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Use of the Hypothetical Lead (HL) Vehicle Trace: A new method for Evaluating Fuel Consumption in Automated Driving*

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***Abstract*— The regulation of fuel consumption and emissions around the world is based on standard drive (SD) cycles. Several autonomous or simple eco-driving methods of smoother driving and smaller acceleration and braking can violate the $\pm$ 2 MPH speed deviation regulation from the SD and hence they are currently not counted towards the vehicle fuel economy, even though they are acceptable from a traffic pattern perspective, namely following a vehicle at a safe and reasonable gap. This paper develops and suggests a prototypical vehicle velocity versus time trajectory that supersedes each SD cycle since the SD cycle is the vehicle trace from following a vehicle with the prototypical velocity trace. The prototypical velocity trace is named from now on as the Hypothetical Lead (HL) vehicle cycle. In essence, the HL cycle recreates the traffic conditions followed by the drivers of the standard drive cycles. Finally, the paper concludes with a demonstration of using the HL cycle for assessing the fuel economy benefits of autonomous following in relation to standard test cycles and limits on the following distances to ensure that the different drive traces follow the same prototypical traffic conditions in a reasonable and safe way for real world applications.**

I. INTRODUCTION

Autonomous vehicles have been the focus of researchers for several decades and there are several ideas in the literature regarding technologies that can be utilized to implement automated driving. While a lot of research has been focused on the safety aspect of autonomous driving with technologies to prevent collisions, lane departure or blind spot crashes, autonomous technologies also can be used for decreasing fuel consumption of vehicles. Implementation of advanced vehicle following strategies to optimize engine performance and fuel economy for autonomous vehicles could change the way a light-duty autonomous vehicle negotiates traffic as compared to a human negotiating the same traffic conditions. Unfortunately, the current certification of vehicle fuel efficiency cannot account for such efficiency benefits so there is a lot of interest in devising a methodology that will quantify the benefits with minimum deviation from the existing rules [1].

Presently the US Environmental Protection Agency (EPA) and other regulatory agencies around the world use pre-specified velocity versus time traces called standard drive (SD) cycles to approximate how a driver navigates through different road types and traffic conditions as shown schematically in the upper section of Fig. 1. Only a $\pm$ 2 miles per hour (MPH) deviation is allowed by the EPA from the standard velocity trace for a valid test [2]. Despite their limitations in capturing every possible driving style or traffic, the standard drive cycles are good approximations of a set of everyday driving conditions and are used to compare the fuel consumption of various vehicles.

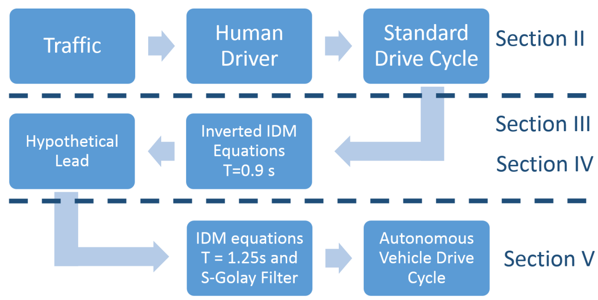

Fig. 1. Schematic describes the development of the hypothetical lead (HL) vehicle and the sections of the paper with an example of the HL trace used to evaluate the fuel consumption of a particular following strategy.

Given the importance of the SD cycles in the regulatory framework, many autonomous longitudinal driving studies concentrate on intelligent following of a lead vehicle that traces the SD cycles [3]. This would in theory increase the fuel efficiency of the vehicle but it has been also shown that it can cause higher fuel consumption under following conditions with very small deviation from the SD cycles. Hence, the current trend of evaluating fuel consumption reduction in autonomous driving by following a SD is re-examined and a new methodology is proposed. This paper suggests a new procedure to objectively compare a human driver to an autonomous vehicle and quantify the fuel economy benefits of using autonomous driving technologies.

