Safe and Efficient Automated Freeway Traffic Control

Benjamin Coifman, ORCID 0000-0002-8201-964x
Yuan Liu, ORCID 0009-0005-4330-8923
The Ohio State University

FINAL REPORT

https://ppms.cit.cmu.edu/projects/detail/424

August 1, 2024

DISCLAIMER

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, under [grant number 69A3552344811] from the U.S. Department of Transportation's University Transportation Centers Program. The U.S. Government assumes no liability for the contents or use thereof.

Abstract

The goal of this work is to eliminate unexpected stops to improve safety with the added benefit of reducing accelerations to improve fuel efficiency and reduce vehicle emissions. Congested traffic is characterized by signals and waves propagating upstream through the queued traffic. Freeway drivers do not expect to encounter abrupt drops in speed or stopped traffic, as a result, shockwaves sharply increase the accident rates, particularly in the context of rear end collisions. This work seeks to use connected and automated vehicles (CAV) to smooth out traffic disturbances on a freeway. The CAV integrates the instantaneous state information from the downstream vehicles to forecast the trajectory of the CAV's leader and proactively respond to changes in state that have not yet reached the lead vehicle. Using empirical vehicle trajectory data, it is shown that the methodology can rapidly nullify stop and slow waves and yield large reduction in vehicle emissions.

Keywords

Connected and Automated Vehicles; Freeway Traffic; Congestion; Safety; Stop waves; Vehicle emissions

1. Introduction

This work seeks to use connected and automated vehicles to smooth out traffic disturbances on uninterrupted flow facilities like freeways, eliminating unexpected stops to improve safety with the added benefit of reducing accelerations to improve fuel efficiency and reduce vehicle emissions. Shockwaves are a naturally emerging phenomena in freeway traffic, but they represent one of the largest safety risks on freeways. Freeway drivers do not expect to encounter abrupt drops in speed or stopped traffic, as a result, shockwaves sharply increase the accident rates, particularly in the context of rear end collisions. For example, US interstate highways in 2021 saw the following rear-end collision numbers: Fatality 985, Injury-Only 71,408, Property-Damage-Only 152,011 (NHTSA, 2023). Rear end collision severity is directly related to the relative speed between the involved vehicles, shockwaves increase these relative speeds, and thus, they also increase accident severity. Shockwaves also reduce freeway capacity and have a detrimental impact on fuel consumption and emissions because accelerating engines are less efficient than when cruising. In this way, the research not only address the primary objective of improving safety (eliminating unexpected speed drops), it should also lead to secondary benefits of reducing emissions and fuel consumption (avoiding unnecessary accelerations), and increasing throughput (stable traffic has a higher capacity than fluctuating traffic states).

Connected and autonomous vehicles (**CAV**) hold the promise to attenuate and eliminate shockwaves (and thus, also reduce the severity and number of accidents), but only if the system is explicitly designed to do so. The very factors that give rise shockwaves in human driven vehicles (**HDV**) can also do so in CAV. While CAV offer new ways to manage traffic dynamics, an automated freeway will still be subject to traffic dynamics. The real challenge is designing the CAV system so that it ensures the safest possible operation, and then within those bounds, the greatest operational efficiency (maximizing capacity, minimizing delays, etc.).

This research essentially seeks to take conventionally unstable queued traffic and bring it to a stable flow while queued. The approach assumes all vehicles are connected and report their current state (location and speed) to all other vehicles. The main objective is to integrate the state across vehicles so that the system can efficiently anticipate and respond to disturbances over large distances. It is this look ahead that will allow the system to detect and attenuate shockwaves, resulting in smoother conditions for safety and efficiency. The methodology is demonstrated using microscopic vehicle trajectory data from real shockwaves in HDV traffic as both the initial conditions and bounding constraints of how the system can respond.

The primary focus of this work is the initial transition from unstable stop and go traffic to the first follower with a smooth trajectory, i.e., dissipating large shockwaves after they have formed and begun propagating. As a result, the modeling assumes that all vehicles downstream of a key vehicle are connected-HDV (**cHDV**) that simply communicate their state, but are otherwise HDV; whereas the key vehicle is a CAV that proactively responds to the downstream conditions. This approach is taken to illustrate how the system can nullify a stop wave across a single vehicle pair. If all vehicles were CAV operating under this approach stop waves would rarely arise and would quickly be dissipated. Future work will extend the methodology to scenarios where only a fraction of vehicles are either cHDV or CAV.

With the focus on queued traffic, it is important to recognize that a queue simply represents the storage of demand in excess of capacity as the excess vehicles wait to be served.

To eliminate a queue requires increasing capacity or decreasing demand. This work does not seek to achieve freely flowing traffic out of queued traffic. Rather, this work seeks to take conventionally unstable queued traffic and bring it to a stable flow while queued.

1.1. Motivation

The research touches on numerous aspects of the USDOT (2023) RD&T plan. The research addresses issues falling within Data-Driven System Safety. The primary objective of attenuating and eliminating shockwaves is data driven Safe Design, falling squarely within: "Evaluate the safety performance of infrastructure design and develop and promote the use of effective safety countermeasures," (p.19). Furthermore, in line with Safe Technology, this work is contingent on the use of CAV to "Leverage innovative technologies to... reduce injuries and fatalities among the transportation workforce and traveling public," as it develops and evaluates, "connected digital infrastructure designed to enhance transportation safety outcomes," (p.19).

Key to this work are several Transformation priorities. The work relies on Integrated Systems to develop Digital Infrastructure that will, "support enhanced transportation safety, efficiency, and connectivity," as well as developing, "procedures, guidance, standards, testing, and evaluation of cooperative automation, which enables communication and cooperation between vehicles, infrastructure, and other road users to support driving automation features," (p.55). The work explicitly relies on Connectivity, "to improve the safety and efficiency of the transportation system [reducing accidents], while improving equity and environmental outcomes [reducing emissions]," (p.56). The approach is Data-Driven by design, relying on Data Science to "Harness advanced data collection and data processing capabilities to create timely, accurate, credible, and accessible information to support transportation operations," (p.59). The research relies on Novel Technologies through Automation, by taking care to deliberately design the operation of CAV in, "the development and responsible deployment of automated technologies that improve the safety, efficiency, equity, and accessibility of transportation," by optimizing operations, "for digital and automated systems and operations," (p.59).

The research should have secondary Economic impacts improving Resiliency by improving the reliability of freight shipments (p.24) and improve System Performance through Transportation System Management (p.30). As well as Climate Sustainability by reducing emissions (p.44).

1.2. Background

There are studies that are looking into modeling the car following behavior of CAV with an emphasis on the autonomous vehicle aspects (Wei, 2019), others emphasize the communication aspect for vehicle routing (Jin, 2022).

Several projects hold promise for end-to-end compatibility with this research: developing simulation platforms (Ban, 2021), modeling microscopic vehicle interactions for maneuvering without specific consideration of the macroscopic dynamics (Stern, 2022; Wei, 2021; Peta, 2018). The closest related studies to this work consider using CAV to harmonize speed or dampen disturbances (Wei, 2022; Samiul and Zaki, 2020; Labi, 2020).

