Coordinated Control Algorithm at Non-Recurrent Freeway Bottlenecks for Intelligent and Connected Vehicles

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ABSTRACT Intelligent and Connected Vehicle (ICV) technology is considered to be a solution to improve the traffic performance. Through the information exchange in real-time among the vehicles, the roadside infrastructures, and the cloud platform, the sensing of the vehicles can be enhanced. This also enables coordinated driving decisions, which can improve traffic operations, especially at bottleneck locations. This paper addresses the problem of coordinating the vehicles near the bottleneck locations to help the vehicles passing the area quickly and smoothly. A lane advisory algorithm is designed to reduce conflicts by encouraging early lane changes. A coordinated vehicle movement planning algorithm is proposed to achieve a smooth longitudinal reference speed profiles for vehicles in the subject area. The algorithm can open enough headway for vehicles to change the lane and continue their trips. The effectiveness of the algorithm is evaluated using SUMO (Simulation of Urban MObility) as the simulation tool with no communication between vehicles as the benchmark case as well as the case where the vehicular traffic follows the so-called First-in-First-Out (FIFO) principle. The results of the evaluation summarize and indicate that the Coordinated Control Algorithm (CCA) proposed in this paper can improve traffic performance in terms of the average speed, the waiting time, the total travel time, and the traffic flow rate under different levels of service.

INDEX TERMS Coordinated control, coordinated movement planning, intelligent and connected vehicles, lane advisory, non-recurrent bottlenecks.

I. INTRODUCTION Intelligent and Connected Vehicle (ICV) is expected to revolutionize the current features of traffic and vehicles [1]. With the real-time communication among the vehicles, the roadside infrastructures, and the cloud platform, the sharing of extra-vehicular data can improve the safety, efficiency, comfort, and convenience of the transportation system [2]. The cloud platform for ICV can provide applications from cooperative safety systems [3] to enhanced driver information, as well as fleeting management [4], parking payment [5] and multimedia application system [6]. This paper focused on the applications related to the cooperative safety systems supported by the cloud platform. The applications can interfere with the vehicles’ behavior to improve the traffic performance and enhance safety by gathering and computing the information, providing lane changing recommendations and even precise executing behaviors [7].

One promising feature of ICV is the coordinated control of the vehicles through the cloud platform [8], particularly in the scenario of any bottleneck on the road. One reason is that drivers tend to choose some high-risks driving operations in such scenario, including emergency brake, constrained lane change [9], which is unsafe and is likely to bring down the traffic performance. There are two kinds of bottlenecks, recurrent and non-recurrent. Approximately half of the bottlenecks are recurrent and usually caused by road layout changes, like on-ramp merging and lane-drops. Another half is non-recurrent and can be caused by incidents such as traffic accidents, and work zones that can happen...
any case of non-recurrent one is more complicated because of the complex network topology or the dynamic and stochastic traffic flow operation [11]. The recurrent bottlenecks are often predictable, so it’s relatively easy for the vehicles to shift their lane in advance to avoid conflicts with the merging vehicles, and the corresponding lane change behaviors only happen in a rather restricted area or even a fixed point. Unlike the recurrent situation, because of the unpredictability of the bottleneck, there would be more disruptive lane change behaviors near the non-recurrent bottleneck area, which are more likely to cause traffic congestion and traffic accidents. In this circumstance, those vehicles rushing on a freeway need a see-through sensing technology, highly available and reliable traffic coordination methods to support them to avoid the non-recurrent bottlenecks in advance. With the cloud platform of ICV, it is possible for the vehicles to choose their target lane earlier and the lane change point more freely, making the driving behavior even more stochastic. Thus, an appropriately designed coordination method is needed to help vehicles traverse the bottleneck area safer and quicker. This paper mainly discusses the non-recurrent bottlenecks, especially on the freeway, which has much impact on ICV vehicles’ safety.

Under the current circumstances of the ICV industry, due to the restriction of sensing, vehicles will not be able to know that there is a bottleneck on the coming route until they arrive at the spot. Then, they always have to wait and try to cut in, which will cause a severe drop in the flow of the adjacent lanes and may further trigger congestions. In the system of ICV, the intelligent roadside infrastructures can detect all the vehicles and other traffic participants like VRUs (Vulnerable Road User) by target detection and recognition using deep learning methods. The results of the detection can be further computed to obtain the speed and acceleration for each participant, and the ICV can report their state information to the cloud platform by V2I/V2N communication. What’s more, the infrastructures can also detect the possible bottlenecks on the road and relay the information to all the subject vehicles. This can greatly expand the sensing range of the vehicles, and the vehicles can adjust their driving behavior based on the information computed by the cloud platform. If there are enough portion of vehicles which are ICV in the network, then the overall traffic performance can be improved by specific speed and lane changing commands given by a central control algorithm on the cloud platform.