In previous work, [4] achieved $0.5\% - 10\%$ reduction in CO2 emissions through Adaptive Cruise Control (ACC) acting between speeds of 18mph and 100 mph in velocity profiles based on expert-rules derived by observing real-world pilots. While, [5] used an optimization algorithm that computed the appropriate acceleration based on traffic conditions so as to improve fuel economy. They were able to show a 8.8% reduction in fuel consumption. In [6] an optimization algorithm was developed to reduce deviations in velocity and thus accelerations by having a velocity preview. Fuel consumption reductions of up to 33% in a vehicle

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powered by a standard SI engine was shown in simulations over the FTP-75 drive cycle. However, in changing the SD the distance between the optimized cycle and SD was very large, exceeding 300 m in some cases and overshooting the SD in some cases as well. To avoid distances that are so large that other vehicles could cut-in or too short to be safe rendering real-world implementation impractical one has to impose constraints in the following scenario.

Unfortunately, there is a trade-off between the following distance and the fuel consumed as shown in Fig. 2 which shows the cases where vehicles were trailing a vehicle executing the FTP-72 drive trace for different time headways. This entire simulation will be discussed in detail later, but it is worth noticing the vehicle following case with following distance equal to 1.8 car lengths per 10 MPH matched the fuel consumption of its lead vehicle but increased for larger headways creating a confusion on what should be considered as the baseline. If the SD is the baseline itself, then a lead velocity trace must be determined for the automated driving vehicle to follow.

This paper develops a hypothetical lead (HL) velocity trace from the standard drive cycles to simulate the lead traffic conditions that can be followed by automated driving algorithms to compare the differences between human and automated following. Beyond the EPA testing procedures, this method can also be used to simulate various autonomous technologies and optimization algorithms and evaluate the benefits of using one over the other. Figure 1 provides an overview of the paper and the rationale for the analysis. Section II reviews the development of the standard drive cycles. Section III analyzes vehicle following models while Section IV describes the development of the hypothetical lead vehicle from the inverted equations of a vehicle following model. Section V provides a simple example to evaluate the fuel consumption reduction via the hypothetical lead vehicle.

II. BACKGROUND ON CURRENT EPA FUEL ECONOMY TEST PROCEDURES

Current certification tests for fuel economy as carried out by the U.S. Environmental Protection Agency involve running all vehicles through standard drive cycles on a chassis dyanamometer [2] . The first drive cycle, the Federal Test Procedure (FTP-72) was developed by authorities in Los Angeles (LA) in 1971 trying to reduce smog in their city. They concluded that the morning drive to work was the biggest contributor to the city's smog. They approximated the morning drive to work of an average LA driver by specifying a route with a combination of different road speeds and traffic conditions. Six drivers drove the trace, in the same car, with five producing remarkably similar results. The actual trace closest to the mean of all traces was taken with minor modifications to its length as the standard drive cycle [10]. The rationale was to find a vehicle velocity trace that a driver executes while navigating through traffic. It was assumed that to navigate through the given traffic scenario, the FTP-72 velocity profile would have to be adopted for all vehicles and individual vehicle capabilities would not change the velocity

