Experimental validation of connected automated vehicle design among human-driven vehicles — impacts on traffic safety and efficiency

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Abstract

In this paper, we present results regarding the experimental validation of connected automated vehicle design. In order for the connected automated vehicle to integrate well with human-dominated traffic, we propose a general framework of connected cruise control based on human driving behavior. We test the connected cruise controllers under several driving scenarios while utilizing beyond-line-of-sight motion information obtained through vehicle-to-vehicle communication. We demonstrate that both traffic safety and efficiency can be significantly improved for the connected automated vehicle as well as the human-driven vehicles around.

Keywords: connected automated vehicle, connected cruise control, vehicle-to-vehicle communication, beyond-line-of-sight information, human car-following behavior, traffic safety and efficiency

1. Introduction

Since the invention of cars more than a century ago, the safety and efficiency of road transportation system have been revolutionized by the advances in automotive and infrastructure technologies. While traffic accidents
and congestion problems continue to exist on the U.S. roadways [1, 2], advancements in autonomous driving technologies are promising a much safer and highly efficient future in transportation [3]. However, despite the rapid developments in autonomous driving [4], automated vehicles still have difficulties when interacting with other vehicles in real traffic [5]. This is partially due to the fact that the sensing system is not robust against various road and weather conditions. Moreover, sensors are only able to extract the current information about its immediate neighborhood. As a result, an autonomous vehicle only relying on sensors has no access to beyond-line-of-sight information, which limits its capability to reliably anticipate the motion of surrounding vehicles and thus its controller performance [6].

Therefore, in order to fully exploit the benefits of automated vehicles, it is desirable to introduce beyond-line-of-sight information through vehicle-to-vehicle (V2V) communication [7]. V2V communication was first tested in early platooning experiments [8], and more recently was utilized in cooperative adaptive cruise control (CACC) aimed for improving fuel economy and traffic efficiency [9, 10, 11, 12, 13, 14, 15, 16, 17, 18]. While CACC often requires a fleet of automated cars that are connected with V2V communication and controlled by cooperative algorithms, driving automation in its early stage of implementation will have to deal with a mixed traffic system where most surrounding vehicles are human-driven.

Thus, it is necessary to consider connected automated vehicle design in partially automated traffic. For this purpose, some algorithms have been proposed for the longitudinal and lateral control of connected automated vehicles [19, 20], and some results exist regarding their influence on traffic flow [21]. In our earlier work, we have proposed connected cruise control based on human car-following behavior and utilizing information from multiple vehicles ahead [22, 23]. Through theoretical analysis and simulations we have shown that connected cruise control has great potential in improving active safety, fuel economy, and traffic efficiency [24, 25, 26, 27].

While automated vehicles have been experimentally shown to benefit the road transportation [28, 29], there is a lack of experimental results regarding how V2V communication may improve the performance of automated vehicles and the human-driven vehicles around them. In this paper we present three groups of experiments to demonstrate the benefits of beyond-line-of-sight information for connected automated vehicles and the human-driven vehicles behind them in real traffic.

The rest of this paper is organized as follows: in Section 2 we describe
the human car-following behavior based on the optimal velocity model; in Section 3 we propose a general framework for connected cruise controllers; in Section 4 we present two sets of experiments that demonstrate how a connected automated vehicle improves traffic safety using beyond-line-of-sight information; in Section 5 we present a set of experiments showing the improvements on traffic efficiency using beyond-line-of-sight information; finally in Section 6 we conclude our results and discuss future directions.

2. Human car-following behavior

In this section we model the car-following behavior of human drivers. For simplicity we only consider longitudinal motion of vehicles in a single lane; see Fig. 1(a).

Based on [22, 23, 30], we use the optimal velocity model to describe the dynamics of the human-driven vehicle $i$, that is,

$$
\begin{align*}
\dot{s}_i(t) &= v_i(t), \\
\dot{v}_i(t) &= \alpha_{h,i}(V_i(h_i(t - \tau_i)) - v_i(t - \tau_i)) + \beta_{h,i}(W(v_{i+1}(t - \tau_i)) - v_i(t - \tau_i)).
\end{align*}
$$

(1)

Here the dot stands for differentiation with respect to time $t$, $s_i$ denotes the position of the rear bumper of vehicle $i$ while $v_i$ denotes its speed. Moreover, the headway $h_i$ denotes the bumper-to-bumper distance between vehicle $i$ and its predecessor, that is,

$$
h_i = s_{i+1} - s_i - l_i,
$$

(2)
where $l_i$ is the length of vehicle $i$, as shown in Fig. 1(a).