1.3. Overview

The remainder of this document is as follows. Section 2 presents the methodology, starting with the underlying theory and then empirically demonstrating the approach using microscopic vehicle trajectory data. Then this report closes with a brief discussion and conclusions in Section 3.

2. Methodology

Congested traffic is characterized by signals and waves propagating upstream through the queued traffic. This work develops a methodology for a CAV to nullify stop and slow waves from propagating upstream within a queue of vehicles on an uninterrupted flow facility, e.g., a freeways. The work assumes that all vehicles downstream of the CAV are connected and report their instantaneous state (location and speed). The CAV integrates the instantaneous state information from all of the downstream vehicles to forecast the trajectory of the CAV's leader and proactively respond to changes in state that have not yet reached that vehicle.

The method is inspired by Coifman (2002), which used measurements of vehicles passing a dual loop detector station to estimate vehicle trajectories over space for up to one mile away from the station. The basic principle is that many freeways exhibit a triangular fundamental relationship, thus, the traffic state should propagate upstream through the traffic at roughly constant velocity, corresponding to the "wave velocity," i.e., the slope of the congested regime of the flow-density curve (see, e.g., Coifman and Wang, 2005). This feature is illustrated in Fig. 1A using real human driven vehicle (HDV) trajectories reextracted from the NGSIM I-80 video in lane 2 (Coifman and Li, 2024). Note that the horizontal axis is in 1/10 seconds, which corresponds to the original video rate used to sample the NGSIM data. So frame 6800 corresponds to 680 sec or 5 min and 20 sec into the sample. Thirteen "signals" are superimposed on the vehicle trajectories, each signal is at -15 mph. Between any pair of signals one can observe that the trajectories show roughly the same speed over the entire band defined by the pair of signals. Of course this approximation is not perfect, upon close inspection one can see the traffic state between a given pair of signals change shape over time and space, both due to natural human variability and abrupt lane change maneuvers.

While Coifman (2002) derived the trajectory estimation using measurements at a point in space (as would be represented by a horizontal cutline in Fig. 1A), this work re-derives the method using conditions at an instant in time (a vertical cutline). Consider Fig. 1B, which shows the complete trajectories up to time t_1, 630 sec. Suppose we were interested in establishing the optimal trajectory for the CAV at (t_1, x_1) in the lower left corner of this plot, we do so by first estimating the trajectory for its leader at $(t_1, 100ft)$. For this work we assume that this leader vehicle and all vehicles downstream are connected HDV, or cHDV for short. The cHDV communicate their state but are otherwise HDV. For this work we use the instantaneous location and speed reported by all of the downstream cHDV. While the real traffic state varies continuously over time and space, we approximate it with thin bands of constant speed. Specifically, imagine that each cHDV were to continue traveling at the same speed, yielding a chord of constat slope in the time-space plane. Whereas each vehicle passage is taken to represent the start of a new band of constant speed, with the signal between bands propagating upstream at the wave velocity from the triangular fundamental relationship, set to -15 mph in this case. So each cHDV yields a downstream moving chord at the vehicle's speed and an upstream moving signal at the fixed wave velocity. Then, when a chord reaches the first signal emanated by the vehicle ahead that chord is terminated. The result is illustrated in Fig. 1C. Since the bands are assumed to be at constant speed, we shift the truncated chords end to end, starting at the lead vehicle's current position of $(t_1, 100ft)$, yielding the estimated trajectory of the leader in Fig. 1D. Fig. 1E compares the estimated trajectory at t_1 to the actual trajectory that is eventually realized by the same vehicle. While the estimate is not perfect, it does capture the key features like the passage of the stop wave.

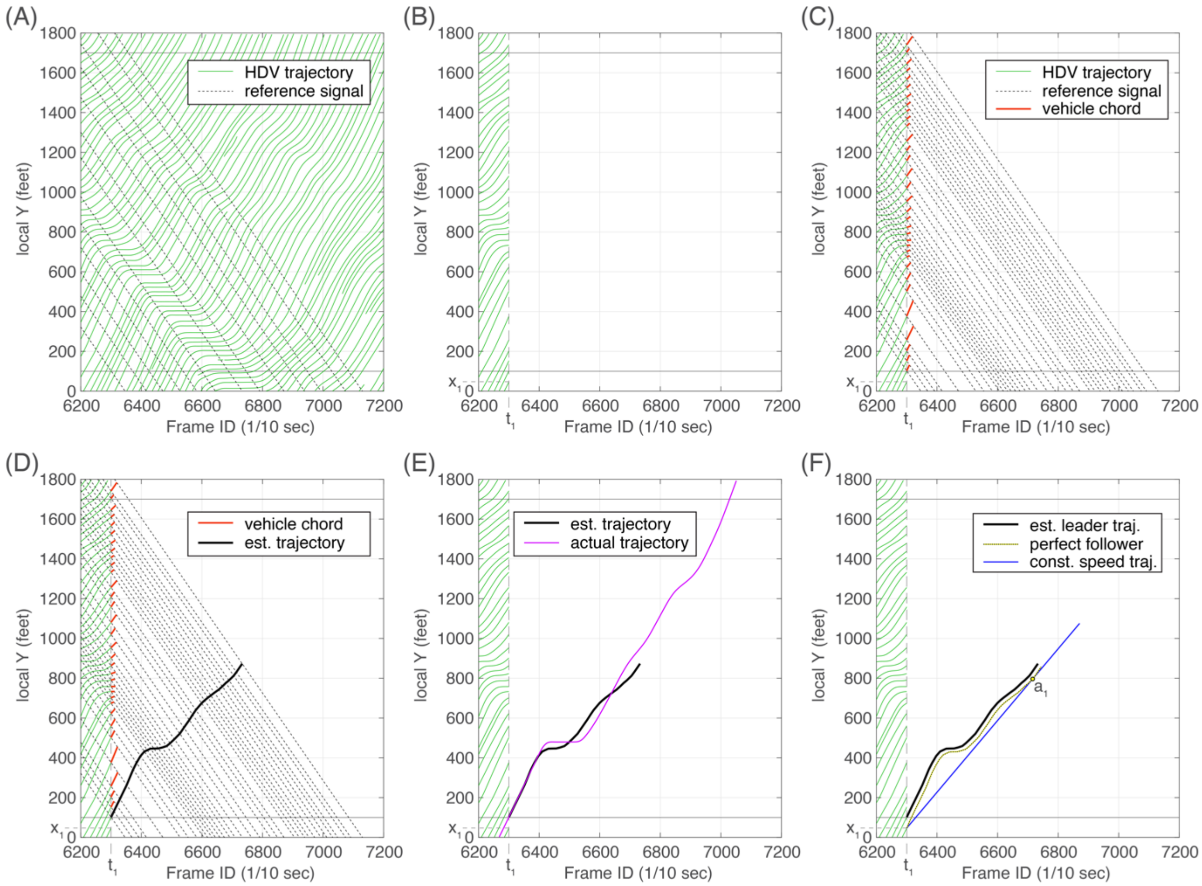

Figure 1, (A) vehicle trajectories from congested traffic and several upstream moving reference signals. (B) Traffic state up to time t_1, (C) roughly steady state bands and their measured vehicle chords, (D) aligning the chords at t_1 end to end to estimate the lead vehicle's trajectory, and (E) comparing the estimate to what will eventually occurs. (F) Establishing the perfect follower trajectory and finding the intersection with the fastest constant speed radial for the CAV at t_1.