Coordinated control using wireless communication among vehicles has proven to be effective to avoid collision and improve traffic performance [12]. And there are several core issues that need to be discussed in this kind of algorithm. The first one is to determine the vehicle sequence [7], [12]. In current studies, there is a tendency towards less computational load or optimal performance. The second one is to design the strategy to adjust the speed. The adjustment has to be finished rather quickly, or the vehicles have to stop to avoid the collision. However, the acceleration has to be small enough to avoid the uncomfortable driving experience.

Given that the real world demonstration of most ICV solutions is based on the deployment of wide area roadside infrastructures and the reconstruction of an efficient communication network along the roads, it is usually infeasible to carry out real car experiments directly on freeways, but rather to validate the methods by a series of simulation tests. Our motivation is exactly based on this background.

To solve the aforementioned problems, a novel coordinated control algorithm (CCA) is proposed for ICVs at the non-recurrent freeway bottlenecks. In this algorithm, first, a method based on a decision tree is used to determine the vehicle sequence. Then, an adaptive speed adjustment strategy is designed to generate the trajectory for each vehicle, the speed of which has the same smoothness as its leading vehicle. Finally, to reduce the computational load in the coordinated control process, a lane advisory algorithm is proposed to give the recommendation of the vehicle on which lane to take while they are rather far away from the bottleneck.

To validate the proposed method, we used the common recognized benchmark tool SUMO (Simulation of Urban MOBility) and carried out the experiments under five different LOS levels. The results show that CCA can improve the traffic performance in terms of average speed, waiting time, and traffic flow rate. Our experiments also considered the adopting rate of the connected vehicles. The result shows a better performance when the adopting rate is higher than 0.5. These results indicate that the method proposed in this paper is worth implementing for real world applications.

The rest of the paper is organized as follows. After the introduction, Section 2 reviews some current studies on the coordinated control for connected vehicles at both recurrent and non-recurrent bottlenecks. Section 3 formulates the coordinated control problem at non-recurrent freeway bottlenecks. Section 4 presents the Coordinated Control Algorithm (CCA) to provide the vehicle with possible better lane choices as well as a smooth and safe speed profile to pass the bottleneck area. Section 5 analyses the simulation results. Finally, some concluding remarks are given in Section 6.

II. RELATED WORK

There has been a lot of work aimed at optimizing the traffic flow at freeway bottlenecks mainly regarding two aspects including the detection of the traffic bottlenecks and the coordinated control methods to pass the traffic bottlenecks section.

First, as to the bottleneck detection, the amounts of literature about traffic participant recognition methods based on kinds of sensors like visual, ultrasonic, LiDAR and radar are increasing rapidly [13]–[16]. Although most of the methods among them are focusing on enhancing the vehicle side intelligence, some of these works are also enlightening researches on the roadside intelligence which is more essential than ever to ICVs safety on the freeway. Li and Yang, et al. proposed several pedestrian detection models based on the
frontier deep learning network Yolo, to recognize potential bottlenecks which could be caused by VRUs under poor lighting conditions like haze to ensure the safety of autonomous vehicles [13]. Research on fusion methods based on heterogeneous sensors to detect road obstacles is becoming the trend of traffic bottleneck detection and avoidance [17].

Both two parts of the traffic flow optimization at bottlenecks are influential to the ICVs at freeway, while in this paper we particularly summarize those deeply related works on post traffic bottleneck detection. Thus, on the second, there are plenty of the published literatures mostly focusing on the coordinated control methods to solve the merging and control problem of vehicles on freeway especially at the recurrent bottleneck scenarios. Only a small amount of them are discussing the coordinated control methods at the non-recurrent bottleneck scenarios.

According to the study of Rios-Torres and Malikopoulos [18], the coordinated merging problem can be solved sequentially, and some researches have been done to generate the vehicle sequence used in coordinated control. FIFO (First in first out) is a widely used rule-based method, and it decides the sequence by the time-till arrival of each vehicle. Miculescu and Karaman [19] applied this method in a polling-system-based coordination in intersections with no traffic signals, which can reduce the delay time and is computationally efficient. Ding et al. [20] formulates the scheduling process as a mixed integer linear programming problem and can generate a near-optimal merging sequence which can improve the traffic efficiency and reduce the computational cost.

The optimal control method adopts the idea of control theory. For the optimal control problem with constraints, using Hamiltonian function can get the optimal results. Rios-Torres and Malikopoulos [18] applied this method to the address ramp metering problem. And the method can reduce significantly both fuel consumption and travel time under the hard constrains of collision avoidance and without creating congestions.

Athans [21] proposed an optimization-based method to formulate the merging problem as a linear optimal regulator minimizing the speed errors, without considering the travel time. Raravi et al. [22] formulated the merging problem as a non-linear optimization problem which can generate a local optimum. Xie et al. [23] provided an optimal control strategy for freeway ramp operation, giving the vehicles second-by-second accelerations to maximize the total speed of all vehicles over a projected short time period. One problem that lies in optimization-based method is that the computing time cannot meet the requirement for real-time applications with a large number of vehicles (e.g., more than 15 vehicles). Wang et al. [24] used virtual platooning method to the merging problem which can give the smooth speed trajectory to the merging vehicle, and the simulation results showed that letting one vehicle on the ramp to enter into the main lane in turn affects the traffic flow of the main lane less than making a platoon to merge into the main lane.

