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--Manuscript Draft--

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A FEEDBACK CONTROL STRATEGY FOR TRAFFIC FLOW HARMONIZATION IN MIXED-TRAFFIC ENVIRONMENTS

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ABSTRACT

Autonomous driving systems present promising methods for congestion mitigation in mixed autonomy traffic control settings. In particular, when coupled with even modest traffic state estimates, such systems can plan and coordinate the behaviors of *automated vehicles* (AVs) in response to observed downstream events, thereby inhibiting the continued propagation of congestion. In this paper, we present a simple feedback control strategy that exploits average speed estimates to mitigate the evolution of stop-and-go traffic in decentralized mixed-autonomy settings. Within this paradigm, our controller assigns desired speeds to automated vehicles that 1) predicatively react to the downstream state of traffic while 2) maintaining safe and reasonable headways with leading vehicles. This method is demonstrated to achieve an average of over 15% energy savings within simulations of congested events observed in Interstate I-24 with only 4% AV penetration, while restricting negative externalities imposed on traveling times and mobility.

Keywords: Mixed-autonomy traffic, Traffic control, Highway speed harmonization

INTRODUCTION

Vehicle autonomy is rapidly becoming a viable feature of many road networks. Early demonstrations in vehicle platooning (*1–3*) and similar successes spurred on by ambitious driving challenges (*4, 5*) have motivated equally ambitious efforts in the industrial sector, with companies including Tesla (*6*), Google (*7*), GM (*8*), and others all attempting to push the limitations and scope of vehicle autonomy. This trajectory is expected to continue as well, with studies projecting and discussing the implications of autonomy in the vicinity of 20-40% by 2050 (*9*).

The developments in vehicle autonomy, coupled with similar progressions in the proliferation of connectivity (*10*), have enabled researchers and practitioners to ask interesting questions on the quality of implemented driving policies. In particular, through carefully defined control and planning architectures, scientists have aimed to identify methods for reducing the energy footprint of future automated vehicles (AVs). This research has taken multiple interesting forms, and has ranged in scale from the macroscopic eco-routing of AVs (*11, 12*) to the sub-microscopic planning of powertrain systems in response to gear-shifting behaviors (*13, 14*) and network topology (*15, 16*).

In this paper, we are interested primarily in the role of *longitudinal* driving behaviors on the energy-efficiency of a given network. This is a topic that has formerly been heavily explored in the context of platoons of connected and automated vehicles, whereby platoons of fully-automated vehicles have successfully maintained string-stable driving responses in tight platoons, thereby providing notable benefits to both energy-efficiency and throughput. More relevant to the present paper, however, AVs in mixed-autonomy setting may provide significant benefits in mitigating string-instabilities among *human drivers* as well. This was demonstrated empirically in the seminal work of (*17*), whereby a single AV within a circular track stably operating near the effectively uniform driving speed of the network manages to dampen stop-and-go oscillations existing prior to actuation.

The above empirical study provides a useful insight that is frequently parroted (*18, 19*): significant gains to energy-efficiency may be achieved by harmonizing the speeds of subsets of vehicles near a desirable target. This deduction, however, introduces new challenges to autonomous driving systems. In particular, under the every-evolving dynamics of a particular network as demand waxes and wanes, AVs must reactively identify desirable speeds that match current spatio-temporal trends while not inhibiting the safety or mobility of the vehicle. To this, traffic state estimates may offer a helping hand. Estimates of flow, density, and speed produced either from fixed sensors or probe vehicles (*20*) may elucidate spatio-temporal patterns that may be exploited by AVs in a largely decentralized manner. This is in part demonstrated in the work of (*21*), for instance, with devises an optimal speed profile for vehicles provided speed measurements forwards in space and time. Solutions such as these, however, are often studied in the context of fully-observable macroscopic environment, and as such become brittle and unsafe in the presence of inaccurate traffic state estimates and microscopic fluctuations in speed and spacing.

In this paper, we present a feedback control strategy that exploits both macroscopic traffic-state estimates and microscopic observations to produce a reasonable car-following response while also attempts to harmonizing driving speeds across a desirable spatio-temporal target. The key contributions of this paper are as follows:

- We construct a simple longitudinal feedback control strategy for AVs that attempts to maintain reasonable headways with preceding vehicles when appropriate, and adjusts its spacing when sudden reductions in driving speeds are anticipated in the near future.

