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The study of cooperative merging algorithm based on the assignment model for connected and automated vehicles

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Abstract: A cooperative control algorithm based on an assignment model is proposed for the merging areas of urban roads and highways, specifically designed for connected and automated vehicles. The primary objective of this algorithm is to optimize the positional distribution and operational speed of mainline vehicles located upstream of the merging area, thereby reserving the space resources of the outer lane of the mainline for ramp vehicles to merge effectively. The algorithm generates virtual slots based on the positions of vehicles on the roadway. To minimize the vehicles lane-changing time, a time cost matrix is created, an assignment model is established, and the Hungarian algorithm is emploed to solve this model. Utilizing the Python-SUMO simulation platform, two scenarios-free traffic and congested traffic-are simulated to evaluate the peformance of the proposed model. The results show that the proposed cooperative control algorithm can significantly reduces the occurrence of traffic deceleration waves and improve driving efficiency. In free traffic conditions, the driving time and fuel consumption can be reduced by 18% and 20.03%; in congested traffic scenarios, the driving time can be reduced by 13.47%, while fuel consumption can be reduced by 13.82%. The research results have important practical value for traffic control in merging areas for connected and automated vehicles.

Keywords: traffic engineering; merging area; connected and automated vehicles; cooperative control; assignment model; virtual slots

1 Introduction

Ramps are an important part of expressways or urban expressways and are necessary road components to connect the main line and local traffic. When the vehicles on the ramp enter the mainline, the vehicles decelerate to avoid a collision, so that a traffic bottleneck is formed. In most Chinese cities, traffic congestion at the merging area is a kind of recurrent congestion during commuting rush hours. The existing solutions for solving it include alternate merging and ramp signal control. The alternate merging in the Shanghai expressway is investigated. The flow rate of the outside lane on the mainline is 936 veh/h, that of the inside lane on the mainline is 1603 veh/h, and that of the ramp is 984 veh/h. The queue length of the outside lane on the mainline is 9 vehicles. The ramp signal control meters the inflow rate of the ramp by signal control. Compared to no management, these two approaches avoid the gridlock of the merging area. However, the throughput of the merging area still has significant room for improvement. Thus, this study aims to do it.

With technological advancement, Connected and Automated vehicles (CAVs) are the future tendency. Chinese cities, such as Beijing, and Nanjing, carry out public road tests of CAVs. Compared to an isolated Automated Vehicle (AV), the cooperation of CAVs can improve traffic throughput. The existing papers are divided into two categories: individual AV control and platoon control. For the first category, Dresner and Stone[1] proposed a reservation-based mechanism for intersection management. Gao, et al.[2] proposed a reward function based on a reverse reinforcement learning algorithm

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and analyzed longitudinal automated driving for different speeds. Liu, et al.[3] proposed a movement planning algorithm based on trajectory prediction, then selected an optimal trajectory. For the second category, vehicle-to-everything communication technology is used to fulfill the information exchange. Rupp, et al.[4] used vehicle-to-vehicle communication to reduce the space gap and form a platoon, which increases the throughput. Jin, et al.[5] proposed a multi-agent intersection management system and formed a platoon based on vehicle-to-everything technology. Compared to the traditional signal control method, the proposed method reduces 30% travel time and 23% fuel consumption and CO_2. Chen, et al.[6] proposed three platoon organizing schemes for trucks. Chen[7] proposed a platoon-organizing optimization model for different road conditions. Clark, et al.[8] proposed a merging algorithm for maximizing average speed. Hao[9] proposed a real-time heuristic dispatching algorithm for merging and optimized the merging sequence. Jiang, et al.[10] proposed a central merging approach for computing the optimal speed curve of each vehicle and analyzed the impact of the merging point on fuel consumption. Uno[11] proposed a virtual vehicle concept for optimizing the merging, which maps the vehicle position on the ramp to the mainline to generate a virtual vehicle. Ntousakis, et al.[12] proposed two distributed merging algorithms for computing the merging sequence. Li, et al.[13] proposed a distributed merging control strategy and validated it in the Beijing expressway.