There are plenty of papers on the traffic control method. Li and Sun [25] proposed a signal control optimization method for urban traffic network based on the cell transmission model. It is proposed to solve the coordination at intersection while in this paper we mainly focus on those works proposed to solve the coordination at freeway. Milanés et al. [26] proposed a cooperative adaptive cruise control algorithm using an open-loop controller with a second-order transfer function. The controller was designed under the standard PD (Proportional and Derivative) control structure and used to maintain the desired time gap. It can be also used to control the gap between two interested vehicles. Zhang and Ioannou [27] used a variable speed limit with lane change control to improve the traffic mobility, in which the relationship between the bottleneck capacity and the lane change behavior as well as the length of the lane change area are studied.

For recurrent bottleneck scenarios, the reduction in discharge rate typically ranges from 5% to 15% [28]. But for the non-recurrent bottlenecks, the reductions are much more significant and trigger moderate to severe congestion [29], and speed and flow rate may vary significantly among lanes with lower speed and flow closer to the bottleneck [30]. Therefore, the methods mentioned above are not very suitable for the non-recurrent bottlenecks involving lane blockage. In fact, there are very few researches aiming at the coordinated control problem at the non-recurrent bottlenecks. Chen et al [31] developed a variable speed limit (VSL) strategy to proactively improve the discharge rate of non-recurrent bottlenecks and manage the upstream queue for smoother speed transition, achieved by clearing the queue near the bottleneck and the maintaining a stable maximum flow with harmonized speed to minimize disruptive lane changes. This method regulates the driving behavior in a macroscopic way without coordinated control of each vehicle in the network, and it is less effective in the microscope simulations or tests.

III. PROBLEM FORMULATION

This paper focuses on the non-recurrent bottleneck scenario illustrated in Fig. 1, with a typical freeway section that has a bottleneck blocking one lane, which is used to formulate the proposed algorithm.

Table. 1 summarizes some of the major variables and corresponding definitions used in the paper. The section is 1000m long. 20m ahead of the location of the bottleneck is called the latest lane-change point, for 20m is generally the space a vehicle needs to perform a lane change maneuver [32].
The lane blocked by the bottleneck is referred to as lane \textsubscript{BN}. Each vehicle is subject to second-order dynamics:

\[ \ddot{x}(t) = a(t) \] (1)

where \( 0 \leq \dot{x}(t) \leq v_{\text{max}} \) are the constraints for velocity, and \( |\ddot{x}(t)| \leq a_{\text{max}} \) is the constraints for accelerations.

Before we move to the details of the algorithm, we need to introduce some brief background on drivers’ lane changing behavior. There are basically two kinds of lane change behaviors, including discretionary and mandatory lane changes [33]. A driver may change the lane just to improve the driving conditions or yield to other vehicles and help them gain better conditions (called a discretionary lane change). Or, a driver can be forced to shift the lane because of some unavoidable factor (called a mandatory lane change), and in our case, it is the bottleneck that blocks the lane. Mandatory lane change maneuvers will cause conflicts among vehicles, even result in congestions. On the other hand, discretionary lane change behavior can help to reduce the conflicts. In other words, the influence can be better contained by encouraging some early discretionary lane changes in advance of the subject area caused by the bottleneck.

Based on the aforementioned discussion on lane change behavior, the subject area is then divided into two zones according to the distance from the bottleneck, as shown in Fig. 1. As the name implies, the discretionary lane change only happens in the Discretionary Driving Zone (DDZ), and the mandatory lane change only happens in the Coordinated Control Zone (CCZ).

The length of each zone is designed to deal with the fact that the density of vehicles is changing constantly, which is strongly related to the interference among vehicles. Therefore, the length of each zone is dynamically decided according to the current LOS (Level Of Service) of the freeway. LOS is one of the criteria for the measurement of driving experience. And the relation between LOS and the density of the freeway is shown in Table 2. The higher LOS is, the crowder the road is, and thus the interference among cars is stronger. And CCA needs the information of a larger cluster of vehicles to make the vehicles move smoother and safer.

\begin{align*}
L_{\text{CC}} &= (\text{LOS} - 1) \times 100 \\
L_{\text{DD}} &= \text{dis}_{\text{LC}} \times n
\end{align*}

As (2) shows, when LOS is 1, the length of CCZ is 0. This is because when the LOS is 1, interference among vehicles is infinitesimal, and small accidents are not going to cause congestions or a noticeable decrease in the traffic flow. When the speed limit is smaller, the length of each zone can be reduced accordingly.

