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EVALUATING ADVANTAGE OF SHARING INFORMATION AMONG VEHICLES TOWARD AVOIDING PHANTOM TRAFFIC JAM

Shota Ishikawa
Sachiyo Arai

Department of Urban Environment Systems,
Graduate School of Engineering,
Chiba University
Chiba, 263-8522, JAPAN

ABSTRACT

In this paper, we introduce an intelligent vehicle in traffic flow where a phantom traffic jam occurs for ensuring traffic-flow stability. The intelligent vehicle shares information on the speed and gap of the leading vehicle. Furthermore, the intelligent vehicle can foresee changes in the leading vehicles through shared information and can start accelerating faster than human-driven vehicles can. We propose an intelligent-vehicle model, which is a generalized Nagel–Schreckenberg model that allows sharing information with leading vehicles. The generalized Nagel–Schreckenberg model can arbitrarily set the number of leading vehicles to share information with, and we found that phantom traffic jams are resolved by an intelligent vehicle that shares information with two or more vehicles in front.

1 INTRODUCTION

Traffic congestion is a severe problem on freeways in many countries. In order to decrease traffic congestion, considerable research in the area of intelligent transportation systems (ITS) has been performed for achieving more efficient road usage and increasing the capacity of a road network.

Automated driving, which is partly related to ITS research, is commercially available for undertaking basic driving tasks such as accelerating and braking using adaptive cruise control (ACC) (Kesting, Treiber, Schönhof, and Helbing 2008, Knorr and Schreckenberg 2012, Jerath and Brennan 2012). Recently, cooperative adaptive cruise control (CACC) (van Arem, van Driel, and Visser 2006), an extension of ACC was developed. Both ACC and CACC require no particular infrastructure, as only inter-vehicle communication is used. The aim of the present study is to avoid phantom traffic jams through the modification of systems such as ACC and CACC.

We employed the extended Nagel–Schreckenberg model (hereinafter referred to as the ExNS model) (Nagel and Schreckenberg 1992), which can determine information on leading vehicle in the Nagel–Schreckenberg model (hereinafter referred to as the NS model) a type of cellular automaton model (Masubuchi and Arai 2009). The ExNS model can generate a meta-stable phase, in which the traffic flow is increased to a level similar to that in the free-flow phase even if the traffic density is greater than the critical density. We also employed an intelligent pace car in traffic flow to control cars that follow it and showed that the pace car can reduce phantom traffic jams (XU and Arai 2013). Although a pace car reconstitutes traffic from a congestion phase to a meta-stable phase, phantom traffic jams still need to be prevented.

The task of ACC and CACC systems is to determine the appropriate acceleration or deceleration according to the traffic situation. For this purpose, the system needs to detect and track the vehicle ahead while measuring variables such as the actual distance to and speed difference with the vehicle ahead by using a radar or infrared sensors. Recent developments have enabled obtaining information on not only

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the leading vehicle but also a number of other vehicle in front by utilizing inter-vehicle communication (Onishi and Yoshioka 2012). Therefore, we focus our attention on evaluating the advantage of sharing information among vehicles toward avoiding phantom traffic jams.

In the present paper, we propose a generalized Nagel–Schreckenberg modle (hereinafter referred to as GNS) that enables sharing information with leading vehicles in the NS model. As the GNS model can arbitrarily set number of leading vehicles, we showed through a GNS-model simulation that sharing information with no less than two leading vehicles can prevent phantom traffic jams. We also showed that increasing the amount of information shared with leading vehicles helps solve phantom traffic jams more quickly.

In Section 2, we define the terminology used in this study and introduce the ExNS model, which is the basis of our approach. In Section 3, we propose the GNS model, in which an intelligent vehicle shares information on speeds and gaps with leading vehicles. In Section 4, we explain the related work. In Section 5, we describe our simulation set up. In Section 6, we present the results and examine the effect of the intelligent vehicle. Finally, in Section 7, we discuss the implications of the results and summarize the advantages of our approach.

2 TERMINOLOGY

2.1 Road Model

The road model involves a single-lane freeway with a periodic boundary condition. The periodic boundary condition is generally used in the cellular automaton model because vehicle density is stable throughout the simulation.

Figure 1 shows the notation for the road model used in this paper. Note that vehicle $i+1$ is ahead of vehicle i, where the vehicle index is incremented by one. In this figure, $x_i(t)$ and $v_i(t)$ indicate the coordinates and velocity of vehicle i at time t, respectively. The inter-vehicle distance between vehicle i and $i+1$ is denoted by d_i, which is the number of empty cells before vehicle i.

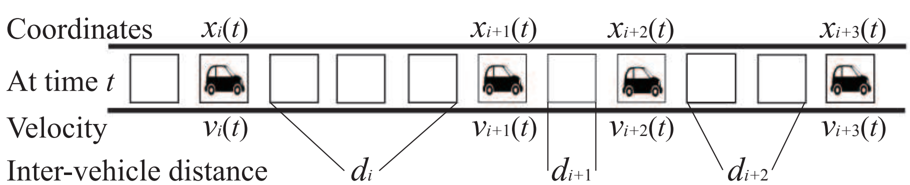


Figure 1: Notation for the vehicle index.