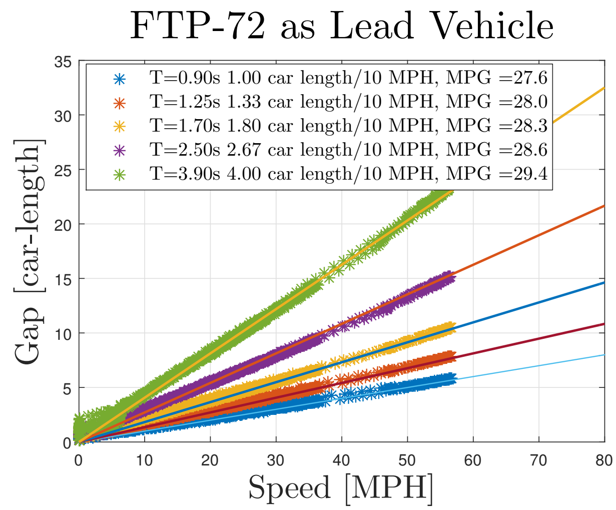

Fig. 2. Comparison of fuel economy results predicted through the ALPHA model for 2013 Ford Escape with a 1.6L Ecoboost engine. Parameter T is the time headway that a follower vehicle maintains from the lead vehicle. Smaller headway indicates more aggressive following. Aggressiveness in following distances significantly changes the fuel consumption. Standard FTP gives 28.3 MPG on the chosen vehicle that is 4.5 m long.

profile if driven by an average human. Similar methods were used to develop other drive cycles such as Higway Fuel Economy Test (HFET) where drivers were instructed to follow traffic, i.e. pass as many vehicles as passed them [11]. It must be kept in mind that human drivers generated all velocity traces that were finally set as standard drive cycles.

III. VEHICLE FOLLOWING MODEL IMPLEMENTATION

In traffic simulation research, several car following models have been developed to predict the speed of the trailing vehicle in the single lane case. Lefévre et al [12] compared various parametric approaches that differently predicted the speed of vehicle in a vehicle following mode for a given traffic condition. Of all the parametric approaches, the mean average error and the root mean squared error was found to be the least for the Intelligent Driver Model (IDM). Hence, the IDM was selected as the vehicle following model for this paper. It uses a combination of safe time headway and comfortable braking distance to compute the desired distance from the lead vehicle and then the actual distance and speed to find the acceleration.

The model used in this paper to evaluate fuel consumption over a drive-cycle is the Advanced Light-Duty Powertrain and Hybrid Analysis Tool (ALPHA) model developed at the US Environmental Protection Agency [14]. Any drive cycle in 1Hz resolution can be loaded into the program and the tool incorporates a driver model that is able to track the velocity. The vehicle used is a 2013 Ford Escape with a 1.6L EcoBoost engine [15].

While IDM does show the smallest error with actual traffic data compared to other parametric approaches, there are still some driving characteristics of humans that cannot be captured by the model. Humans change their driving pattern depending on the traffic conditions. In our case, it is assumed that each standard driving trace is created for a certain traffic pattern and hence changing the parameters for each trace would capture this effect. Humans have other signals apart from the speed of the front vehicle such as brake lights and perception of lead driver's intentions which allow them to react early. Additionally they have a perception threshold and only significant changes in speed are determined by the follower vehicle delaying their reaction. Early perception would cause the following driver to act before the IDM would predict and the perception threshold would cause the driver to act after the IDM predicts a response. From the experimental work done by Lefévre it can assumed that IDM misses the overshoots and undershoots but is a reasonable approximation of what the driver would do. The RMS error was shown to be about $0.25\,\mathrm{m/s}$ for a $1\,\mathrm{s}$ prediction horizon. In actual dyanomometer testing, for the FTP-72 an RMS error of $0.2\,\mathrm{m/s}$ was seen between the ALPHA model velocity and the actual velocity trace driven by an experienced driver. This indicates an acceptable error margin being given by the IDM equations.

Vehicle following using eco-driving strategies are being encouraged amongst drivers across the world, to help them improve fuel economy while driving in their daily lives. These tips include maintaining an even driving pace, accelerating moderately from 2000 to 2500 RPM and anticipating traffic flow to avoid sudden starts and stops. A conservative estimate of eco-driving benefits calculates a reduction of 33 million metric tons of CO2 annually from being emitted into the atmosphere [9]. It is reasonable to assume that vehicles with autonomous technologies would implement such driving strategies to reduce fuel consumption and emissions.