According to (1) the acceleration is determined by two terms: the difference between the headway-dependent desired velocity and the actual velocity, and the velocity difference between the vehicle and its predecessor. The gains $\alpha_{h,i}$ and $\beta_{h,i}$ are used to correct velocity errors, while the delay $\tau_i$ represents the sum of driver reaction time and actuator delay of the vehicle. The desired velocity is determined by the nonlinear range policy function

$$V_i(h_i) = \begin{cases} 0 & \text{if } h_i \leq h_{st,i}, \\ \kappa_i (h_i - h_{st,i}) & \text{if } h_{st,i} < h_i < h_{go,i}, \\ v_{\max} & \text{if } h_i \geq h_{go,i}, \end{cases}$$

(3)

as shown in Fig. 1(b), where $\kappa_i = v_{\max}/(h_{go,i} - h_{st,i})$. That is, the desired velocity is zero for small headways ($h_i \leq h_{st,i}$) and equal to the speed limit $v_{\max}$ for large headways ($h_i \geq h_{go,i}$). Between these, the desired velocity increases with the headway linearly, with gradient $\kappa_i$. Note that when $h_{st,i} = 0$ [m], $1/\kappa_i$ is often referred to as the time headway. Many other range policies may be chosen, but the qualitative dynamics remain similar if the above characteristics are kept [30].

In (1) the saturation function

$$W(v_{i+1}) = \begin{cases} v_{i+1} & \text{if } v_{i+1} \leq v_{\max}, \\ v_{\max} & \text{if } v_{i+1} > v_{\max}, \end{cases}$$

(4)

is used to consider the situation when a human-driven vehicle refuses to go beyond its speed limit $v_{\max}$ while its predecessor is speeding.

Thus, for $v_i(t) < v_{\max}$, (3) defines the steady-state behavior of vehicle $i$ and, in aggregation, the steady-state traffic flow where vehicles travel with the same constant velocity:

$$s_i(t) = v^* t + \bar{s}_i, \quad v_i(t) \equiv v^*,$$

(5)

such that

$$\bar{s}_{i+1} - \bar{s}_i - l_i = h_i^*, \quad v^* = V_i(h_i^*).$$

(6)

In a vehicle string, the equilibrium velocity $v^*$ is determined by the head vehicle while the equilibrium headway $h_i^*$ can be calculated from the range policy (3).
3. Longitudinal controller design for connected automated vehicles

In this section we present a general framework for the longitudinal motion control of connected automated vehicles. We consider the scenario shown in Fig. 2 where a connected automated vehicle (blue) receives motion information from several vehicles ahead. The blue arrows indicate that the connected cruise controller contains feedback terms using the motion information of the preceding vehicles. Then we write the dynamics of this connected automated vehicle as

\[
\begin{align*}
\dot{s}_1(t) &= v_1(t), \\
\dot{v}_1(t) &= \sum_{i=2}^{n} u_i(t - \xi_i - \sigma),
\end{align*}
\]

(7)

where \( u_i \) denotes the connected automated vehicle’s acceleration in response to the motion of a preceding vehicle \( i \). Moreover, \( \xi_i \) represents the delay of information from vehicle \( i \) due to sampling and intermittency in vehicle-to-vehicle communication (0.1 \( \leq \xi_i \leq 0.2 \) [s] when the transmission rate is 10 [Hz]), and \( \sigma \) is the actuator delay whose value is around 0.5 [s]. Note that instead of the actuator delay \( \sigma \), a first-order lag approximation is also used [22, 31].

