

Combined Longitudinal and Lateral Control for Automated Lane Guidance of Full Drive-by-Wire Vehicles

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ABSTRACT

This paper presents a simultaneous longitudinal and lateral motion control strategy for a full drive-by-wire autonomous vehicle. A nonlinear model predictive control (NMPC) problem is formulated in which the nonlinear prediction model utilizes a spatial transformation to derive the dynamics of the vehicle about the reference trajectory, which facilitates the acquisition of the tracking errors at varying speeds. A reference speed profile generator is adopted by taking account of the road geometry information, such that the lateral stability is guaranteed and the lane guidance performance is improved. Finally, the nonlinear multi-variable optimization problem is simplified by considering only three motion control efforts, which are strictly confined within a convex set and are readily distributed to the four tires of a full drive-by-wire vehicle. Simulation results demonstrate the capability of the proposed controller to follow the reference trajectory while adjusting the vehicle speed automatically.

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INTRODUCTION

A full drive-by-wire vehicle is a kind of over-actuated mechanical system whereby the traction/braking torque and the steering angle of each road wheel are controlled independently from the others [1, 2, 3]. Thanks to its flexibility in the tire force distribution, this 4-wheel-distributed driving, braking and steering system is capable of enhancing the dynamics control performance by maximizing the target resultant force of the four tires [4]. Based on the control hierarchy summarized in [5], the vehicle dynamics control algorithm is generally divided into two levels: the motion control and the control allocation. As for a full drive-by-wire vehicle, the motion control efforts are linear with regard to the tire forces, the magnitudes and directions of which are then individually translated to the steering angle and the traction/braking torque of each wheel. Therefore, the complexity of the motion control problem is greatly reduced by taking into account only the longitudinal, lateral and yaw efforts and their constraint can be directly derived from the allocation method [6].

Because all the actuators in a full drive-by-wire vehicle are using X-by-wire technology, autonomous driving will be realized just by introducing the exteroceptive sensors and by re-programming the electronic control unit (ECU). The control objective is to follow a desired path, while keeping the longitudinal velocity as close as possible to a given reference. Model predictive control (MPC) or receding horizon control (RHC) is effective in solving the combined motion control problem under the state and input constraints, which

predicts the evolution of the plant model over a finite horizon based on a sequence of future inputs in order to optimize a performance index by using the preview information. This makes it an attractive method for use in the automated lane-keeping tasks [7, 8]. On account of the nonlinearities of the vehicle and tire dynamics, the trajectory following problem of a traditional vehicle at varying speeds is often decomposed in a path following and a velocity tracking subtasks so as to simplify the optimization problem [9, 10]. Thus, the reference speed should be specified in advance and the control strategy based on this formulation may yield a sub-optimal solution, which could potentially be enhanced by incorporating the longitudinal and lateral control within the same framework. Another option to reduce the computational complexity of the constrained finite-time optimal control (CFTOC) problem is by means of successive online linearization of the nonlinear plant model, which is approximated by a linear time-varying (LTV) system with a parameter-varying state transition and a parameter-varying input matrix [8, 11, 12, 13, 14]. However, the performance of the LTV-MPC deteriorates when the prediction horizon is large. Moreover, in order to obtain the reference trajectories in the prediction horizon, their assumption on the constant travel velocity is invalid especially in extreme handling situations, which can affect the performance and stability of the closed-loop system [7]. In an attempt to overcome this, the spatial transformation is employed in [15]. The proposed spatial MPC framework provides good real-time performance but is only validated on a straight track mainly for letting the observed

avoidance strategy. Meanwhile, the longitudinal reference velocity is usually a given constant and should be adapted automatically according to the road geometry information.

Based on the above-mentioned consideration, this study presents a combined longitudinal and lateral control method for the automated lane guidance of a full drive-by-wire vehicle by using the nonlinear model predictive control (NMPC). The vehicle dynamics model and its spatial transformation as well as the trajectory generation are described in section 2; The detailed formulation of the CFTOC problem is illustrated in section 3; Simulation results are presented in section 4 followed by concluding remarks.