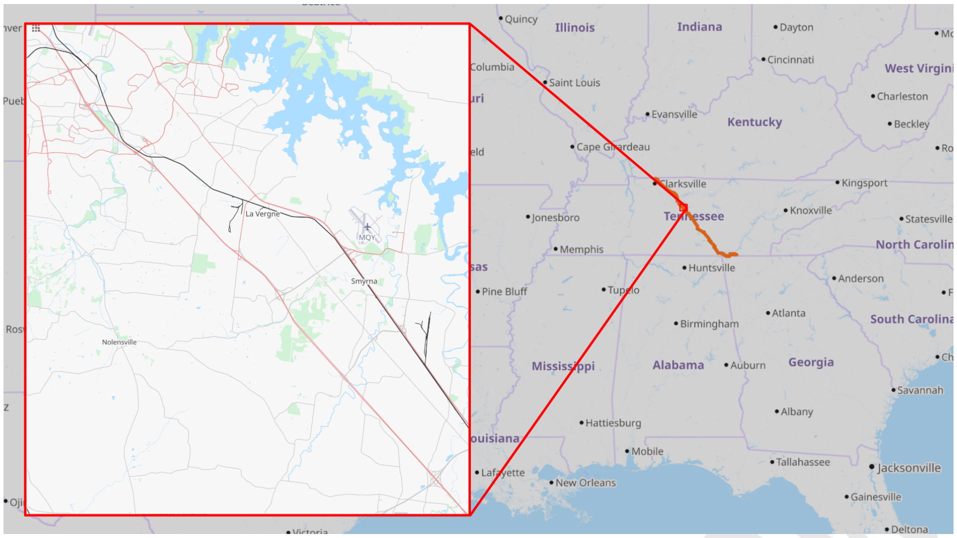


FIGURE 1: An illustration of the targeted highway network within this study (I-24 Westbound in Nashville, Tennessee), seen as the red diagonal line within the highlight region.

- We validate the efficacy of the above method on a simulation of throughput-restricted traffic aimed at capturing the high degree of variability in driving behaviors and traffic state estimates common to real-world networks, and demonstrate that our method can consistently achieve large energy savings in congested states of traffic.

PROBLEM STATEMENT

In this paper, we are interested in exploring methods for ameliorating congestion in mixed autonomy highway networks. The considered network, see Figure 1, is a 14.5-km long segment of Interstate I-24 located in Nashville, Tennessee. This network has been the topic of some interest in recent years, with researchers attempting to both reconstruct (*22, 23*) and address (*23–25*) characteristic of driving within this network that produce inefficiencies in energy consumption. In particular, we here explore the implications of automated driving on addressing inefficiencies arising from string instabilities in human driving behaviors, which result in the formation of stop-and-go traffic during peak demand intervals within this network.

To validate the efficacy of our longitudinal driving strategy within the I-24, we utilize a microsimulation model presented in (*23*). In particular, to capture a degree of variability in driving behaviors that is difficult to recreate with common microsimulation tools (*26, 27*), we instead model the platoon response of both simulated human-driven and automated vehicles following leading trajectories collected directly from the target network. These leading trajectories consist of position and velocity measurements $\tau := \{(x_1, v_1), \ldots, (x_T, v_T)\}$ sampled in increments of 0.1 seconds, and vary in terms of time collected and severity of congestion witnessed, and as such offer a robust assessment of the influence of automated vehicles within viable states of traffic.

To model the behaviors of platoons of vehicles following the aforementioned trajectories, we initially place N vehicles upstream of the leading vehicle and equidistant from one another[1], and update the state of said vehicles via logic specified either by a car-following model $f_{\text{human}}(\cdot)$

[1] Vehicles are initially placed with 2-second gaps between one another and driving with the same speed as the leading vehicle.

