

Prediction of Preceding Driver Behavior for Fuel Efficient Cooperative Adaptive Cruise Control

Dominik Lang, Roman Schmied, and Luigi Del Re
Johannes Kepler Univ. Linz

ABSTRACT

Advanced driver assistance systems like cooperative adaptive cruise control (CACC) are designed to exploit information provided by vehicle-to-vehicle (V2V) and/or infrastructure-to-vehicle (I2V) communication systems to achieve desired objectives such as safety, traffic fluidity or fuel economy. In a day to day traffic scenario, the presence of unknown disturbances complicates achieving these objectives. In particular, CACC benefits in terms of fuel economy require the prediction of the behavior of a preceding vehicle during a finite time horizon. This paper suggests an estimation method based on actual and past inter-vehicle distance data as well as on traffic and upcoming traffic lights. This information is used to train a set of nonlinear, autoregressive (NARX) models. Two scenarios are investigated, one of them assumes a V2V communication with the predecessor, the other uses only data acquired by on-board vehicle sensors. Depending on the applied approach and the moving space of the controlled vehicle, the thus obtained (imperfect) prediction allows fuel benefits in a range of 5% to 25% in the case of moderate, non-congested traffic. This is confirmed both by simulation and measurement. Compared to existing prediction methods, the proposed strategy delivers quite promising results.

CITATION: Lang, D., Schmied, R., and Del Re, L., "Prediction of Preceding Driver Behavior for Fuel Efficient Cooperative Adaptive Cruise Control," *SAE Int. J. Engines* 7(1):2014, doi:10.4271/2014-01-0298.

INTRODUCTION

Adaptive cruise control is a well established technology [1], [2] in modern commercial vehicles. It allows combining comfort (constant speed) and safety (minimum distance). Despite the positive effects of constant speed on fuel consumption, ACC is not primarily designed for fuel economy.

A cooperative approach expands the targets of ACC to exploit different potential benefits. A very substantial work has been done on assessing these possibilities, including platooning [3], [4] and traffic management at intersections [5], [6]. However, there are several key problems related to these approaches: they assume the driver to agree to giving up control over the vehicle to some extent [7], which especially in the case of mixed traffic (coordinated/not coordinated) is difficult. Another issue is the stability of the overall system, which is not evident. Furthermore in some conditions, V2V communication is a necessary requirement for CACC [8].

In earlier works [9], [10], we have introduced fuel efficient ACC. We tackled the problem from a single vehicle point of view, from which it could be stated in terms of minimizing the fuel consumption of a vehicle traveling from one place to another, in spite of the presence of other vehicles on the road. In this way, the targets of the adaptive cruise control can be recast as constraints on the optimization problem. Both simulation and

experimental results have been shown in [9], with achievable consumption reductions in the range of 5% to 35% according to the inter-vehicle information and the driving conditions.

Despite these promising results, fuel efficient ACC faces two major problems: The non-linearity of vehicle dynamics complicates an online implementation. In [11] we propose an identification of the control strategy, reducing the computational efforts to a small fraction of the original optimal control problem, while retaining a large amount of the potential fuel benefits. A second challenge is the prediction of driver behavior, a necessary requirement for evaluating fuel optimal vehicle control.

With the advent of connected vehicle technology, the estimation of driver behavior is receiving more and more attention. A review of the field can be found in [12]. [13] proposes systems for traffic prediction based on digital road maps, travel time curves and information on current traffic data provided by stationary sensors, in order to decrease travel time. A stochastic approach is suggested in [14]. Therein, driver behavior is represented by the on-board learning of a Markov chain. Stochastic model predictive control is used to determine a driver-aware, efficient vehicle control. In other works [15], [16], a prediction of the upcoming traffic scenario is used for efficient control of traffic light signals.

In this paper we investigate two data-based scenarios, employing a set of NARX models trained and evaluated along an urban road segment. In one of these scenarios, we assume cooperation with a preceding vehicle, using information from its electronic control unit (ECU) or radar sensor. The other scenario employs a single vehicle's point of view and only onboard sensors. The traffic prediction is then used to determine a fuel optimal vehicle control. It will be shown, that the quality of the prediction significantly influences the potential fuel benefits.

This paper starts by recalling the basic concept of fuel efficient CACC. As mentioned above, the determination of fuel optimal vehicle control requires the prediction of the behavior of a preceding vehicle. Accordingly, the following section proposes two data-based prediction scenarios and discusses their quality. Finally, we will show the impact of the imperfect prediction on the potential fuel benefits and summarize our conclusions.

FUEL EFFICIENT COOPERATIVE ADAPTIVE CRUISE CONTROL

In [9] it has been shown both by simulation and measurement that the potential of predictive, fuel optimal vehicle control can be quite high. Considering a vehicle moving through moderate, non-congested traffic a significant fuel benefit with respect to a preceding vehicle can be achieved. This chapter offers a short overview of the regarded, receding horizon optimal control problem and the corresponding results.