2.2 Fundamental Diagram

Here, we define the basic traffic-flow terminology used in this paper. Generally, traffic flow is analyzed by focusing on the relationship between the traffic flow and vehicle density. Such a relationship is the fundamental diagram. The traffic flow represents the number of vehicles passing through a measurement point per unit time. The vehicle density represents the number of vehicles per unit length. In the fundamental diagram, the traffic flow is smooth in the area having a positive linear relationship between traffic flow and vehicle density; as the vehicle density does not limit vehicle velocity in this scenario, this state is called the free-flow phase. On the other hand, in the area having a negative linear relationship between flow and vehicle density, phase transits from the free-flow phase to the congestion phase; the vehicle density at which this phase transition occurs is called the critical density. On a real highway, we have observed the formation of a phase in which the traffic flow is as high as that in the traffic free-flow phase even if the vehicle density is greater than the critical density. This phase is called the meta-stable phase. This result in a discontinuous gap occurs between the flow in a meta-stable phase and the flow in a congestion phase at the same density, and the fundamental diagram becomes an inverse-λ from that in (Barlovic, Santen, and Schadschneider 1997).

2.3 Extended Nagel–Schreckenberg (ExNS)

Here, we introduce the ExNS model which is a cellular automaton model as is the case of the original NS model. In the original NS model, an agent can directly determine the velocity of vehicle i and the distance between vehicles i and $i+1$. The vehicle positions are updated based on a four step process that expresses the velocity adaptation with respect to the distance between vehicles i and $i+1$, and with respect to the stochastic deceleration rate. In our ExNS model, the agent can also determine information for vehicle $i+1$; thus, the agent's information is extended to the velocity of vehicle $i+1$ and the distance between vehicles $i+1$ and $i+2$.

Figure 2 shows the steps of the ExNS model. In particular, consider the ExNS model when the time is updated from $t \to t+1$. Each agent sequentially executes steps 1–4 at time t, and step execution is performed simultaneously by all agents; this process is called a parallel update. First, in "Acceleration" step, $v_i(t)$ becomes $v_i(t+1) \leftarrow \min(v_i(t)+1, v_{\text{limit}})$, where v_{limit} is the velocity limit; in other words, vehicle i accelerates if $v_i(t)$ does not reach v_{limit}. Next, in the "Change speed" step, if vehicle i's accelerated velocity $v_i(t+1)$ satisfies $v_i(t+1) > d_i$, $v_i(t+1)$ is changed by v_{i+1}^{pred}, which is the velocity of vehicle $i+1$ predicted by vehicle i. The details of v_{i+1}^{pred} will be described later. Next, in the "Stochastic deceleration" step, vehicle i decelerates, i.e., $v_i(t+1) \leftarrow \max(v_i(t+1)-1, 0)$, with deceleration probability p. Finally, in the "Movement" step, vehicle i moves forward by $x_i(t+1) \leftarrow x_i(t) + v_i(t+1)$.

Here, we explain the predicted velocity v_{i+1}^{pled}. If vehicle $i+1$ exists within $v_i(t+1)$ cells in front of vehicle i, the driver agent of vehicle i can obtain an input consisting of the latest velocity of vehicle $v_{i+1}(t)$ and inter-vehicle distance d_{i+1}. When the time is updated from $t \to t+1$, the decision process of agent i is as follows. The vehicle $i+1$ is able to move forward by at least max(min($d_{i+1}-1$, $v_{i+1}(t)$, $v_{\text{limit}}-1$), 0) cells, even if the deceleration probability $p=1$ is taken into account. Therefore, in the ExNS model, vehicle i determines its velocity to be $v_i(t+1)$ by anticipating that the velocity of vehicle $i+1$ becomes min($d_{i+1}-1$, $v_{i+1}(t)$, $v_{\text{limit}}-1$) or greater. Through the above process, vehicle i predicts the velocity v_{i+1}^{pled}, as shown in Figure 2. Moreover, in the calculation process of this predicted velocity, vehicle i is considered to be unaware that vehicle $i+1$ is also performing a prediction like that of vehicle i. This implies that $v_{i+1}^{\text{pled}} \le v_{i+1}(t)$ is always satisfied.

EXTENDED NS$(x_i(t), v_i(t), d_i)$
1. **Acceleration**
   $v_i(t+1) \leftarrow \min(v_i(t)+1, v_{\text{limit}})$
2. **Change speed**
   if $v_i(t+1) > d_i$
      $v_{i+1}^{\text{pred}} \leftarrow \max(\min(d_{i+1}-1, v_{i+1}(t), v_{\text{limit}}-1), 0)$
      $v_i(t+1) \leftarrow \min(v_i(t+1), v_{i+1}^{\text{pred}} + d_i)$
   else
      $v_i(t+1) \leftarrow v_i(t+1)$
   end if
3. **Stochastic deceleration**
   $v_i(t+1) \leftarrow \max(v_i(t+1)-1, 0)$ with probability p
4. **Movement**
   $x_i(t+1) \leftarrow x_i(t) + v_i(t+1)$

Figure 2: Steps in the extended Nagel–Schreckenberg cellular automaton model.