Parameter	v_0	T	a	b	δ	s_0	ε
Value	45	1	1.3	2.0	4	2	$\mathcal{N}(0, 0.3)$

TABLE 1: Intelligent Driver Model (IDM) Parameters

or the AV model described in the following section. For human-driven vehicles, this acceleration response is dictated by the *Intelligent Driver Model* (*28*) (IDM), a popular model for reconstructing string instabilities and the formation of stop-and-go style behaviors. Through this model, the acceleration for a vehicle α is defined by its bumper-to-bumper space headway s_α, velocity v_α, and relative velocity with the preceding vehicle $\Delta v_\alpha = v_l - v_\alpha$ as:

$$f_{\text{human}}(v_\alpha, \Delta v_\alpha, s_\alpha) = a[1 - (\frac{v_\alpha}{v_0})^\delta - (\frac{s^\star(v_\alpha, \Delta v_\alpha)}{s_\alpha})^2] + \varepsilon \tag{1}$$

where ε is an exogenous noise term designed to mimic stochasticity in human driving behaviors and $s^\star$ is the desired headway of the vehicle denoted by:

$$s^\star(v_\alpha, \Delta v_\alpha) = s_0 + \max(0, v_\alpha T + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{ab}}) \tag{2}$$

and s_0, v_0, T, δ, a, b are fixed parameters set in accordance with (*23*) and provided in Table 1. This model is assigned to all vehicles following the leading trajectory when simulating *human-driven* (baseline) responses to varying downstream conditions, while in *mixed-autonomy* simulations, every $\frac{100}{p}$th vehicle is assigned an AV model to mimic a penetration rate of $p\%$.

Figures 3 (top) and 4 (top) depict the platoon response of human-driven vehicles following a sample of the aforementioned trajectories exhibiting some degree of sharp oscillations in driving behaviors. Seen here, perturbations induced by the leading vehicle are amplified by following vehicles within the platoon and propagate backwards in space and forwards in time, resulting in the formation of stop-and-go like behaviors that inhibit the energy-efficiency of the given network. We present in the following section a method for mitigating said oscillations via knowledge of the state of downstream traffic.

METHODOLOGY

In this section, we present a feedback control strategy that exploits downstream traffic-state estimation data to harmonize driving speeds amongst vehicles while maintaining safe and appropriate gaps between AVs and their leaders. This controller adopts and extends prior heuristic on traffic flow harmonization (*17–19, 21*), which posit that traffic may be homogenized near its desirable *uniform* driving speed by operating a subset of vehicles near accurate predictions of said speed. We demonstrate the effectiveness of this approach at reducing energy emissions in the following section.

Controller design

We begin by designing a velocity-based control strategy that, similar to CACC systems, attempts to adjust its response when future driving speeds are expected to reduce sharply. This prediction, however, must satisfy the following conditions:

1. It must be achieved without shared communication between adjacent vehicles, as in mixed-autonomy settings human-driven vehicles are incapable of sharing their desired

speeds. Instead, we rely on traffic state data, and in particular estimates of average driving speeds $v_{\text{avg}}(t) \in \mathbb{R}^m$ spanning across m segments located in positions $x_{\text{avg}} \in \mathbb{R}^m$.

2. It must regulate its spacing in a manner that is both safe and responsive to the formation of large gaps. In particular, when provided traffic state information overestimate or underestimate the *actual* state of traffic, additional feedback mechanisms must produce a response more similar to adaptive cruise control (*29*). We discuss the safety component further in the following subsection.

According to the above requirements, the designed velocity includes three parts: the desired velocity; the headway error; and the speed difference, as Eq. (3) depicts:

$$v_d = v_{\text{des}} + k_p * (h - h_{\text{des}}) + k_d * (v_l - v) \tag{3}$$

where v_{des} is the desired speed estimated by Eq. (4); h is the time gap between the preceding vehicle and the subject vehicle; h_{des} is the desired time headway; v_l and v are the speed of preceding vehicle and the subject vehicle respectively and k_p and k_d are gain values.

The desired speed is estimated contingent on the headway between the subject vehicle and preceding vehicle. When the headway is relatively small, we focus on microscopic range, while when the headway is large, we focus on the macroscopic range. The relation between the two is smoothly weighted as follows.

$$v_{\text{des}} = \begin{cases} v & \text{if } \ 0 \leq h < 1 \\ (2-h)v + (h-1)v_{\text{avg}} & \text{if } \ 1 \leq h \leq 2 \\ v_{\text{avg}} & \text{if } \ h > 2 \end{cases} \tag{4}$$

where v_{avg} is the average speed of the forward traffic estimated by Eq. (5) and the rest of the variables follow the definitions from the above equations.

The average speed of the downstream traffic can be obtained in a convolution way. Specifically, we choose the uniform kernel to estimate it:

$$v_{\text{avg}} = \frac{\int_{x_0}^{x_0+w} v_{x_i}}{w} \tag{5}$$

where x_0 is the position of the subject vehicle; w is the width of the estimation window and v_{x_i} is the corresponding vehicle at the position x_i.