The aforementioned IDM, described below was used to follow a vehicle executing a drive cycle.

$$d_{actual}(i) = s_L(i) - s_F(i) \tag{1}$$

$$r(i) = v_L(i) - v_F(i) \tag{2}$$

$$d_{des}(i) = d_{min} + T \times v_L(i) - \frac{v_L(i) \times r(i)}{2 \times \sqrt{a_{max} \times b_{comf}}} \tag{3}$$

$$a_F(i+1) = a_{max}(1 - (\frac{v_L(i)}{v_{max}})^4 - (\frac{d_{des}(i)}{d_{actual}})^2) \tag{4}$$

$$b_{max} \leq a_F(i+1) \leq a_{max} \tag{5}$$

Where the subscript L denotes the lead and F the follower. Parameter d is the gap, s the displacement, v the velocity, a the acceleration, b the braking and r is the relative velocity. The value of each parameter (T, a_{max}, b_{comf} and d_{min}) depends on the velocity time trace of different drive cycles. Each standard drive cycle is said to represent a particular type of road with the expected traffic conditions and hence the speed, acceleration and braking.

To generate Fig 2, the standard drive cycle, in this case FTP-72, is the lead vehicle. The FTP-72 involves maximum acceleration and deceleration of $1.5\,\mathrm{ms}^{-2}$ and $-1.5\,\mathrm{ms}^{-2}$ respectively. Since drivers don't tend to push the car to the limit the maximum acceleration (a_{max}) was chosen to be double the maximum acceleration seen in the drive cycle. The comfortable braking (b_{comf}) was kept the same as the maximum braking of standard drive cycles and the maximum braking in IDM, double of that. The minimum distance was kept at $2\,\mathrm{m}$. An important assumption of the selected model is that the reaction time and attention span of the driver are merged to $1\,\mathrm{s}$ and used as the time step for the iterations. Prior work [7] shows that this is reasonable. The parameters values for the FTP-72 case are given in Table 1.

TABLE I

PARAMETER DEFINITIONS

Parameter Name	Parameter Definition	FTP-72
d_{des}	Desired Gap (m)	$Calculated$
d_{min}	Minimum Gap at 0 velocity (m)	2
T	Time Headway (s)	0.9
v_L	Lead vehicle speed (m/s)	$Calculated$
v_F	Follower vehicle speed (m/s)	$Calculated$
v_{max}	Maximum vehicle speed (m/s)	45
r	Relative speed of lead and follower vehicle (m/s)	$Calculated$
a_{max}	Maximum acceleration (m/s^2)	3.0
b_{comf}	Comfortable deceleration (m/s^2)	1.5
a_F	Acceleration of follower vehicle (m/s^2)	$Calculated$
b_{max}	Maximum deceleration (m/s^2)	3.0

The time headway (T) can be varied to find the optimal gap that should be maintained from the vehicle in front. The gap can be increased or decreased by appropriately tuning T. The eco-driving strategies are implemented while keeping in mind that that the gap between the lead vehicle and the follower vehicle has to be long enough to ensure a safe braking distance but at the same time not too long such that other vehicles can cut in and cause the autonomous vehicle to brake thus negating the objective of maintaining an even driving pace.

A time headway of $0.9\,\mathrm{s}$ for the FTP drive cycle would achieve the desired gap between the lead and the follower vehicle such that it is safe, does not allow cut-ins and is good for traffic flow. However, the given velocity trace violated the $\pm 2\,\mathrm{MPH}$ for less than $2\,\mathrm{s}$ regulation on 15 occasions and still showed a worse fuel economy than the FTP-72 drive cycle as shown in Fig 2. Close following made the follower vehicle speed vary significantly as it tried to keep up with the lead vehicle and maintain a safe distance. The RMS error between the standard drive cycle and the following velocity trace was $0.4\,\mathrm{ms}^{-1}$. Increasing the time headway to $1.7\,\mathrm{s}$ produced a velocity trace that matched closely with the standard cycle, did not violate the regulations, showed an RMS error of $0.2\,\mathrm{ms}^{-1}$ and a fuel consumption that matched the FTP-72. However, in this case the following distances were larger (1.8 car-lengths), and would allow cut-ins. Increasing the time headway further reduced fuel consumption and for $T = 3.9\,\mathrm{s}$ a 4% increase in MPG could be seen however, the following distances were very large and the RMS error was $1.2\,\mathrm{ms}^{-1}$.

