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Rolling horizon stochastic optimal control strategy for ACC and CACC under uncertainty

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ABSTRACT

This paper presents a rolling horizon stochastic optimal control strategy for both Adaptive Cruise Control and Cooperative Adaptive Cruise Control under uncertainty based on the constant time gap policy. Specifically, uncertainties that can arise in vehicle control systems and vehicle sensor measurements are represented as normally-distributed disturbances to state and measurement equations in a state-space formulation. Then, acceleration sequence of a controlled vehicle is determined by optimizing an objective function that captures control efficiency and driving comfort over a predictive horizon, constrained by bounded acceleration/deceleration and collision protection. The optimization problem is formulated as a linearly constrained linear quadratic Gaussian problem and solved using a separation principle, Lagrangian relaxation, and Kalman filter. A sensitivity analysis and a scenario-based analysis via simulations demonstrate that the proposed control strategy can generate smoother vehicle control and perform better than a deterministic feedback controller, particularly under small system disturbances and large measurement disturbances.

1. Introduction

Automated Vehicle (AV) technologies, enabled by advanced sensing and communication, can fundamentally change driver interactions and present unprecedented opportunities to drastically improve traffic efficiency, stability and safety. AVs can be generally divided into two categories based on communication capability: autonomous systems and connected autonomous systems. Autonomous systems have no communication function and make decisions based on the information collected by vehicle sensors. In contrast, in connected autonomous systems, vehicles can communicate with each other and make decisions through cooperative sensing and control.

Adaptive Cruise Control (ACC) is one of the earliest autonomous systems and has been widely studied and designed in the last few decades. Perhaps the most widely known ACC is linear feedback control, where acceleration is proportional to the deviation from target spacing and relative speed with the vehicle immediately ahead. Based on different target spacing, the linear feedback control can be further divided into constant time headway (CTH) policy (Rajamani and Shladover, 2001) and constant spacing (CS) policy (Darbha and Rajagopal, 1999). In the CTH policy, the equilibrium spacing is defined as the speed multiplied by a predefined constant time headway plus a standstill spacing, whereas, in the CS policy, spacing

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is time-invariant. The CS policy requires at least level 2 automation and isolated and dedicated lanes due to the aggressive gap setting. In contrast, the CTH policy, where inter-vehicle spacing increases with speed, only requires level 1 automation with shared lanes with other automated or non-AVs. Furthermore, many studies suggest that the CTH policy is more appealing since it is more robust to error propagation through traffic (e.g., Li and Shrivastava, 2002; Shrivastava and Li, 2000; Swaroop et al., 1994).

Other than the two car following strategies mentioned above, more complex car following strategies were proposed for different purposes, such as finding the optimal speed to prevent a collision, mitigate traffic congestion, etc. Two notable models are the Optimal Velocity Model (OVM) (Hasebe et al., 2003) and Intelligent Driver Model (IDM) (e.g., Kesting et al., 2008; Kesting and Treiber, 2013). OVM was proposed to regulate the controlled vehicle's speed at optimal/desired speed based on a fundamental diagram; however, the model does not explicitly incorporate a collision-free mechanism. On the other hand, IDM extends the optimal velocity family models by determining the deceleration needed to prevent a collision. However, IDM has extra parameters such as acceleration exponential, and comfortable deceleration rate.

Connected autonomous systems incorporate communication technologies, such as the vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, into autonomous systems to enable cooperative sensing and control. Cooperative Adaptive Cruise Control (CACC) is particularly promising due to its high performance potential to drastically improve traffic capacity and stability (e.g., Lu et al., 2002; Milanés et al., 2014; Pérez et al., 2013; Shladover et al., 2012, 2015; Talebpour and Mahmassani, 2016). For example, Rajamani and Shladover (2001) proposed a coordinated vehicle platooning strategy based on the CS policy and showed that the capacity of a dedicated lane can increase by about 150% via field testing. While not as drastic, the CTH policy can still realize a significant improvement of traffic capacity as much as 110% compared to manual traffic as evidenced by simulation (Vanderwerf et al., 2001). Due to the promising performance, the design of connected autonomous systems has been widely researched in recent years (e.g., Ma et al., 2017; Öncü et al., 2014; Ploeg et al., 2015). For example, many systems are formulated as decentralized systems using the time invariant linear feedback and feedforward controller based on the CTH policy (e.g., Stipanović et al., 2004; Morbidi et al., 2013).

Despite the simplicity, linear feedback/feedforward controllers have some notable shortcomings. Particularly, they have a time invariant feedback gain: i.e., vehicles cannot dynamically choose the feedback gain according to the current inter-vehicle spacing and speed difference. Furthermore, they do not explicitly incorporate collision-free constraints and vehicle acceleration and deceleration boundaries. Alternatively, optimal control theory provides a flexible framework in modeling the control objective function and constraints, which gives the optimal control solution (e.g., vehicle acceleration) at each time step. Thus, it is applied to formulate ACC and CACC control problems that capture safety, efficiency, and comfort with bounded acceleration. This problem can be efficiently solved via convex programming (e.g., Hoogendoorn et al., 2012; Wang et al., 2012; Gao and Jiang, 2016).

Recognizing that these control models have no predictive ability, a deterministic rolling horizon control framework for both ACC and CACC was proposed, where the optimal current vehicle acceleration is determined by optimizing the performance over a future time horizon based on the current system dynamics and measurements (Wang et al., 2014a,b). Building on this framework, Wang et al. (2016a) later developed a distributed CACC algorithm, which treats each vehicle as an individual system while assuming that the leading vehicle's acceleration remains constant during the prediction horizon. This deterministic receding horizon framework offers a certain degree of robustness against uncertainty since control is implemented in a rolling horizon manner. However, its deterministic formulation does not explicitly incorporate uncertainties within the control system and in sensor measurements. Thus, disturbances in these elements may impact the system evolution, resulting in poor model performance and suboptimal control (Bernardini and Bemporad, 2009).

In light of the above shortcoming, the objective of this paper is to develop a rolling horizon stochastic optimal control framework under uncertainty based on the widely accepted CTH policy for both ACC and CACC with bounded acceleration/deceleration and collision free constraints. Particularly, we extend the rolling horizon control framework for both ACC and CACC systems with two types of uncertainty: uncertainty in system dynamics and uncertainty in sensor measurements. Since the system equation is typically formulated based on vehicle kinematic characteristics, it disregards vehicle dynamics such as aerodynamic drag force, road gradient, and vehicle condition. Therefore, the actual acceleration and speed implemented by the vehicle may deviate from what are prescribed by the controller. Measurement error can further contribute to the difference in actual and prescribed acceleration and speed. In this paper, rather than assuming that the vehicle can implement perfectly the acceleration given by the controller (as in Wang et al. (2014a,b), we add an external disturbance term to incorporate the uncertainty in system dynamics and measurement. To incorporate these uncertainties, the stochastic optimal control problem is formulated as a discrete linearly constrained linear quadratic Gaussian control problem, which is solved using a separation principle (Lim et al., 1996a,b). Specifically, the problem is decomposed into a discrete linearly constrained linear quadratic problem to obtain time-varying feedback gains and an on-line estimation problem, in which a Discrete Kalman filter is used to estimate the system state. The proposed control systems were evaluated through simulation for different disturbance scenarios. The results demonstrate that the proposed controllers generally perform better than the deterministic counterparts: the performance improved by approximately 8.5% for ACC and 10.0% for CACC systems on average. Moreover, the proposed controllers perform significantly better when the system disturbance is small and the measurement disturbance is large. In this case, the performance improvement reaches up to 60% for ACC and 80% for CACC.