In order for the connected automated vehicle to be readily accepted by its passengers and other road users, we design \( u_2, \ldots, u_n \) based on the human car-following behavior (1), that is,

\[
\begin{align*}
u_2 &= A(V_1(h_1) - v_1) + B_2(W(v_2) - v_1), \\
u_i &= B_i(W(v_i) - v_1),
\end{align*}
\]

(8)
for \( i = 3, \ldots, n \) (see Fig. 2). The feedback gains are varied based on the distances

\[
A(s_2, s_1) = \begin{cases} 
\alpha & \text{if } (s_2 - s_1 - l_1) \leq h_{sw}, \\
\alpha_{cc} & \text{if } (s_2 - s_1 - l_1) > h_{sw},
\end{cases}
\]  

(9)

and

\[
B_i(s_i, s_1) = \begin{cases} 
\beta_i & \text{if } (s_i - s_1 - l_1) \leq h_{on}, \\
\beta_i \frac{s_i - s_1 - l_1 - h_{sw}}{h_{on} - h_{sw}} & \text{if } h_{on} < (s_i - s_1 - l_1) < h_{sw}, \\
0 & \text{if } (s_i - s_1 - l_1) \geq h_{sw},
\end{cases}
\]  

(10)

where \( h_{sw} \) denotes the switching distance and \( h_{on} \leq h_{sw} \), as shown in Fig. 3(a,b). Such switching mechanisms are introduced to ensure that the connected automated vehicle does not consider speed information from vehicles too far ahead. Notice that in (9) the headway \( h_1 = s_2 - s_1 - l_1 \) is used while in (10) the bumper-to-bumper distance \( s_i - s_1 - l_1 \) shows up. Also note that based on (3,8,9,10), when the preceding vehicles are far from the connected automated vehicle, i.e., \( (s_i - s_1 - l_1) > h_{sw} \), the connected cruise controller (7,8) becomes a cruise controller with the feedback gain \( \alpha_{cc} \).

Note that for simplicity, the connected cruise controller (7,8) does not contain feedback terms on the headways \( h_2, h_3, \ldots, h_n \) of vehicles farther ahead, which differs from the connected cruise control algorithms previously proposed in [24, 32].

Figure 3: Switching functions (9,10) for feedback gains \( A(s_2, s_1) \) and \( B_i(s_i, s_1) \), for \( i = 2, \ldots, n \).
4. Experimental validation of beyond-line-of-sight safety

In this section we evaluate the performance of the controller (7,8) in two traffic scenarios. We will demonstrate that in both cases the connected automated vehicle benefits from the beyond-line-of-sight information obtained through vehicle-to-vehicle communication. Moreover, we argue that the behavior of the connected automated vehicle may have a positive impact on the safety of other vehicles around it.

4.1. A connected automated vehicle on curvy road

Here we consider a scenario where a connected automated vehicle travels on a road with a right turn, as shown by the blue dashed trajectory in Fig. 4(a). Another vehicle is stopped where the road starts to turn, as marked by the red square. Due to road curvature and elevation, a human driver or sensors would only be able to perceive the stationary vehicle shortly before entering the curve, as indicated by the light blue square at position B. At this moment, the distance between two vehicles (light blue and red) is about 25 meters. The corresponding driver’s view is shown in Fig. 4(b).
Figure 5: Speed and acceleration profiles of a human-driven vehicle when it approaches the stationary vehicle shown in Fig 4(a) and responds to the stationary vehicle. This sudden appearance of the stationary vehicle, a harsh braking must be applied to avoid collision.

Fig. 5 shows the speed and acceleration profiles of a human-driven vehicle when it approaches this curve and responds to the stationary vehicle. At around 20 [s], the driver sees the stationary vehicle, and a harsh braking follows. While the human driver is able to stop the vehicle safely, the deceleration reaches $-8 \text{ m/s}^2$. Such a deceleration rate may not always be achievable when the road surface is not ideal, and it may trigger a cascade of harsh braking among the following vehicles. In the same way, an automated vehicle that relies solely on sensors would also enter such hazardous situations due to obstructions in its line of sight.

To solve such a problem, we replace the human driver with the controller $(7,8)$, where $n = 2$ since there is only one car ahead. For the range policy function $V_1(h_1)$, we set the distances $h_{st,1} = 5 \text{ [m]}$, $h_{go,1} = 30 \text{ [m]}$, and the speed limit $v_{\text{max}} = 15 \text{ [m/s]}$, such that the gradient becomes $\kappa_1 = 0.6 \text{ [1/s]}$. The feedback gains are $\alpha_{cc} = 0.9 \text{ [1/s]}$, $\alpha = 0.2 \text{ [1/s]}$, $\beta_2 = 0.4 \text{ [1/s]}$, with switching distances $h_{on} = 30 \text{ [m]}$ and $h_{sw} = 70 \text{ [m]}$. With vehicle-to-vehicle communication, the connected cruise control algorithm is aware of the stationary vehicle even when it is a few hundred meters away, and the connected automated vehicle is able to slow down in a much milder way as shown in Fig. 6. In particular, the deceleration only reaches $-2 \text{ [m/s}^2]$, which would remain safe with less than ideal road surface and is unlikely to trigger a cascade of harsh braking.

