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A Cyber-physical Framework for Optimal Coordination of Connected and Automated Vehicles on Multi-lane Freeways

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Abstract: Uncoordinated driving behavior is one of the main reasons that cause bottlenecks on freeways. This paper presents a novel cyber-physical framework for optimal coordination of connected and automated vehicles (CAVs) on multi-lane freeways. We consider that all vehicles are connected to a cloud-based computing framework, where a traffic coordination system optimizes the target trajectories of individual vehicles for a smooth and safe lane change or merging. In the proposed framework, the vehicles are coordinated into groups or platoons, and their trajectories are successively optimized in a receding horizon control (RHC) approach. The optimization of the traffic coordination system aims to provide sufficient gaps when a lane change is necessary while minimizing the speed deviation and acceleration of all vehicles. Then the coordination information is provided to individual vehicles that are equipped with local controllers, and each vehicle decides its control acceleration to follow the target trajectories while ensuring a safe distance. Our proposed method guarantees fast optimization and can be used in real-time. The proposed coordination system is evaluated using microscopic traffic simulations and benchmarked with the traditional driving (human-based) system. The results show significant improvement in fuel economy, average velocity, and travel time for different traffic volumes.

Keywords: Cyber-physical framework; connected and automated vehicles; successive optimization; vehicle coordination, vehicle platoon.

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1. Introduction

Over the past few decades, the primary issues in road transportation systems around the world have been traffic congestion, fuel consumption, greenhouse gas (GHG) emissions, and accidents due to an increase in the number of vehicles and travel demand [1]. Furthermore, traditional human driving remains to be one of the major causes of traffic bottlenecks since humans have difficulty accurately anticipating future road traffic conditions and frequently perform acceleration and braking, or an instant lane change. Schrank et al. [2] reported that traffic congestion caused American drivers to spend 8.8 billion extra hours on the road, consuming extra 3.3 billion gallons of fuel in 2017. Particularly, field studies show that stop-and-go vehicles produce 14% more emissions than vehicles traveling at a constant speed [3]. It is evident that effective measures should be taken to reduce the burden of uncontrolled traffic issues for better mobility, fuel economy, and the environment. Therefore, the concept of a coordinated traffic system is currently receiving great interest due to its potential to address a number of issues caused by human drivers, such as stop-and-go driving, travel delays, and traffic accidents [4,5].

The recent developments in connected and automated vehicle (CAV) technologies enable real-time data access and sharing with other vehicles and infrastructure via vehicle-vehicle (V2V), infra-vehicle (I2V), and vehicle-infra (V2I) communications [6,7]. When such necessary information is available, such as states (position, velocity, and acceleration) of other vehicles, destination, and speed limit, it is possible to precisely control the movement and trajectory of individual vehicles to enhance traffic flow efficiency, fuel economy, and driving safety under a connected vehicle environment (CVE) [8,9]. The CVE offers both opportunities for effectively realizing better-coordinated traffic in a road network and difficulties in utilizing a large amount of data. Additionally, it is feasible to coordinate vehicles utilizing a cloud-based centralized or decentralized controller to enhance traffic flow performance and safety [10,11]. A traffic coordination system can improve traffic flow rate and capacity by making intelligent decisions using guidance information from the global controller. Moreover, the coordination can be repeated to ensure seamless operation even if the vehicle does not execute the command or if unexpected disruptions happen [12]. As a result, it can accurately modify the whole system, which would be very challenging for a human driver to achieve.

A number of studies have developed vehicle coordination systems for CAVs using centralized or decentralized controllers to achieve safe and efficient control of traffic. Some studies developed automated vehicle intersection control systems based on reservation algorithms [13–15], whereas some works utilized signal phase and timing (SPAT) information in advance via I2V communication to control the movement of automated vehicles [16–18]. Some works proposed optimization of traffic signal phases using the state information (e.g., location and speed) of autonomous vehicles [19–21], while some studies developed coordinated intersection control systems for autonomous vehicles under CVE without using traffic signals [22–24]. Some works reported coordinated merging control systems for a safe and smooth merging of automated vehicles using ramp metering [25–27], whereas some other works developed coordinated merging control schemes for efficient merging of CAVs into roundabouts [28–30]. These works [13–30] mainly focused on vehicle coordination systems for signalized intersections or merging roads.

On the other hand, some works proposed cooperative lane-changing methods for CAVs. For example, Hu et al. [31] and Awal et al. [32] proposed local lane change coordination of autonomous vehicles, which is limited to local modifications of the traffic condition. Atagoziyev et al. [33] developed a traffic coordination system for changing lanes of autonomous vehicles before reaching a critical position. In each scenario, only one vehicle has the intention to change lanes; the surrounding connective vehicles cooperate together to adjust the formation until the central lane-change vehicle can do so safely; this single-vehicle lane change process continues sequentially if more than one vehicle intends to change lanes. Li et al. [34] proposed a two-stage multi-vehicle motion planning (MVMP) algorithm for cooperative lane changes of CAVs. After re-configuring a CAV platoon into a sufficiently sparse configuration, all lane changes are carried out simultaneously without attempts to avoid collisions. An and Jung [35] proposed a cooperative lane change protocol considering the impact of V2V communication delay. Although the aforementioned techniques [31–35] can enhance individual driving abilities, they are still inadequate to guarantee smooth lane changes for connected vehicles in congested situations.