3 PROPOSED MODEL : GNS MODEL

3.1 Road Model Replicating Phantom Traffic Jam

The NS model, ExNS model, and proposed GNS model have a step of stochastic deceleration in which vehicle is decelerated with probability p. We apply this step to replicate a phantom traffic jam in the cellular automaton model.

When a phantom traffic jam occurs, a congestion column with high density and low velocity is formed. The congestion column is formed by the propagation of deceleration to upstream traffic flow from the starting point of limited section such as sag and tunnels. Therefore, the cell with the applied stochastic deceleration is defined as B of all number of cells L ($B \leq L$). Figure 3 shows a road model introducing the cell B in the cellular automaton model.

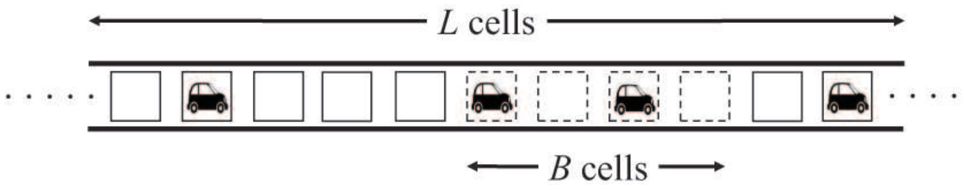


Figure 3: Road model introducing the cell B.

3.2 GNS Model

The GNS model is a cellular automaton model as is the case of the original NS model. In the GNS model, the agent can share information on the velocity and inter-vehicle distance with some leading vehicles through inter-vehicle communication. By utilizing the information of the vehicle ahead, vehicle i can get the shared velocity v_{i+1}^{share} when the time is updated from $t \to t+1$. The GNS model can also set the number of leading vehicles to share information with arbitrarily.

Figure 4 shows the steps of the GNS model. Each agent sequentially executes steps 1–3 at time t, and step execution is simultaneously performed by all agents (parallel update). First, in the "1. Decide speed" step, vehicle i sets vehicle i^{head} based on $size^{\text{share}}$, in addition to its own velocity $v_i(t+1)$, to CHANGE SPEED($v_i(t)$, d_i, i, i^{head}), where i^{head} is the foremost vehicle with which vehicle i can share information and $size^{\text{share}}$ is number of leading vehicles with which information on velocity and inter-vehicle distance can be shared. The details of CHANGE SPEED($v_i(t)$, d_i, i, i^{head}) will be described later. Next, in the "2. Stochastic deceleration" step, the speed of vehicle i becomes $v_i(t+1) \leftarrow v_i(t+1)-1$ with deceleration probability p. Finally, in the "3. Movement" step, vehicle i moves forward with velocity $v_i(t+1)$.

CHANGE SPEED is a function used to determine vehicle i's velocity when the time is updated from $t \to t+1$. Vehicle i executes the "I. Acceleration" step, and sets its own velocity $v_i(t+1)$ to $v_i(t)+1$. If vehicle i does not have adequate inter-vehicle distance for velocity $v_i(t+1)$ after acceleration, vehicle i executes either the "II-a. Cooperative" or "II-b. Non cooperative" step.

In the "I. Acceleration" step, vehicle i sets its own velocity $v_i(t+1)$ to $v_i(t)+1$, when the time is updated from $t \to t+1$. If vehicle i's accelerated velocity $v_i(t+1)$ satisfies $v_i(t+1) \leq d_i(t)$, the CHANGE SPEED function ends after returning $v_i(t+1)$. If vehicle i's accelerated velocity $v_i(t+1)$ does not satisfy $v_i(t+1) \leq d_i(t)$ but $i+1 \leq i^{\text{head}}$ is satisfied, vehicle i executes the step "II-a. Cooperative". If vehicle i's accelerated velocity $v_i(t+1)$ does not satisfy $v_i(t+1) \leq d_i(t)$ and $i+1 \leq i^{\text{head}}$ is not satisfied, vehicle i executes step "II-b. Non Cooperative".