The lead vehicle's estimated trajectory bounds where the CAV at (t_1, x_1) can travel. We first project the lead vehicle's trajectory upstream to derive the perfect follower trajectory, as shown in Fig. 1F using Newell (2002) with jam distance of 20 ft and reaction time of 1 sec. Next, we find the fastest constant speed radial from (t_1, x_1) that touches the perfect follower trajectory, in this case doing so at point a_1. The CAV then takes the speed of this radial for the next time step.

This process of sampling the current traffic state to estimate the leader's trajectory and then setting the CAV speed to intersect the perfect follower trajectory at the furthest point downstream is repeated at each time step. The result for this example is shown in Fig. 2A using one second time steps. The left-most dashed trajectory shows the path taken by the actual HDV in the NGSIM data (termed the "Original HDV trajectory"), while final trajectory taken by the CAV s shown with a bold, multi-color curve. Each colored segment represents a one second time step. While the speed of the final CAV trajectory slowly varies, it anticipates the stop wave and, in this case, neutralizes the stop. The final CAV trajectory is much smoother than the cHDV that preceded it. Fig. 3A-B show the time series speed and acceleration for the CAV in this case, clearly showing a smoother speed and attenuated accelerations. While this work does not consider the vehicles behind the final CAV trajectory, clearly the impacted trajectories upstream of the CAV would follow from the final CAV trajectory rather than the original HDV trajectory.

Meanwhile, Fig. 2B repeats the analysis for another CAV, in this case at (t_2, x_2). For this second case, while some slowing is evident at the end of the segment at t_2, when we start charting the CAV trajectory the stop wave had not yet formed. Still, the CAV is able to avoid an unnecessary acceleration and once more neutralizes the stop wave. Fig. 3C-D show the time series speed and acceleration for the CAV in this case.

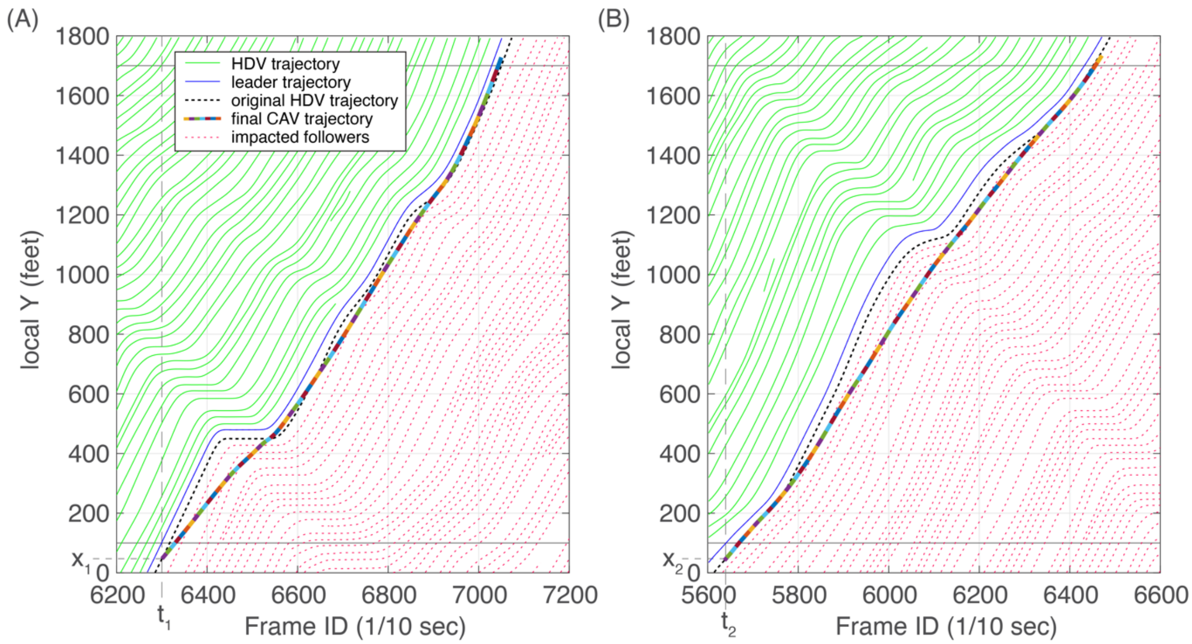

Figure 2, The final CAV trajectory for the CAV in (A) case 1 starting at (t_1, x_1), and (B) case 2 starting at (t_2, x_2). In both cases note how the CAV neutralizes the stop wave seen in the leader trajectory and original HDV trajectory.

2.1. Extending the look ahead

So far, the cHDV look ahead has been limited to the span of the recorded HDV trajectory data, which ends at 1800 ft. So at t_1 in Fig. 1D the CAV used a 1700 ft look ahead, which yielded an estimated trajectory to almost 900 ft, or roughly half the distance to the end of the segment. As the CAV travels further downstream, the range off the cHDV look ahead shrinks because it can never "see beyond" the 1800 ft limit of the collected vehicle trajectory data. To this end, we repeat the method from Coifman (2002) to synthesize the trajectories between 1800 ft and 2800 ft using the last reported speed from each vehicle as they depart the surveillance region. This speed is used to project a chord downstream from the last observation of the vehicle while also generating a signal with a velocity of -15 mph, thus, each of these signals effectively moves backward in time as it travels downstream in space. Each vehicle chord is truncated upon reaching the first signal. Once more, the bands are assumed to be constant speed and whenever a vehicle departs the field of view at 1800 ft the corresponding vehicle chords are aligned end to end to estimate that vehicle's trajectory beyond 1800 ft. An example of the resulting synthetic trajectories to 2500 ft is shown in Fig. 4.