For the case where vehicles are made to follow the FTP-72 drive cycle, it was shown that for $T = 0.9\,\mathrm{s}$, fuel consumption was more than the lead FTP-72. Conversely for larger following distances lower fuel consumption is observed. An autonomously driven vehicle should be able to negotiate this trade off and achieve an optimal fuel economy. Through this example we have seen that in an attempt to decrease fuel consumption the regulations for speed are violated. Hence we need to determine another methodology that can evaluate the reduction in fuel consumption by use of self-driving algorithms that deviate in navigation through traffic from humans.

IV. HYPOTHETICAL LEAD VEHICLE PROFILE

A systematic evaluation technique has to be developed that can objectively determine the fuel economy benefits of self-driven cars. To do this we could turn back to the rationale of the original standard drive cycles. These cycles were developed as an approximation of how an average human driver would navigate through different road and traffic conditions. The same thinking can also be used for evaluating autonomous driving capabilities. Since the standard drive cycles were humans navigating through traffic conditions, to find autonomous driving benefits we should compare it to how a controller based off an optimization algorithm would navigate through the same traffic conditions.

To recreate the traffic conditions for the standard drive cycles, this paper inverted the IDM equations. By inverting the equations the velocity trace of the lead vehicle being followed by the driver driving the standard drive cycles could be found. It is important to note that the driver of the standard drive trace would not just be following a single vehicle in a single lane but rather reacting to lane changes, stop lights, stop signs etc. The standard drive cycles are a simplified trace and the recreated traffic conditions are simplified single lane hypothetical lead vehicle velocity traces. Hence, the lead vehicle is essentially a hypothetical velocity trace that drivers of the standard drive traces followed to produce their respective drive cycles.

Since we are trying to determine the velocity profile of the lead vehicle from the follower vehicle data. The follower speed v_F and acceleration a_F are already known. The actual gap between the lead and follower can be defined by equation 6, where $s_L(i-1)$ and $s_F(i-1)$ are known but $r(i)$ is unknown.

$$d_{actual}(i) = s_L(i-1) - s_F(i-1) + r(i) \tag{6}$$

Then by rearranging equation 4 we get equation 7, where $d_{des}(i)$ and $d_{actual}(i)$ are unknown. Since the vehicles do not crash the desired and actual distance between the vehicles is always positive.

$$\frac{d_{des}(i)}{d_{actual}(i)} = \sqrt{1 - \frac{a_F(i+1))}{a_{max}} - \left(\frac{v_F(i))}{v_{max}}\right)^4} \tag{7}$$

Finally rearranging equation 3 gives equation 8, where $r(i)$ and $d_{des}(i)$ unknown.

$$r(i) = (d_{min} + T \times v_F(i) - d_{des}(i)) \frac{2 \times \sqrt{a_{max} b_{comf}}}{v_F(i)} \tag{8}$$

Hence there are 3 equations and 3 unknowns. Substituting equations 6 and 7 into equation 8 produces equation 9 from which the relative velocity $r(i)$ can be determined

$$r(i) = \frac{[d_{min} + T_F(i) - (s_L(i-1) - s_F(i-1))]}{\frac{v_F(i)}{2\sqrt{a_{max} b_{comf}}} + \sqrt{1 - \frac{a_F(i+1))}{a_{max}} - \left(\frac{v_F(i))}{v_m ax}\right)^4}} \times \frac{2\sqrt{a_{max} b_{comf}}}{v_F(i)} \sqrt{1 - \frac{a_F(i+1))}{a_{max}} - \left(\frac{v_F(i))}{v_m ax}\right)^4} \tag{9}$$

From the relative velocity the velocity of the lead vehicle can be found from equation 2. The initial conditions are assumed to be $v_F(0) = v_L(0) = a_F(0) = s_L(0) = 0$ and $s_F(0) = -d_{min} = -2$.