In the "II-a. Cooperative" step, vehicle $i+1$ applies the "CHANGE SPEED" function, and vehicle i obtains the shared velocity of vehicle $i+1$, v_{i+1}^{share}, through inter-vehicle communication. Vehicle i sets the predicted velocity of vehicle $i+1$, v_{i+1}^{pred}, to $\max(v_{i+1}^{\text{share}}-1, 0)$ while decelerating. The reason why the

GNS$(x_i(t), v_i(t), d_i, i, size^{\text{share}})$
1. **Decide speed**
$i^{\text{head}} \leftarrow i + size^{\text{share}}$
$v_i(t+1) \leftarrow \text{CHANGE SPEED}(v_i(t), d_i, i, i^{\text{head}})$
2. **Stochastic deceleration**
$v_i(t+1) \leftarrow \max(v_i(t+1)-1, 0)$ with probability p
3. **Movement**
$x_i(t+1) \leftarrow x_i(t) + v_i(t+1)$

CHANGE SPEED$(v_i(t), d_i, i, i^{\text{head}})$
I. **Acceleration**
$v_i(t+1) \leftarrow \min(v_i(t)+1, v_{\text{limit}})$
if $(v_i(t+1) \leqq d_i)$
return $v_i(t+1)$
end if
II-a. **Cooperative**
if $(i+1 \leqq i^{\text{head}})$
$v_{i+1}^{\text{share}} \leftarrow$ **CHANGE SPEED**$(v_{i+1}(t), d_{i+1}, i+1, i^{\text{head}})$
$v_{i+1}^{\text{pred}} \leftarrow \max(v_{i+1}^{\text{share}}\text{-}1,0)$
II-b. **Non cooperative**
else
$v_{i+1}^{\text{pred}} \leftarrow \max(\min(d_{i+1}-1, v_{i+1}(t), v_{\text{limit}}-1), 0)$
end if
return $\min((v_i(t+1), v_{i+1}^{\text{pred}} + d_i)$

Figure 4: Steps of generalized Nagel–Schreckenberg cellular automaton model.

shared velocity $i+1$ v_{i+1}^{share} of vehicle $i+1$ is reduced by one, is that the GNS model cannot forgive vehicle i to move ahead if the inter-vehicle distance $d_i = 0$.

In “II-b. Non cooperative” step, vehicle i sets the predicted velocity of vehicle $i+1$ v_{i+1}^{pred} to max(min($d_{i+1}-1$, $v_{i+1}(t)$, $v_{\text{limit}}-1$), 0) as is the case with the ExNS model when the time is updated from $t \to t+1$.

After applying either “Cooperative” or “Non Cooperative” step, the vehicle i’s velocity $v_i(t+1)$ is set to min($v_i(t+1)$, $v_{i+1}^{\text{pred}} + d_i$).

3.3 Relationship of the Proposed Model with the Existing Model

The GNS model recursively repeats only the number of $size^{\text{share}}$. Therefore, the behavior of the GNS model is changed by the number $size^{\text{share}}$. Here, we show the relationship of the GNS model with the existing model according to the number $size^{\text{share}}$ as follows.

- $size^{\text{share}} = 0$: The vehicle moves while sharing no information through inter-vehicle communication. The GNS model is equivalent to the ExNS model.
- $size^{\text{share}} = 1$: The vehicle moves while sharing information on the vehicle ahead through inter-vehicle communication. The vehicle moving in the GNS model is equivalent to a vehicle with an ACC or a CACC device.

- $size^{\text{share}} \geq 2$: The vehicle can move while sharing information on some leading vehicles through inter-vehicle communication.

4 RELATED WORK

Traffic flow has been analyzed and studied since the 1950s. There are three types of models that analyze traffic flow. The first type adopts the fluid flow model, which describes continuous motion of vehicles using differential equations; however, since this model is from a macro perspective, it is difficult to distinguish behavior of an individual vehicle (J. and Whitham 1955, Richards 1956). The second type is the car following model, which was proposed as part of a microscopic traffic simulation model (Chandler, Herman, and Montroll 1958, Gazis, Herman, and Potts 1959, Gazis, Herman, and Rothery 1961, Pipes 1953). This model describes how one vehicle follows a leading vehicle in an uninterrupted flow. The third type is the cellular automaton model, which was also proposed as part of a microscopic traffic simulation but considers the discrete flow against others. This model characterizes the behavior of active vehicles. In this paper, we use the cellular automaton model because we want to maintain traffic-flow stability in order to modify the rule for individual vehicle movement.

The following describes the cellular automaton model and explains the rule of individual vehicle motion. The Rule-184 is one of the simplest rules that permits a vehicle to move forward one spaces if the prior cell is empty (Wolfram 1986). The Asymmetical Simple Exclusion Process (ASEP) model introduced Rule-184 to probability (Rajewsky, Santen, Schadschneider, and M. 1998). Instead of moving forward only one cell, the Fukui-Ishibashi model proposed that a vehicle can go forward two or more spaces (Fukui and Ishibashi 1996). The NS model introduced stochastic deceleration into the Fukui-Ishibashi model (Nagel and Schreckenberg 1992). The Quick-Start model focuses on leading vehicle information but the vehicle is only permitted to move forward one cell (Nagel, Nishinari, and Takahashi 2000). Similar to the Quick-Start model, in our ExNS model, vehicle changes speed based on the leading vehicle but is able to move forward two or more spaces (Masubuchi and Arai 2009).