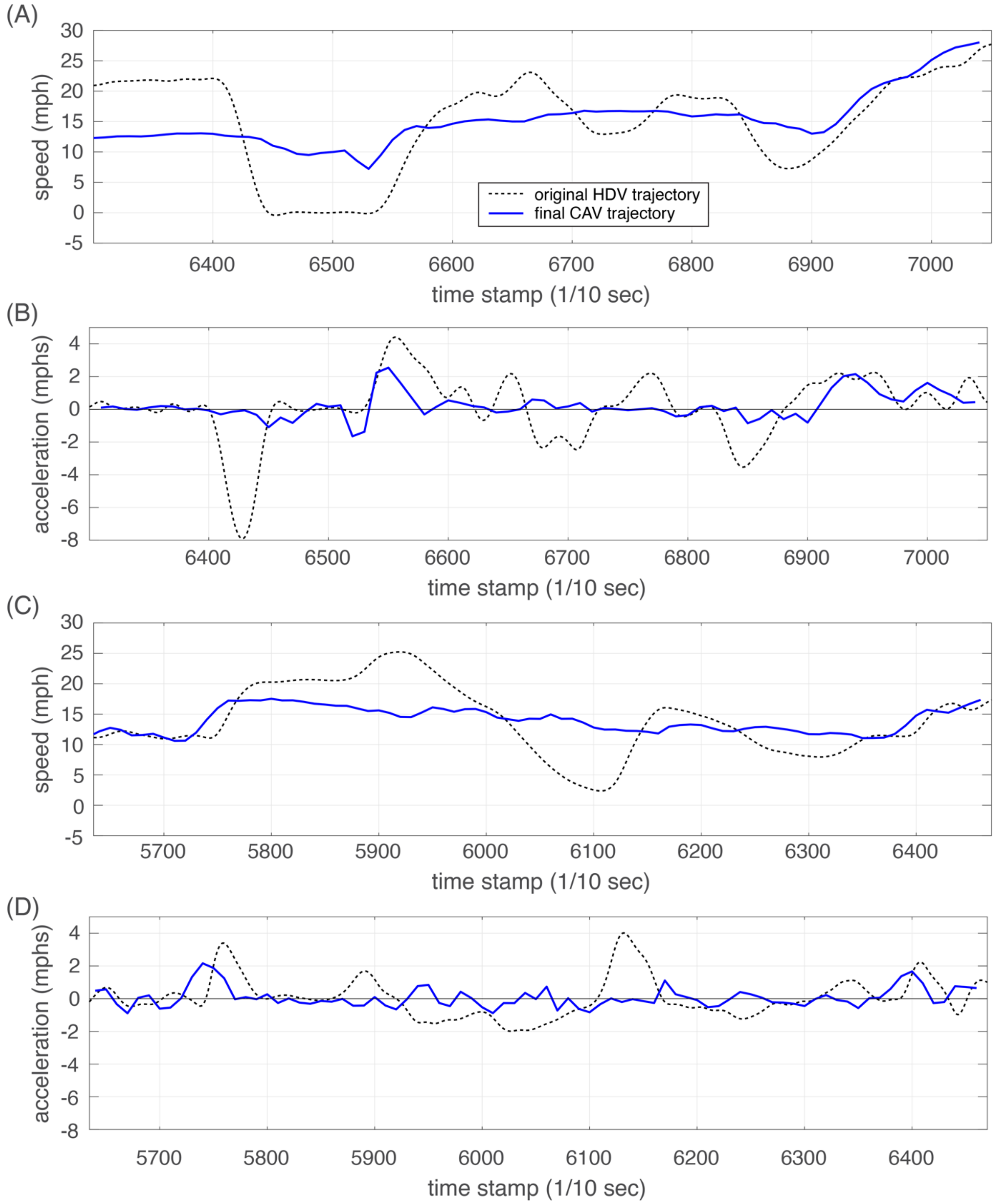

Figure 3, Case 1 time series (A) speed and (B) acceleration; and case 2 time series (C) speed and (D) acceleration.

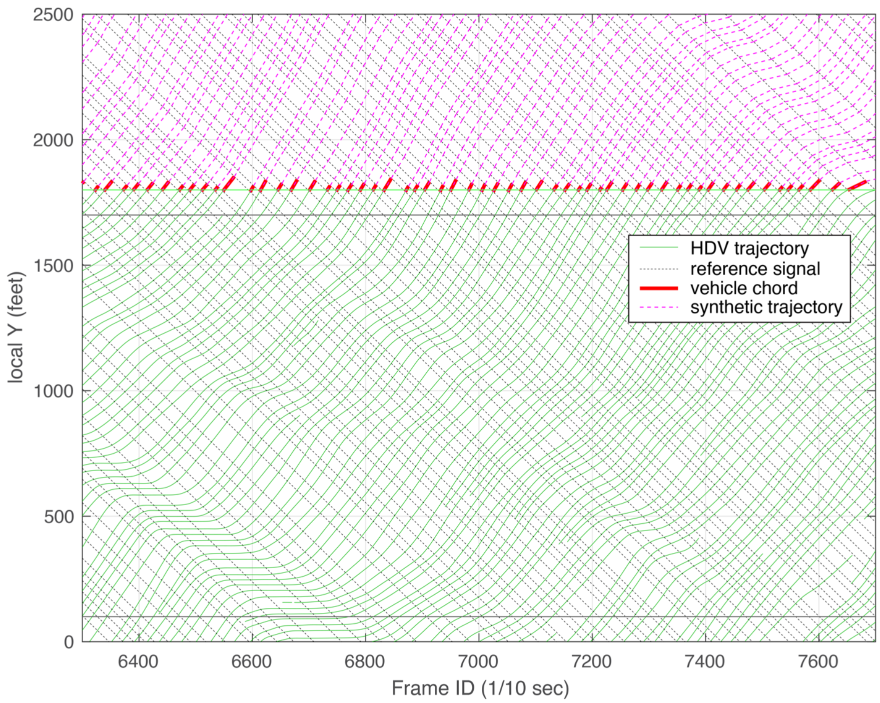

Figure 4, An example illustrating how conditions upstream of 1800 ft are used to generate vehicle chords representative of steady state bands. The speed in these bands are combined with the time that vehicles depart the surveillance region at 1800 ft to synthesize the unobserved vehicle trajectories downstream of 1800 ft.

With the synthetic trajectories we are able to consider longer look ahead distances for estimating the lead vehicle's trajectory. In in addition to the original estimate from 0-1800 ft from Fig. 2A and repeated in Fig. 5A for case 1, we consider 0-2500 ft in Fig. 5B and a fixed moving window of 1000 ft downstream of the CAV in Fig. 5C. In this way, the 0-2500 ft estimates represent the best possible with these data while the fixed 1000 ft window represents a practical implementation of the method. As shown with long dashed lines in the subplots, none of the methods use information before t_1, part A only uses the measured trajectories up to 1800 ft, part B adds the synthetic trajectories up to 2500 ft, and part C only uses the trajectories within the dashed region. At each time step the lead vehicle's trajectory estimation only uses the cHDV data from that instant. For this case there is very little difference between the final CAV trajectory in the three different scenarios. The original CAV trajectory from Fig. 5A is shown below the CAV trajectory in the other two scenarios. For Fig. 5B the two estimates only differ in the last few samples, around 1700 ft. Whereas the shorter look ahead with the 1000 ft fixed window is more susceptible to the stop wave, pulling a little ahead of the original CAV trajectory around 300 ft, and then repeating the difference around the last few samples around 1700 ft. Fig. 6 repeats the comparisons for case 2, seen previously in Fig. 2B. In this case the stop wave passes the CAV further downstream, so by the time the look ahead to 1800 ft captures the stop wave the CAV has started speeding up into the lead up to the wave. Whereas Fig. 6B shows that the look ahead to 2500 ft provides enough forewarning to allow the CAV to maintain a more constant speed as it nullifies the stop. On the other hand, Fig. 6C shows that the fixed 1000 ft window is more sensitive to the acceleration in the lead up to the stop wave as it pulls ahead of the original curve, only to have to slow later. Still, this fixed window look ahead is able to nullify the stop.