In Fig. 7 we show the speed and acceleration of both the human-driven
Figure 6: Speed and acceleration profiles of a connected automated vehicle when it approaches the curve shown in Fig 4(a) and responds to the stationary vehicle. In panel (b), the thin curve is the commanded acceleration from (7,8), and the thick blue curve is the acceleration profile of the car.

Figure 7: Comparison of the human-driven vehicle (red curves) and connected automated vehicle (blue curves) approaching the stationary vehicle. (a) Speed as a function of the position. (b) Acceleration as a function of the position.
vehicle (red curves) and the connected automated vehicle (blue curves) as functions of the vehicle position while it travels along the road. The stationary vehicle is located at $s_2 \equiv 260 \text{[m]}$, while vehicle 1 travels from $s_1 = 0 \text{[m]}$ to $s_1 \approx 250 \text{[m]}$ in both cases, i.e., the headway $h_1$ varies between $5 \text{[m]}$ and $255 \text{[m]}$ when $l_1 = 5 \text{[m]}$. In Fig. 7(a) one may observe that both vehicles were traveling with similar speeds before braking. Yet the human-driven vehicle only starts to brake at $s_1 \approx 230 \text{[m]}$, i.e., when it is 25 meters from the stationary vehicle and the stationary vehicle becomes visible to the driver (see Fig. 4(a,b)). On the other hand, the connected automated vehicle starts to brake at $s_1 \approx 185 \text{[m]}$, i.e., when it is 70 meters from the stationary vehicle and the stationary vehicle is still beyond its line of sight (see Fig. 4(a,c)). As a result, the connected automated vehicle is able to avoid the harsh braking and the potential safety hazard, as shown in Fig. 7(b).

4.2. A connected automated vehicle handling a cascade of braking

Here we consider a scenario where a connected automated vehicle travels on a straight road behind three human-driven vehicles, as shown in Fig. 8(a). We consider the traffic situation where the leading vehicle (green car) decelerates and triggers a cascade of severe decelerations among the two following human-driven vehicles (black and red cars); see the green, black and red curves in Fig. 8(b,c). In Fig. 8(c), for $0 < t < 10 \text{[s]}$, the deceleration rates of green, black, and red cars reach $-4$, $-8$, and $-10 \text{[m/s}^2]]$, respectively. That is, while the head vehicle 4 (green) brakes moderately, vehicle 2 (red) brakes at its physical limit. Such a phenomenon is quite common when human drivers are not sufficiently attentive to the changes in traffic. It is thus desirable for a connected automated vehicle to not only stay safe when driving behind human-operated cars, but also mitigate such disturbances propagating from them.

To demonstrate the benefits of connected cruise control utilizing beyond-line-of-sight information, we first assume the connected automated vehicle 1 (blue) only uses motion information from its immediate predecessor, vehicle 2 (red); as shown by the arrow in Fig. 8(a). Thus, we have $n = 2$ in (7), and we may say that this connected automated vehicle is ”degraded” as it is not using beyond-line-of-sight information. For the range policy function $V_1(h_1)$, we set the distances $h_{st,1} = 5 \text{[m]}$, $h_{go,1} = 35 \text{[m]}$, and the speed limit $v_{\text{max}} = 18 \text{[m/s]}$, so that the gradient remains $\kappa_1 = 0.6 \text{[1/s]}$. We also set switching distances $h_{on} = h_{sw} = 300 \text{[m]}$. The feedback gains are $\alpha = 0.4 \text{[1/s]}$, $\beta_2 = 0.5$.
Figure 8: A connected automated vehicle travels on a straight road behind three human-driven vehicles. (a) The connected automated vehicle only utilizes motion information from vehicle 2 with feedback gains $\alpha = 0.4 \ [1/s]$, $\beta_2 = 0.5 \ [1/s]$. (b,c) Speed and acceleration profiles of the four vehicles during one experiment.