The second and third term of the Eq. (3) is similar with the design of the ACC vehicle model (*30*). This design intends to capture the human-like car following behavior so that the subject vehicle can maintain a reasonable gap from the preceding vehicle. Equipped with the first term, our controller tries to drive smoothly while maintains reasonable gap with the anticipation of future oscillations in driving speeds.

Safety filter

To avoid any potential collisions with the preceding vehicle, we add a safety filter to the proposed controller. Our safety filter design is inspired by the simple idea that the gap between the preceding vehicle and the subject vehicle should be larger than the minimum space gap and the headway between the two vehicles should also be larger than the minimum time headway. We start with the time headway requirement and add a heuristic in terms of the space gap requirement. The upper bound of the velocity determined by safety filter design is calculated by Eq. (6)

$$v_{\text{fs}} = \frac{s - s_{\min} + v_l \tau_s + \frac{1}{2} a_l \tau_s^2 - \frac{1}{2} v \tau_s}{h_{\min} + \frac{1}{2}\tau_s} \tag{6}$$

where s is the space gap between the preceding vehicle and the subject vehicle; $s_{\min}$ is the minimum space gap between the two vehicles; τ_s is the decision making horizon; a_l is the acceleration of the preceding vehicle[2]; $h_{\min}$ is the minimum time headway between the two vehicles and the rest of the variables follow the definitions from the above equations.

The detailed design procedure is as follows: Eq. (7) shows the requirement on time headway at time $t = t + \tau_s$.

$$\frac{x_l(t+\tau_s) - x(t+\tau_s)}{v(t+\tau_s)} \geq h_{\min} \tag{7}$$

where $x_l(t+\tau_s)$ is the position of the preceding vehicle at time $t+\tau_s$; $x(t+\tau_s)$ is the position of the subject vehicle at time $t+\tau_s$; $v(t+\tau_s)$ is the speed of the subject vehicle at time $t+\tau_s$ and the rest of the variables follow the definitions from the above equations. Following simplified dynamics of motion, the position of each the ego and preceding vehicles at time $t+\tau_s$ is:

$$x_l(t+\tau_s) = x_l(t) + v_l(t)\tau_s + \frac{1}{2} a_l(t)\tau_s^2 \tag{8}$$

$$x(t+\tau_s) = x(t) + v(t)\tau_s + \frac{1}{2} a(t)\tau_s^2 \tag{9}$$

where $a(t)$ is the target decision variable, and for a fixed desired speed across the decision-making horizon may be expressed as:

$$a(t) = \frac{v_{\text{des}} - v(t)}{\tau_s} \tag{10}$$

Plugging in Eq. (8), Eq. (9), and Eq. (10) to solve Eq. (7), we can get an initial upper bound of v:

$$v \leq \frac{s + v_l \tau_s + \frac{1}{2} a_l \tau_s^2 - \frac{1}{2} v \tau_s}{h_{\min} + \frac{1}{2}\tau_s} \tag{11}$$

We also want to take the space gap requirement into consideration and get a slightly tighter upper bound. To achieve this, we add an heuristic by replacing the s in Eq. (11) with s - $s_{\min}$ which leads to our final design of the safety filter velocity as Eq. (6) shows.

Combine the velocity design and safety filter, our final controller can be expressed as:

$$v_c = \max(0, \min(\underbrace{\overbrace{v_{\text{des}}}^{\text{Desired speed}} + \overbrace{k_p * (h - h_{\text{des}}) + k_d * (v_l - v)}^{\text{Regulate spacing}}}_{\text{Controller design}}, \underbrace{v_{\text{fs}}}_{\text{Safety filter}})) \tag{12}$$

NUMERICAL RESULTS

In this section, we present numerical results for the proposed controller across several simulations of the previously described environment. These results aim to answer the following:

[2]While multiple estimates for this acceleration may be assigned in practice, we ~~TODO~~.

Parameter	Description	Value
k_p	Proportional gain	2.0
k_d	Differential gain	0.5
h_{des}	Desired time headway	2.0 s
w	Sliding window length for speed estimation	3000 m
$s_{\min}$	Minimum safe space headway	5.0 m
$h_{\min}$	Minimum safe time headway	0.5 s
τ_s	Safety decision-making horizon	5.0 s

TABLE 2: Proposed controller parameters.