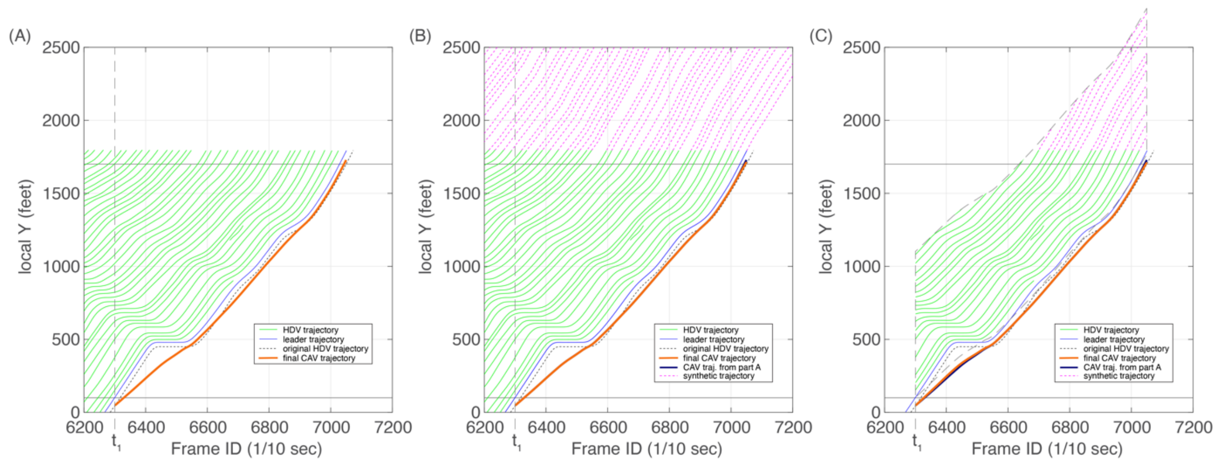

Figure 5, Estimating the final CAV trajectory for Case 1 (A) using the original look ahead region out to 1800 ft, (B) the extended surveillance region out to 2500 ft, and (C) the fixed 1000 ft moving window.

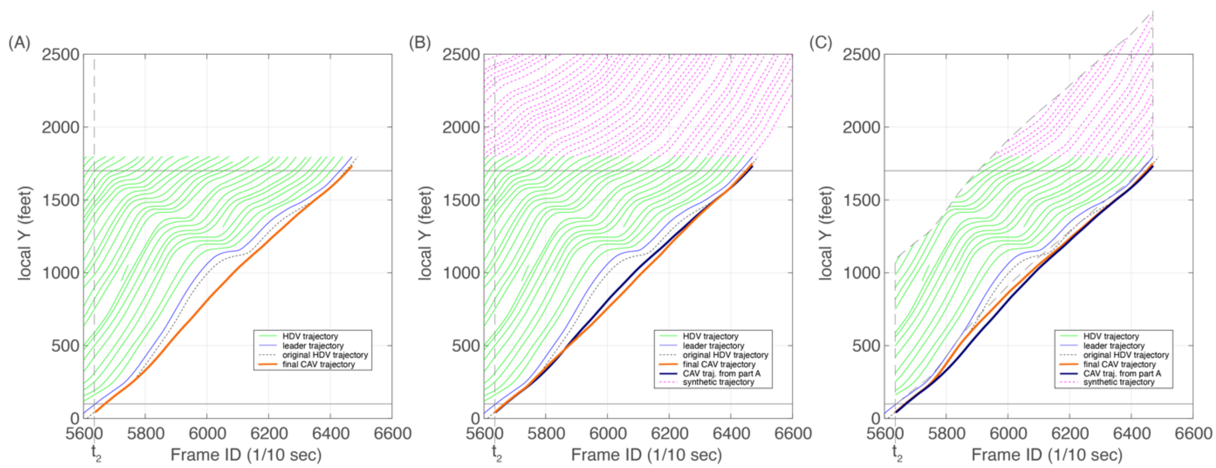

Figure 6, Estimating the final CAV trajectory for Case 2 (A) using the original look ahead region out to 1800 ft, (B) the extended surveillance region out to 2500 ft, and (C) the fixed 1000 ft moving window.

2.2. Limiting acceleration

Having demonstrated that the CAV can nullify the propagation of stop waves, this work now considers the impacts of limiting the CAV acceleration. To be clear, the limits are strictly on acceleration, but for safety's sake, no limit is placed on the magnitude of deceleration. This section uses the fixed 1000 ft window for illustration because it has the smallest overall look ahead and thus, also exhibits the largest fluctuations among the three different look ahead scenarios, but the results are consistent with the other scenarios. Fig. 7A repeats the unlimited results from Fig. 5C. Fig. 7B repeats the analysis, only now limiting the CAV acceleration, $a_{CAV} \leq 1\ mphps$, while Fig. 7C repeats the process except $a_{CAV} \leq 0.5\ mphps$. The differences between the three scenarios only becomes apparent at close inspection, namely, in Fig. 7B the dark curve corresponding to the original unlimited CAV trajectory pulls to the left of the lighter curve for $a_{CAV} \leq 1\ mphps$ around $Y = 500\ ft$ and again around $Y = 1400\ ft$. Despite the slower response within the segment, the departure time from the segment is nearly unchanged. The differences are easier to see in Fig. 7C where $a_{CAV} \leq 0.5\ mphps$. In this case the slower acceleration actually eliminates one acceleration-deceleration cycle that occurred in the CAV trajectory between 500 and 1300 ft in the other two scenarios. At the end of the link the $a_{CAV} \leq 0.5\ mphps$ trajectory is within 1.5 sec of unlimited CAV trajectory and is closing the gap. This slower response time is inherent with the limited acceleration and as evident earlier in the progression, primarily serves to smooth out the trajectories, provided it can eventually rejoin the unlimited trajectory it will do so without adding delay. Fig. 8A shows the corresponding speed for these three scenarios along with the original HDV trajectory's speed. All of the CAV curves greatly reduce the undulations of the HDV, while the maximum acceleration of the latter two scenarios is clearly evident by the maximum slope of the given speed curve. As one should expect, the $a_{CAV} \leq 0.5\ mphps$ shows the least fluctuations as it slowly tracks the changing speed, and this smoother trajectory provides more stable conditions to any vehicle following the CAV. Fig. 8B shows the corresponding time series acceleration for the HDV and three scenarios of the CAV. Note how much the $a_{CAV} \leq 0.5\ mphps$ scenario reduces the acceleration spikes throughout the timespan. Meanwhile, although deceleration is not restricted, because of the look ahead, all three of the CAV scenarios keep the magnitude of deceleration below 2 mphps whereas the HDV deceleration briefly reached a magnitude of 8 mphps.