The above-proposed approaches improve the performance index of mering by optimizing the trajectory curves. However, improving the throughput in the merging area by optimizing the uses of lanes has not been reported. In this paper, the proposed algorithm optimizes the position and speed of the vehicles on the upstream section of the merging area, so that the road space on the outside lane is reserved for merging the cars on the ramp.

2 Problem description and assumption

2.1 Problem description

A practical example of Shanghai expressway mentioned in the introduction part shows that the flow rate drops 667 veh/h in the outside lane, compared to that in the inside lane. If the vehicles in the outside lane are instructed to move into the inside lane at the upstream of the merging area, the density in the outside lane decreases, then the throughput at the merging area can increase. Table 1 summarizes some of the major variables and corresponding definitions used in this paper.

Table 1 Variables and definitions

Variables	Definition
L	Length of the cooperative control area
Z	Objective function
t_{ij}	Time cost for vehicle i to enter slot j
m	The number of vehicles on the outside lane
n	The number of virtual slots on the inside lane
$x(t), y(t)$	The lateral and longitudinal positions of the vehicle at time point t
$v(t)$	The speed of the vehicle at time point t
$a(t)$	The acceleration of the vehicle at time point t
r_d	The desired space gap
κ	The number of vehicles on the inside lane
t_0	Initial time point
t_g	The time point of completing the position adjustment
t_f	The time point of completing the merging
X	Objective function
$u(t)$	The change in acceleration between two time intervals
N	A large integer number

For CAVs, a CAV can get all vehicle information around it through V2X. A merging scenario is shown in Figure 1. There are two lanes in the mainline, and a single lane in the ramp. The communication range of V2X is defined as L. The merging point is the intersection of the centerlines of the mainline and the ramp.

2.2 Assumption

The assumptions are as follows.

(1) All vehicles are CAVs. The onboard units and roadside units are available. There is no communication delay.

(2) The vehicles on different lanes in the upstream control area shown in Figure 1 have the same speed and keep constant before they receive the instructions.

(3) Only cars drive on the expressway.

3 The vehicle organizing algorithm based on the assignment model

3.1 The proposed model

The optimization objective of the assignment model is

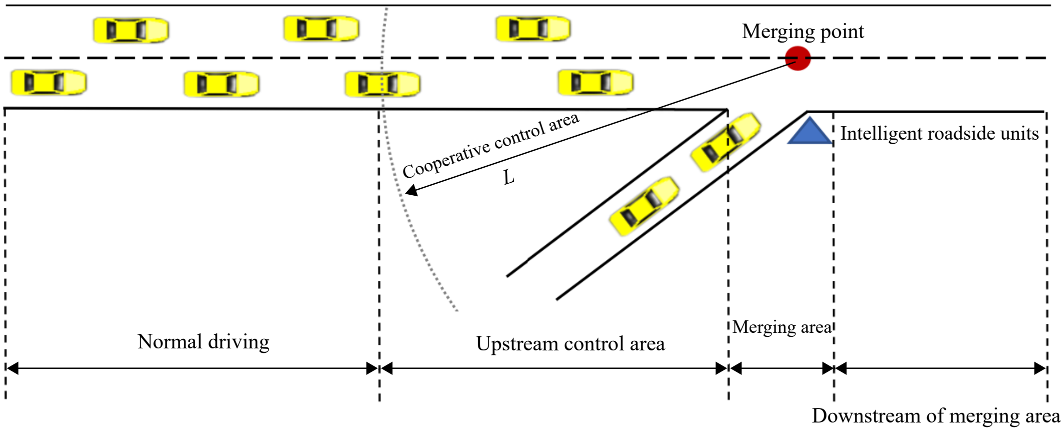


Fig. 1 A merging scenario

to minimize the total cost of vehicles moving from the outside lane of the mainline to the inside lane.

$$Z=\sum_{i=1}^{m}\sum_{j=1}^{n}x_{ij}t_{ij} \tag{1}$$

$$\sum\nolimits_{i=1}^{m}x_{ij}\leqslant 1 \tag{2}$$

$$\sum\nolimits_{j=1}^{n}x_{ij}\leqslant 1 \tag{3}$$

$$x_{ij}=\begin{cases}1,\text{When a target vehicle } i \text{ is assigned into a virtual slot } j\\ 0,\text{When a target vehicle } i \text{ is not assigned into a virtual slot } j\end{cases}$$
$$i=1,2,3,\cdots,m,\ j=1,2,3,\cdots,n \tag{4}$$

Z in Equation (1) is the objective function, which represents the total time cost required by vehicles to enter virtual slots. The smaller the objective function value is, the best a vehicle organization option is. One virtual slot is only assigned to one vehicle.