- Is the proposed controller effective at improving the energy-efficiency and homogeneity of driving across both human-driven and automated vehicles?
- Is this approach sensitive to unforeseen events that are common within multi-lane highway networks, and in particular to disturbances induced by sudden and/or aggressive lane changing behaviors?

Simulation procedure

Simulations were conducted on the one-lane environment described above with a step size of 0.1 sec/step and a following platoon consisting of 200 vehicles. Among the drives recorded within Interstate I-24, we evaluate our method on trajectories that were collected during morning peak demand intervals (6am - 7am) and exhibit some degree of sharp oscillations in driving speeds. This amounts to a total of 10 varying trajectories, seven of which, we note, observe what may deemed as *light-to-moderate* congestion (e.g. Figure 3), whereby vehicles alternate between free-flowing and congested states of traffic, while the remaining three exhibit more *severe* forms of congestion (e.g. Figure 4), whereby driving speeds are consistently slow and stop-and-go behaviors are frequent. To model an AV penetration rate of 4% we replace every 25th vehicle model in the platoon with the controller depicted in the previous section. The parameters of this controller used within this assessment are depicted in Table 2.

To capture realistic traffic state estimation measurements within the above simulations, we synchronize the above trajectories real world estimates collected from Inrix. Historical average speed measurements are collected from Inrix for the target network, and these values are adjusted in position and time with the leading vehicle to produce results similar to those expected in real world settings. These measurements are collected in segments of length approximately equal to 0.5 miles, and are updated in increments of 5 minutes.

Performance metrics

We evaluate the response of vehicles within the above simulation across the following metrics:

1. **Energy Efficiency.** Improving energy efficiency can incentivize more uniform, and on average slower driving speeds. To analyze the performance of the proposed controller in terms of energy efficiency, we adopt a semi-principled energy model that has a physics-based component (*22*). The model takes as inputs the instantaneous vehicle speed v, acceleration a, and road grade θ, and outputs engine speed, engine torque, fuel con-

			Distance traveled (km)	MPG (AVs)	MPG (total)
Light/Moderate		Human-driven	13.71	–	45.41
	Experiment 1	Mixed-autonomy	13.60 (−0.80%)	49.87 (+9.82%)	52.76 (+16.19%)
		Human-driven	13.863	–	39.45
	Experiment 2	Mixed-autonomy	13.77 (−0.65%)	42.55 (+7.86%)	43.48 (+10.22%)
		Human-driven	14.58	–	40.36
	Experiment 3	Mixed-autonomy	14.47 (−0.75%)	44.93 (+11.32%)	46.66 (+15.61%)
		Human-driven	14.09	–	40.46
	Experiment 4	Mixed-autonomy	14.04 (−0.35%)	48.21 (+19.15%)	51.17 (+26.47%)
		Human-driven	13.23	–	44.19
	Experiment 5	Mixed-autonomy	13.16 (−0.53%)	46.14 (+4.41%)	45.11 (+2.08%)
		Human-driven	14.24	–	39.79
	Experiment 6	Mixed-autonomy	14.2 (−0.28%)	46.24 (+16.21%)	48.16 (+21.04%)
		Human-driven	14.48	–	38.65
	Experiment 7	Mixed-autonomy	14.36 (−0.83%)	48.12 (+24.50%)	49.31 (+27.58%)
Heavy		Human-driven	13.32	–	36.67
	Experiment 8	Mixed-autonomy	13.31 (−0.08%)	42.95 (+17.13%)	41.42 (+13.50%)
		Human-driven	13.10	–	36.34
	Experiment 9	Mixed-autonomy	13.00 (−0.76%)	52.48 (+44.41%)	48.69 (+33.98%)
		Human-driven	10.70	–	30.97
	Experiment 10	Control	10.61 (−0.84%)	38.48 (+24.25%)	36.03 (+16.34%)
		Human-driven	13.53	–	39.20
	Average	Mixed-autonomy	13.45 (−0.58%)	46.0 (+17.3%)	46.3 (+18.0%)

TABLE 3: Performance of both fully human-driven and mixed-autonomy simulations, individually and average across 10 runs for each leading experiment/trajectory. Our controller consistently produces driving behaviors that significantly improve the energy-efficiency to both human-driven and automated vehicles at virtually no cost to vehicle miles traveled.