We present each vehicle as a two-dimensional object with length \( l_i \), and the vehicle will take up the lateral space of the lane, so the width of the vehicle won’t be considered and only the longitudinal gap will be considered for the lane change maneuver. For the discretionary lane change, the algorithm will check whether the ego vehicle can change to a better lane based on the gaps between the vehicle and its surrounding vehicles. For the mandatory lane change, first, the leader and follower of the vehicle on lane \textsubscript{BN} needs to be determined in advance. If the gaps between the ego vehicle and its leader and follower on the target lane are less than the minimum safety gap (\( l_{\text{safetyGap}} \)) based on their current speed, then, the speed...
adjustment is performed and the mathematical modeling is described in (3):

\[
\begin{align*}
\int_{t_{\text{start}}}^{t_{\text{LC}}} v_{\text{EV}} (t) \, dt &= |x_{\text{EV}} (t_{\text{start}}) - x_{\text{EV}} (t_{\text{LC}})| \\
\int_{t_{\text{start}}}^{t_{\text{LC}}} v_{\text{LV}} (t) \, dt &= |x_{\text{LV}} (t_{\text{start}}) - x_{\text{LV}} (t_{\text{LC}})| \\
&= \frac{v_{\text{EV}} (t_{\text{LC}}) - v_{\text{LV}} (t_{\text{LC}})}{v_{\text{EV}} (t) - v_{\text{LV}} (t)} \\
&\leq |x_{\text{EV}} (t_{\text{LC}}) - x_{\text{NV}} (t_{\text{LC}})| + (|v_{\text{EV}} (t_{\text{LC}}) - v_{\text{LV}} (t_{\text{LC}})|) \\
&\leq |x_{\text{EV}} (t_{\text{LC}}) - x_{\text{LV}} (t_{\text{LC}})| + (|v_{\text{EV}} (t_{\text{LC}}) - v_{\text{LV}} (t_{\text{LC}})|) \\
&\leq \frac{a_{\text{EV}} (t_{\text{LC}}) - a_{\text{LV}} (t_{\text{LC}})}{a_{\text{EV}} (t) - a_{\text{LV}} (t)} \\
&t_{\text{start}} \leq t_{\text{LC}} \leq t_{\text{end}}
\end{align*}
\]

where EV represents the ego vehicle that is currently under the observation, LV represents the leading vehicle driving in front of EV on the target lane for the lane change maneuver, and BN represents the bottleneck on the road.

(a) The first two lines in equation (3) calculate the distance that EV and LV travel during the speed adjustment process respectively.

(b) The third line in equation (3) ensures that the distance between EV and LV after the speed adjustment process is no less than \( t_{\text{safetyGap}} \), which is determined by Algorithm 3.

(c) The fourth and fifth constraints in equation (3) are the speed and acceleration after the speed adjustment process.

For real-time implementation, after the speed adjustment process, the gap between EV and LV should be no less than \( t_{\text{safetyGap}} \). At the same time, the speed and acceleration of EV also become the same as LV to keep the smoothness of the lane change maneuver from more frequent interfere for the vehicles on the target lane.

This modeling is a special type of two point-boundary-value problem, which is hard to find an optimal real-time solution. So, the optimization method is unsuitable for the time-sensitive application on the cloud platform. Thus, an adaptive speed adjustment strategy is proposed to solve the modeling in equation (3) for real-time implementation.

The adaptive speed adjustment strategy can coordinate the vehicles’ movement near the bottleneck area and split the relevant vehicles on the target lane into a proper space for vehicles on \( Lane_{\text{BN}} \) to cut in. While proper lane change control is proven to be very useful to increase the traffic flow. So we combine the coordinated movement planning with lane change control to form the core concept of CCA.

The details of CCA are shown in Algorithm 1.

As shown in Algorithm 1, CCA basically contains two main algorithms, including the lane advisory algorithm and the coordinated movement planning algorithm.

First, CCA decides the current LOS of the bottleneck section based on the density calculated in the last step and decides \( L_{DD}, L_{CC} \) accordingly. Second, after collecting data for all vehicles in the bottleneck section, each vehicle will be sorted into different zones ordered by the distance to \( x_{\text{BN}} \). For vehicles in DDZ, LAA (Lane Advisory Algorithm) is applied, and for those in CCZ, CMPA (Coordinated Movement Planning Algorithm) is applied, and the recommending or control messages will be sent to the vehicles respectively.

### Algorithm 1 Coordinated Control Algorithm (in Each Time Step)

**Input:** data for vehicles including vehicle ID, lane index, speed, location, vehicle length

**Output:** the velocity profiles and lane change information

1. \( \text{los} := \text{S.getCurrentLOS(density)} \)
2. \( L_{DD}, L_{CC} := \text{S.getZoneLength(los)} \)
3. // collect the real-time data of all the vehicles in the subject area
4. \( \text{S.collectData}(x_{\text{BN}}) \)
5. for every vehicle \( v_i \) do:
   6. // decide the zone the vehicle is in based on its position
   7. \( \text{S.decideZone}(v_i) \)
   8. for every vehicle \( v_i \) in \( DDZ \) do:
   9. // apply the lane advisory algorithm to vehicles in \( DDZ \)
   10. \( \text{S.laneAdvisory}(v_i) \)
   11. for every vehicle \( v_i \) in \( CCZ \) do:
   12. // apply the coordinated movement planning algorithm to vehicles in \( CCZ \)
   13. \( \text{S.movementPlanning}(v_i) \)
14. end

### IV. COORDINATED CONTROL ALGORITHM

This section elaborates CCA applied at non-recurrent freeway bottlenecks, which is composed of two algorithms used in different zones as mentioned in section 3.