3.2 Generate the virtual slots

The desired space gap in Ref. [14] is determined by the Equation (5).

$$r_d(t)=6.33\cdot v^{0.48}+2 \tag{5}$$

The virtual slots are generated by the desired space gap. Determine the desired space gap between vehicles based on their speed, and determine the number of virtual slots. This value represents the maximum number of vehicles that can exist on the road at this time. Virtual slots include two states: occupied and unoccupied, with blue slots indicating unoccupied and red slots indicating occupied. Taking Figure 2 as an example, the target vehicle A can change lanes to adjacent slots B_2 or B_3.

The minimum safe space gap between vehicles and the ideal space gap both are set to r_d. When the randomly generated vehicle space gap is not an integer multiple of r_d, the vehicle position needs to be adjusted. In this paper, the genetic algorithm is chosen to optimize the vehicle position in order to generate virtual slots. The objective function is to minimize the adjustment of the vehicle:

$$\min X=\sum_{i=1}^{K}x_i(t_g)-x_i(t_0) \tag{6}$$

The constraints are shown below:

$$x_{i+1}(t_g)-x_i(t_g)=nr_d,\ n=1,2,3,\cdots,N \tag{7}$$

$$\begin{aligned}V_i&=\{v_i\,|\,0\leqslant v_i(t)\leqslant v_{\max}\}\\ A_i&=\{a_i\,|\,a_{\min}\leqslant a_i(t)\leqslant a_{\max}\}\\ U_i&=\{u_i\,|\,u_{\min}\leqslant u_i(t)\leqslant u_{\max}\}\end{aligned} \tag{8}$$

Using genetic algorithm to solve, generate virtual gaps, and match each vehicle to the virtual slots.

3.3 The cost functions

The cost of changing the lane from the outside lane to

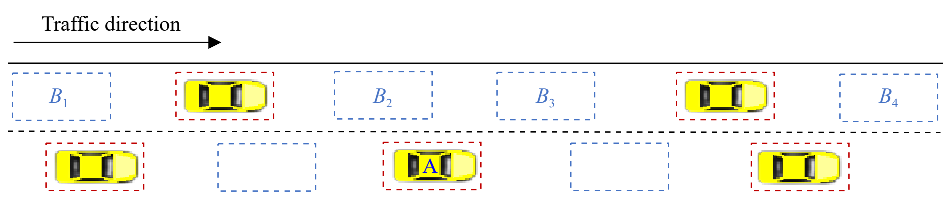


Fig. 2 The virtual slots

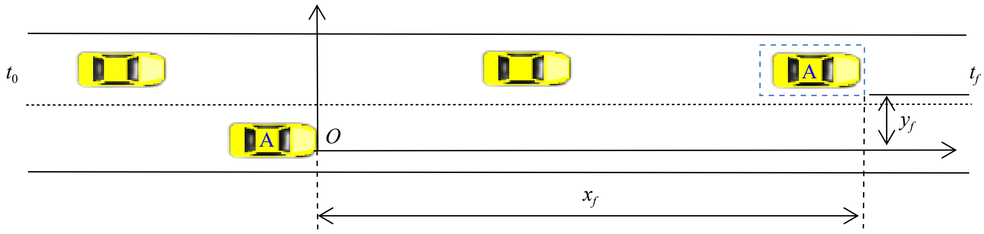


Fig. 3 The lane-changing process

the inside lane is measured by lane-changing time. The lane-changing process is shown in Figure 3.