The controlled vehicle is assumed to be disturbed by the presence of preceding traffic, as will be the case in many day-to-day traffic scenarios. To simulate this disturbance, we use measurements of speed profiles in moderate, rural traffic obtained by a radar sensor. Figure 1 shows the schematic of the simple but common scenario which was examined. The picture points out two velocity dependent constraints on the distance between our two regarded vehicles ($d_{min}(v(t)) < d(t) < d_{max}(v(t))$), ensuring safety (lower bound) and maintaining traffic fluidity (upper bound). The concept of a velocity dependent spacing policy is quite common in car-following problems [4], [17]. Different approaches have been examined in [18], [19]. The controlled vehicle is free to move within the above mentioned bounds.

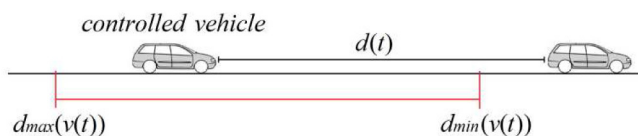


Figure 1. Regarded traffic scenario.

In the case of an imperfect prediction, using hard constraints can render the control problem infeasible. For this reason, relaxed constraints on the upper and the lower bounds are introduced. To ensure safety, an additional hard constraint on the lower bound remains (Figure 2).

The objective of the optimal control problem is to minimize the fuel consumed during the finite time horizon T , respecting the constraints on the inter-vehicle distance and of course those on the vehicle dynamics. For simplicity, we disregard in this presentation gear changes, curves, lane changes and overtaking.

Figure 2 portrays an example of a numerically calculated fuel optimal solution to the problem explained above. It shows that knowledge of the future behavior of a preceding vehicle can be used for fuel economy by omitting unnecessary accelerating and braking maneuvers.

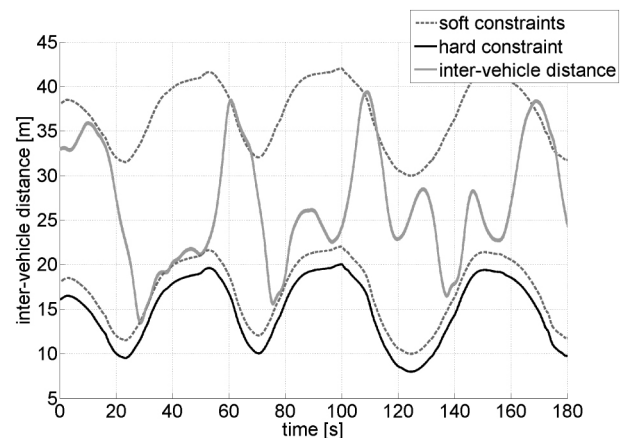


Figure 2. Example of fuel optimal inter-vehicle distance.

The potential consumption reduction is strongly dependent on two factors, the prediction horizon T and the margin, which is the free moving space of our vehicle $d_{max}(v(t)) - d_{min}(v(t))$. Increasing the latter has negative effects on traffic flow, so a compromise must be aspired. The potential fuel benefits as a function of the prediction horizon and the free moving space can be seen in Figure 3. The displayed values were obtained under the assumption of perfect knowledge of the disturbances during the upcoming T seconds. It can be seen that the fuel benefits increase monotonically with the prediction horizon. Figure 4 additionally reveals that fuel benefits reach saturation after exceeding a certain horizon length. A further increase in prediction time will not lead to a significant further consumption reduction. Of course, increasing margin leads to a reduction of traffic capacity, i.e. cars per minute passing a steady location, as shown in Figure 5.

However these imply a perfect knowledge of the upcoming traffic behavior. As this is hardly realistic, it is of interest to investigate the effect of the imperfect prediction on the fuel economy of the controlled vehicle.

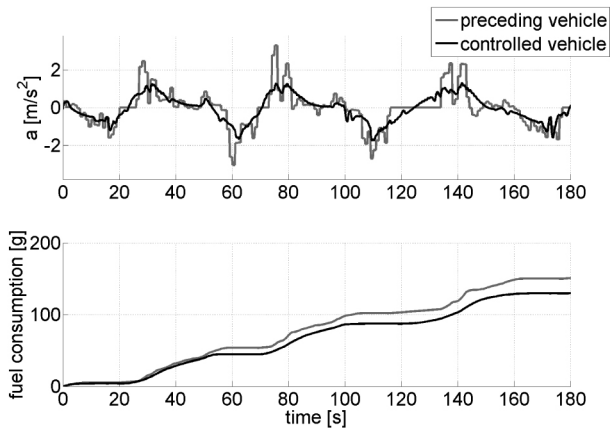


Figure 3. Example of fuel optimal vehicle acceleration and its effects on fuel consumption.