#### A. LANE ADVISORY ALGORITHM

LAA (Lane Advisory Algorithm) is applied to vehicles in DDZ. The basic concept of this algorithm is shown in Fig. 2, which depicts a traffic scenario in two successive time steps. Suppose there is a bottleneck on the lane 1, in time step \( t(0) \), vehicle C performs a lane change maneuver to avoid the collision with the bottleneck since there is enough space to make the change happen. But for vehicle A, it is a little trickier because the target lane for its lane change maneuver is crowded, if vehicle A were to change the lane, it would cause conflict with vehicle B and the vehicles behind it in time step \( t(1) \). Meanwhile, if LAA is applied since there are sufficient gaps for vehicle B to make a discretionary lane change to the right-side lane, a new gap is made for vehicle A to change to lane 2 consequently, as well as reducing the possible conflicts.

In this algorithm, we suppose that: (1) connected vehicles can take the information from the cloud platform; (2) the speed and position tracking error of the vehicles is small enough; (3) the physical attributes of the vehicle including types and dimensions are accessible to the cloud platform. The recommendation information including the best lane to take will be sent to the vehicles that can safely shift the lane in the next time step. The algorithm doesn’t relay control information to the vehicles.
The final step is to determine the list of vehicles which can perform the lane change maneuver safely. Specifically, the gaps between the given car and its leader and follower on the target lane should be larger than the required gap size $l_{\text{safetyGap}}$. For every vehicle, the gap is calculated using the following equations:

$$
gap_{LV} = x_{LV}(t) - x_{EV}(t) - l_{LV}$$
$$
gap_{FV} = x_{EV}(t) - x_{FV}(t) - l_{EV}
$$

where $EV$ is the ego vehicle that is currently considered; $LV$ is the leading vehicle on the target lane; and $FV$ is the following vehicle on the target lane. And $l_{\text{safetyGap}}$ is decided using algorithm 3.

Once the gaps are determined, the algorithm adds the vehicles with gaps larger than the required gap size to the changing list of the target lane. Then the algorithm will randomly send lane advisory information including the lane change direction to these vehicles, the number of which is bounded by the remaining capacity of the target lane.
Algorithm 3 Calculation on the Safety Gap

Input: positions, speeds and the maximum accelerations of the ego vehicle (EV) and its leader (LV), the length of the leader when time is \( t \)

Output: \( l_{\text{safetyGap}} \): safety gap needed for the ego vehicle to perform the lane change maneuver

1. if \( v_{LV}(t) \geq v_{EV}(t) \) then:
2. \( l_{\text{safetyGap}} = \min(l_{\text{safeGap}}) \)
3. else:
4. \( \text{duration} = \frac{[v_{EV}(t) - v(LV)]}{a_{\max}} \)
5. \( n = \lceil\text{duration}/\Delta t\rceil \)
6. \( x_{EV}(t + n) = \Delta t(m_{EV}(t) - a_{\max}\Delta t n(n + 1)/2) \)
7. if \( a_{LV}(t) \geq 0 \) then:
8. \( x_{LV}(t + n) = \Delta t(m_{LV}(t) - a_{LV}(t)\Delta t n(n + 1)/2) \)
9. else:
10. if \( v_{LV}(t) - v_{LV}'(t) \geq a_{LV}(t) \times n\Delta t \) then:
11. \( x_{LV}(t + n) = \Delta t(m_{LV}(t) - a_{LV}(t)\Delta t n(n + 1)/2) \)
12. else:
13. \( \text{duration} = \frac{[v_{LV}(t) - v_{LV}'(t)]}{a_{LV}(t)} \)
14. \( n_{LV} = \lceil\text{duration}\rangle/\Delta t\rceil \)
15. \( x_{LV}(t + n) = \Delta t\left(n_{LV}(v_{LV}(t) - a_{LV}(t)\Delta t(m_{LV}(t) - n_{LV}v_{LV}'(t)))/2\right) + \Delta t(n - n_{LV})(v_{LV}'(t)) \)
16. \( l_{\text{safetyGap}} = x_{LV}(t + n) + x_{LV}(t) - x_{EV}(t + n) - x_{EV}(t) + \min(l_{\text{safeGap}}) \)
17. \( \text{end} \)

1) SEQUENCE PLANNING STRATEGY

Just like the ramp metering problem, deciding the vehicle sequence is the first problem to deal with, because it determines the vehicles’ leader and follower for speed adjustment. A widely used method to plan the vehicle sequence is called the “first in first out (FIFO)” rule. This rule uses the distance to the bottleneck to decide the sequence. It is easy to implement, but cannot generate the best traffic flow. On the other hand, the optimization method can generate the best possible results for the given problem, but it is time consuming and cannot be applied to the real-time application in ICV.

