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Cooperative energy management of automated vehicles

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A B S T R A C T

This paper presents a cooperative adaptive cruise controller that controls vehicles along a planned route in a possibly hilly terrain, while keeping safe distances among the vehicles. The controller consists of two predictive layers that may operate with different update frequencies, horizon lengths and model abstractions. The top layer plans kinetic energy in a centralized manner by solving a quadratic program, whereas the bottom layer optimizes gear in a decentralized manner by solving a dynamic program. The efficiency of the proposed controller is shown through several case studies with different horizon lengths and number of vehicles in the platoon.

1. Introduction

In today's globally interconnected market, freight and passenger transport have a great share in the worldwide greenhouse gas emissions and energy consumption. In the OECD (Organization for economic cooperation and development) countries, surface transportation is particularly culpable, since about 35% of the total CO_2 emissions is due to surface freight. The share is expected to raise to about 50% in the next 35 years (OECD/ITF, 2013).

Among the measures that can alleviate the impact of transportation, an obvious factor is the improvement of energy efficiency. It is possible to use the vehicle kinetic and potential energy storage in favor of a more economic drive, by controlling velocity profile, i.e., by varying the vehicle speed in a hilly terrain, while not exceeding the maximum allowed travel time. For example, decreasing speed when climbing uphill and building up speed when rolling downhill is clearly preferable compared to wasting energy at the braking pads. This behavior can be implemented with rule-based control strategies when the topographic profile is relatively simple. For more complex topographic profiles, with successive hills of various shapes, model based control is the preferred implementation, where the energy use is coordinated by an optimal control algorithm.

The use of dynamic programming (DP) algorithm (Bellman, 1957) has been proposed in Hellström, Ivarsson, Åslund, and Nielsen (2009) and Hellström, Åslund, and Nielsen (2010a), for optimal control of gear shifts and vehicle acceleration of conventional trucks. The algorithm is able to enforce a constraint on trip time and achieve close to optimal fuel consumption. However, the computation time in DP increases exponentially with the number of dynamic states and control signals (Bertsekas, 2000). Thus, for systems with more energy states, as in, e.g., hybrid electric vehicles (HEVs), methods have been proposed that adjoin the system dynamics to the objective, while simplifying the problem by neglecting state constraints, or by approximating the discrete-gear transmission to a continuously variable transmission (Schwarzkopf & Leipnik, 1977; Hellström, Åslund, & Nielsen, 2010b; van Keulen, de Jager, Foster, & Steinbuch, 2010; van Keulen, de Jager, & Steinbuch, 2011; Lindgärde, Feng, Tenstam, & Soderman, 2015). An alternative approach published recently decouples the integer from the real-valued decisions, such that gear and powertrain mode is decided by DP, while control of energy buffers is decided by convex optimization (Johannesson, Murgovski, Jonasson, Hellgren, & Egardt, 2015a). For a historical overview and a comprehensive list of methods for optimal velocity control of both conventional and electrified vehicles, see, e.g., (Sciarretta, Nunzio, & Ojeda, 2015) and references therein.

An additional aspect when controlling vehicle speed is the surrounding traffic. In Johannesson, Nilsson, and Murgovski (2015b) a decoupled optimization approach is proposed, an extension of the method in Johannesson et al. (2015a), for optimal velocity control of a hybrid electric truck with safety constraints

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on time headway. The proposed approach, however, does not utilize cooperative control, which is made possible by the communication possibilities of the modern intelligent transportation. The cooperative control is also known as platooning, while the term platoon refers to the group of vehicles at close inter-vehicle distances.

Vast amount of scientific literature has addressed the safety and stability of vehicle platoons, see e.g. (Levine & Athans, 1966; Peppard, 1974; Swaroop & Hedrick, 1996; Dunbar & Murray, 2006). These approaches typically consider a simple powertrain model and idealized road conditions, e.g., a flat road profile. Optimal energy management that employs aerodynamic drag reduction of platoons, (Zabat, Stabile, Farascaroli, & Browand, 1995), to maximize the cumulative energy efficiency, has been studied in Bonnet and Fritz (2000), Kemppainen (2012), Bühler (2013), Alam (2014), Alam, Besselink, Mårtensson, and Johansson (2015), Yu, Liang, Yang, and Guo (2016) and Liang, Mårtensson, and Johansson (2016). These studies typically consider a hilly terrain and a detailed powertrain model (Guzzella & Sciarretta, 2013), but they also require tracking of a particular headway, time or distance, which may not be optimal. Recent approaches where headway is not explicitly penalized as long as safety is satisfied, have been proposed in Jeber (2015), Wahnström (2015) and Nilsson, Murgovski, and Johannesson (2015).