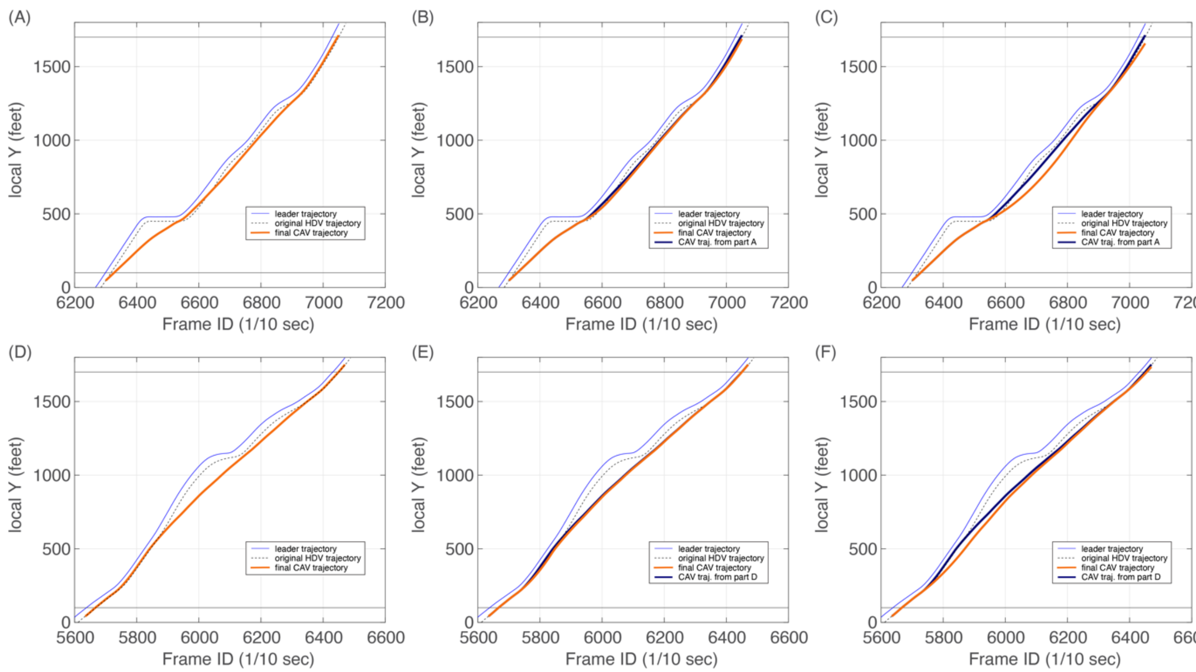

Figure 7, The final CAV trajectory for case 1 with the fixed 1000 ft moving look ahead window and (A) unlimited acceleration, (B) $a_{CAV} \leq 1\ mphps$, and (C) $a_{CAV} \leq 0.5\ mphps$. (D)-(F) repeat the analysis for case 2.

Fig. 7D-F repeat the analysis for case 2, with Fig. 7D showing the unlimited results from Fig. 6C. Recall from Fig. 6 that the fixed 1000 ft look ahead was more sensitive to the stop wave than the other two variants that considered a larger look ahead to either 1800 ft or 2500 ft. Specifically, the fixed 1000 ft look ahead pulls ahead of the original curve, only to have to slow later. Fig. 7F shows that the $a_{CAV} \leq 0.5\ mphps$ trajectory is able to compensate for this overly aggressive behavior, reducing the impacts of the transient increase in speed on the CAV trajectory. Fig. 8C shows the corresponding speed for these three scenarios along with the original HDV trajectory's speed. As with case 1, the smoothing properties of the CAV are readily apparent. Fig. 8D shows the corresponding time series acceleration for the HDV and three scenarios of the CAV. Once more, the $a_{CAV} \leq 0.5\ mphps$ scenario is notable in how much it reduces the acceleration peaks.

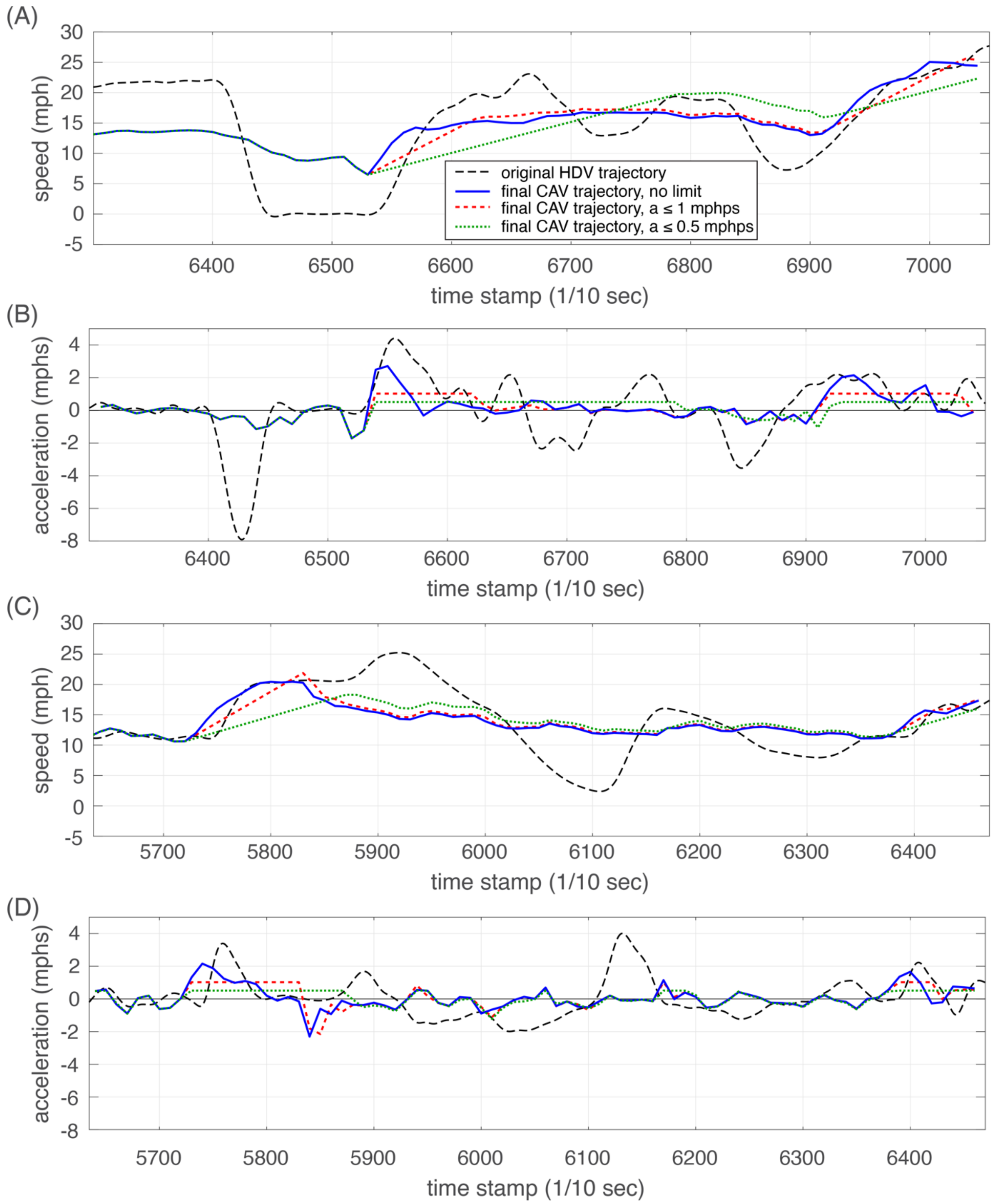

Figure 8, Time series (A) speed and (B) acceleration for case 1 under the three limitation scenarios; and the corresponding time series (C) speed and (D) acceleration for case 2.