[1/s]. The response of this connected automated vehicle with no beyond-line-of-sight information is plotted as blue curves in Fig. 8(b,c). We note that while it brakes milder than its immediate predecessor, its deceleration reaches $-6 \ [m/s^2]$, and its speed is reduced significantly. While this vehicle might perform slightly better with more gain-tuning, without information from cars farther ahead the improvement to its performance will be limited.

We then consider the cases where motion information from multiple preceding vehicles is available to the connected automated vehicle through vehicle-to-vehicle communication. We start with adding the motion information from vehicle 3 (black), see Fig. 9(a). The corresponding gains are $\alpha = 0.4 \ [1/s]$, $\beta_2 = 0.2 \ [1/s]$, $\beta_3 = 0.3 \ [1/s]$. Parameters in the range policy function and the switching distances are the same as in Fig. 8. In Fig. 9(b,c), the human-driven cars (green, black, and red curves) have similar motion profiles as in Fig. 8(b,c), while the connected automated car (blue) applies less severe braking with smaller speed oscillations and peak deceleration rate at $-3.5 \ [m/s^2]$.

While [33] proposed an algorithm to identify from which vehicle ahead a certain motion signal originates, it can be challenging to pinpoint the exact
Figure 9: A connected automated vehicle travels on a straight road behind three human-driven vehicles. (a) The connected automated vehicle utilizes motion information from vehicle 2 and vehicle 3 with feedback gains $\alpha = 0.4 \ [1/s], \beta_2 = 0.2 \ [1/s], \beta_3 = 0.3 \ [1/s]$. (b,c) Speed and acceleration profiles of the four vehicles during one experiment. (d) The connected automated vehicle utilizes motion information from vehicle 2 and vehicle 4 with feedback gains $\alpha = 0.4 \ [1/s], \beta_2 = 0.2 \ [1/s], \beta_4 = 0.3 \ [1/s]$. (e,f) Speed and acceleration profiles of the four vehicles during one experiment.
Figure 10: A connected automated vehicle travels on a straight road behind three human-driven vehicles. (a) The connected automated vehicle utilizes motion information from all three preceding vehicle with feedback gains $\alpha = 0.4$ [1/s], $\beta_2 = 0.2$ [1/s], $\beta_3 = 0.3$ [1/s], $\beta_4 = 0.3$ [1/s]. (b,c) Speed and acceleration profiles of the four vehicles during one experiment.

number of cars between a transmitting vehicle and the connected automated vehicle at any time. Thus, we consider the case where signals from vehicle 4 (green) is used instead of vehicle 3 (black), see Fig. 9(d). The corresponding gains are $\alpha = 0.4$ [1/s], $\beta_2 = 0.2$ [1/s], $\beta_4 = 0.3$ [1/s]. In Fig. 9(e,f) the connected automated vehicle 1 (blue) maintains a similar level of deceleration as in Fig. 9(b,c), which demonstrates the robustness of connected cruise control in real traffic scenarios. The two cases in Fig. 9 demonstrate that using motion information from more than one vehicle ahead enables the connected automated vehicle to avoid severe braking maneuvers even when the immediately preceding vehicle deploys maximum braking. Such performance is robust against uncertainties in the source of V2V information.

To further explore the potential of beyond-line-of-sight information, we consider the case where motion information from all three preceding vehicles is available, see Fig. 10(a). We use the same parameters as in Fig. 8 and Fig. 9, and the feedback gains are $\alpha = 0.4$ [1/s], $\beta_2 = 0.2$ [1/s], $\beta_3 = 0.3$ [1/s], $\beta_4 = 0.3$ [1/s]. In Fig. 10(c) the deceleration peaks at $-2.5$ [m/s$^2$], compared with $-6$ [m/s$^2$] in Fig. 8(c) and $-3.5$ [m/s$^2$] in Fig. 9(c,f). Note
that the peak deceleration for the head vehicle 4 (green) is about \(-3.5 \text{ m/s}^2\). That is, the connected automated vehicle utilizing motion information from three vehicles ahead not only stays safe, but also stops the cascading of braking events. This illustrates how beyond-line-of-sight information can significantly improve active safety in traffic flow.