The lateral direction is the x-axis, and the vertical direction is the y-axis. The origin of the coordinate system locates in the front bumper of a vehicle. The initial position at t_0 is $[x(t_0), y(t_0)]$, the lateral speed is $v_x(t_0)$, the vertical speed is $v_y(t_0)$, the lateral acceleration is $a_x(t_0)$, and the vertical acceleration is $a_y(t_0)$. The initial value of these parameters are as follows.

$$\begin{cases} x(t_0)=0, & v_x(t_0)=v_0, & a_x(t_0)=0 \\ y(t_0)=0, & v_y(t_0)=0, & a_y(t_0)=0 \end{cases} \tag{9}$$

At the time instant of completing the lane changing, the corresponding values of these parameters are as follows.

$$\begin{cases} x(t_f)=x_f, & v_x(t_f)=v_f, & a_x(t_f)=0 \\ y(t_f)=y_f, & v_y(t_f)=0, & a_y(t_f)=0 \end{cases} \tag{10}$$

The ideal lane-changing trajectory is approximated by the polynomial equation. The cubic polynomial equation has second-order smooth characteristics and can avoid the complexity of the higher polynomial equation. Therefore, the cubic polynomial equation is used.

$$y=a_1+a_2x+a_3x^2+a_4x^3 \tag{11}$$

where a_1, a_2, a_3, a_4 are parameters.

Input Equations (9) and (10) into Equation (11), the vehicle trajectory is

$$y(x)=\frac{3y_f}{x_f^2}x^2-\frac{2y_f}{x_f^3}x^3 \tag{12}$$

The ideal lane changing time is

$$t=\frac{2\int_0^{x_f}\sqrt{1+y'^2}\mathrm{d}x}{v_0+v_f} \tag{13}$$

3.4 The construction of a cost matrix

Vehicle lane changing should minimize disturbance to the mainline traffic flow as much as possible. When the virtual slot is behind the lane changing vehicle, the vehicle needs to slow down to enter the slot, which will disturb the traffic flow. Therefore, the cost of this situation is set as M (M is approximately infinite), which is a penalty; When the virtual slot is in front of the lane changing vehicle, but there are other vehicles blocking the process of entering the slot, the cost is set to N (N is approximately infinite). The final cost matrix is in the form of m rows and n columns, as shown below:

$$\boldsymbol{T}=\begin{matrix} \\ A_1 \\ A_2 \\ \vdots \\ A_k \\ \vdots \\ A_m \end{matrix}\begin{matrix} \begin{matrix} B_1 & B_2 & \cdots & B_k & \cdots & B_n \end{matrix} \\ \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1k} & \cdots & t_{1n} \\ t_{21} & t_{22} & \cdots & t_{2k} & \cdots & t_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ t_{k1} & t_{k2} & \cdots & t_{kk} & \cdots & t_{kn} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ t_{m1} & t_{m2} & \cdots & t_{mk} & \cdots & t_{mn} \end{bmatrix} \end{matrix} \tag{14}$$

where, $(A_1, A_2, \cdots, A_m)^{\mathrm{T}}$ is the vehicle label on the outside lane; $(B_1, B_2, \cdots, B_n)^{\mathrm{T}}$ is the virtual slot label on the inside lane.

3.5 Hungarian algorithm

The Hungarian algorithm is used to solve the proposed model. The algorithm steps are as follows.

Step 1: The rows or columns of the matrix are complemented with zero elements to make it as a square matrix.

Step 2: The cost matrix undergoes a row transformation and a column transformation to ensure that there is at least a zero element in each row and column.

Step 3: Make the minimum number of straight lines that can cover all zero elements. If the number of straight lines is equal to the number of rows, the optimal solution is found, otherwise go to step 4.

Step 4: Transform the cost matrix so that zero elements appear in the elements that are not covered by a straight line. Return to step 2.

Step 5: Assignment is applied based on the computation results to find the optimal solution.

4 Numerical simulation

4.1 Parameter setting

The simulation parameter settings are shown in Table 2.