We now discuss the originality of this paper. Both the Quick-Start and ExNS models use speed and gap information of leading vehicles to predict a vehicle's velocity. In contrast to these models, the proposed GNS model predicts a vehicle's velocity more definitively by using the information of forward vehicles. Furthermore, the GNS model arbitrarily sets the number of leading vehicles to share information with. Therefore, the GNS model represents traffic flows where intelligent vehicles drive like self-driving cars.

In recent years, more research has been conducted on controlling driving through inter-vehicle communication. In particular, a control system for small-distance vehicle platooning (Fritz, Bonnet, and Seeberger 2004, Shida and Nemoto 2009) and a real-time implementation of a general merging algorithm for automated highway systems (Lu, Tan, Shladover, and Hedrick 2004) have been proposed, while other researchers have considered the formation of flexible platoons over multiple lanes while performing lane changing merges, and leaving platoons (Tsugawa, Kato, Tokuda, Matsui, and Fujii 2001). Computational simulations suggest that it is possible for intelligent vehicles to communicate within 600 meters of one another (Onishi and Yoshioka 2012). Therefor, the number of vehicles that can share information is important for efficient communications.

5 SIMULATION

5.1 Simulation Environment

The following describes the environment of the road and driver in the simulation.

- The road model is a single-lane freeway with a periodic boundary.
- The road length L is 100 cells.
- The velocity limit v_{limit} is 5 cells per time step.

A cell is 5 [m] in length based on the actual length of a vehicle. The velocity limit which is 5 cells per time step, is equal 90 [km/h], assuming that 1 time step is equal to 1 [s]. This velocity limit is comparable to the velocity limit in Japan.

5.2 Simulation Setting

First, the traffic flow q, vehicle density ρ, and average velocity $\bar{V}(t)$ are defined as follows. Traffic flow q is the number of vehicles passing through a measurement point per unit time. Vehicle density ρ is defined by the number of vehicles per unit length. Average velocity $\bar{V}(t)$ is the average velocity of all vehicles on the road. Traffic flow q is given by equation (1) using vehicle density ρ and average velocity $\bar{V}(t)$.

$$q = \rho \bar{V}(t) \tag{1}$$

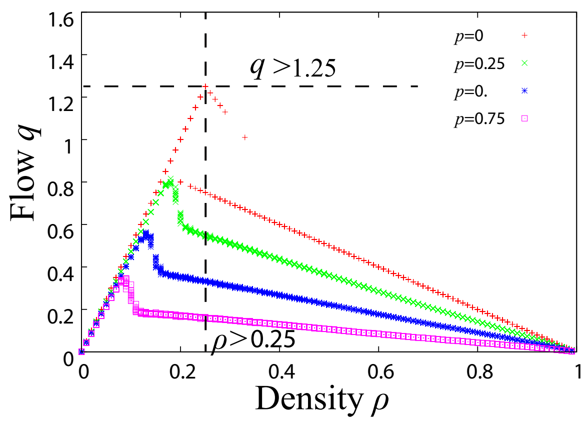
To investigate the effect of introducing the intelligent vehicle sharing information through inter-vehicle communication on traffic flow, the following computer simulation was performed. The following describes the details of three simulations.

1. The traffic flow q is calculated using equation (1). The fundamental diagram is drawn to observe the difference in the number of leading vehicles with which information can be shared between $size^{\text{share}} = 0$ and $size^{\text{share}} = 3$. The traffic flow q is calculated as the average value of 1000 time steps which is regarded as 1 episode. The traffic density ρ which is increased by 0.01 increments within a range $0 \leq \rho \leq 1$ as 10 episode is executed, 1000 episodes are executed in total. This simulation is performed for two patterns of cells with applied stochastic deceleration: at $B = 100$ and at $B = 10$.
2. We show the space–time diagram obtained from the experimental results of the first simulation to determine the difference between $size^{\text{share}} = 0$ and $size^{\text{share}} = 3$. This simulation is conducted for 100 steps and sets the cell with applied stochastic deceleration at $B = 10$, deceleration probability as $p = 0.75$, and vehicle density as $\rho = 0.18$.
3. This simulation considers the relationship between the number of leading vehicles with which information can be shared $size^{\text{share}}$ and traffic flow q. The traffic flow q is calculated as the average value of 1000000 time steps which is regarded as 1 episode. This simulation is conducted for 20 episodes to obtain average values, and it sets the cell with applied stochastic deceleration at $B = 10$, deceleration probability as $p = 0.75$, and the vehicle density as $\rho = 0.18$. The number of leading vehicles with which information can be shared $size^{\text{share}}$ is increased by 1 increment within a range $0 \leq size^{\text{share}} \leq 18$ as 20 episodes is executed; 380 episodes are executed in total.