5. Experimental validation of beyond-line-of-sight efficiency

In this section we evaluate the performance of the connected automated vehicle using the controller (7,8) when traveling behind six human-driven vehicles. Through a series of experiments, we observe that while motion perturbations are amplified through human-driven vehicles, by using beyond-line-of-sight information, the connected automated vehicle is able to mitigate such perturbations, which may lead to increased traffic throughput. Moreover, it also improves the energy efficiency for itself and vehicles behind it.

5.1. Using motion information from one vehicle ahead

Fig. 11(a) shows the configuration of an eight-car vehicle chain. Vehicle 1 (blue) is a connected automated vehicle, while all other vehicles are human-driven and only broadcast their motion information through vehicle-to-vehicle communication. Vehicle 7 (light brown) leads the vehicle chain with a series of mild braking events, while its average speed is about 20 [m/s], as shown in Fig. 11(b). This speed profile is chosen because such mild speed perturbations have been observed frequently in urban and highway traffic.

In Fig. 11(c), we demonstrate how an automated vehicle with no beyond-line-of-sight information behaves during one mild braking event. The controller (7,8) is implemented on vehicle 1 with \( n = 2 \) and feedback gains \( \alpha = 0.4 \text{ [1/s]}, \beta_2 = 0.5 \text{ [1/s]}, \) cf. Fig. 8(a). The switching distances \( h_{\text{on}} \) and \( h_{\text{sw}} \) are the same as in Section 4.2, while the range policy function has \( h_{\text{st},1} = 5 \text{ [m]}, h_{\text{go},1} = 55 \text{ [m]}, \) and the speed limit \( v_{\text{max}} = 30 \text{ [m/s]}, \) yielding \( \kappa_1 = 0.6 \text{ [1/s]} \). In Fig. 11(c), the head vehicle 7 (light brown) reaches minimum speed \( v_7(t) \approx 14 \text{ [m/s]} \) at \( t \approx 385 \text{ [s]} \). As the braking event cascades through the vehicle chain, the minimum speed of vehicle 2 (red) immediately in front of the automated vehicle becomes \( v_2(t) \approx 9 \text{ [m/s]} \) at \( t \approx 391 \text{ [s]} \). Using only motion information from vehicle 2, the minimum speed of the automated vehicle 1 reaches \( v_1(t) \approx 10 \text{ [m/s]} \) at \( t \approx 393 \text{ [s]}, \)
Figure 11: (a) A connected automated vehicle (blue) traveling behind six human-driven vehicles while being followed by a human-driven vehicle (pink). The connected automated vehicle only utilizes motion information from vehicle 2 with feedback gains $\alpha = 0.4 \ [1/s]$ and $\beta_2 = 0.5 \ [1/s]$. (b) The speed profile of the head vehicle 7. (c) Speed profiles of the eight vehicles during one braking event. (d-k) Histograms for the acceleration of the vehicles. For demonstration purposes, the y-axis is limited to 100 occurrences.
forcing the human-driven vehicle 0 at the tail (pink) to slow down to a similar speed value. As the minimum speed drops lower and lower along the vehicle chain, a stop-and-go traffic jam is highly likely to emerge, which typically leads to decreased throughput in transportation systems [30]. Speed profiles in Fig. 11(c) demonstrate that an automated vehicle with no beyond-line-of-sight information has limited capability to mitigate cascading braking events.

To further discuss the performance without beyond-line-of-sight information, we consider the acceleration of each vehicle throughout the whole experiment shown in Fig. 11(b), and plot the histograms of the acceleration data in Fig. 11(d-k). From Fig. 11(d), we see that the range of the head vehicle’s acceleration is $-5 \leq a_7 \leq 2$ [m/s$^2$]. As the perturbations propagate, this range becomes $-8 \leq a_2 \leq 3$ [m/s$^2$] for the car immediately in front of the automated vehicle, and the number of occurrences for acceleration above 2 [m/s$^2$] and below $-4$ [m/s$^2$] increases significantly; see Fig. 11(i). While Fig. 11(j) shows slightly fewer instances of severe braking and accelerating in the automated vehicle, the improvements are limited. The automated vehicle is also unable to induce significant improvements for the vehicle behind, as Fig. 11(k) shows many braking events around $-7$ [m/s$^2$] and accelerating events around 4 [m/s$^2$].

