}) \quad (3)$$

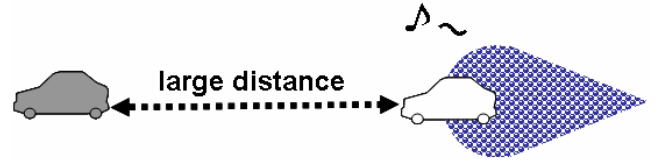


Figure 3: Image of car agents depositing distance pheromone

3.3 Transition Function

Each place maintains a scalar variable corresponding to each pheromone flavor. Our model is based on the pheromone transition model proposed by Brueckner [2]. Brueckner’s model is a kind of coupled map lattice (CML) [12] or continuous cellular automaton. It performs the basic functions of aggregation (as mentioned above), evaporation and propagation.

Evaporation: Aggregated pheromone decreases over time due to evaporation. Let the amount of pheromone of pheromone flavor f at place p and time t be $s(\Phi_f, t, p)$. The predicted amount of a single pheromone flavor $s(\Phi_f, t+1, p)$ is represented as follows.

$$s(\Phi_f, t+1, p) = E_f * (1 - G_f) * (s(\Phi_f, t, p) + d(\Phi_f, t, p)) + g(\Phi_f, t, p) \quad (4)$$

E_f reflects evaporation of pheromone, the $1 - G_f$ factor calculates the amount remaining after propagation to its neighbors, $d(\Phi_f, t, p)$ represents the total deposits made since that last update cycle, and $g(\Phi_f, t, p)$ represents the total pheromone propagated in from all the neighbors of p .

Propagation: Another fundamental equation describes the propagation received from neighboring places. The transition function of the propagated amount $g(\Phi_f, t, p)$ is shown as follows.

$$g(\Phi_f, t, p) = \sum_{p' \in N(p)} \frac{G_f}{|N(p')|} (s(\Phi_f, t-1, p') + d(\Phi_f, t-1, p')) \quad (5)$$

$N(p')$ represents the upper stream neighbors of location p that affect the next status of location p . G_f is the propagation rate, which is a function of the pheromone value of the upper stream in our model.

3.4 Combination of Multiple Pheromones

In a previous section (section 3.2), we explained three kinds of pheromone and classified two types of signal (A sign to make a traffic congestion increase and a sign to make a traffic congestion decrease). In this section, we describe how to combine different flavors of pheromone. This mechanism is based on how each pheromone affects predicted link travel time. We propose a combination method of three patterns in addition to a basic model.

First, we describe only uni-flavor pheromone, that is, basic traffic pheromone. When using it, we derive Equation (6). Predicted link travel time is a scaled pheromone amount based on a scaling parameter and the length of each link. Let $Prt(t, p)$ be the predicted link travel time, S be the global scaling parameter and $l(p)$ be the length (m) in a link p .

$$Prt(t, p) = s(\Phi_{traffic}, t, p) \times S \times l(t, p) \quad (6)$$

Second, we use two flavor pheromones, that is, traffic pheromone (repulsive pheromone) and distance pheromone (attractive pheromone). We derive Equation (7). Distance pheromone makes a traffic congestion decrease, so predicted travel time is given as follows.

$$Prt(t, p) = (s(\Phi_{traffic}, t, p) - s(\Phi_{distance}, t, p)) \times S \times l(t, p) \quad (7)$$

Third, we use another set of two pheromones, that is, basic traffic pheromone (repulsive pheromone) and braking pheromone (repulsive pheromone). We derive Equation (8). Braking pheromone makes a traffic congestion increase further, so predicted travel time is given as follows.

$$Prt(t, p) = (s(\Phi_{traffic}, t, p) + s(\Phi_{braking}, t, p)) \times S \times l(t, p) \quad (8)$$

Finally, we use the all above three pheromones, that is, basic traffic pheromone (repulsive pheromone), distance pheromone (attractive pheromone), and braking pheromone (repulsive pheromone). We derive Equation (9).

$$Prt(p) = (s(\Phi_{traffic}, p) - s(\Phi_{distance}, p) + s(\Phi_{braking}, p)) \times S \times l(t, p) \quad (9)$$

Here, we only used a linear combination of pheromones, and the combination ratio of each semantic of pheromone was tuned by sensitivity analysis.

4. PRACTICAL IMPLICATION

In this section, we discuss the above-described pheromone model as it might be implemented in actual services. To develop the pheromone system, we must first consider its system architecture. An implementation of a pheromone system has two components: the agents (which deposit and react to the field maintained by the environment), and the environment (which maintains the pheromone field and performs aggregation, evaporation, and propagation). Our implementations use an ITS infrastructure which currently exists.

The internet-based ITS project in Japan is moving ahead through public and private sector cooperation to create new categories of ITS services. One of the key technologies is the probe-car system (Figure 4). The probe-car information system utilizes vehicles as mobile sensors for collecting traffic data, which are stored and processed to produce new information useful for providing various public services, among other applications. It can collect data over a much larger area at a much higher precision data, than conventional fixed detectors. Many experiments are carried out using of “taxi-type” or “bus-type” probe-cars in many countries [7, 19]. Moreover, a commercial probe-car service mounted on common vehicles through a cellular network has started in Japan [8]. We use these probe-cars as agents (which deposit pheromone and calculate travel time by reacting to pheromone).

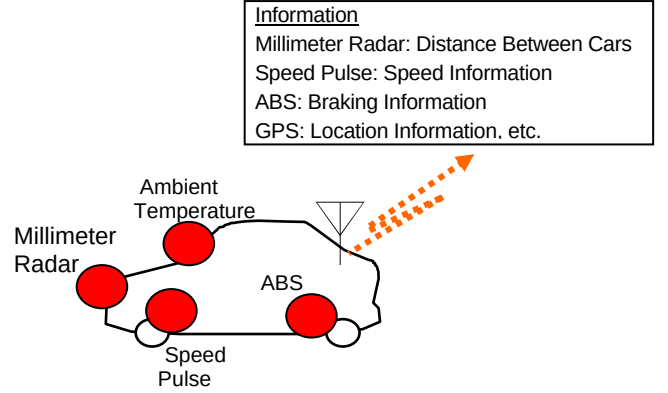


Figure 4: Probe-car system

On the other hand, there are two ways of implementing the environment. One method is to realize a virtual pheromone map on the car navigation system. Each car receives surrounding probe information from the probe-car information server, then maps it and calculates pheromone on the digital map in the car navigation system (Figure 5 (a)). The other method is to realize a virtual pheromone environment using intervehicle communication technology. Some researchers have proposed a virtual information server on an inter-vehicle communication system [18], such that these technologies would make a complete distributed system which is called a “center-less probe car system” (Figure 5 (b)). This will bring about effectiveness in pheromone calculation because no communication between the probe-server and cars in required.

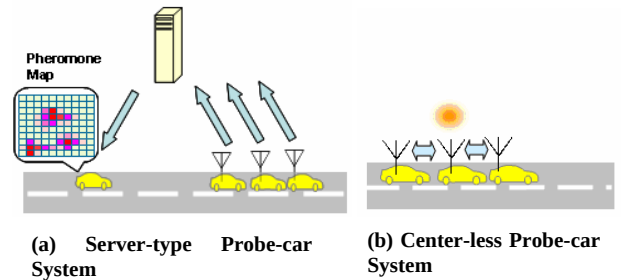


Figure 5: Realization of Pheromone System

5. EVALUATION

We conducted a simulation of our model using actual traffic benchmark data. Then we evaluated how accurate our model predicts traffic on the basis of error indices. This section describes the data used in the simulation and simulator specification.

5.1 Data

The data we chose has high time granularity and a relatively sharp fluctuation in traffic. The real data used in the simulation is the “Kichijoji-Mitaka benchmark dataset” provided by i-Transport Lab. Co., Ltd. This dataset consists of road link information, complete trail data of approximately 12000 cars in an area between Kichijoji and Mitaka stations on a certain day (see Figure 6) [9]. These data were collected by human observers at about 100 observation points in the area. Each trail data includes license plate data and time data to the minute, representing the time at which a car passed an observation points.