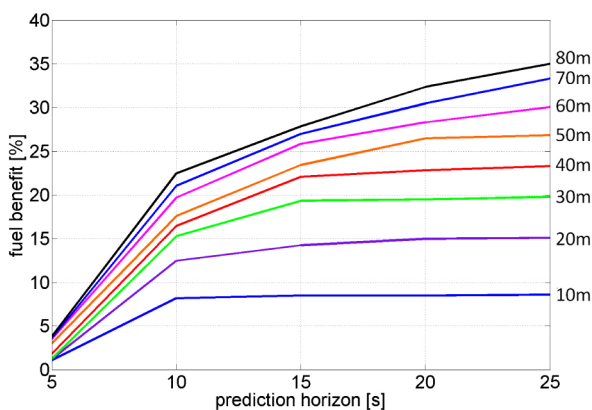


Figure 4. Potential fuel benefits as a function of prediction horizon and free moving space.

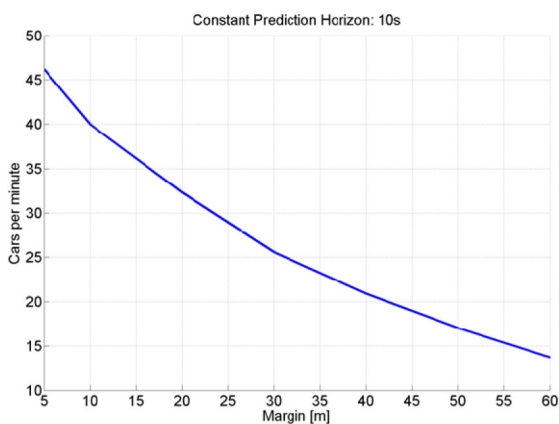


Figure 5. Traffic capacity with respect to the provided margin.

ESTIMATION OF DRIVER BEHAVIOR

As mentioned above, fuel optimal vehicle control requires the prediction of a preceding vehicle's behavior during a finite time horizon. This chapter proposes a data-based prediction approach, using a set of NARX models.

Training and Validation Data

[20] suggests that traffic is highly regular. In order to exploit this regularity, a series of measurements were collected along an urban road segment, attempting to gather as much relevant information on the traffic scenario and the surrounding infrastructure as possible. In addition to the ECU, our test vehicle is equipped with a radar sensor to obtain information on the behavior of preceding vehicles. Furthermore, information on the current signal of upcoming traffic lights was recorded.

Given the above mentioned measurements, two different scenarios for the estimation of driver behavior have been examined. They differ by the input information of the prediction models Table 1. Scenario 1 assumes an existing communication with a preceding vehicle, meaning that besides information on the predecessor's position, velocity and acceleration ($s_p(t)$, $v_p(t)$ and $a_p(t)$), also information on the state of its predecessor ($s_{pp}(t)$, $v_{pp}(t)$ and $a_{pp}(t)$) can be used for training and validation purposes. In addition to this, knowledge on the predecessor's pedal positions and their derivatives is available. The variables $\alpha_p(t)$, $\beta_p(t)$ and $\kappa_p(t)$ represent accelerator pedal, brake pedal and clutch respectively. In Scenario 2 only information through the onboard sensors is assumed available to train and validate our models.

In both cases the aim is to predict the velocity of the preceding vehicle in τ seconds from the actual time.

Table 1. Input and output of NARX prediction models

	Scenario 1	Scenario 2
Input u	$s_p(t)$, $v_p(t)$, $a_p(t)$, $s_{pp}(t)$, $v_{pp}(t)$, $a_{pp}(t)$, $\alpha_p(t)$, $\dot{\alpha}_p(t)$, $\beta_p(t)$, $\dot{\beta}_p(t)$, $\kappa_p(t)$, $\dot{\kappa}_p(t)$ traffic light signals	$s_p(t)$, $v_p(t)$, $a_p(t)$, traffic light signals
Output y	$v_p(t + \tau)$	$v_p(t + \tau)$

Figure 6 depicts a set of measurements of $v_p(t)$. The road segment includes three crossings visualized by an increased number of stops of the preceding vehicle.

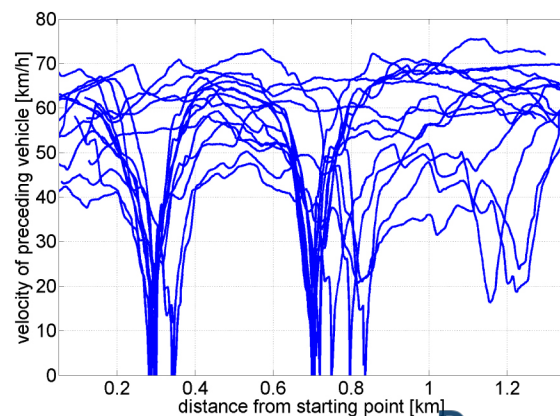


Figure 6. Radar measurement on a real road segment.