Vehicle emissions and fuel consumption are highly dependent on acceleration. We use the Comprehensive Modal Emission Model, CMEM, (Scora and Barth, 2006) to quantify the impact of the various scenarios under case 1. Table 1 shows the CMEM results for the final CAV trajectories given the three different look ahead ranges and the three different acceleration limits, as well as the original HDV trajectory. Table 2 shows that with unlimited acceleration the CAV reduces fuel consumption and CO_2 by roughly 15% from the HDV trajectory, while CO, HC and NOx respectively drop by roughly 30%, 39% and 35% from the HDV trajectory. Under the most restrictive $a_{CAV} \leq 0.5\ mphps$ scenario the CAV reduces fuel consumption and CO_2 by roughly 17% from the HDV trajectory, while CO, HC and NOx respectively drop by roughly 42%, 47% and 67% from the HDV trajectory. The savings from the smoother CAV trajectory should be passed to any following vehicle, even if that follower is a HDV.

Table 1, CMEM results for the original HDV trajectory and the final CAV trajectories under three different look ahead regions and three different acceleration limitations.

look ahead	Fuel (g)	CO2 (g)	CO (g)	HC (g)	NOx (g)
HDV	50.37	157.56	1.255	0.0738	0.1486
unlimited accel					
1800 ft	43.6	136.6	0.900	0.046	0.096
2500 ft	42.2	132.3	0.846	0.044	0.093
fixed 1000 ft	42.7	134.1	0.870	0.045	0.100
accel ≤ 1 mphps					
1800 ft	42.3	132.7	0.807	0.042	0.065
2500 ft	42.3	132.7	0.807	0.042	0.065
fixed 1000 ft	42.5	133.4	0.817	0.043	0.071
accel ≤ 0.5 mphps					
1800 ft	41.1	129.1	0.711	0.039	0.046
2500 ft	41.1	129.1	0.711	0.039	0.046
fixed 1000 ft	41.7	131.1	0.733	0.039	0.049

3. Conclusions

This research developed an approach to enable a single CAV to smooth out traffic disturbances and as a direct result, eliminate unexpected stops to improve safety. This traffic smoothing has secondary benefits of reducing accelerations which in turn reduces vehicle emissions and improves fuel efficiency. To be clear, the CAV is not acting in isolation, it requires all of the vehicles within the look ahead region to be connected, reporting their current location and speed. These instantaneous individual vehicle states are integrated over space to forecast the trajectory of the CAV's leader. This forecast is then used to derive a "perfect follower" for the leader, i.e., the downstream limit of where the CAV is likely to be able to travel over time. At which point the highest constant speed radial is found between the CAV's current location and the perfect follower trajectory. The CAV takes this speed for the current time step and then the process is repeated in the next time step. A one second time step was used in this proof of concept study and yielded good results, but future research should explore the impacts of using other time steps.

The smooth CAV trajectory provides more stable conditions to any vehicle following the CAV. Thus, resulting in smoother trajectories for safety and efficiency to the followers. At present the work only contemplates the first CAV. Ongoing research is looking at how multiple CAV can provide a coordinated response, where each subsequent follower takes the estimated trajectory of its leader as the starting point to derive the perfect follower and find the radial that meets it at a tangent. In so doing, the subsequent CAV's react earlier in the evolution of the developing traffic state and thus, will continue to smooth out the traffic state.

Table 2, The relative reduction of CAV CMEM results compared to the HDV under three different look ahead regions and three different acceleration limitations.

look ahead	Fuel (g)	CO2 (g)	CO (g)	HC (g)	NOx (g)
unlimited accel					
1800 ft	-14%	-13%	-28%	-38%	-35%
2500 ft	-16%	-16%	-33%	-40%	-37%
fixed 1000 ft	-15%	-15%	-31%	-39%	-33%
accel ≤ 1 mphps					
1800 ft	-16%	-16%	-36%	-43%	-56%
2500 ft	-16%	-16%	-36%	-43%	-56%
fixed 1000 ft	-16%	-15%	-35%	-42%	-52%
accel ≤ 0.5 mphps					
1800 ft	-18%	-18%	-43%	-47%	-69%
2500 ft	-18%	-18%	-43%	-47%	-69%
fixed 1000 ft	-17%	-17%	-42%	-47%	-67%

There is a clear dependency between the smoothness of the resulting trajectory and the look ahead distance. This work considered three look ahead distances: all vehicles out to the limit of the empirical data (1800 ft) at all times, then the work synthesized trajectories out to 2500 ft to capture a longer look ahead and considered all vehicles out to 2500 ft, and finally, the work sought to mimic a practical deployment using a fixed moving window of 1000 ft. The shortest look ahead tends to yield trajectories that speed up only to have to slow down again, whereas the longer look ahead allows the CAV to anticipate the undulating conditions better. We suspect a longer fixed moving window, e.g., 2000 ft, would yield better results, but we are constrained by the empirical data and currently do not have sufficient microscopic data to test that large range.

The work also considered three different acceleration conditions: unlimited, max accel = 1 mphps, and max accel = 0.5 mphps. As the acceleration restriction became more binding the CAV trajectory proved more stable to acceleration waves, but it also exhibited more lag to the leader. Under all of the conditions the CAV was able to nullify a stop wave with accel reaching −8 mphps before reaching the CAV. Nullifying stop waves like this should greatly reduce the risk of rear end collisions. Meanwhile, all of the CAV scenarios exhibited a large reduction in fuel consumption and emissions, on the order of 16% reduction in fuel consumption and CO2 emissions, and over 30% reduction of CO, HC and NOx. The emissions reduction should have a direct benefit to public health due to the reduction of toxic gases.

There are aspects of this research that are idealized, the largest of which is the assumption that all vehicles are either cHDV or CAV. New research is exploring how to use sparse cHDV and CAV (on the order of 10% penetration) to provide anticipative slowing. Meanwhile, by the very nature of slowing down the CAV in anticipation of the lead vehicle soon slowing, this approach can give rise to a large but short lived gap between the CAV and the cHDV ahead of it, e.g., Fig. 2A shows a roughly 200 ft gap between these two vehicles around 640 sec (6400 on the horizontal axis). For this work it is assumed that no vehicle will enter that gap from another lane. It is recognized that in real traffic such a large gap might attract vehicles from the adjacent lane, and some means of preventing those maneuvers will need to be implemented. That could be via enforcement, coordination across lanes, or simply the CAV control. While it is an important element that needs to be addressed for deployment, it is left as future work at the current proof of concept stage.