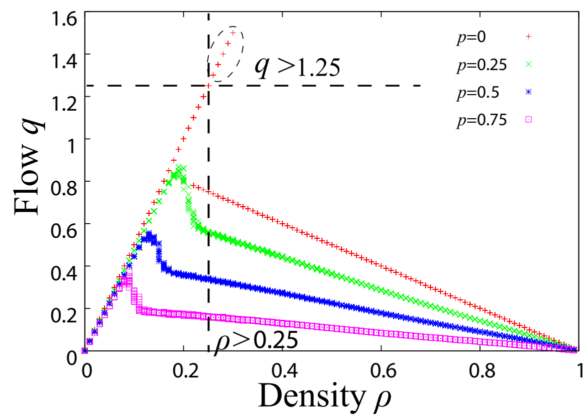
6 SIMULATION RESULTS

1. In case of the cell with applied stochastic deceleration at $B = 100$, the fundamental diagrams of the GNS model with $size^{\text{share}}$ of 0 and 3 are shown in Figure 5(a) and Figure 5(b). Here, the vertical axis, which represents traffic flow, shows the number of vehicles passing through a measurement point per unit time, and the horizontal axis, which represents vehicle density, shows the number of vehicles per unit length. For $p = 0$ and $\rho > 0.25$, the traffic flow begins to decrease, and the maximum value of traffic flow $q = 1.25$, as shown in Figure 5(a). For $p = 0$ and $\rho > 0.25$, as shown in Figure 5(b), the traffic flow continues to increase and surpass $q = 1.25$ (area surrounded by the dashed circle in Figure 5(b)).

   In case of the cell with applied stochastic deceleration at $B = 10$, The fundamental diagram of the GNS model with $size^{\text{share}}$ of 0 and 3 are shown in Figure 6(a) and Figure 6(b), respectively. Here, the vertical axis represents traffic flow and the horizontal axis represents vehicle density. For $p = 0$ and $\rho > 0.25$, the traffic flow begins to decrease, and the maximum value of traffic flow $q = 1.25$



(a)Fundamental diagram of GNS model ($size^{\text{share}} = 0$)



(b)Fundamental diagram of GNS model ($size^{\text{share}} = 3$)

Figure 5: The first simulation results in case of the cell with applied stochastic deceleration at $B = 100$.

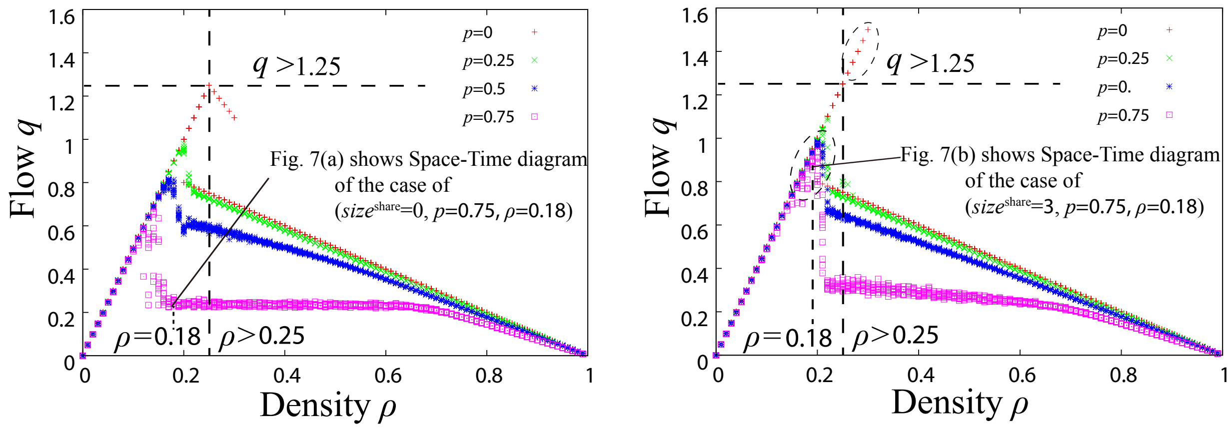
as shown in Figure 6(a), which is equal to the case of Figure 5(a). For $p = 0$ and $\rho > 0.25$, as shown in Figure 6(b), the traffic flow continues to increase and surpass $q = 1.25$, which is equal to the case of Figure 5(b) (area surrounded by the dashed circle in the upper panel of Figure 6(b)). For $p = 0.75$ and $\rho = 0.18$, the traffic flow for $size^{\text{share}} = 3$ shown in Figure 6(b) is greater than the traffic flow for $size^{\text{share}} = 0$ shown in Figure 6(a) (area surrounded by the dashed circle in the lower panel of Figure 6(b)).