Table 2 Simulation parameters

Variables	Value
length of the virtual slot (m)	4×2.5
length of the vehicle (m)	4
v_{min}, v_{max} (m/s)	0, 33.3
a_{min}, a_{max} (m/s^2)	−4 , 4

4.2 Simulations

(1) Case Study 1: free traffic flow

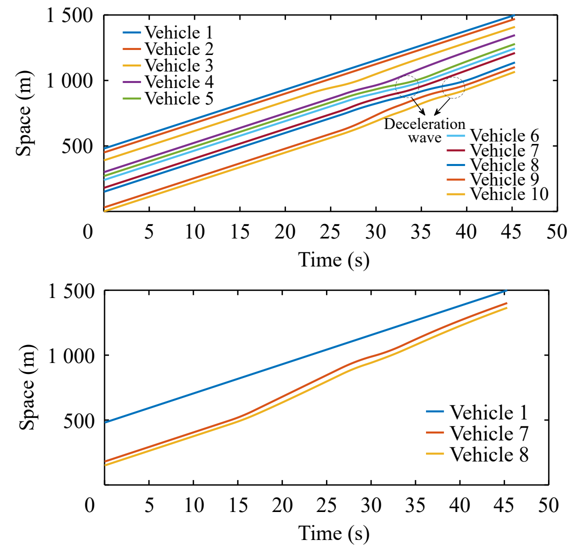
At the initial time t=0, 10 vehicles are randomly generated on both inside mainline lane and outside mainline lane, and the ramp vehicle arrivals obey a normal distribution. The speed values of all cars are 22.5 m/s. The car trajectories and speed curves are shown in Figure 4. As can be seen from the left figure of Figure 4(a), the deceleration of one car can cause multiple subsequent cars to decelerate. In contrast, the right figure of Figure 4(a) shows that the proposed model moves 7 cars to the inside lane; 3 cars are left on the outside lane and there is no deceleration wave.

The entire merging process was analyzed from two aspects: driving time and fuel consumption (using SUMO's built-in fuel consumption model), and the comparison of evaluation results is shown in Table 3. According to the minimum safe vehicle spacing merging control model in Ref. [14], it takes 41.12 s for the outside mainline vehicle to fully pass through the merging area, and a total of 653.13 g of fuel is consumed during this process. According to the cooperative control model proposed in this article, it takes 33.72 s for vehicles on the outside mainline to fully pass through the merging area, a decrease of 18%. During this process, a total of 522.28 g of fuel was consumed, a decrease of 20.03%.

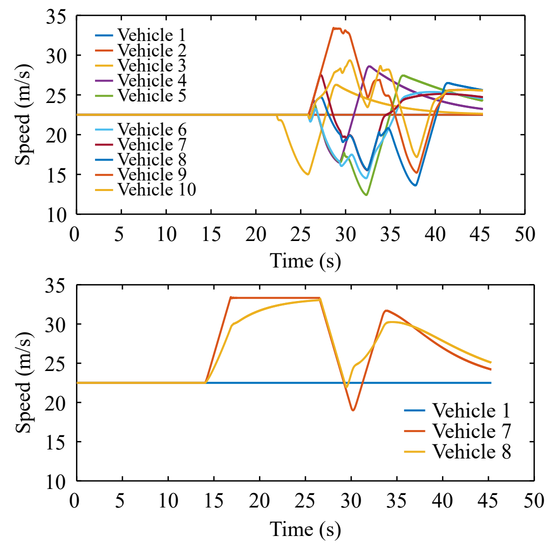
(2) Case Study 2: congested traffic flow

At the initial time t=0, 16 vehicles are randomly generated on both inside mainline lane and outside mainline lane, and the ramp vehicle arrivals obey a normal distribution. The speed values of all cars are 16 m/s. The speed curves and car trajectories are shown in Figure 5. As can be seen from Figure 5, the proposed model can reduce the deceleration wave formed by the outside mainline vehicles due to slowing down to allow the ramp vehicles to go ahead.

