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Integrated stability and traction control for electric vehicles using model predictive control

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ABSTRACT

In this paper, an integrated vehicle and wheel stability control is developed and experimentally evaluated. The integrated structure provides a more accurate solution as the output of the stability controller is not altered by a separate unit, therefore its optimality is not compromised. Model predictive control is used to find the optimal control actions. The proposed control scheme can be applied to a wide variety of vehicle driveline and actuation configurations such as: four, front and rear wheel drive systems. Computer simulations as well as experiments are provided to show the effectiveness of the proposed control algorithm.

1. Introduction

Active vehicle stability control systems have played a major role in reducing the number of road fatalities over the past few decades. These systems assist the driver to control the vehicle in harsh driving conditions, such as high-speed collision avoidance maneuvers and slippery road conditions. In spite of these safety systems, road fatalities continue to claim lives. Therefore, further development of such safety enhancement systems is required. Besides, new types of personal vehicles continue to gain popularity in the market, such as hybrid and fully electric vehicles. This highlights the importance of development of active safety systems that are tailored for these particular types of vehicles.

Along with development of electric vehicles, development of powerful computing hardware has led to increased popularity of control algorithms that are computationally expensive, namely Model Predictive Control (MPC). MPC has the advantage of being a model-based control algorithm. Therefore, transferring the controller from one vehicle to another can be done with minimum changes in the controller parameters. In addition, in the MPC approach, the constraints on the actuator limits as well as system states can be explicitly considered in the control design stage; therefore, the control actions are calculated with the system constraints considered, which results in a more accurate control system. Several variations of MPC has been employed in vehicle stability control applications. Given the nonlinear nature of vehicle dynamics, using a nonlinear prediction model provides a more accurate representation of the system. Some authors have used nonlinear MPC (NLMPC) in their work. For instance, Borrelli, Falcone, Keviczky, and Asgari (2005) studied active steering of autonomous vehicle systems using Model Predictive Control with a nonlinear bicycle model as the prediction model. Using NLMPC, they tried to find optimal control actions for path tracking. They evaluated the performance of their controller in a double lane change maneuver with increasing entry speeds. They studied the required size of the prediction horizon and control horizon necessary to stabilize the vehicle with different entry speeds. Falcone, Tseng, Borrelli, Asgari, and Hrovat (2008) used model predictive control to perform path following via combined active front steering and differential braking. They used a 10-DOF nonlinear vehicle model as well as a simple bicycle model for comparison. Performing computer simulations, they observed that the braking and steering actions of the controller cooperate well towards the objective of trajectory tracking. They also observed that as the vehicle speed is increased beyond a certain threshold, the controller using the simple bicycle model fails to stabilize the vehicle. Similar technique has been used in (Canale, Fagiano & Razza, 2010; Falcone, Borrelli, Asgari, Tseng, and Hrovat, 2008; Palmieri, Falcone & Tseng, Glielmo, 2008).

Even though a nonlinear model gives better prediction accuracy in a wider range of vehicle operation, it results in a nonlinear programming problem (NLP). NLPs are computationally expensive to solve, thus not an attractive option for real-time implementation. An alternative to a nonlinear prediction model, is a hybrid or mixed integer model. In this approach, the important

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Nomenclature

MPC	Model Predictive Control
NLMPC	Nonlinear Model Predictive Control
LTV MPC	Linear Time Varying Model Predictive Control
hMPC	Hybrid Model Predictive Control
LP	Linear Programming
QP	Quadratic Programming
NLP	Nonlinear Programming
AIT	Acceleration In Turn
FWD	Front Wheel Drive
RWD	Rear Wheel Drive
4WD	Four Wheel Drive
C.G.	Center of Gravity
R_{eff}	Effective wheel radius
L_i	Distance from C.G. to front ($i=F$) or rear ($i=R$) axle
L	Wheel base
w	Track width
u	Vehicle C.G. forward velocity
v	Vehicle C.G. lateral velocity
r	Vehicle yaw rate
g	Gravitational constant (9.81 $\mathrm{m/s^2}$)
α_{ij}	Slip angle of tire ij
k_{us}	Desired understeer gradient of the vehicle

nonlinearities in the system (such as tire saturation) are expressed in terms of piece-wise affine (PWA) elements. For instance, Borrelli, Bemporad, Fodor, and Hrovat (2006) used a PWA function to model the force developed in the tire contact patch in terms of the coefficient of friction and slip. The limits of the engine torque and engine torque gradient are expressed as the constraints of the system. They designed a hybrid MPC (hMPC) controller to regulate the engine torque so that the wheel slip remains in the target zone where the traction force is maximal. Solving the optimal control actions in this approach requires solving a mixed integer linear programming (MILP) or quadratic programming (MIQP) problem. A similar approach has been used in (Di Cairano, Tseng, Bernardini & Bemporad, 2012; Giorgetti, Bemporad, Tseng & Hrovat, 2006).