In this paper, we propose a strategy based on the decision tree to decide the vehicle sequence. The sequence is initially formed using the FIFO strategy. Then, a decision tree is used to adjust this sequence. There are generally five cases when vehicles on lane_{BN} try to cut in and shift to the target lane, and the cases are shown in Fig. 3. And the ego vehicle in Fig 3 is the white one. The index of the vehicle in the figure indicates the order of the initial sequence.

The first case is shown in Fig. 3(a). In this case, the ego vehicle will cut in and in front of its current leader (Vehicle 2). This is because the ego vehicle is fast enough to overtake Vehicle 2, so the updated sequence will be \( (1, 3, 2) \).

The second case is shown in Fig. 3(b). In this case, the ego vehicle will cut in between its current leader (Vehicle 1) and follower (Vehicle 3) and no changes will be made to the sequence.

The third case is shown in Fig. 3(c). In this case, the ego vehicle will cut in behind its current follower (Vehicle 3). This is because the ego vehicle is too slow andVehicle 3 can never make a sufficient gap for the lane change maneuver, so it will switch the position in the sequence with Vehicle 3 and the updated sequence will be \( (1, 3, 2) \).

The fourth case is shown in Fig. 3(d). In this case, the ego vehicle and its current leader (Vehicle 1) are both on lane_{BN}. The ego vehicle will not shift the lane until Vehicle 1 does. After that, it will fit into the other four cases. No changes will be made to the sequence in the case.

The fifth case is shown in Fig. 3(e). In this case, the ego vehicle and its current follower (Vehicle 3) are both on lane_{BN}. The ego vehicle will shift the lane before Vehicle 3 does, and the rear gap is considered to be safe. No changes will be made to the sequence in the case.

For the first case, whether the vehicle can overtake its current leader on the target lane is decided by checking a list of necessary conditions:

a. the ego vehicle is faster than its current leader \( (dv = \text{plannedSpeed} - \text{leaderSpeed} \geq 0) \). The plannedSpeed incorporates speed requests by the leading vehicle on the same lane, as shown in (6).

\[
v_{\text{EV}}'(t) = \begin{cases} 
\min\left(v_{\text{safe}}, v_{\text{EV}}(t)\right), & \text{if } a_{LV}(t) < 0 \\
\min\left(v_{\text{safe}}, v_{\text{LV}}(t)\right), & \text{if } a_{LV}(t) \geq 0 
\end{cases} \tag{6}
\]

where \( v \) is the speed, \( a \) is the acceleration and \( v_{\text{safe}} \) is the maximum following speed generated using the existing car
following model. The car following model used in this paper is the Krauss Model [36].

b. the remaining distance to the bottleneck location is sufficient. In this paper, to improve the robustness of the algorithm, the remaining distance is count as the current position to the midpoint of CCZ.

c. the remaining time is sufficient to overtake the leader at the current speed difference \(dv\).

If all conditions are satisfied, the sequence will be adjusted, and the ego vehicle will update its leader to the current leader’s leader.

For the third case, the algorithm will decide whether its current follower can slow down and create sufficient space for the lane change maneuver. This is because as the ego vehicle approaches the bottleneck (specifically, when the remaining distance is less than the braking distance), it has to slow down to make sure it will not collide with the bottleneck if it does not have the chance to shift the lane. If the follower uses the maximum deceleration and still cannot make enough space, the sequence will be adjusted.

2) ADAPTIVE SPEED ADJUSTMENT STRATEGY
One difficulty in this coordinated control problem is that during this process, the leading vehicles’ speeds are time varying and new cars entering the subject area constantly. To overcome this difficulty, an adaptive speed adjustment strategy is proposed, considering both the speed of the leading vehicle, if it exists, and the safety gap requirement for the lane change maneuver. It uses a variable structure approach to design a reference speed for the vehicles on \(lane_{BN}\), which has the same smoothness property as that of the speed of its leader on the target lane.

According to the optimal control theory, the latter vehicles should not affect the former ones. So, the algorithm adjusts the speed of vehicles with respect to its leading vehicle. There are two cases according to the lane index of the vehicle and its leader in a sequence.

(1) the two vehicles are on the same lane. In this case, the ego vehicle uses the car following model to plan its speed.

(2) the two vehicles are on different lanes. In this case, the ego vehicle uses the adaptive speed adjustment strategy to plan its speed.

The following adaptive speed adjustment strategy is proposed to address the mathematical modeling in (3).