5.2. Using motion information from two vehicles ahead

Now we consider the cases when the connected automated vehicle uses motion information from two vehicles ahead. In Fig. 12(a) the blue car uses the connected cruise controller (7,8) with $n = 3$ and feedback gains $\alpha = 0.4$ [1/s], $\beta_2 = 0.2$ [1/s], and $\beta_3 = 0.3$ [1/s]; cf. Fig. 9(a). In Fig. 12(c) we still see the minimum speed decreasing from $v_{7 \min} \approx 14$ [m/s] to $v_{2 \min} \approx 9$ [m/s], while the connected automated vehicle brings its minimum speed to above 10 [m/s]. Note that $v_{1 \min} \approx v_{4 \min}$, that is, the adverse influence of human-driven vehicles 2 and 3 is successfully mitigated by the connected automated vehicle. Similar conclusions can be drawn from the acceleration histograms shown in Fig. 12(d-k). The histogram for the connected automated vehicle 1 (panel (j)) shows fewer instances of large accelerations and decelerations when compared with the head vehicle 7 (panel (d)). As a result, the tail vehicle 0, despite being human-driven, exhibits less harsh braking or accelerating; see panel(k).

Similar as in Fig. 9(d), we consider the case when motion information from vehicle 4 is used instead of vehicle 3, that is, the feedback gains are
Figure 12: (a) A connected automated vehicle (blue) traveling behind six human-driven vehicles while being followed by a human-driven vehicle (pink). The connected automated vehicle utilizes motion information from vehicle 2 and vehicle 3 with feedback gains $\alpha = 0.4 \ [1/s]$, $\beta_2 = 0.2 \ [1/s]$, and $\beta_3 = 0.3 \ [1/s]$. (b) The speed profile of the head vehicle 7. (c) Speed profiles of the eight vehicles during one braking event. (d-k) Histograms for the acceleration of the vehicles.
Figure 13: (a) A connected automated vehicle (blue) traveling behind six human-driven vehicles while being followed by a human-driven vehicle (pink). The connected automated vehicle utilizes motion information from vehicle 2 and vehicle 4 with feedback gains $\alpha = 0.4 \ [1/s]$, $\beta_2 = 0.2 \ [1/s]$, and $\beta_4 = 0.3 \ [1/s]$. (b) The speed profile of the head vehicle 7. (c) Speed profiles of the eight vehicles during one braking event. (d-k) Histograms for the acceleration of the vehicles.
\(\alpha = 0.4 \, [1/s], \beta_2 = 0.2 \, [1/s], \) and \(\beta_4 = 0.3 \, [1/s];\) see Fig. 13(a). In Fig. 13(c), the connected automated vehicle again exhibits improvements in the speed cascading, as the minimum of \(v_1\) is only 1 \([m/s]\) less than the minimum of \(v_7.\) More importantly, when looking at histograms in Fig. 13(d-k), we see fewer harsh braking/accelerating instances from the connected automated vehicle 1 (panel (j)) and the human-driven vehicle 0 at the tail (panel (k)) when compared with the lead vehicle 7 (panel (d)). This illustrates the robustness of the connected cruise controller (7,8) in improving traffic flow by intercepting perturbation waves.

5.3. Using motion information from three vehicles ahead

Similar to Fig. 10(a), we consider the case when motion information from three vehicles ahead is used, that is, (7,8) with \(n = 4\) and feedback gains \(\alpha = 0.4 \, [1/s], \beta_2 = 0.2 \, [1/s], \beta_3 = 0.3 \, [1/s], \) and \(\beta_4 = 0.3 \, [1/s];\) see Fig. 14(a). In Fig. 14(c) we see larger minimum speed in the connected automated vehicle 1 than the head vehicle 7, which is related to the fact that the connected cruise controller is now head-to-tail string stable [24]. In panels (d-i), we still see increasingly harsher acceleration/deceleration among human-driven cars. Yet panel (j) shows that the connected automated vehicle is able to maintain \(a_1 \geq -3 \, [m/s^2]\) except a few instances. As a result, the human-driven vehicle 0 at the tail also has milder braking than the head vehicle 7; see panels (d,k). Thus, by using motion information from three cars ahead, the connected automated vehicle significantly mitigates the severe maneuvers from preceding vehicles so that even the human-driven vehicle behind it exhibits milder driving behavior than the head vehicle. This indicates that we may start to see significant benefits in traffic throughput even when a low percentage of cars on road are using motion information beyond their line of sights.