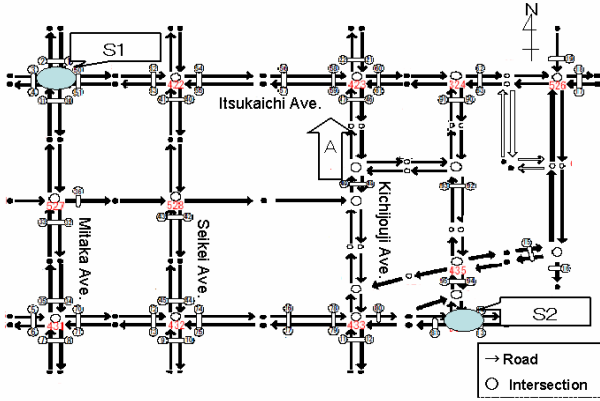


Figure 6: Map of the area where actual survey data were observed

5.2 Simulator

We use Pramics which is a widely used commercial microscopic traffic simulation platform [15] to evaluate the pheromone model and some other baseline model. It calculates the error rate of these models. It also has visualization features to read actual traffic and predicted traffic through animation (See Figure 7).

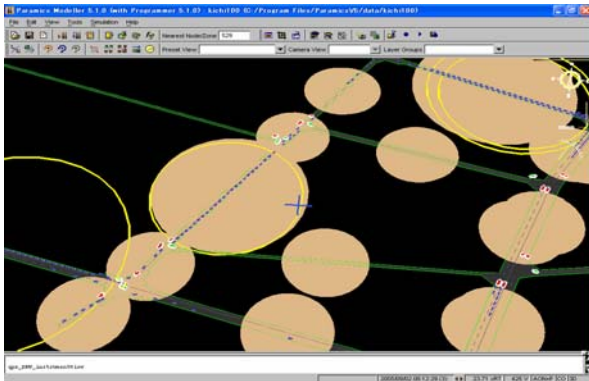


Figure 7: Screenshot of Simulator.
(Shaded circles denote pheromone on each road link)

5.3 Assumptions for Simulation

The average link travel time is around 1 minute since the average link length on the map is around 1 km and the speed of the fastest car is around 60 km/h. Therefore, it would take 1 minute for a car to reach the next link after a prediction has been provided from a preceding car. Thus, in the simulation, the transition time step is set to 1 minute and the pheromone model predicts the situation 1 minute into the future (See Figure.8)

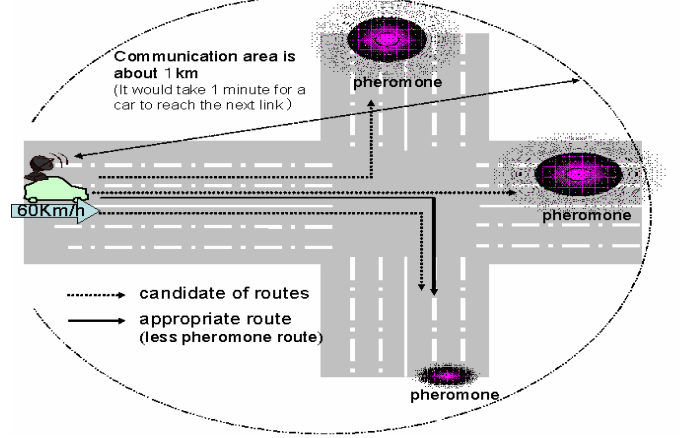


Figure 8: A Communication range of a car and relation of prediction time.

6. EXPERIMENTAL RESULTS

Evaluation has been performed from the standpoint of (i) the prediction accuracy of the basic model, (ii) the relationship between model type (uni-semantics of pheromone or multi-semantics of pheromone) and prediction accuracy, and (iii) the relationship between model parameters and accuracy.

6.1 Prediction Accuracy of Basic Model

Prediction accuracy is calculated as error rates between the predicted link travel time sequence and the actual link travel time sequence. The error rate indices we used are correlation coefficients. The prediction results are compared with two types of baseline predictions. One is a prediction based on a simple moving average time. The other is a prediction based on a persistent prediction model which assumes that the current situation will persist for some duration of time. The traffic information by current traffic control center can be received within 5 minutes or more after sensing; thus, we can assume that the persistent prediction model corresponds with the data of traffic information system.