2. We will show the space–time diagram of the area surrounded by the dashed circle in the lower panel of Figure 6(b) to focus attention on the difference between Figure 6(a) and Figure 6(b). A space–time diagram show the evolution of traffic flow over time, with the horizontal axis representing position, and vertical axis representing time, and the positions of all vehicles present in the space at each time. The space–time diagram for the GNS model corresponding to Figure 6(a) and Figure 6(b) are shown in Figure 7(a) and Figure 7(b), respectively. The tenth cell at the far right of the horizontal axis in the space–time diagram is the cell $B = 10$ with applied stochastic deceleration. In Figure 7(a), the congestion column is formed the upstream of the cell with applied stochastic deceleration. In contrast to Figure 7(a), smooth traffic flow is observed in Figure 7(b).
3. In Figure 8, for $B = 10$, $p = 0.75$ and $\rho = 0.18$, we show the relationship between $size^{\text{share}}$ and q with the horizontal axis representing $size^{\text{share}}$ and vertical axis representing q. When $size^{\text{share}} \leq 2$ is satisfied, the traffic flow increases with $size^{\text{share}}$. However, when $size^{\text{share}} > 2$ is satisfied, the traffic flow shows is no significant difference in the 1 % significance level.

7 DISCUSSION

7.1 Effective Situation of Sharing Information

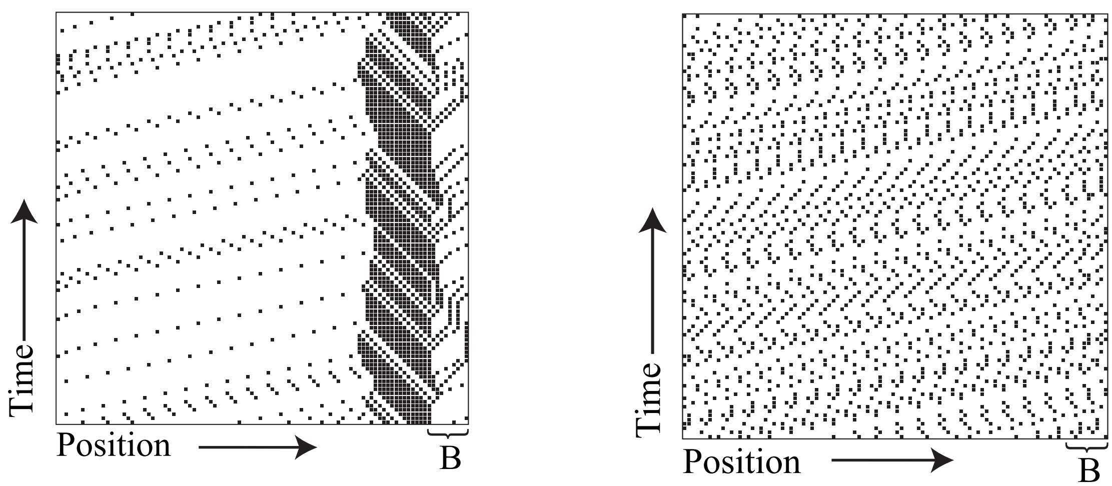
From Figure 5(a)-Figure 6(b), the traffic flow with the intelligent vehicle shown in Figure 6(b) for $size^{\text{share}} = 3$, $p = 0.75$, and $\rho = 0.18$ has increased relative to the traffic flow with no intelligent vehicle shown in Figure 6(a), in other cases, the intelligent vehicle is relatively–ineffective for increasing traffic flow. The traffic flow in Figure 6(b) and Figure 7(b) is higher than that shown in Figure 6(a) and 7(a) as a congestion column is formed. In other words, introducing the intelligent vehicle sharing information is effective when a phantom traffic jam is caused by human driving. The traffic flow is a function of $size^{\text{share}}$ as shown in Figure 8. From Figure 8, an intelligent vehicle that shares information with two or more vehicles in front of it can obtain the best level traffic flow. Therefore, in traffic where phantom traffic jams are likely to



(a)Fundamental diagram of GNS model ($size^{\text{share}} = 0$)

(b)Fundamental diagram of GNS model ($size^{\text{share}} = 3$)

Figure 6: The first simulation results in case of the cell with applied stochastic deceleration at $B = 10$.



(a)Space–Time diagram of GNS model ($B = 10, size^{\text{share}} = 0, p = 0.75, \rho = 0.18$)

(b)Space–Time diagram of GNS model ($B = 10, size^{\text{share}} = 3, p = 0.75, \rho = 0.18$)

Figure 7: The second simulation results of the first simulation to determine the difference between $size^{\text{share}} = 0$ and $size^{\text{share}} = 3$.

occur, introducing the intelligent vehicle that shares information with two or more vehicles in front of it can prevent phantom traffic jams.

7.2 Effective number of leading vehicles with which information can be shared

We see from Figure 8, that $size^{\text{share}}$ should be at least two for effectiveness. Increasing $size^{\text{share}}$ helps prevent phantom traffic jam. However, simulation 1–3 are concerned with the influence of transition from the free-flow phase to the congestion phase. Therefore, we observe the influence of transition from the congestion phase to the free-flow phase in the following simulation.