First, a parameter named \(preGap\) is calculated to identify the relative position between the ego vehicle and its leader.

\[
preGap = x_{LV}(t_{start}) - x_{EV}(t_{start}) - l_{LV} - l_{safetyGap} \tag{7}
\]

\(preGap\) is the initial gap between vehicles considering the security need \(l_{safetyGap}\). If \(preGap > 0\), that means that the two vehicles already have the safety gap to change the lane, thus, no adjustment is needed. And if \(preGap < 0\), the algorithm is triggered and the following reference speed in (8) for the ego vehicle is sent to make the longitudinal speed adjustment.

\[
\begin{align*}
V_{EV}(t) &= \begin{cases} 
(1 - \alpha(t))V_{EV}(t_{start}) + \alpha(t)V_{LV}(t), & t_{start} \leq t \leq t_{LC} \\
v_{LV}(t), & t_{LC} < t \leq t_{end} 
\end{cases} \\
\alpha_0(t) &= \frac{\int_{t_{start}}^{V_{LV}(t) \, ds}}{l_{LC} - preGap} \\
\alpha(t) &= \alpha_0(t) \, \beta, \quad \beta > 0
\end{align*}
\tag{8}
\]

where \(\alpha(t)\) is a parameter that controls the variation of \(V_{EV}(t)\) according to the relative distance of the ego vehicles and its leader. \(\alpha(t)\) can also make sure after the speed adjustment is finished, the gap between the two vehicles meets the safety requirement. \(\beta\) is a parameter that controls the acceleration of the ego vehicle. The bigger \(\beta\) is, the quicker the speed adjustment will finish. Thus, the choice of \(\beta\) is not unique, it highly depends on the factors that can affect the max acceleration like the vehicle’s physical feature and the texture of the road.

Urgency is determined to help choose the value of \(\beta\). The mandatory lane change is deemed urgent if the following relation holds true.

\[
maxFollowingSpeed \times f > remainDistance - occupation \times length \tag{9}
\]

where \(f\) is a factor that encodes the time typically needed to perform a successful lane change maneuver and is set to 10 in this paper, and \(length\) is the average length of vehicles on \(lane_{BN}\) in CCZ.

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**FIGURE 3.** The relative position and speed of EV, LV and FV in CCZ in different cases of the sequence planning strategy.
If the lane change maneuver is urgent, $\beta$ is set to be 2. If not, $\beta$ is set to be 1.

Besides, to successfully apply this algorithm, for $t \geq t_{\text{start}}$, there should hold

$$v_{LV}(t) \geq v_{EV}(t_{\text{start}})$$

(10)

In fact, this condition is not necessary for the algorithm, but is helpful to smooth the changing of speed, because the direction of acceleration can stay the same. If not so and the leading vehicle is slower, then, the ego vehicle can slow down first to make it satisfied.

When the speed adjustments with both the leader and follower are finished, the ego vehicle can perform the mandatory lane change. When $x_{EV}(t) \geq x_{BN}(t)$ and the vehicle passes the bottleneck area, CCA no more collects data from the vehicle.

V. SIMULATION RESULTS

We have implemented CCA in a simulation tool called SUMO. In this section, we first introduce the design of the simulation experiments. Then, we analyze the results of the simulation.

A. SIMULATION DESIGN

To evaluate the improvement of the traffic operation caused by CCA, we use SUMO to simulate the control process at non-recurrent freeway bottlenecks. With SUMO, the positions, speeds, accelerations, and other physical attributes can be relayed to the cloud platform precisely.

First, a simple simulation is performed using the default driving model in SUMO as the benchmark case. In this simulation, there is no communication among vehicles. Then, to validate the effectiveness of the sequence planning strategy proposed in the paper, we compare CCA with the FIFO strategy.

All simulations are carried out under the same environment. The key parameters are presented in Table 3. To evaluate the robustness of the proposed method, different levels of traffic demand are considered based on the LOS of freeways. According to the LOS, we set five different traffic arrival rates $\lambda$ corresponding to the LOS from B to F. LOS A is not considered since there is no CCZ in this scenario. The portion of drivers who comply with the LAA is controlled by the adopting rate $\gamma$.

In the simulation, vehicles randomly choose the departing lane and the departing speed (varying from half of $v_{\text{max}}$ to $v_{\text{max}}$), and the traffic arrival rates follow the Poisson distribution.

B. ANALYSIS OF RESULTS

In this section, average speed, average total waiting time, total travel time (TTT), and the traffic flow rate are used to evaluate the performance of different methods. The average speed is computed as the average instantaneous speed of the vehicles in the network at 20 minutes after the simulation starts. Total waiting time is defined as the duration when the speed is less than 0.1 m/s, which includes both waiting time in the network and departure delay time caused by the slowing down of the traffic flow. Table 4 shows the simulation results of different methods under different LOSs.

Fig. 4 shows the average speed results with different LOSs. The expected average speed shown in Table 2 is generated based on the LOS criteria and Greenshields model [37], which defines the relation between density and speed in an interested area. The average speed can be significantly improved using CCA. The reason why it is higher than the expected average speed is that the expected average speed is for more general cases with man-driving vehicles, the safety gap of which is much higher at a slower speed. Compared with the FIFO-based method, when the LOS is no higher than 4, the two methods can both improve the average speed with almost the same amount. But when the LOS is higher, the FIFO-based method shows the inherent defect in the planning of the sequence. The average speed is smaller compared with the sequence planning strategy proposed in this paper.

In the simulation with SUMO, the vehicles on lane$_{BN}$ have to wait at the bottleneck and form a waiting queue while vehicles...
on other lanes will travel with the maximum safe speed. The average speed will be higher if there are more vehicles on other lanes.