The equations can be applied to any naturalistic drive cycle to produce the hypothetical lead drive traces. Specifically this process was carried out for five standard drive cycles, FTP-72, HWFET, LA92, US06 and SC03, to determine the traffic conditions being followed by the driver of these traces. The parameter values are given in Table II. For this paper the following gap was kept at $T = 0.9$ s, which gives a 1 car-length/10 MPH intervehicle distance. This can be reduced to simulate closer following.

TABLE II

PARAMETER VALUE

Parameter Name	FTP-72	US06	LA92	SC03	HFET
$d_{min}(m)$	2	2	2	2	2
$T(s)$	0.9	0.9	0.9	0.9	0.9
$v_{max}(m/s)$	45	45	45	45	45
$a_{max}(m/s^2)$	3.0	6.0	4.0	6.0	3.0
$b_{comf}(m/s^2)$	1.5	2.5	1.5	2.5	1.5
$b_{max}(m/s^2)$	3.0	6.0	4.0	4.0	3.0

V. USE OF THE HYPOTHETICAL LEAD VEHICLE

This sections provides a simple example to show how the lead vehicle can be used to compare the fuel economy of a vehicle driven by a human driver to one driven by electronic controllers. Due to the IDM inversion for a $T = 0.9$ s the standard drive cycles will be identical to a human driver trailing the hypothetical lead vehicle. For the autonomous case, various technologies can be simulated by trailing this lead vehicle. The controller's objective would be to reduce fuel consumption by optimizing any of the vehicle's parts from the engine to the powertrain to a simple velocity smoothing algorithm that would result in less fuel consumption. The optimization algorithm to be used can be simulated to trail the hypothetical lead and produce the velocity trace that the autonomous vehicle would drive.

The control objective in this example is to reduce the fuel consumption through trace smoothing, or the reduction of accelerations and decelerations. The first step to achieve trace smoothing is by using IDM. The time headway was taken to be higher than the 0.9 s at 1.25 s. All other parameter values were kept the same. The second step involved trying to compute an even smoother trace by using the low pass

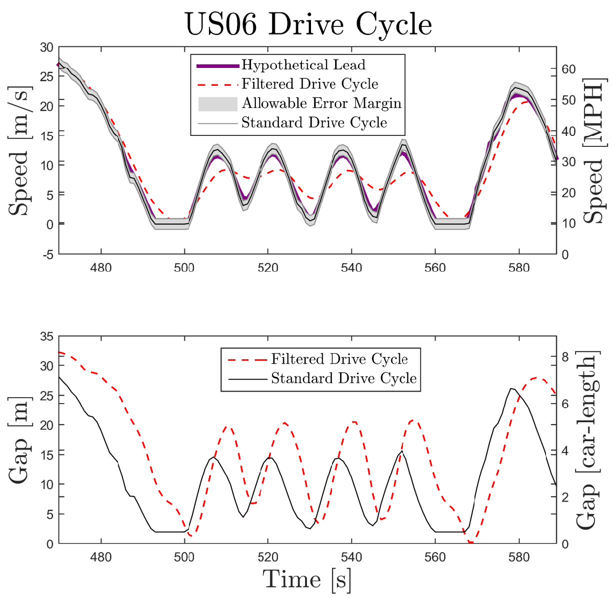

Fig. 3. Lead vehicle computed by analytically inverting the equations of the intelligent driver model is shown for a part of the US06 drive cycle along with the S-Golay filtered trace