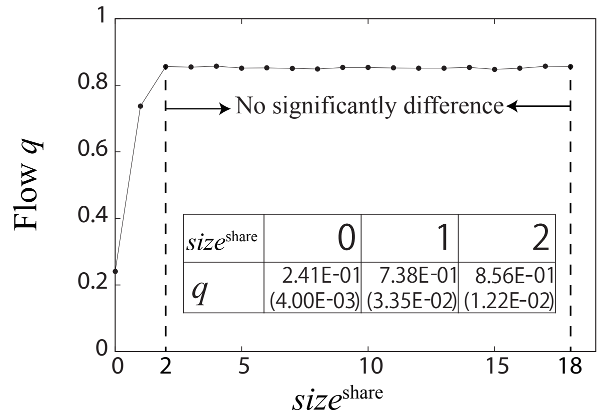


Figure 8: Traffic flow as a function of $size^{\text{share}}$ in the GNS model ($B = 10, p = 0.75, \rho = 0.18$)

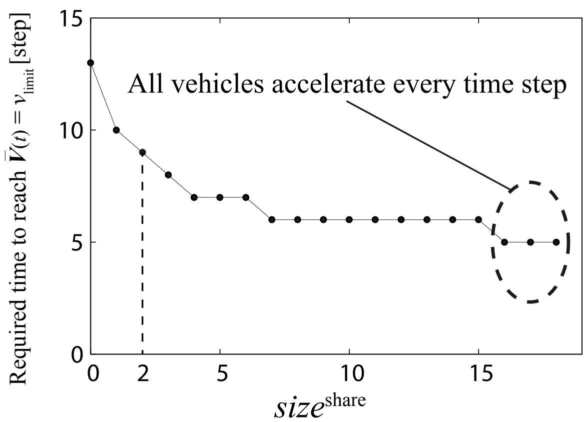


Figure 9: Time from 0 to v_{limit} for different $size^{\text{share}}$ in the GNS model ($B = 0, p = 0, \rho = 0.18$, initial step with regular intervals)

In the simulation, $p = 0$ and $\rho = 0.18$; the beginning is at regular intervals and the initial speed is zero, i.e., the vehicle is in congested traffic. In Figure 9, we show the relationship between $size^{\text{share}}$ and the return speed from the initial step to the time at which all vehicles reach a limiting velocity, with the horizontal axis representing $size^{\text{share}}$ and vertical axis representing the time of from $\bar{V}(0) = 0$ to $\bar{V} = v_{\text{limit}}$. Here, $size^{\text{share}}$ is increases as the time from $\bar{V}(0) = 0$ to $\bar{V} = v_{\text{limit}}$ decreases shown in Figure 9. This result implies that increasing $size^{\text{share}}$ decreases the time required for resolving a phantom traffic jam.

7.3 Effective initial position

In this section, we consider the relationship between the initial position in the simulation and traffic flow q. The setting of this experiments is the same in the simulation described in section 5.2. The maximum value of the traffic flow $q = 1.75$ is observed for $size^{\text{share}} = 3$ and $\rho = 0.35$. Therefore, $q > 1.25$ in the area surrounded by the dashed circle in Figure 5(b) and Figure 6(b) because of the initial position. This result implies q is influenced by inter-vehicle distance. Therefore, for significantly increasing traffic flow with the intelligent vehicle sharing information through inter-vehicle communication, it is necessary to adjust inter-vehicle distance.

8 CONCLUSION

In this study, a computational simulation for controlling traffic flow using an intelligent vehicle sharing information through inter-vehicle communication was performed to alleviate or eliminate phantom traffic jams. This intelligent vehicle follows the GNS model, which generalizes the NS model of cellular automaton.

The GNS model can arbitrarily set the number of forward leading vehicles with which information can be shared, enabling the observation of the effect of the number of leading vehicles with which information can be shared.

From the results of computational simulation, in which information on the leading vehicle including velocity and inter-vehicle distance is shared, we showed that introducing the intelligent vehicle can prevent phantom traffic jams. Further, increasing the number of leading vehicles with which information can be shared promotes transition from the congestion phase to the free–flow phase.

Furthermore, for a significantly increasing traffic flow with an intelligent vehicle sharing information through inter-vehicle communication, it is necessary to adjust the inter-vehicle distance. We also plan to incorporate agents that model individual characteristics to represent mixed traffic using both self-driving and manually-driving agents to ensure traffic-flow stability when intelligent vehicles are introduced. These two topic will be the focus of our future research.

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AUTHOR BIOGRAPHIES

SHOTA ISHIKAWA is Student of Department of Urban Environment Systems Graduate School of Engineering, Chiba University. He received the B.S degree in engineering from Chiba University. He is interested in automatic driving vehicle. His email address is aefa3392@chiba-u.jp.

SACHIYO ARAI is Professor of Department of Urban Environment Systems Graduate School of Engineering, Chiba University. She received the B.S degree in electrical engineering, the M.S. degree in control engineering and cognitive science, and Ph.D degree in artificial intelligence, from Tokyo Institute of Technology. Her research interests include discrete-event simulation, agent-based simulation, and their applications in social networks, service systems, transportation networks, and energy markets, and manufacturing. Her email address is sachiyo@faculty.chiba-u.jp.