This paper proposes a predictive cruise controller that decouples the optimal control problem into two model predictive layers that may operate with different model abstractions, update frequencies and prediction horizons. The top layer plans the optimal kinetic energy and time trajectories by solving a convex program in space coordinates. Convex modeling steps are shown for two convex formulations, a semidefinite program (SDP) and a quadratic program (QP). The bottom layer plans transmission gear in a DP by using the state and costate trajectories from the top layer.

Besides the convex modeling steps, this paper presents several contributions. In the case of optimal cruise control of a single vehicle, a method is proposed that extends the method from Johannesson et al. (2015a) by propagating gear decisions back to the top layer and by applying real-time iteration sequential QP (Diehl, 2001) in order to remove possible linearization errors. The optimized solution of the decoupled approach is compared to that obtained by DP, confirming that near globally optimal solutions are achieved. The proposed predictive cruise controller is then extended to a centralized controller for a cooperative energy management of an entire vehicle platoon by considering safety constraints on headway. Two different QP formulations are shown for the top layer, a formulation with three states per vehicle, i.e. time, speed and distance, and a reduced complexity formulation where distance is removed from the state vector. Several case studies are investigated, showing the dependence on travel time and aerodynamic drag reduction modeling. The results indicate that keeping a constant time headway is not always optimal.

The paper is outlined as follows. Powertrain modeling and problem formulation for a single vehicle cruise controller is provided in Section 2. The proposed predictive cruise controller with decoupled integer and real-valued decisions is presented in Section 3. Case studies for optimized energy management of a single vehicle are provided in Section 4. The optimization method is extended to cooperative energy management of a platoon of vehicles in Section 5. Case studies with multiple vehicles are provided in Section 6. The paper is ended with discussions in Section 7 and conclusions and future work in Section 8.

2. Energy management of a single vehicle

Before going into formulation of the cooperative energy management problem, which is deferred to Section 5, the energy management of a single vehicle is addressed here, without considering the surrounding traffic. The adopted control structure is discussed and a non-convex, nonlinear and mixed-integer problem is formulated.

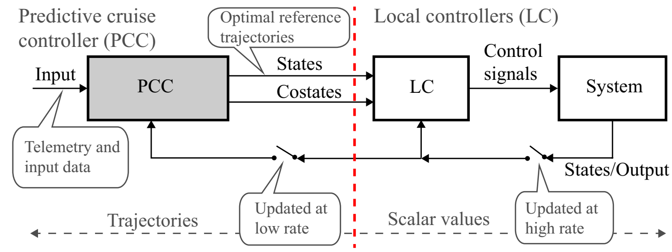

Fig. 1. Predictive cruise control (PCC) and local (feedback) controllers (LC). The PPC generates state and costate trajectories by solving an optimal control problem over a receding horizon. The state and costate trajectories are used as a reference for the LC.

2.1. Predictive cruise control

Automated cruise controllers currently in production typically employ standard feedback PID controllers that are tuned to track a reference speed trajectory in real-time. The design of these controllers is often complicated when input/state constraints are present and when predictive information has to be incorporated. One way to overcome the limitations, without the need to significantly change the existing system, is to augment the system with an additional controller that generates optimized references or set points for the local feedback controllers, see Fig. 1.

The system with a predictive cruise control (PCC), depicted in Fig. 1, resembles a reference governor, since predictive control is applied to the reference trajectories rather than to the control inputs (Bemporad & Mosca, 1998; Gilbert, Kolmanovsky, & Tan, 1995). The difference to a typical reference governor is that the PCC in Fig. 1 does not guarantee constraints satisfaction for the reference tracking in the local feedback controllers. Instead, constraints satisfaction is guaranteed only for the model used within the PCC.

Although extracting control inputs from the PCC is not necessary, the PCC still considers future control actions in order to guarantee constraints fulfillment. The future control actions and state/costate trajectories are a result of an optimization procedure that is re-evaluated in a receding horizon model predictive control (MPC) framework (Mayne, Rawlings, Rao, & Scokaert, 2000). The length of the receding horizon has to be long enough to guarantee a required average cruising speed, while leaving freedom for speed variations in a hilly terrain.

The goal of this section is to propose a computationally efficient PCC. In particular, the goal is to design a real-time implementable controller for receding horizons with length to about 20 km. For longer horizons that cover an entire trip, e.g. with range greater than 100 km, the goal is to deliver a controller that is suitable for off-line assessment of optimal energy management strategies.

2.2. Travel time and velocity constraints

Consider a vehicle driving on a planned route in a possibly hilly terrain. In the studied scenario the vehicle does not stop or change direction of movement. A preferred cruising speed is set by the driver, or set automatically by a telemetry system. The preferred speed is filtered (see Appendix A), in order to construct a reference speed trajectory $v_r(s)$. The vehicle does not necessarily track the reference. Instead, the vehicle speed v is allowed to vary between two limits