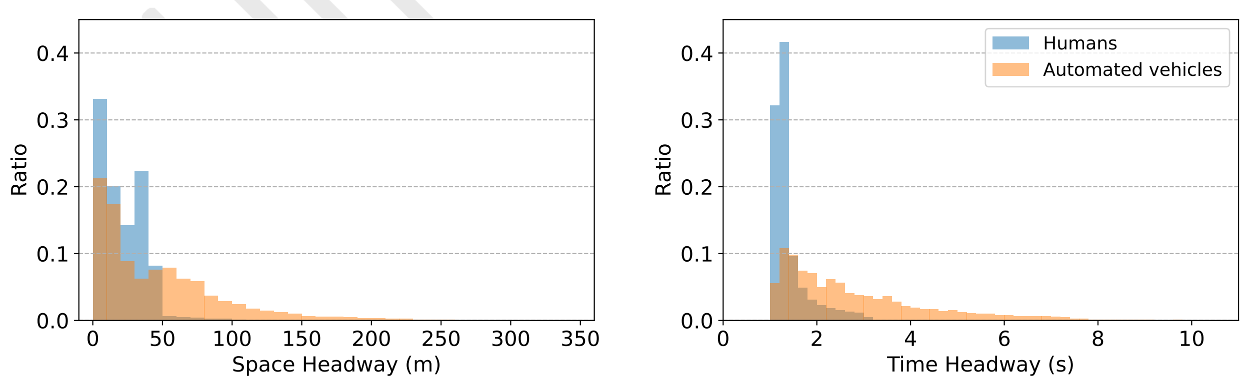


FIGURE 2: Accepted space headway and time by human-driven and automated vehicles in each of the fully human-driven and mixed-autonomy simulations, respectively. As we can see, automated vehicles primarily maintain reasonable headways that distributionally match those of human-driven vehicles but are willing to adopt larger gaps when required to avoid future anticipated congestion.

sumption, gear, transmission output speed, wheel force, wheel power, and feasibility of the given (v,a,θ) with respect to engine speed and engine torque. In our training process, we take Toyota RAV4 as the prototype vehicle and simplify the energy model to a fitted polynomial model of the form The energy consumption obtained from the model will be converted into Miles-Per-Gallon (MPG) as the metric to indicate energy efficiency.

2. **Throughput.** Since the simulation experiment will end if it reaches the end of the leading trajectory, regulation on controlled vehicles may reduce the throughput near and upstream of these vehicles. For fixed regions, measuring the distanced traveled can be an equivalent representation of measuring the traffic flow. Therefore, we use controlled vehicles' travel distance as a representation of the throughput.
3. **Proximity to leader.** Close proximity may denote unsafe driving behaviors while large distances between vehicles may denote reductions in throughput and may encourage cut-ins and cut-outs by following vehicles. We use time headway and space gap as the metrics to measure the proximity to leader.