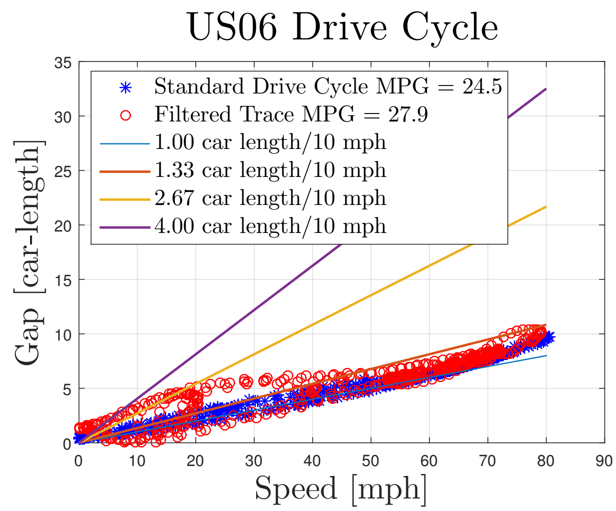

Fig. 4. Plot comparing the following distances to the hypothetical lead vehicle for the Standard Drive Cycle and the S-Golay filtered trace

Savitzky-Golay filter [13]. The entire distance over time trace was filtered to produce a smoother drive cycle. The filter is used in signal processing to smooth the signal and remove noise such that a derivative without artificial peaks can be found. In our case by smoothing out the distance over time trace the derivative i.e. the velocity peaks are reduced. Thus achieving the eco-driving goals of maintaining an even driving pace with minimal acceleration and declaration.

The filtered drive cycle following the hypothetical lead is shown in Fig 3 for the US06 drive cycle. For comparison the standard drive cycles are also plotted and the smoothed trace for the filtered drive cycle can be clearly seen. For practical use of this smoothing method, a preview of almost the entire drive cycle would be required, which is an unreasonable assumption. The point of this example is to show how the lead vehicle can be used to quantify fuel consumption of different driving patterns.

The fuel economy improvements are achieved by avoiding certain regions of high accelerations and decelerations. The lead vehicle in these cases provides bounds that the autonomous vehicle must adhere to while traversing traffic. Specifically the autonomous vehicle while reducing fuel consumption has to avoid two scenarios of not following too closely such that it is unsafe, or following too far behind such that other vehicles can cut-in forcing a change in velocity trajectory.

Fig 4 shows the gap maintained by the following vehicles to the hypothetical lead as a function of speed. Different following distances are drawn as solid lines for reference. It can be seen that the following vehicle associated with the Savitzky-Golay filter maintains a reasonable gap from the hypothetical lead. Although the gaps of the filtered drive cycle are larger than the vehicle of the standard cycle at low speeds, cut-ins at low speeds are not expected. On the other hand, at high speeds of over 40 MPH, the following distances are similar to the standard drive cycles and risk-averse drivers in other lanes would not cut-in.

Table III shows the miles per gallon (MPG) computed for the standard and the filtered drive cycles of five different velocity traces. Clearly the highest fuel economy improvements are observed in LA92 and US06 drive cycles, which have several stops and starts, that are eliminated to reduce energy losses. From Fig 5 it can be seen that at 345 s the standard cycle is able to go to a higher gear and thus reduce its fueling rate. However, at 375 s the filtered trace maintains a higher gear and correspondingly has a much lower fueling rate. Similarly at 495 s the filtered trace, which decelerates less than the standard cycle is able to maintain a higher gear and lower fueling rate for a longer time. In Fig 6, the filtered trace does not decelerate and accelerate as much as the standard cycle and therefore is able to eliminate energy losses through braking. This means that the vehicle does not loose momentum and is able to maintain the desired speed with use of lesser energy and correspondingly less fuel. Finally, the highway drive cycle (HFET) shows the least improvement in fuel economy through trace smoothing and this is expected as the velocity trace is already quite smooth.