Figure 9 shows fluctuations of actual traffic and traffic predictions in about 1 hour between 8:00 and 9:00 at a certain link. Actual traffic is the average link travel time of all cars that passed the link at the time the actual data was collected. Predicted link travel times of three types of prediction method are also drawn in the same graph. The correlation coefficient is shown in Table 1. These results show that our method outperforms baseline predictions. We can say that baseline predictions become worse when traffic fluctuations become very sharp.

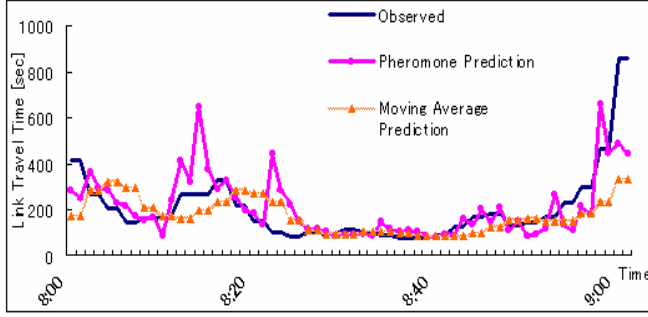


Figure 9: Prediction examples of each prediction methods in a certain link

Table 1. Accuracy of phormone and other prediction schemes in a certain link

	Phormone	Persistent	Moving Average
Correlation Coefficient	0.67	0.55	0.57

Additionally, the overall result of all links on the map, presented in Table 2, shows that phormone prediction has higher accuracy than the other methods.

Table 2. Average accuracy of phormone and other prediction schemes

	Phormone	Persistent	Moving Average
Correlation Coefficient	0.36	0.34	0.30

6.2 Prediction Accuracy of Multiple Semantics of Phormone

Next, we study the effect of different configurations of the phormone model described in sections 3.2 and 3.4 (uni-semantics of phormone or multi-semantics of phormone).

The overall prediction accuracies of uni-semantic phormone and multi-semantic phormone are shown in Table 3. We confirmed the correlation coefficient of multi-semantic phormone is significantly greater than that of the traffic phormone.

Table3. Overall accuracy of uni-semantic and multi-semantic phormone models

	Uni-semantics of Phormone (only Traffic Phormone)	Traffic + Braking	Traffic + Distance	Traffic + Braking + Distance
Correlation	0.36	0.44	0.38	0.45

The result implies that combining of some phormones can be used to refine the prediction accuracy. Here, we only used a linear combination of phormones that have different semantics. However, this scheme might contain nonlinear or logical combinations of semantics. Furthermore, more factors (such as

ambient weather, traffic rules, and various events) might affect the prediction accuracy.

6.3 Parameter Modeling

In a previous work, the parameter of this phormone model was tuned by learning algorithms such as GA [13, 14]. However, such a method is not so feasible for practical use because much learning data (empirical factor) and calculation costs are necessary.

In our experiment, we analyzed the relationship between the optimal parameters and real-world traffic data, and studied the effective parameters modeling schema to simplify determination of optimal parameters. In this section, we introduce a few example of the parameter modeling that got the most influential result in experimental results. The two examples of experimental results are as follows:

Modeling Example 1

First, we take the following assumption regarding the evaporation parameter and evaluated the relationship.

When the velocity of cars in a certain place is fast, evaporation occurs frequently (evaporate much phormone). The model function is as follows.

$$E_f = 1 - \frac{v(t, p)}{v_{\max}(t, p)} \quad (10)$$

Equation (10) implies the following.

- The evaporation decreases with decreasing speed at the given place (much congestion information remains behind).
- The evaporation increases with increasing speed at the given place (much congestion information disappears).

Modeling Example 2

Second, we take the following assumption regarding the propagation parameter and evaluated the relationship.

When the velocity of cars in a neighboring place is fast, propagation occurs frequently (propagate much phormone). The model function is as follows.

$$G_f = 1 - \frac{v(t, p')}{v_{\max}(t, p')} \quad (11)$$

Equation (11) implies the following.

- The propagation decreases with decreasing speed at the neighboring place (much congestion information remains behind).
- The evaporation increases with increasing speed at the neighboring place (much congestion information disappears).

Results of the parameter modeling of the evaporation parameter and the propagation parameter are shown in Table 4. We confirmed that modeling of phormone parameters based on real-world traffic data can be used to refine the prediction accuracy.