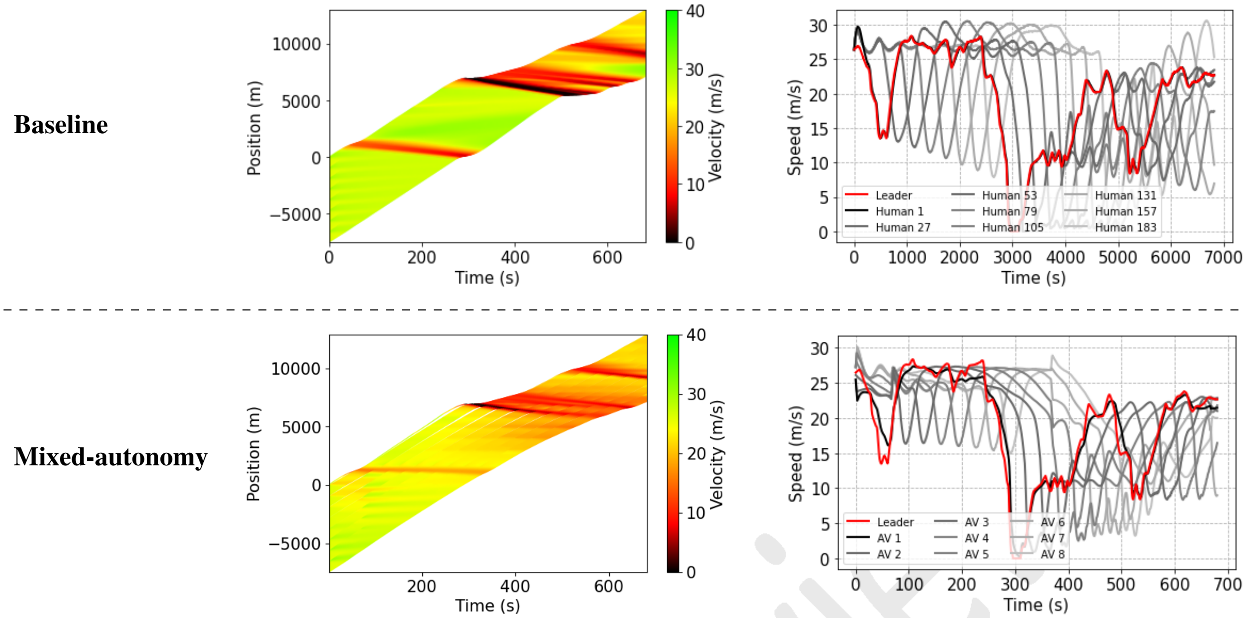
Comparative analysis

Table 3 depicts the average performance of the system on all 10 utilized trajectories for the metrics we described above. We can see significant improvement on energy efficiency at little cost to the throughput of the system. Comparing to the baseline, the proposed controller provides on average 18.0% savings to energy consumption with only 0.58% reduction on distance travelled by the controlled vehicle. As Figure 2 shows, the controlled vehicles leave a more conservative gap with the preceding vehicle. In controlled cases, both space headway and time headway spread in a wider range. With the knowledge of the congestion at downstream, the controlled vehicles should deliberately leave more gap to avoid sharp deceleration, as a result, drive in a smoother speed and save energy consumption. This behavior propagates to other vehicles immediately upstream of the automated vehicles as well, resulting in more uniform driving speeds throughout the platoon. This is for instance true in Figure 3, where AVs dampen the magnitude of oscillations experienced by consecutive vehicles within the platoon. In contrast, oscillations in driving speeds in fully human-driven setting are amplified by trailing drivers within the platoon, resulting in the subsequent formation of stop-and-go traffic.

Sensitivity to lane changes

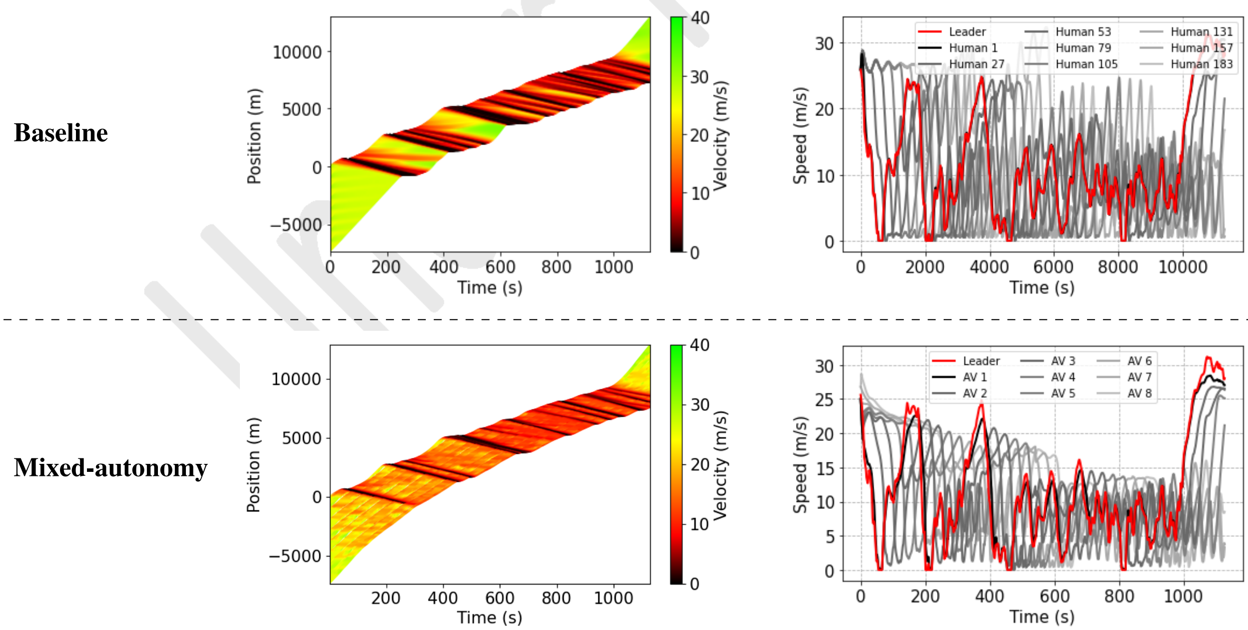
Finally, we evaluate the ability of our approach to cope with external and unforeseen disturbances common to multi-lane networks. In particular, knowing that our method mitigates congestion in part by forming large gaps with leading vehicles when predicted forward speeds are low, we explore the sensitivity of our solution to lane changing events when AVs form large gaps with their immediate leaders. In order to do so, we use a simple lane change model inspired by the work of (*31*) that stochastically inserts vehicles into the network when the headway between adjacent vehicles is high and periodically removes vehicles to maintain approximate consistency with the total number of vehicles within a simulation.