Fig. 5 shows the average total waiting time of different algorithms under different LOSs. Vehicles complied with the CCA have nearly no waiting time inside the network, and this is a very important factor when the bottleneck appears and the congestion occurs. In the case of the FIFO-based method, on the other hand, some vehicles have to wait because they may pass the bottleneck section before its leader in the sequence, but instead, they have to stop and wait until their leaders pass first. For the benchmark case, since there is no coordination among vehicles, the vehicles on lane$_{BN}$ have to wait a long time to pass the bottleneck section, and the waiting time accumulates as the simulation goes on. And we also consider the time in which the vehicles have to wait outside the road network due to the slowness of the traffic flow. CCA can reduce a great amount of the departure delay, and when LOS is 6, CCA can reduce 18% of the departure delay compared with the FIFO-based method.

Table 5 shows the average total travel time in different cases. For the cases where the LOS is less than 5, using both CCA and the FIFO-based method can significantly shorten the travel time, and can keep the travel time roughly aligned with the best case. In the best case, the vehicle travels at the maximum speed (120km/s) and the travel time will be 30s. When the LOS is higher, where the traffic flow is considered to be crowded, using CCA shows the most improvement and reduces the total travel time by at least 42% compared with the benchmark case. Moreover, travel time with different lanes can be more balanced.

As shown in Fig. 6, CCA can maintain the traffic flow rate to the expected one when LOS is not higher than 4. When LOS is higher than 4, the traffic flow will be severely disturbed, but CCA can reduce the impact and improve traffic flow by rate by at least 10% compared with the benchmark case and can still outperform the FIFO-based method.

To examine the impact of the adopting rate to CCA, we conduct the following simulation. In this simulation, five cases of different adopting rates (0, 0.3, 0.5, 0.8, 1.0) under different LOSs were considered and the results were presented in Fig. 7. It should be mentioned that even if all...
FIGURE 7. Simulation results on three perspectives under different LOSs per adopting rate. (a) the relation between the average speed and the adopting rate; (b) the relation between the average waiting time and the adopting rate; (c) the relation between the traffic flow rate and the adopting rate.

the vehicles in the networks are ICV, they will not fully comply with LAA. This is because the better lane chosen in the algorithm may have conflicts with their route plan. For example, if the vehicle is about to make a right turn, it may choose to stay on the right lane instead of changing to the left side lane according to the recommendation from the algorithm.

As shown in Fig. 7(a), there is a positive correlation between the adopting rate and the average speed. When LOS is 2, CCA can work perfectly without the help of LAA. When LOS is 3 or higher, LAA shows its positive effect in reducing the density on the subject lanes. Without LAA, that is to say, the adopting rate is 0, CCA using CMPA alone can still beat the default control strategy in SUMO. And when the adopting rate is higher than 0.5, LAA can improve the performance of CCA by up to 50%. When the adopting rate is under 0.5, LAA becomes less effective, but the average speed can still be improved by around 15% when LOS is 5 or 6 if the adopting rate is 0.3. Fig. 7(b) shows the relation between the average waiting time and the adopting rate. When LOS under 5, the average waiting time is almost 0 regardless of the adopting rate. When LOS is higher, the average waiting time can be greatly reduced by encouraging early lane change behavior. Fig. 7(c) shows the change in traffic flow rate under different adopting rates. CMPA alone can meet the traffic demand when LOS is under 5. When LOS is higher than 5, the traffic flow rate can be improved by LAA since the vehicles will change to the unblocked lanes earlier without evident loss of speed.

VI. CONCLUSION

This paper delves into the coordinated control problem at non-recurrent bottlenecks on freeways for ICVs. A lane advisory algorithm is proposed to encourage early discretionary lane changes in DDZ to reduce the conflicts among vehicles when they approach the bottleneck. The simulation results show that the algorithm can effectively reduce the interference among vehicles and improve the traffic performance. Meanwhile, this algorithm can perform well when the adopting rate is higher than 0.5. Secondly, a coordinated vehicle movement planning algorithm is exploited to provide the vehicles in CCZ with the speed profiles using the vehicle sequence determined by a strategy based on the decision tree. The results from the SUMO simulation tool show that the proposed CCA can improve the traffic performance in terms of average speed, waiting time, and traffic flow rate under different LOS scenarios. When LOS is under 5, CCA can generally eliminate the negative impact of the bottleneck. When the LOS is 5 or 6, CCA still outperforms the benchmark case with no coordination among vehicles, but has an evident drop in the overall performance.

Since the study is based on the data generated from the SUMO simulation tool, the validation and calibration process from other simulation tools and field data is still needed. Meanwhile, the paper also has a shortcoming on standardizing the different data formats of the simulation environment to improve system robustness and portability. Besides, the penetration rate of ICVs is another future work. We assumed vehicles in the network all to be ICVs in the study. However,
the algorithm should also consider the impact of human-driven vehicles. One goal for our future work is to adjust the algorithms to fit with the lower penetration rate of ICVs.

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