We tried much variation of parameter modeling; however, they cannot be discussed here for lack of space.

Table 4. Impact of Parameter Modeling

	Basic Model	Example 1 After Modeling	Example 2 After Modeling
Correlation Coefficient	0.36	0.42	0.49

7. RELATED WORK

An application of the pheromone mechanism has been studied in the so-called swarm intelligence research field. On the other hand, traffic congestion prediction has various kinds of solutions such as the statistical method and simulation-based method. Such related works are discussed in the following sections.

7.1 Application of Pheromone Mechanism

There are various studies concerning applications of the pheromone mechanism. This study regards cars as mobile agents that deposit pheromone, which is similar to the approaches used in actual agents for sensors or planes.

One example of an application is an unmanned plane in a war zone [16, 20]. The unmanned plane would launch mobile agents which would deposit alarm pheromone when they encounter enemy missile sites. The plane would analyze the pheromone potential field and then determine a route to its destination.

Another example of an application is a mobile sensor network [10]. Studies in this field of application are concerned with methods to improve the efficiency of the overall monitoring task by making mobile sensors deposit alarm pheromone to indicate that it has observed a certain area so that other mobile sensors can avoid observing the same place again.

These researches use alarm (negative) pheromone while most of the researches regarding swarm intelligence use trail (positive) pheromone. These researches also deal with the flexible nature of pheromone appropriately. However, note that previous research studies involve evaluations using virtual data and not actual data. Our study has performed evaluations using real traffic data to confirm the applicability to a practical traffic system.

7.2 Traffic Congestion Prediction

There are two types of short-term traffic congestion prediction methods in the field of traffic engineering research. One is based on statistics of past traffic fluctuation patterns. The other is based on traffic simulation.

Statistical prediction is performed by matching current traffic patterns (time series data) to typical traffic patterns in the past. The most applicable pattern among the past traffic patterns is used for future-pattern prediction. The time span may vary from minutes to days depending on the application.

The matching process for short-term prediction uses algorithms such as those based on neural networks [24] or Bayesian networks [26]. The cost incurred for processing is significant since large amounts of past traffic history data are used. Furthermore, prediction of irregular traffic patterns cannot be achieved using only this pattern-matching-based method.

On the other hand, traffic simulation is used for short-term traffic prediction [1]. The simulation based model describes the mutual interference of cars that consists of running car dynamics, various road types, traffic flow model, and driver model. Thus, the simulation tends to be complicated and time consuming. Distributive methods of simulation such as cellular automata (CA) are also introduced into this traffic prediction scheme [3]. While prediction using CA has proved to be effective when information regarding incoming stream volume is available, it does not seem to be effective when the information is partially not available, such as in the case of normal road data.

Naturally, since these predictions are carried out based on information from a traffic information center, data will have low granularity (only three levels: "normal," "congested," and "stacked").

The traffic prediction method using pheromone which we have introduced does not require past traffic data and much processing cost, and it works with a relatively simple mechanism.

8. CONCLUSION

In this paper, we proposed a traffic prediction method that employs a pheromone mechanism and described the practical implication of this method. Cars are regarded as agents that deposit pheromone at virtual places. The pheromone would then evaporate and propagate on the basis of a modified version of the state transition model of digital pheromone. A car would be able to predict traffic on the road ahead from the information provided by preceding cars. On the basis of the results of the experiments that used real traffic data, we confirmed the applicability of our method to short-term traffic prediction.

Moreover, we introduced multiple semantics of pheromone as well as parameter modeling of the evaporation and propagation parameters. We confirmed that both approaches can refine the prediction accuracy of the method. However, we only used a linear combination of multiple pheromones; thus, we have to examine nonlinear or logical combinations of semantics because the semantics can be affected by factors such as traffic rule, some buildings, various events on road side, and weather. The contribution of such factors to traffic might be optimized by GA.

Furthermore, we have to validate the global optimization of this traffic system through a multi-agent traffic simulation. Because previous research efforts have revealed that individually optimizing performance with only traffic congestion information by traffic control center is difficult [25], thus, we believe that swarm-based decentralized traffic system is best approach that may achieve the global optimization.

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