Another approach that is frequently used is successive linearization of a nonlinear model. This results in a linear prediction model at each sample time. Based on the norms used in the objective function, finding the optimum control actions requires solving a linear programming (LP) or a quadratic programming (QP) problem, which is much easier than a nonlinear programming or mixed integer programming problem. Many authors have used this approach in vehicle stability control. Barbarisi, Palmieri, Scala, and Glielmo (2009) addressed the problem of vehicle yaw rate tracking and sideslip angle control using differential braking. They used a double track model of the vehicle along with a Pacejka tire model which was linearized to provide a linear prediction model. Based on the calculated tire capacity and tire lateral forces, the limits on braking forces is determined. A supervisory algorithm uses the error in yaw rate and sideslip angle to determine when the controller should be activated or deactivated. The controller is tested in simulations with different cars and provides satisfactory performance. A similar method is used in (Falcone, Tufo, Borrelli, Asgari & Tseng, 2007; Turri, Carvalho, Tseng, Johansson & Borrelli, 2013; Beal, 2011; Jalaliyazdi, Khajepour, Chen & Litkouhi, 2015). To improve the robustness of the controller to uncertainties such as modeling uncertainties, some authors use reachability analysis and invariant set theory (Blanchini and Miani, 2008; Raković and Barić, Morari). Palmieri, Barić et al. Palmieri, Barić, Glielmo, and Borrelli (2012) used a set-based approach for vehicle lateral stabilization based on active front steering and differential brakes.

Controlling the tire slip ratio is an important part of the vehicle stability control. If the slip ratio of a tire exceeds a certain threshold, its force capacity in lateral direction is severely reduced. This can lead to a significant understeer or oversteer during cornering especially on low friction surfaces, which can not be easily corrected by stability controllers. It is a common practice to assume a separate tire slip control module exists that keeps the tire slip ratio within the permissible range (see (Falcone, Borrelli et al., 2008) for example). However, having separate slip control and stability control modules means that the torque adjustments made by the stability controller are altered by a separate module; therefore, its optimality is compromised. Few authors have attempted to design an integrated stability and traction control systems.

Palmieri, Barbarisi, Scala, and Glielmo (2009) investigated integration of a model predictive stability control module with a slip control system. The method of actuation was differential braking. The desired braking forces are calculated in the stability controller and then passed to a slip control module to generate the actual barking forces. The feedback part in the slip control module is an integral controller that tries to reduce the error between the desired slip ratio and the actual slip ratio to keep the longitudinal slip ratio in a stable range. However, even in this structure, the slip control and stability control modules are separate entities and not fully integrated. A better integration of the vehicle and wheel dynamics is done by Zhou and Liu, (2009). The state vector of their prediction model involves the yaw rate and sideslip angle of the vehicle as well as the slip ratio of all four tires. They evaluated the performance of their MPC controller using computer simulations. It was observed that careful tuning of controller parameters is necessary to achieve good performance and avoid wheel lock.

The main contribution of this paper is designing an integrated vehicle stability and slip control system using model predictive control. The prediction model involves a double track vehicle model as well as the wheel dynamics, thus the integration between stability control and slip control modules is realized. In this formulation, no separate slip control module is required as the integrated controller maintains the vehicle stability and tire grip at the same time. Another contribution of the paper is that it can be quickly reconfigured to work with different driveline configurations, including front wheel drive (FWD), rear wheel drive (RWD) as well as four wheel drive (4WD). Furthermore, the designed controller can work with vehicles equipped with differential barking in addition to torque vectoring.

In this paper, first the formulation of the integrated MPC controller is presented. Then, the performance of the designed controller is illustrated with computer simulations using Simulink/CarSim. The controller is also implemented in two electric Equinox vehicles: a four wheel drive (4WD) used for torque vectoring and a rear wheel drive (RWD) equipped with differential braking. The performance of the controller is investigated in various maneuvers and road conditions.

2. MPC controller design

The integrated model predictive controller is designed in this section. First, the prediction model involving vehicle directional dynamics and wheel dynamics is introduced. Then, the desired system response for the vehicle and wheels is defined. Next, the