Figure 5 depicts the spatio-temporal performance of human-driven and automated vehicles when lane changes of the form above are introduced into the simulation environments. As we can see, while more frequent oscillations are observed in the presence of lane changes, AVs continue to produce uniform driving amongst vehicles in the mixed-autonomy settings, providing an on average 9.84% MPG improvement among all 10 experiments. The stochastic injection of vehicles does



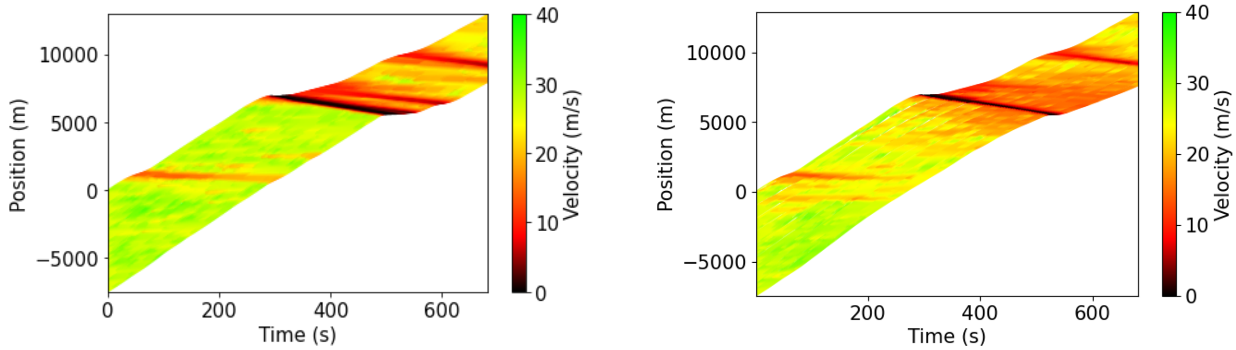
(a) Time-space diagram (b) Speed profile

FIGURE 3: A sample response from sporadic perturbations induced by a leading trajectory. **Top)** Perturbations are amplified by trailing drivers within the platoon and result in frequent transitions between free-flowing and congested states of traffic. **Bottom)** This response is effectively mitigated in the mixed-autonomy setting, with AVs harmonizing driving speeds amongst vehicles.



(a) Time-space diagram (b) Speed profile

FIGURE 4: A sample response from frequent perturbations induced by a leading trajectory. **Top)** The strength of severity of oscillations from the leading vehicle produce frequent stop-and-go responses from those upstream. **Bottom)** By maintaining speeds near the aggregate state of the network, AVs are capable of negative many of these stop-and-go responses.



(a) Fully human-driven

(b) Mixed autonomy

FIGURE 5: A sample response from sporadic perturbations induced by a leading trajectory and the simple lane change model.

not result in vehicle-to-vehicle collisions either, demonstrating the effectiveness of the proposed safety filter as well. We leave analyses of this control strategy under more elaborate lane change models for future work.

CONCLUSION

This paper explores the problem of designing congestion mitigation control strategies through automated vehicles. We depict a simple feedback control strategy that utilizes downstream traffic state information to plan and coordinate a smoother driving trajectory for the purpose of harmonizing driving speeds and improving energy efficiency. Evaluated with simulations that capture high degree of variability in driving behaviors and traffic state estimates common to real-world networks, our proposed method could achieve an average of over 15% energy savings with only 4% AVs introduced to the simulated Interstate I-24 network. Future works can include extending this with more accurate and robust simulations of traffic flow dynamics, and devising methods for performing similar congestion mitigation without the need for downstream traffic state estimates.

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