TABLE III

FUEL ECONOMY IMPROVEMENT

Drive Cycle	**Standard Cycle MPG**	**Filtered Cycle MPG**	**Percentage Increase**
FTP-72	28	30	7
US06	25	28	12
LA92	26	30	15
SC03	28	30	7
HWFET	39	41	5

VI. FUTURE WORK

While the filtering used here is unreasonable due to the length of preview needed, it does show significant reduction

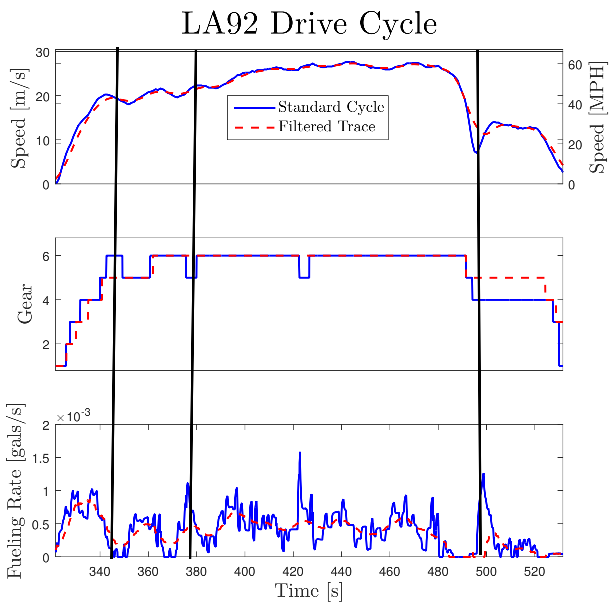

Fig. 5. Plot compares the gears for the standard drive cycle and the filtered trace. By reducing downshifts, the filtered trace is able to maintain higher gears for a longer time and hence reduce fuel consumption

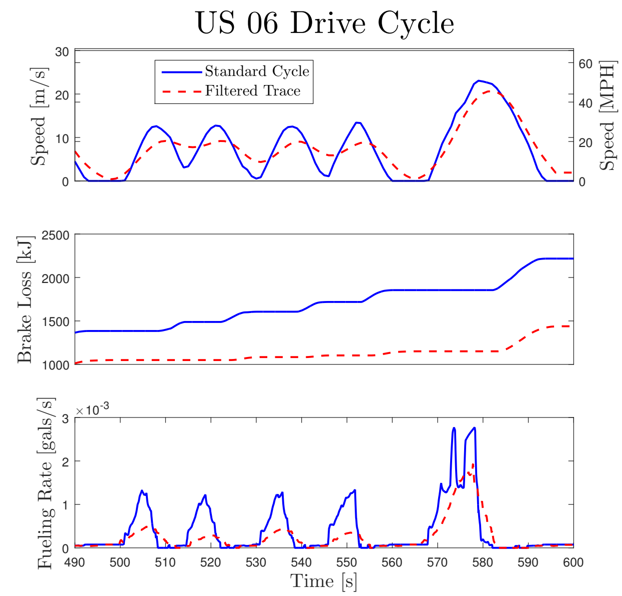

Fig. 6. Plot compares the energy loss in braking for the standard drive cycle and the filtered trace. By eliminating the regions of braking, the filtered trace does not loose energy in braking and also does not require additional acceleration for reaching the desired speed

in fuel consumption by the use of trace smoothing algorithm applied to following the hypothetical lead vehicle. This analysis hence points to an exciting potential of improvement of fuel economy through optimization algorithms. The optimization need not be restricted to reducing accelerations but it could also be used to determine optimal engine load and gear ratios and ensure that the engine traverses a line in the torque speed curve that is at minimum fuel consumption. Optimizing for the engine and the powertrain would allow for greater engine downsizing. There is further potential in eliminating torque reserves that conventional engines and powertrains carry as the path is already know and the systems can function at the point of least fuel consumption.

VII. CONCLUSIONS

The hypothetical lead vehicle provides a good baseline for comparing automated driving with the vehicle executing an SD. The rationale of the method developed in this paper is that given the HL a human followed to produce the SD, how would an autonomous vehicle with eco-driving capabilities follow the HL. To judge the fuel consumption reduction by use of autonomous technologies the autonomous trace produced through the vehicle following algorithm can be compared to the SD trace thus giving a straightforward comparison under the same principles.

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