One can view the roadway as a pipe. If you use CAV to automate the pipe, it is still subject to the operating limitations of a pipe, e.g., the maximum throughput remains constrained. With the focus on queued traffic, it is important to recognize that a queue simply represents the storage of demand in excess of capacity as the excess vehicles wait to be served. To eliminate a queue requires increasing capacity or decreasing demand. This work does not seek to achieve freely flowing traffic out of queued traffic. Rather, this work seeks to take conventionally unstable queued traffic and bring it to a stable flow while queued. So one must resist going to higher speeds since the slow traffic is storing the vehicles until the downstream link is ready to accommodate their demand. If the downstream capacity does not change, the number of vehicles per hour that we can deliver through the current link also does not change. If the vehicles still enter the freeway at the same time, they will have to wait somewhere for their turn to pass. To this end, we seek to drive the state to constant speeds that are below the speed limit to provide the storage while delayed, but more importantly- keep conditions as safe as possible by smoothing out the disturbances.

Acknowledgements

The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange. The report is funded, partially or entirely, by a grant from the U.S. Department of Transportation's University Transportation Centers Program. However, the U.S. Government assumes no liability for the contents or use thereof.

References

Ban, J. (2021). A Multiscale Simulation Platform for Connected and Automated Transportation Systems, Connected Cities for Smart Mobility towards Accessible and Resilient Transportation Center (C2SMART)

Coifman, B. (2002). Estimating Travel Times and Vehicle Trajectories on Freeways Using Dual Loop Detectors, *Transportation Research: Part A*, vol 36, no 4, pp. 351-364.

Coifman, B., Li, L. (2024). Partial Trajectory Method to Align and Validate Successive Video Cameras for Vehicle Tracking, *Transportation Research Part C*. Vol. 158.

Coifman, B., Wang, Y. (2005). Average velocity of waves propagating through congested freeway traffic. *Transportation and Traffic Theory. Flow, Dynamics and Human Interaction. 16th International Symposium on Transportation and Traffic Theory*, University of Maryland, College Park. pp 165-179.

Jin, Y. (2022). Establishing a Simulation Package and Testbed for Traffic Congestion Reduction Using Deep Reinforcement Learning. Transportation Consortium of South-Central States (Tran-SET)

Labi, S. (2020). Development of AI-based and control-based systems for safe and efficient operations of connected and autonomous vehicles, Center for Connected and Automated Transportation

Peeta, S. (2018). Cooperative control mechanism for platoon formation of connected and autonomous vehicles - Phase 1 and 2, Center for Connected and Automated Transportation

Newell, G. (2002). A simplified car-following theory: a lower order model. Transportation Research Part B: Methodological, 36(3), 195-205.

NHTSA (2023). https://cdan.dot.gov [accessed on May 18, 2023].

Samiul, H., Zaki, M. (2020). A Co-Simulation Study to Assess the Impacts of Connected and Autonomous Vehicles on Traffic Flow Stability during Hurricane Evacuation, SaferSim

Scora, M., Barth, M. (2006). *Comprehensive Modal Emission Model (CMEM) Version 3.01 User's Guide.* https://www.cert.ucr.edu/sites/g/files/rcwecm1251/files/2019-07/CMEM_User_Guide_v3.01d.pdf [accessed on July 1, 2024].

Stern, R. (2022). Understanding Risks and Opportunities for Ramp Metering Control in a Mixed-autonomy Future, Minnesota Department of Transportation

USDOT (2023). *U.S. DOT RD&T Strategic Plan (FY 2022-2026)–Building a Better Transportation Future for All*, https://www.transportation.gov/rdtstrategicplan [accessed on July 23, 2024]. 96p.

Wei, F. (2019). Machine Learning-based Trajectory Optimization of Connected and Autonomous Vehicles (CAVs), Center for Advanced Multimodal Mobility Solutions and Education

Wei, F. (2021). Online Cooperative Lane-changing Model of Connected and Autonomous Vehicles, Center for Advanced Multimodal Mobility Solutions and Education

Wei, F. (2022). Dynamic Coordinated Speed Control and Synergistic Performance Evaluation in Connected and Automated Vehicle Environment, Center for Advanced Multimodal Mobility Solutions and Education

1. Report No.
Enter the report number assigned by the sponsoring agency.

2. Government Accession No.

3. Recipient's Catalog No.

4. Title and Subtitle
Safe and Efficient Automated Freeway Traffic Control -Phase 1 Final Report

5. Report Date
July 31, 2024

6. Performing Organization Code
Enter any/all unique numbers assigned to the performing organization, if applicable.

7. Author(s)
Benjamin Coifman, PhD, https://orcid.org/0000-0002-8201-964X

Yuan Liu, https://orcid.org/0009-0005-4330-8923

8. Performing Organization Report No.
Enter any/all unique alphanumeric report numbers assigned by the performing organization, if applicable.

9. Performing Organization Name and Address
Ohio State University
Department of Civil Environmental and Geodetic Engineering 2070 Neil Ave
Hitchcock Hall 470
Columbus, OH 43210

10. Work Unit No.

11. Contract or Grant No.
Federal Grant No. 69A3552344811

12. Sponsoring Agency Name and Address
Safety21 University Transportation Center
Carnegie Mellon University
5000 Forbes Avenue
Pittsburgh, PA 15213

13. Type of Report and Period Covered
Final Report (July 1, 2023-June 30, 2024)

14. Sponsoring Agency Code
USDOT

15. Supplementary Notes
Conducted in cooperation with the U.S. Department of Transportation.
x

16. Abstract
The goal of this work is to eliminate unexpected stops to improve safety with the added benefit of reducing accelerations to improve fuel efficiency and reduce vehicle emissions. Congested traffic is characterized by signals and waves propagating upstream through the queued traffic. Freeway drivers do not expect to encounter abrupt drops in speed or stopped traffic, as a result, shockwaves sharply increase the accident rates, particularly in the context of rear end collisions. This work seeks to use connected and automated vehicles (CAV) to smooth out traffic disturbances on a freeway. The CAV integrates the instantaneous state information from the downstream vehicles to forecast the trajectory of the CAV's leader and proactively respond to changes in state that have not yet reached the lead vehicle. Using empirical vehicle trajectory data, it is shown that the methodology can rapidly nullify stop and slow waves and yield large reduction in vehicle emissions.

17. Key Words
Connected and Automated Vehicles; Freeway Traffic; Congestion; Safety; Stop waves; Vehicle emissions

18. Distribution Statement
No restrictions. This document is available through the National Technical Information Service, Springfield, VA 22161. Enter any other agency mandated distribution statements. Remove NTIS statement if it does not apply.

19. Security Classif. (of this report) Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 18	**22. Price** Refers to the price of the report. Leave blank unless applicable.

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized