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Integrated model predictive control and velocity estimation of electric vehicles☆

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ABSTRACT

In this paper, an integrated estimation and control system is developed for the stability and traction control of electric vehicles. A model predictive control technique is used to track the desired vehicle yaw rate while maintaining small lateral velocity and tire slip ratios. This paper proposes a new method to control the lateral stability of the vehicle. In this method, the lateral vehicle velocity is controlled indirectly by adjusting the reference yaw rate. This reduces the size of the prediction model and its computational complexity. The controller requires the vehicle's lateral and longitudinal velocities as well as its tire forces for stability and traction control. This paper also proposes a novel velocity estimation scheme that uses the combined vehicle kinematics and tire model. The developed Kalman-based estimator provides velocities and lateral forces at each corner that are robust to changes in the road condition. The combined model-based and kinematic-based estimation structure mitigates some common problems of the widely used kinematic-based estimators such as the spikes and drifting issues. The stability of the proposed time-varying estimator is also investigated. The designed control and estimation scheme are experimentally validated on various driveline configurations and proven to provide reliable results.

1. Introduction

Active vehicle stability systems have significantly reduced the number of road accidents over the past decades [1–3]. These systems help the driver maintain vehicle stability in critical driving situations, such as high speeds, sudden lane changes, and slippery road conditions. Despite high adoption rate of the stability control systems [1], road accidents still continue to claim lives. Therefore, development of more advanced stability control algorithms is required.

Vehicle stability control systems require vehicle states (velocities and forces) to control wheel slips, vehicle yaw rate, and sideslip angle. Longitudinal and lateral velocities make major contributions to traction and stability control systems, respectively. They can be measured with the advent of GPS, but the poor accuracy of the most commonly implemented conventional GPSs and their lack of reception in some geographical areas are their primary impediments. Two approaches for longitudinal/lateral velocity estimation have been adopted by the literature. One is the modified kinematic-based approach which uses available acceleration and yaw rate measurements from an Inertial Measurement Unit (IMU) and estimates the vehicle states by employing Kalman-based [4], or nonlinear [5] observers. This method does not employ a tire model, but instead, sensor bias and noise should be meticulously identified as shown in [6], using an accurate GPS for a reliable estimation, which imposes additional costs on commercial vehicles.

The other velocity estimation method is tire model-based. It uses IMU data and corrects the estimation with an observer on the tire forces. Although promising, it requires a good perception of the road condition as well as a precise tire model, especially in the tire saturation region. To address the time-varying tire parameters, nonlinear observers in [7] and extended Kalman filter (EKF) in [8,9] are employed for estimation of the longitudinal and lateral states. Vehicle states and parameters of the tire model are estimated in [10,11] using EKF along with the Burckhardt tire model [12]. An unscented Kalman filter (UKF) [13] is introduced for the velocity estimation in [14,15], by using tire friction parameters. Kayacan et al. [16] addressed the estimation of the lateral states and sideslip angle of an autonomous tractor-trailer vehicle with a nonlinear moving horizon estimation combined with a fast distributed nonlinear model predictive control. However, road friction information is required in these approaches.

Alternatively, to tackle the unknown road friction issue, some studies estimated road friction and the longitudinal/lateral veloci-

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Nomenclature

$\bar{z}_x, \bar{z}_y$	longitudinal and lateral LuGre internal states
β	vehicle sideslip angle
$\boldsymbol{\omega}^*$	vector of zero slip (rolling) wheel speeds
$\boldsymbol{\omega}_d$	vector of desired wheel speeds
δ_f	front wheel steering angle
$\hat{v}_x, \hat{v}_y$	estimated velocities at the vehicle's C.G.
$\mathbb{V}, \mathbb{W}$	observability and controllability grammians
$\boldsymbol{\Omega}_x$, $\boldsymbol{\Omega}_y$	velocity estimation uncertainties
$\mathbf{P}_k$, $\mathbf{P}_{mk}$	updated and predicted error covariances in UKF
ω_{ij}	rotational speed of wheel ij
ϕ_v, θ_v	vehicle roll and pitch
$\phi_{m,\,n}$	state transition matrix
a_x, a_y	measured longitudinal and lateral accelerations
$f_{x_{ij}}, f_{y_{ij}}$	normalized longitudinal and lateral tire forces
$F_{x_{ij}}, F_{y_{ij}}, F_{z_{ij}}$	longitudinal, lateral, and vertical tire forces
g	gravitational constant (9.81 m/s^2)
I_w	wheel's moment of inertia about the rolling axis
I_z	vehicle's yaw moment of inertia
K_k	Kalman gain in UKF
k_{us}	desired vehicle understeer gradient
l	vehicle wheelbase
L_i	distance from C.G. to the center of axle i
m	vehicle mass
M_{F_y}	moment of lateral tire forces about vehicle C.G.
N_c	size of the control horizon
N_p	size of the prediction horizon
r	vehicle yaw rate
r_d	desired vehicle yaw rate
R_e	wheel effective radius
$T_{t_{ij}}$	total torque applied to wheel ij
$v_{rx_{ij}}, v_{ry_{ij}}$	corner relative velocities in tire coordinates
$v_{x_{ij}}, v_{y_{ij}}$	velocities at corners in vehicle coordinates
$v_{xt_{ij}}, v_{yt_{ij}}$	corner velocities in tire coordinates
v_x, v_y	velocities at the vehicle's C.G.
W_i	trackwidth of axle i

ties concurrently. Grip et al. suggest a nonlinear sideslip observer in [17] that incorporates time-varying gains and estimates vehicle states as well as the surface friction using a tire model. A sliding-mode observer is proposed in [18] based on the LuGre friction model [19] to estimate the speed and the road condition simultaneously. Wheel braking torques, speed, and acceleration measurements are used in [20] for a sliding-mode observer to estimate vehicle velocity together with an EKF for the estimation of the Burckhardt model's friction parameter. Li et al. proposed a method in [21] to estimate the lateral velocity and road friction limits using steering torque sensors. In their work, the longitudinal speed is assumed to be known. To cope with the road friction changes, Zhang et al. [22] considered nonlinear lateral dynamics as an uncertain model and proposed a gain scheduling scheme due to the longitudinal velocity changes. A longitudinal speed estimation method is developed in [23] which combines the tire model and vehicle's longitudinal kinematics and uses a Kalman observer. However, high-slip cases and non-Gaussian process and measurement noises are challenges in their approach. Therefore, developing velocity and tire force estimators using conventional sensor measurements (wheel speeds, steering angle, accelerations, and yaw rate) which is robust to the road friction changes is desirable.

Improvements in the fields of computer hardware and computational power of vehicle electronics have led to an increased popularity of the computationally expensive control algorithms such as model predictive control (MPC). MPC consists of an optimization in-the-loop algorithm, therefore, it results in highly optimized solutions. The drawback of MPC is that it is computationally expensive, especially compared to conventional algorithms such as PID or LQR techniques.

Several variations of model predictive control have been studied in the literature. In nonlinear MPC (NLMPC), a nonlinear prediction model is used for improved accuracy in a wider range of system operation. For instance, Falcone et al. [24] studied path following using a nonlinear tenth-order prediction model. They used active steering and differential braking to adjust vehicle's behavior in order to track a desired path. They compared the results with another predictive controller based on a simplified bicycle model. The results confirm that the nonlinear model can better stabilize the vehicle while increasing the computational complexity of the controller. A similar approach is used in [25,26]. Another variations of MPC is hybrid model predictive control (hMPC). In hMPC, a piece-wise affine prediction model is used, which is simpler than a nonlinear model. A few authors have tried implementing hMPC in their work. The interested reader is referred to [27–29] for more information. Another variation of the MPC is the linear time-varying model predictive control (LTV-MPC). In this approach, the nonlinear model of the vehicle is successively linearized around the current vehicle state. This approach results in a linear prediction model and a linear or quadratic programming (LP or QP) problem. The LTV-MPC controllers are in general easier to formulate and tune, and thus, widely used in the literature. For instance, Palmieri et al. [30] used a linear time-varying MPC method to stabilize a vehicle during a high-speed double-lane change by using differential brakes. A separate slip controller unit is used to generate the desired differential braking forces at the contact patch. Computer simulations are used to examine the performance of the proposed control scheme. A similar approach is used in [31–34].

In an attempt to reduce the online computational cost of the model predictive controllers, some authors have tried the explicit MPC technique (e.g. [27,35]). In this technique, the programming problem is solved offline in terms of the system states using multi-parametric programming methods. However, this method requires a significant memory to store the solution of the multi-parametric programming problem. In addition, the application of the explicit MPC is mostly limited to linear systems.

In this paper, the suggested velocity estimation method treats acceleration measurement noises and the road condition as uncertainties and implements an unscented Kalman filter. The longitudinal and lateral velocity estimators take advantage of combining kinematic-based and model-based schemes without requiring road friction information. Another contribution of this paper is proposing a new method for indirect control of the vehicle sideslip angle. In this method, the reference yaw rate is adjusted based on the sideslip angle. By tracking this adjusted reference yaw rate, the controller maintains a small sideslip angle at the same time. This results in a smaller and simpler prediction model, thus, reducing the amount of online calculations. The proposed velocity estimation method and model predictive controller are implemented in real-time and tested on an AWD electric vehicle. The accuracy and performance of the estimation and control schemes are verified through several experiments conducted on various road conditions.

This paper is organized into five sections. The proposed longitudinal/lateral state estimation method is provided in Section 2 where the stability of the time-varying estimator is also explored. The proposed model predictive control scheme is developed in Section 3. Road test experiments have been conducted on various road surfaces and the results of the state estimators and performance of the proposed model predictive control are presented in Section 4. Section 5 includes conclusions and some of the findings of this paper.