5.4. Energy efficiency with connected automated cars

Here we demonstrate another benefit of beyond-line-of-sight information. We consider the energy consumption per unit mass of vehicle \(i\) during one experiment, that is, we define

\[
E_i(t) = \int_{\theta \in \Omega} a_i(\theta) v_i(\theta) d\theta, \quad \Omega = \{\theta \in [t_0, t] \mid a_i(\theta) \geq 0\},
\]

for \(i = 0, \ldots, 7,\) where \(t_0\) is the starting time of an experiment, and \(t \leq t_f, t_f\) is the ending time of the experiment. The quantity \(E_i(t)\) describes the amount
Figure 14: (a) A connected automated vehicle (blue) traveling behind six human-driven vehicles while being followed by a human-driven vehicle (pink). The connected automated vehicle utilizes motion information from all three preceding vehicle with feedback gains $\alpha = 0.4 \ [1/s]$, $\beta_2 = 0.2 \ [1/s]$, $\beta_3 = 0.3 \ [1/s]$, and $\beta_4 = 0.3 \ [1/s]$. (b) The speed profile of the head vehicle 7. (c) Speed profiles of the eight vehicles during one braking event. (d-k) Histograms for the acceleration of the vehicles.
of kinetic energy introduced into vehicle $i$ during one experiment, which can be related with fuel consumption for cars using internal combustion engines, or electricity consumption for electric cars.

In Fig. 15 we show the energy consumption profiles as functions of time for all the vehicles in the four experiments discussed in this section. Fig. 15(a) shows the energy consumption as a function of time when the automated vehicle is only using motion information from the car immediately ahead; see Fig. 11. Here, human-driven vehicles 7,...,2 consume increasingly more energy (light brown, purple, orange, green, black, red curves), indicating that amplified traffic perturbations have adverse effects on energy efficiency. The
automated vehicle (blue) consumes less energy than its immediate preceding vehicle (red), but the difference is not significant.

Fig. 15(b,c) correspond to the two cases when motion information from two vehicles ahead are used; see Fig. 12 and Fig. 13, respectively. In both cases the connected automated vehicle (blue) consumes less energy than human-driven vehicles 2, 3, 4 (red, black, green), yet it still consumes more energy than human-driven vehicle 5 (orange). Fig. 15(d) corresponds to the case when the connected automated vehicle uses motion information from three vehicles ahead; see Fig. 14. In this case, the connected automated vehicle (blue) only consumes 70% of the energy its immediate predecessor (red) uses by the end of the experiment, and as a result, the human-driven vehicle at the tail (pink) only consumes 82% of the energy the red car uses. This shows that beyond-line-of-sight information may significantly improve the energy efficiency of connected automated vehicles and even human-driven vehicles following them.

6. Discussion and Conclusions

In this paper, we proposed a general framework for the longitudinal control of connected automated vehicles and tested the performance of such connected cruise controllers in real traffic where the surrounding vehicles are human-driven. We first demonstrated that by using V2V communication, a connected automated vehicle is aware of a preceding vehicle obstructed by the road geometry, and is thus able to avoid a severe braking maneuver. We then demonstrated that by using motion information from multiple vehicles ahead, a connected automated vehicle is able to mitigate the cascade of braking events propagating from vehicles downstream. In both cases, the beyond-line-of-sight information exhibited its potential in improving traffic safety. Finally, we performed a set of eight-car experiments and showed that a connected automated vehicle using motion information from more than one vehicles ahead is able to not only maintain mild accelerating/decelerating for itself, but also for the human-driven vehicle behind. Aside from having potential benefits in traffic throughput, the connected automated vehicle is also found to improve energy efficiency. We conclude that connected cruise control using beyond-line-of-sight information is able to improve both the safety and efficiency in human-dominated traffic. The future research could include more experiments to evaluate the performance of connected automated vehicles in more diverse traffic settings, such as lane-changing and intersections.
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Bibliography