In this paper, we develop a novel cyber-physical vehicle coordination system for efficient lane changing or merging of CAVs on multi-lane freeways. To reduce communication volume and computing burden, the vehicles are coordinated into small groups (or platoons) and their trajectories are successively optimized using a receding horizon control (RHC) approach. We assume that the information of CAVs is communicated to a cloud-based computing framework, where an optimization problem is solved to determine target trajectories (speeds and position) of individual vehicles with the goal of providing sufficient gaps during a lane change while minimizing the speed deviation and acceleration of the vehicles. Then the coordination information is provided to individual vehicles, and the local controller of each vehicle determines its control acceleration to follow the desired trajectories while ensuring driving safety. Our proposed traffic coordination system guarantees fast optimization and can be implemented in real-time. We evaluate the performance of the proposed system using microscopic traffic simulations in view of actual traffic behaviors on a real multi-lane road. It is found that our proposed system significantly improves fuel economy, average velocity, and travel time of vehicles for various traffic volumes compared to traditional human driving.

The paper is organized as follows. Section 2 describes the real traffic scenario and the fundamental idea of our proposed cloud-based vehicle coordination system. Section 3 formulates the optimization problem, including the vehicle driving system and the objective function. Section 4 presents the key simulation results. Finally, Section 5 provides the concluding remarks and future research directions.

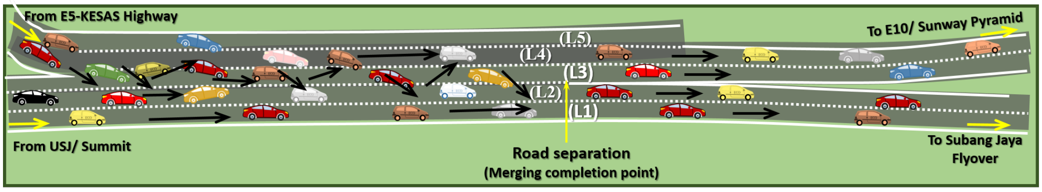


Figure 1. The study route in Subang Jaya, Malaysia, which shows an actual traffic scenario where vehicles from two roads merge and divert in both ways over a short distance, causing massive congestion every day.

2. Vehicle Coordination System

2.1. Real Scenario

In this paper, we consider a real-world traffic scenario on a real road stretch called *Persiaran Kewajipan* in Subang Jaya, Malaysia (as shown in Figure 1) to demonstrate the necessity and evaluate the effectiveness of the proposed cloud-based vehicle coordination system. The road segment is multi-lane and traffic from two roads merges and diverts on both sides over a short distance, causing severe congestion every day. More than half of the vehicles typically perform multiple lane changes within common sections of about 300 meters before diverting onto two distinct routes and often struggle to find a safe gap to execute a lane change in such a congested situation. Traffic congestion worsens when a vehicle cannot change lanes efficiently, slows down or stops other vehicles, causing disruptions in the surrounding traffic and endangering traffic safety. It is possible to prevent this sort of traffic congestion by efficiently coordinating all vehicles for timely arrival and lane changes.

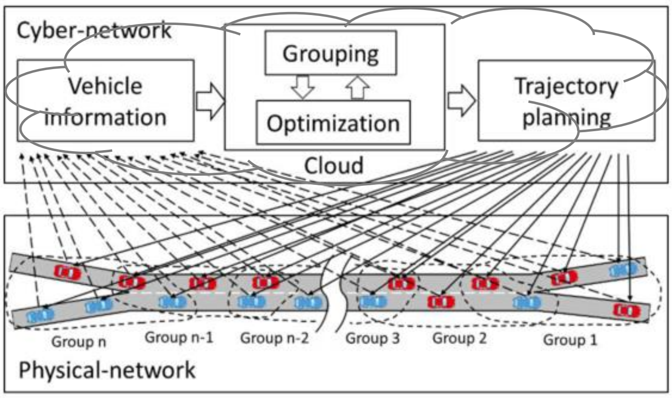


Figure 2. The fundamental idea of our proposed cyber-physical optimal traffic coordinating system. The vehicles are coordinated into groups and their trajectories are successively optimized.

2.2. Fundamental Idea

Figure 2 illustrates the fundamental idea of our proposed traffic coordination system in a cyber-physical framework. It is assumed that every vehicle on the study route is a next-generation CAV that is connected to a cloud or edge computing system, which can perform two-way communications and coordinate vehicles globally with negligible delay. The vehicles transmit their necessary information, such as the current state (position, velocity, and acceleration), the target destination, and other information to the cloud and the coordination system computes the optimal trajectory of each vehicle. Since it is time-consuming to optimize a large number of vehicles in the cloud due to communication volume and computational burden, for online implementation, the vehicles are coordinated into small groups and their trajectories are successively optimized. Specifically, vehicles in each group are simultaneously optimized considering the safety constraint imposed by vehicles in the preceding group, and the optimization is repeated in a receding horizon approach. To maintain maximum traffic performance, the traffic coordination system optimizes vehicle speed and position based on the lane change or merging desires of all relevant vehicles. Based on the coordination information, individual vehicles decide their acceleration by ensuring smooth and safe lane changes or merging on the freeway.

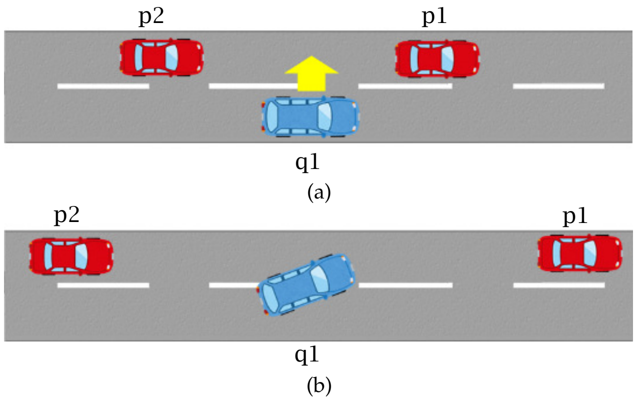


Figure 3. (a) a typical scenario for lane change cooperation request, and (b) expected scenario after coordination.

3. Formulation of Optimization Problem

We consider a two-lane freeway where most vehicles require changing lanes in accordance with the real-world scenario. The coordination method divides all vehicles into groups based on their sequences on the road at regular intervals and successively optimizes each group. Since the optimization is the same for each group of vehicles, we demonstrate the coordination process for one of these groups. In Figure 3 (a), a scenario with three vehicles is depicted, with vehicle q1 (on the right lane) needing coordination with vehicles p1 and p2 (on the right lane) for a smooth lane change. Vehicle q1 requests for a lane change but cannot change lanes due to the low safety gap between vehicles p1 and q1. An example of anticipated solutions is shown in Figure 3 (b). After receiving the request, both vehicles p1 and p2 adjust their relative distance to allow vehicle q1 to change lanes. However, depending on the relative positions and speeds of the vehicles, the expected solutions may differ. Taking into account traffic performance, a standard rule-based or hierarchical solution may not be effective. Therefore, optimal solutions are desired for all vehicles described below.

3.1. Vehicle Driving System

During a trip, a vehicle may change lanes, merge onto a different road, or both, depending on the traffic flow in the lanes and the direction it travels. The state dynamics of any vehicle $n \in \mathcal{N} = \{\mathrm{p1}, \mathrm{p2}, \ldots, \mathrm{q1}, \mathrm{q2} \ldots\}$ on either lane (left or right) in discrete-time, with a time step t of the interval Δt, can be expressed as

$$s_n(t+1) = As_n(t) + Bu_n(t), \tag{1}$$

$$A = \begin{bmatrix} 1 & \Delta t & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \text{ and } B = \begin{bmatrix} \frac{1}{2}\Delta t^2 & 0 \\ \Delta t & 0 \\ 0 & 1 \end{bmatrix}, \tag{2}$$

where $s_n(t) = [x_n(t), v_n(t), \zeta_n(t)]^{\mathrm{T}} \in \mathbb{R}^3$ denotes the state of vehicle n in terms of position $x_n(t)$, velocity $v_n(t)$, and current lane $\zeta_n(t)$, respectively, and $u_n(t) = [a_n(t), \lambda_n(t)]^{\mathrm{T}} \in \mathbb{R}^2$ is the control vector including acceleration $a_n(t) \in \mathbb{R}$ and decision about lane change $\lambda_n(t) \in \{-1, 0, 1\}$, respectively. In this case, $\lambda_n(t) = -1$ or 1 represents a lane change to the left or right, while $\lambda_n(t) = 0$ indicates no lane change. Note that the decision to change lanes is constrained by factors related to driving conditions.

Instantaneous acceleration $a_n(t)$ of vehicle n with its preceding vehicle $n-1$ is calculated using a dynamic microscopic car-following model f_{CF} called Intelligent Driver Model (IDM) [36] as

$$\begin{aligned} a_n(t) &= f_{CF}(s_n(t), s_{n-1}(t)), \\ &= a\left[1 - \left(\frac{v_n(t)}{v_n^{\mathrm{d}}}\right)^4 - \left(\frac{d^*(v_n(t), \Delta v_n(t))}{\Delta x_n(t)}\right)^2\right], \\ d^*(v_n(t), \Delta v_n(t)) &= R_0 + v_n(t)T + \frac{v_n(t), \Delta v_n(t)}{2\sqrt{a_{\max} a_{\min}}}, \end{aligned} \tag{3}$$

where the parameters v_n^{d}, R_0, T, $a_{\max}$, and $a_{\min}$ denote the desired speed, minimum gap between vehicles, safe headway time while following the preceding vehicle, maximum acceleration, and comfortable deceleration, respectively, and $\Delta x_n(t) = x_{n-1}(t) - x_n(t) - l$ (where l is the length of the preceding vehicle) and $\Delta v_n(t) = v_{n-1}(t) - v_n(t)$ are the current gap to the preceding vehicle and the speed difference, respectively. In the framework, the control input at the tth step is updated as $\forall t \in [t\Delta t, (t+1)\Delta t], a_n(t) \equiv a_n(t\Delta t)$.

The lane change decision of vehicle n depends on the states of some vehicles in the current and target lanes, which can be represented using a well-known lane change model f_{LC} called minimizing overall braking induced by Lane Change (MOBIL) [37] as

$$\begin{aligned} \lambda_n(t) &= f_{LC}(s_n(t), s_{n-1}(t), s_{n+1}(t), \bar{s}_{n-1}(t), \bar{s}_{n+1}(t)), \\ &= \begin{cases} \tilde{\zeta}_n(t) - \zeta_n(t), & \text{if } \begin{cases} \tilde{\bar{a}}_{n+1}(t) \geq -b_{\text{safe}} \text{ and,} \\ \Delta a_n(t) + \rho \Delta a_{n+1}(t) \geq \tau, \end{cases} \\ 0, & \text{otherwise,} \end{cases} \end{aligned} \tag{4}$$

where $\bar{s}_{n-1}(t)$ and $\bar{s}_{n+1}(t)$ respectively are the states of the relative preceding and following vehicles in the target lane, $\tilde{\zeta}_n(t) \in \{\zeta_n(t) + 1, \zeta_n(t) - 1\}$ denotes a lane change from the current lane $\zeta_n(t)$ to the target lane, $\tilde{\bar{a}}_{n+1}(t)$ represents an unsafe lane change of vehicle n that may cause aggressive braking of the relative following vehicle $\bar{a}_{n+1}$ in the target lane, $-b_{\text{safe}}$ is the safe braking limit, $\Delta a_n(t)$ and $\Delta a_{n+1}(t)$ respectively denote an increase in acceleration of vehicle n and collective increase in acceleration of the following vehicles in the current and target lanes due to a lane change action, ρ is the politeness factor, and τ is the threshold.

The parameters $\tilde{\bar{a}}_{n+1}(t)$, $\Delta a_n(t)$, and $\Delta a_{n+1}(t)$ are calculated using (3) as $\tilde{\bar{a}}_{n+1}(t) = f_{CF}(\bar{s}_{n+1}(t), s_n(t))$, $\Delta a_n(t) = \tilde{a}_n(t) - a_n(t)$, where $\tilde{a}_n(t) = f_{CF}(s_n(t), \bar{s}_{n-1}(t))$, and $\Delta a_{n+1}(t) = (\tilde{a}_{n+1}(t) - a_{n+1}(t)) + (\tilde{\bar{a}}_{n+1}(t) - \bar{a}_{n+1}(t)$, where $\tilde{a}_{n+1} = f_{CF}(s_{n+1}(t), s_{n-1}(t))$, $a_{n+1}(t) = f_{CF}(s_{n+1}(t), s_n(t))$, and $\bar{a}_{n+1} = f_{CF}(\bar{s}_{n+1}(t), \bar{s}_{n-1}(t)$. Based on these parameters, vehicle n decides whether to perform a safe lane change or stay at its current lane according to (4). If $\lambda_n(t) = 0$, vehicle n remains at the current lane $\zeta_n(t)$.

3.2. Objective Function

For fuel economy, comfortable and safe driving, sudden acceleration or braking is not beneficial [38]. The proposed cyber-physical traffic coordination system receives information on the states of vehicles within a group or platoon and computes the optimal trajectory for any vehicle n using a receding horizon control (RHC) approach. Specifically, we formulate an optimization problem that minimizes an objective function by providing a sufficient gap for smooth and safe lane changing or merging while maintaining the speed deviation and acceleration at the optimum level. Some constraints are defined in optimization considering driving comfort and regulations related to a road network, such as the speed limit. Moreover, to avoid collisions or aggressive braking, a safe distance between any preceding vehicle $n-1$ and its following vehicle n is necessary, which is dynamically given by the nonlinear constraint as $a_n(t) \leq f_{CF}(s_{n-1}(t), s_{n-2}(t))$.

To implement the traffic coordination system, the optimization problem is solved by minimizing an objective function at each time t as

$$\begin{aligned} J(s_n(t), a_n(t)) = \sum_t^H \Bigg\{ \sum_{n\in\mathcal{N}} \Big(w_1 (v_n(t) - v_n^{\mathrm{d}})^2 + w_2 a_n^2(t) \Big) \\ + \sum_{p\in\mathcal{P}} \sum_{q\in\mathcal{Q}} w_3(\delta_p + \delta_q) e^{-\alpha(x_p(t) - x_q(t))^2} \Bigg\}, \end{aligned} \tag{5}$$

subject to

$$\begin{aligned} &v_{\min} \leq v_{\mathrm{n}}(t) \leq v_{\max}, \\ &a_{\min} \leq a_n(t) \leq a_{\max}, \\ &a_n(t) \leq a_{n-1}(t), \end{aligned}$$

where H is the time horizon, $\mathcal{N}$ is the set of vehicles in the partial optimization group, $\mathcal{P}$ and $\mathcal{Q}$ are the number of vehicles in the left and right lanes, $\delta_p, \delta_q \in \{0,1\}$ denotes the need for the vehicles to change lanes (i.e., 1 indicates a lane change is necessary and vice versa), α is a positive constant, x_p and x_q are the position of vehicles on the left and right lanes, and w_1, w_2, and w_3 are the waiting factors corresponding to the velocity, acceleration, and safe lane change terms, respectively. The first term of the objective function implies a penalty when the current velocity $v_n(t)$ of vehicle n deviates from v_n^{d}, the second term is the cost of acceleration along the freeway, and the third term represents a penalty for an unsafe lane change at the target time t due to insufficient gap. The objective function J is minimized by selecting the proper speed for each vehicle n, subject to the aforementioned constraints.

In the above optimization problem, the vehicles coordinate to create sufficient gaps only when a lane change is required while keeping the speed deviation and acceleration at the minimum level. We assume that the states and destination (target lane) of all vehicles are available to the cloud-based computing framework, where the optimization problem is solved for successive groups of vehicles, and the optimized target speeds and positions are subsequently communicated to individual vehicles. After obtaining the coordination information, the lane change of each vehicle is implemented using (4). In such a manner, the controller drives the vehicles safely until the next coordination phase, and the optimization is repeated in the cloud for the new group of vehicles.

4. Simulation Results

To demonstrate the effectiveness of the proposed traffic coordination system, we have developed a multi-lane simulation framework in MATLAB (which has been demonstrated to be mathematically reliable and utilized to model numerous real-world situations) based on the real study route and solved a nonlinear optimization problem (described in (5)) in discrete time. The arrival of vehicles in the simulator is decided randomly using a probability distribution to produce realistic traffic flows. In the simulation, all vehicles are considered to be the same size and length. The simulation parameters are chosen as $v_n^{\mathrm{d}} = 23$ m/s, $R_0 = 2$ m, $T = 1.5$ s, $l = 5$ m, $v_n \in [0, 25]$ m/s, $a_n \in [-2.5, 1.5]$ m/s^2, $b_{\mathrm{safe}} = 5$ m/s^2, $\rho = 0.1$, $\tau = 0.25$, $w_1 = 0.1$, $w_2 = 1$, $w_3 = 0.3$, and $\alpha = 0.001$. We set a suitable prediction horizon of $H = 5$ s with 10 steps and the step size of $\Delta t = 0.5$ s.

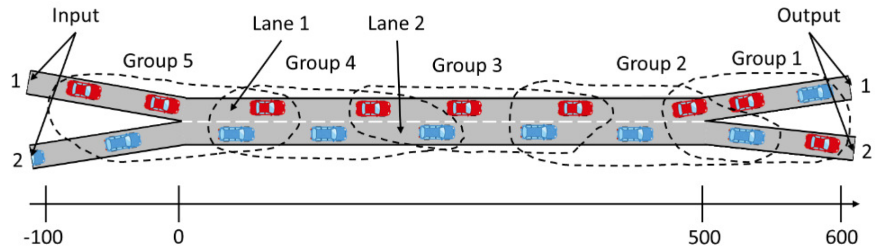
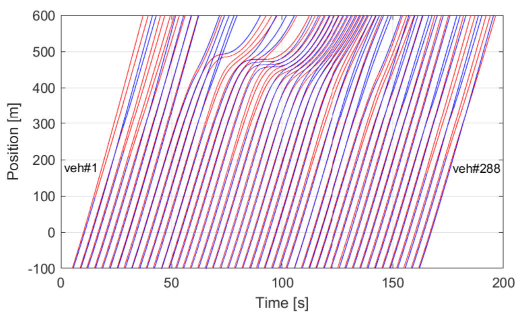


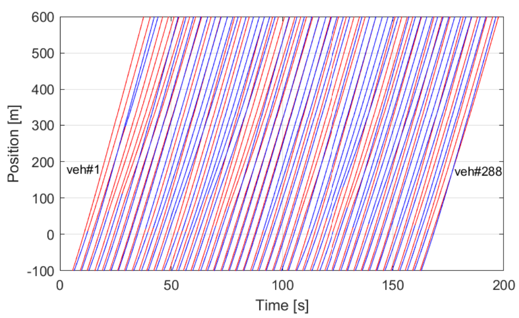
Figure 4. Multi-lane road network used for simulation and evaluation of the proposed traffic coordination system.

The simulation framework is depicted in Figure 4, whereby roadways 1 and 2 share a portion between 0 and 500 m, where vehicles may change lanes depending on their destination. In traditional driving systems, vehicles that need to change lanes slow down and wait for the appropriate time to do so when approaching the merging junction. Consequently, the vehicles in the opposite lane may also slow down to make space for the awaiting vehicles to change lanes, which may reduce the overall traffic flow performance in the network. Moreover, finding safe gaps to perform lane changes in a congested situation is challenging. In the proposed traffic coordination system, vehicles between -100 and 600 m are divided into multiple groups and optimized every 5 s. Note that here we consider a suitable optimization horizon; since traffic flow experiences substantial variations, a long horizon would not be helpful.

Figure 5 shows the trajectory of each vehicle in dense traffic for both traditional and coordinated driving systems while traveling about 600 m on the study multi-lane freeway. In the traditional driving system (Figure 5(a)), some vehicles were unable to change lanes in time, slowing them down and blocking others, causing long queues and traffic congestion, whereas, in the proposed coordination system (Figure 5(b)), vehicles can smoothly change lanes without interrupting surrounding traffic. The velocity profiles of vehicles for the traditional driving system and the proposed coordination system are shown in Figure 6(a) and 6(b), respectively. In the traditional driving system, some vehicles quickly slow down and/or come to a complete stop before lane changes. In the proposed coordination system, however, vehicles can smoothly change lanes by slowing down from the peak speed to a level of about 14 m/s. Figure 7 depicts the acceleration profiles of these vehicles. Compared to the traditional driving system, the proposed coordination system performs significantly low deceleration of about -0.4 m/s^2 during lane changes. The aggressive braking in traditional driving reduces traffic performance and driving safety. In contrast, smooth braking in coordinated driving promotes improved kinetic energy usage, which lowers vehicle fuel consumption.

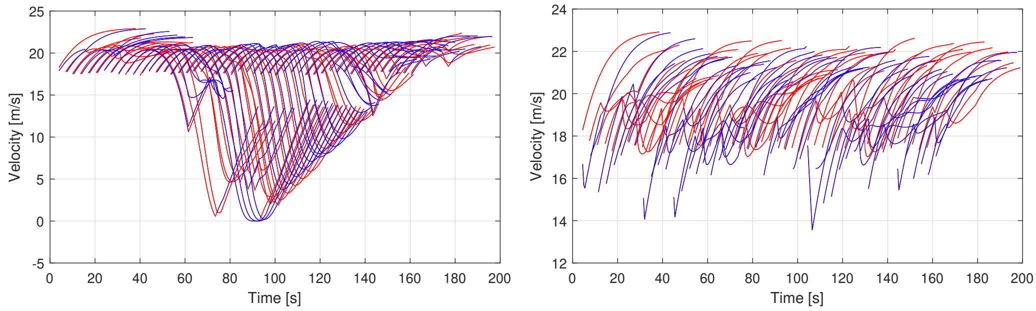


(a)



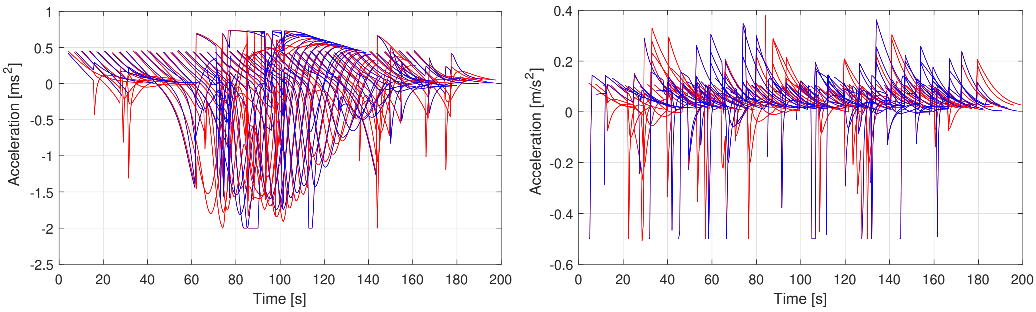
(b)

Figure 5. Trajectories of the vehicles traveling about 600 m in 200 s on the study multi-lane freeway. The sub-figures show (a) the traditional driving system and (b) the proposed traffic coordination system.



(a) (b)

Figure 6. Velocity profiles of the vehicles showing speeding and slowing down characteristics for (a) the traditional driving system and (b) the proposed traffic coordination system.



(a) (b)

Figure 7. Acceleration profiles of the vehicles showing the level of aggressiveness for (a) the traditional driving system and (b) the proposed traffic coordination system.

Figure 8 compares the simulation results of the traditional driving system and the proposed traffic coordination system using four important performance measures of traffic flow, including average travel time, average idling time, average velocity, and average fuel consumption. The traveling time is the time it takes for a vehicle to drive the study road segment, and the idling time is the total time it takes for a vehicle to stop and wait at the merging junction during lane changing. The average speed is the total speed of all vehicles divided by the total number of vehicles in the simulation, while the average fuel consumption is the cumulative fuel consumption divided by the number of vehicles in the road segment.

Figure 8(a) and (b) respectively show that the average traveling time and the idling time of the proposed traffic coordination system are significantly reduced compared to the traditional driving system for different traffic demands. This is due to the fact that the coordinated vehicles make early decisions and require minimal waiting time to execute lane changes. Furthermore, the proposed coordination system considerably increases average speed compared to the traditional system (as shown in Figure 8(c)) because coordinated vehicles rarely need to slow down or stop before changing lanes or merging, resulting in smoother flow. Finally, Figure 8(d) illustrates the comparison of average fuel consumption for both systems. It is evident that the proposed traffic coordination system outperforms the traditional driving system for various traffic volumes. The percentage improvements in average travel time, average velocity, and average fuel consumption by the proposed traffic coordination system are given in Table 1.

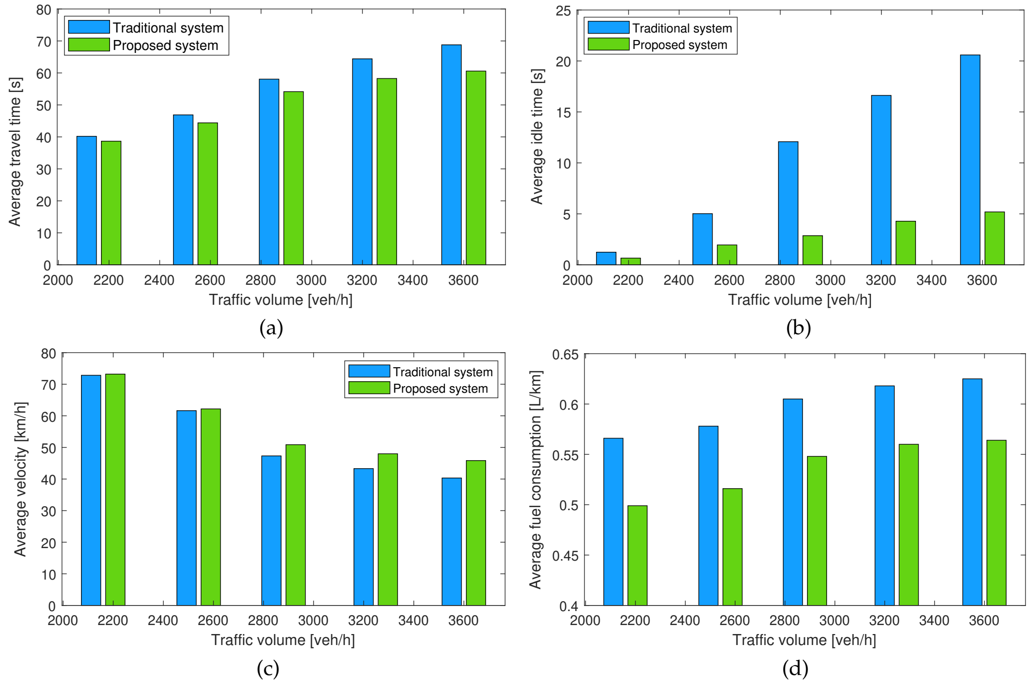


Figure 8. Performance comparison (a) average travel time, (b) average idling time, (c) average velocity, and (d) average fuel consumption of the traditional driving system and the proposed traffic coordination system for various traffic volumes on the study freeway.

Table 1. Performance comparison between the proposed traffic coordination system and the traditional driving system.

	Traditional system	Coordination system	Improvement
Average travel time [s]	55.68	51.20	8.05%
Average velocity [km/h]	53.08	56.02	5.53%
Average fuel consumption [L/km]	0.5984	0.5374	10.19%

5. Conclusions

In this paper, we have developed a novel cyber-physical framework for optimal coordination of CAVs on multi-lane freeways. Using a receding horizon control (RHC) approach, the vehicles are coordinated into successive groups for a smooth and safe lane change or merging. We assume that the information of all vehicles is available to a cloud-based computing framework, where an optimization problem is solved to calculate the target speeds and positions of individual vehicles in a group. Following that, the coordination information is provided to individual vehicles, and the local controller of each vehicle determines its control acceleration to follow the desired trajectories while ensuring driving safety. The proposed traffic coordination system is evaluated considering real-world traffic conditions on a real multi-lane road. The results show that the proposed framework significantly improves the fuel consumption, average velocity, and travel time of vehicles for different traffic demands. Our proposed method can be implemented online, as the computing burden is almost negligible.

In future work, we will investigate mixed traffic performances for various penetration rates of CAVs. The proposed framework can be further extended using distributed model predictive control (MPC) for individual vehicles.

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References

1. Chang, Y. S.; Lee, Y. J.; Choi, S. S. B. Is there more traffic congestion in larger cities?-Scaling analysis of the 101 largest US urban centers. *Transport Policy* **2017**, *59*, 54–63.
2. Schrank, D.; Eisele, B.; Lomax, T. 2019 urban mobility report. Report, Texas A&M Transportation Institute and INRIX, USA, 2019.
3. Xia, H.; Boriboonsomsin, K.; Schweizer, F. et al. Field operational testing of eco-approach technology at a fixed-time signalized intersection. In *Proc. IEEE International Conference on Intelligent Transportation Systems (ITSC)* **2012**, 188–193.
4. Mahbub, A. I.; Malikopoulos, A. A.; Zhao, L. Decentralized optimal coordination of connected and automated vehicles for multiple traffic scenarios. *Automatica* **2020**, *117*, 108958.
5. Liu, C.; Zhang, Y.; Zhang, T.; Wu, X.; Gao, L.; Zhang, Q. High throughput vehicle coordination strategies at road intersections. *IEEE Transactions on Vehicular Technology* **2020**, *69(12)*, 14341–14354.
6. Li, L.; Wen, D.; Yao, D. A survey of traffic control with vehicular communications. *IEEE Transactions on Intelligent Transportation Systems* **2013**, *15(1)*, 425–432.
7. Talebpour, A.; Mahmassani, H. S. Influence of connected and autonomous vehicles on traffic flow stability and throughput. *Transportation Research Part C: Emerging Technologies* **2016**, *71*, 143–163.
8. Hu, X.; Sun, J. Trajectory optimization of connected and autonomous vehicles at a multilane freeway merging area. *Transportation Research Part C: Emerging Technologies* **2019**, *101*, 111–125.
9. Bakibillah, A.S.M.; Hasan, M.; Rahman, M.M.; Kamal, M.A.S. Predictive car-following scheme for improving traffic flows on urban road networks. *Control Theory Technology* **2019**, *17*, 325—334.
10. Jeong, J.; Jeong, H.; Lee, E.; Oh, T.; Du, D. H. SAINT: Self-adaptive interactive navigation tool for cloud-based vehicular traffic optimization. *IEEE Transactions on Vehicular Technology* **2015**, *65(6)*, 4053–4067.
11. Bakibillah, A.S.M.; Kamal, M.A.S.; Tan, C.P. The optimal coordination of connected and automated vehicles at roundabouts. In Proceedings of the 58th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE), Hiroshima, Japan, 10–13 September 2019; pp. 1392–1397.
12. Pendleton, S. D.; Andersen, H.; Du, X.; Shen, X.; Meghjani, M.; Eng, Y. H.; Rus, D.; Ang Jr, M. H. Perception, planning, control, and coordination for autonomous vehicles. *Machines* **2017**, *5(1)*, 6.
13. Dresner, K.; Stone, P. A multiagent approach to autonomous intersection management. *Journal of Artificial Intelligence Research* **2008**, *31*, 591–656.
14. Huang, S.; Sadek, A.W.; Zhao, Y. Assessing the mobility and environmental benefits of reservation-based intelligent intersections using an integrated simulator. *IEEE Transactions on Intelligent Transportation Systems* **2012**, *13(3)*, 1201–1214.
15. Ma, M.; Li, Z. A time-independent trajectory optimization approach for connected and autonomous vehicles under reservation-based intersection control. *Transportation Research Interdisciplinary Perspectives* **2021**, *9*, 100312.
16. Mahler, G.; Vahidi, A. An optimal velocity-planning scheme for vehicle energy efficiency through probabilistic prediction of traffic-signal timing. *IEEE Transactions on Intelligent Transportation Systems* **2014**, *15(6)*, 2516–2523.
17. Yu, K.; Yang, J.; Yamaguchi, D. Model predictive control for hybrid vehicle ecological driving using traffic signal and road slope information. *Control Theory and Technology* **2015**, *13(1)*, 17–28.
18. Kamal, M. A. S.; Tan, C. P.; Hayakawa, T.; Azuma, S. I.; Imura, J. I. Control of vehicular traffic at an intersection using a cyber-physical multiagent framework. *IEEE Transactions on Industrial Informatics* **2021**, *17(9)*, 6230–6240.
19. Hu, J.; Park, B. B.; Lee, Y. J. Coordinated transit signal priority supporting transit progression under connected vehicle technology. *Transportation Research Part C: Emerging Technologies* **2015**, *55*, 393–408.
20. Feng, Y.; Head, K. L.; Khoshmagham, S.; Zamanipour, M. A real-time adaptive signal control in a connected vehicle environment. Transportation Research Part C: Emerging Technologies **2015**, *55*, 460–473.
21. Xu, B.; Ban, X. J.; Bian, Y.; Li, W.; Wang, J.; Li, S. E.; Li, K. Cooperative method of traffic signal optimization and speed control of connected vehicles at isolated intersections. *IEEE Transactions on Intelligent Transportation Systems* **2018**, *20(4)*, 1390–1403.
22. Lee, J.; Park, B. Development and evaluation of a cooperative vehicle intersection control algorithm under the connected vehicles environment. *IEEE transactions on Intelligent Transportation Systems* **2012**, *13(1)*, 81–90.

23. Kamal, M. A. S.; Imura, J. I.; Hayakawa, T.; Ohata, A.; Aihara, K. (2014). A vehicle-intersection coordination scheme for smooth flows of traffic without using traffic lights. *IEEE Transactions on Intelligent Transportation Systems* **2014**, *16(3)*, 1136–1147.
24. Miculescu, D.; Karaman, S. Polling-systems-based autonomous vehicle coordination in traffic intersections with no traffic signals. *IEEE Transactions on Automatic Control* **2019**, *65(2)*, 680–694.
25. Zhang, G.; Wang, Y. Optimizing coordinated ramp metering: a preemptive hierarchical control approach. *Computer-Aided Civil and Infrastructure Engineering* **2013**, *28(1)*, 22–37.
26. Goatin, P.; Göttlich, S.; Kolb, O. Speed limit and ramp meter control for traffic flow networks. *Engineering Optimization* **2016**, *48(7)*, 1121–1144.
27. Chen, J.; Lin, W.; Yang, Z.; Li, J.; Cheng, P. Adaptive ramp metering control for urban freeway using large-scale data. *IEEE Transactions on Vehicular Technology* **2019**, *68(10)*, 9507–9518.
28. Zhao, L.; Malikopoulos A.; Rios Torres, J. Optimal control of connected and automated vehicles at roundabouts: An investigation in a mixed-traffic environment. *IFAC-PapersOnLine* **2018**, *51*, 73-–78.
29. Chalaki, B.; Beaver, L. E.; Malikopoulos, A. A. Experimental validation of a real-time optimal controller for coordination of cavs in a multi-lane roundabout. In Proceedings of the IEEE Intelligent Vehicles Symposium (IV), October 2020; pp. 775–780.
30. Bakibillah, A. S. M.; Kamal, M. A. S.; Tan, C. P.; Susilawati, S.; Hayakawa, T.; Imura, J. I. Bi-Level coordinated merging of connected and automated vehicles at roundabouts. *Sensors* **2021**, *21(19)*, 6533.
31. Hu, J.; Kong, L.; Shu, W.; Wu, M. Y. Scheduling of connected autonomous vehicles on highway lanes. In Proceedings of the IEEE Global Communications Conference (GLOBECOM), December 2012; pp. 5556–5561).
32. Awal, T.; Murshed, M.; Ali, M. An efficient cooperative lane-changing algorithm for sensor-and communication-enabled automated vehicles. In Proceedings of the IEEE intelligent vehicles symposium (iv), June 2015; pp. 1328–133.
33. Atagoziyev, M.; Schmidt, K. W.; Schmidt, E. G. Lane change scheduling for autonomous vehicles. *IFAC-PapersOnLine* **2016**, *49(3)*, 61–66.
34. Li, B.; Zhang, Y.; Feng, Y.; Zhang, Y.; Ge, Y.; Shao, Z. Balancing computation speed and quality: A decentralized motion planning method for cooperative lane changes of connected and automated vehicles. *IEEE Transactions on Intelligent Vehicles* **2018**, *3(3)*, 340–350.
35. An, H.; Jung, J.-i. Design of a Cooperative Lane Change Protocol for a Connected and Automated Vehicle Based on an Estimation of the Communication Delay. *Sensors* **2018**, *18*, 3499.
36. Kesting, A.; Treiber, M.; Helbing, D. Enhanced intelligent driver model to access the impact of driving strategies on traffic capacity. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* **2010**, *368(1928)*, 4585–4605.
37. Kesting, A.; Treiber, M.; Helbing, D. General lane-changing model MOBIL for car-following models. *Transportation Research Record* **2007**, *1999(1)*, 86–94.
38. Bakibillah, A. S. M.; Kamal, M. A. S.; Tan, C. P.; Hayakawa, T.; Imura, J. I. Fuzzy-tuned model predictive control for dynamic eco-driving on hilly roads. *Applied Soft Computing* **2021**, *99*, 106875.