SYSTEM MODELLING

Vehicle Dynamics Model

As shown in Figure 1, the vehicle planar motion within the lane is described by the following set of differential equations, given by:

$$\begin{aligned} m\dot{V}_x &= mV_y\dot{\psi} - C_D A_f \rho V_x^2 / 2 + F_{xd} \\ m\dot{V}_y &= -mV_x\dot{\psi} + F_{yd} \\ I_z\ddot{\psi} &= M_{zd} \\ \dot{e}_\psi &= \dot{\psi} - \dot{\psi}_s \\ \dot{e}_y &= V_x \sin(e_\psi) + V_y \cos(e_\psi) \end{aligned} \quad (1)$$

where m is the total vehicle mass; I_z is the moment of inertia round the vertical axis; V_x and V_y are the longitudinal and lateral velocities of the vehicle at the cog (center of gravity), respectively; ψ is the yaw angle, the first- and second order time derivatives of which are the yaw rate and yaw angular acceleration, respectively and ψ_s is the road path heading angle; e_ψ and e_y denote the vehicle orientation error and the lateral position error, respectively; C_D is the drag coefficient factor; A_f is the vehicle front area; ρ is the air density; F_{xd} , F_{yd} are the target longitudinal and lateral forces, respectively and M_{zd} is the target yaw moment. The range of the motion control efforts F_{xd} , F_{yd} and M_{zd} are considered as the resultant force of each tire. In [6], the constraint between the target forces and moment of the vehicle is modeled as the convex set, expressed as:

$$\lambda_\mu = \sqrt{F_{xd}^2 + F_{yd}^2 + W_r^2 M_{zd}^2} / (mg\mu) \leq \lambda_{\mu\max} < 1 \quad (2)$$

where g is the gravitational constant (9.8 m/s^2); μ is the friction coefficient; W_r is constant weight balancing forces and moment, which, according to [4], is chosen as the reciprocal the of typical length between the wheel and the cog; λ_μ is the μ rate, which is introduced to describe the total workload of the four tires. By using certain tire force distribution methods for the full drive-by-wire vehicle, the upper bound of the factor $\lambda_{\mu\max}$ can be regarded as a constant during the control interval and is set to 0.95 in this paper.

The nonlinear vehicle dynamics can be expressed in the following compact form:

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t)) \quad (3)$$

where the state vector $\mathbf{x}$ and the input vector $\mathbf{u}$ are given by:

$$\begin{aligned} \mathbf{x} &= [V_x \quad V_y \quad \psi \quad e_\psi \quad e_y]^T \\ \mathbf{u} &= [F_{xd} \quad F_{yd} \quad M_{zd}]^T \end{aligned} \quad (4)$$

Spatial Vehicle Model

The vehicle dynamics model described above undergoes a coordinate transformation to derive the dynamics of the vehicle about the reference trajectory, i.e. the spatial vehicle model, such that the independent variable becomes distance along the path instead of time. This transformation allows the position of the vehicle to be known explicitly at each sampling instant even if the vehicle travels a portion of the desired path at varying speeds. The following kinematic equations can be derived from Figure 1:

$$\begin{aligned} v_s &= (\rho - e_y) \dot{\psi}_s = V_x \cos(e_\psi) - V_y \sin(e_\psi) \\ \dot{s} &= ds/dt = \rho \dot{\psi}_s = v_s / (1 - e_y/\rho) \end{aligned} \quad (5)$$

where v_s is the projected vehicle speed along the direction of the reference trajectory; s is the projected vehicle position along the reference trajectory; ρ is the radius of curvature at the sampling point s ; $\dot{\psi}_s$ is the time derivative of ψ_s .

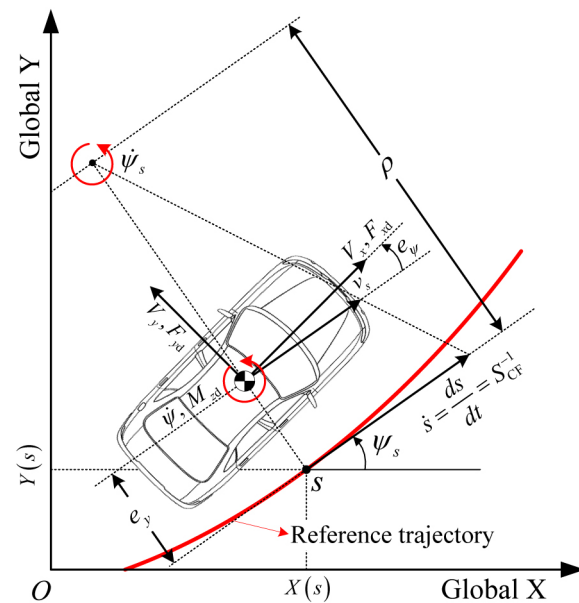


Figure 1. Vehicle model in a road-aligned coordinate frame.

Then the time-dependent vehicle dynamics can be transformed into the position-dependent dynamics, which are calculated as (6). Here and hereinafter, the superscript of $(\cdot)'$ denotes the spatial derivative with respect to the road.