Analyze the entire merging process and compare the evaluation results as shown in Table 4. According to the



(a) The car trajectories using the model in Ref. [14] and the proposed model



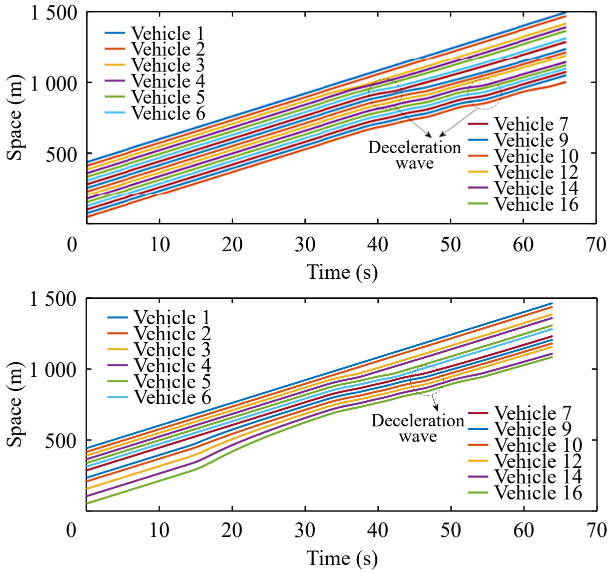
(b) The speed curves using the model in Ref. [14] and the proposed model

Fig. 4 The comparison of the speed curves and car trajectories for a single run

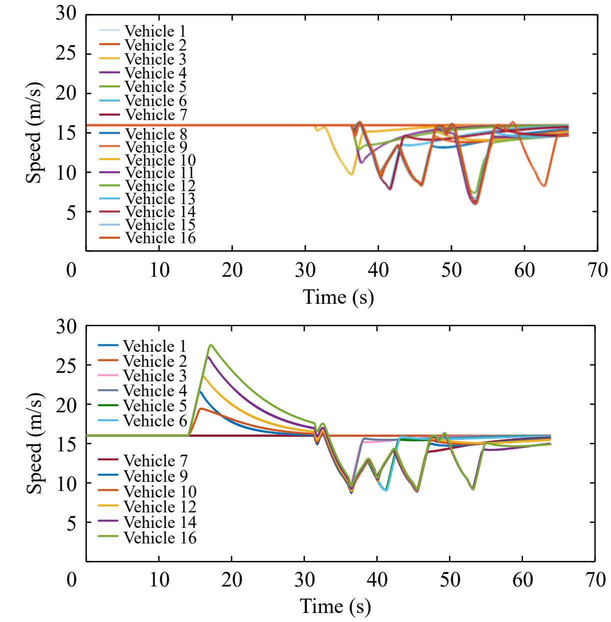
Table 3 The comparison of evaluation results

Comparative indicators	Driving time (s)	Fuel consumption (g)
Ref. [14]	41.12	653.13
This paper	33.72 (−18%)	522.28 (−20.03%)

minimum safe vehicle spacing merging control model in Ref. [14], it takes 66.82 s for the outside mainline vehicle to fully pass through the merging area, and a total of 989.91 g of fuel is consumed during this process. According to the cooperative control model proposed in this paper, it takes 57.82 s for the outside mainline vehicles to fully pass through the merging area, a decrease of 13.47%. During this process, a total of 853.08 g of fuel



(a) The car trajectories using the model in ref. [14] and the proposed model



(b) The speed curves using the model in Ref. [14] and the proposed model

Fig. 5 The comparison of the speed curves and car trajectories for a single run

Table 4 The comparison of evaluation results

Comparative indicators	Driving time (s)	Fuel consumption (g)
Ref. [14]	66.82	989.91
This paper	57.82 (−13.47%)	853.08 (−13.82%)

was consumed, a decrease of 13.82%.

5 Conclusion

In this paper, the assignment model in operation research is applied to the vehicle organization model around the merging area, which assigns vehicles on the outside mainline to the inside upstream of the merging area, and reserves road space on the outside lane for vehicles to merge. The optimization objective is to minimize the total time for changing lanes, and the Hungarian algorithm is used to obtain the optimal assignment plan. The performance of the model was analyzed using numerical simulation and SUMO simulation. The results showed that compared with the minimum safe vehicle spacing merging control model in Ref. [14], the proposed model can reduce the number of traffic deceleration waves, driving time, and vehicle fuel consumption.

Due to the limitations of experimental conditions, the proposed model was only validated under simulation conditions and not under real traffic scenarios. No delays are assumed under simulation conditions. However, under real scenarios, there are computational delays in roadside edge computing units and communication delays in message sending. The effects of these delays on the real-time performance of the model need to be further investigated in the future.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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