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Control of regenerative braking systems for four-wheel-independently-actuated electric vehicles☆,☆☆

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ABSTRACT

Control of regenerative braking systems is considered in this paper. Firstly a modular observer is proposed to estimate the vehicle longitudinal velocity, and input-to-state stability theory is utilized to prove that the estimation error converges to zero. Then based on the estimated velocity, a feedback hierarchical controller is proposed to track a desired velocity and distribute the braking torques to the four wheels to improve energy recovery. Simulation results show the effectiveness of the proposed modular observer and hierarchical controller.

1. Introduction

Electric vehicles (EVs) can convert kinetic energy into electric energy in the braking process, which is known as regenerative braking, and thus can save energy. EVs have raised much interest in both academia and industries. To improve energy the recovery in regenerative braking, feedback controllers need to be designed. However, many vehicle states can not be easily obtained, such as the vehicle velocity, the side slip angle, the mass moments of inertia, and so on [1–4]. Therefore it is necessary to design estimation method to estimate vehicle states.

The vehicle velocity is indispensable for the feedback control of electric vehicles. Many sensors such as optical cross-correlation sensors, high precision Global Positioning System(GPS) and radar sensors can measure vehicle states. Nevertheless, these sensors are expensive. Therefore, numerous effective estimation methods have been proposed by researchers to estimate vehicle velocities instead of using the physical sensors. In general, vehicle velocity estimation methods can be categorized into kinematics-based and model-based methods. Kinematics-based methods are to estimate vehicle states by integrating both side of vehicle kinematics equations. Kinematics-based methods are proposed by Farrelly and Wellstead [5] and Ungoren et al. [6] and this kind of method is robust against vehicle parameters uncertainty because it is only dependent on sensor signals. However kinematics-based methods could be affected by the biases of sensor signals. Efforts are made to improve the estimation accuracy in [2] by filtering white noise of sensors. However, the drawbacks of kinematics-based methods still exist. Model-based methods are to estimate vehicle states based on the modeling of tire, wheel and vehicle body. Many model-based estimation methods are proposed in the literature. A modular nonlinear observer is proposed in [3] to estimate the vehicle velocity. However, the longitudinal velocity is estimated while the lateral vehicle dynamics is neglected. This may deteriorate the estimation accuracy of longitudinal velocity when the longitudinal or lateral slip can't be neglected. In [4], the differences between the measured and estimated accelerations are utilized to design the velocity observer and the strategy overcomes the shortcomings of the method in [3]. Most researchers propose estimation methods by assuming that the tire force friction coefficient (TRFC) is known. However it is difficult to obtain TRFC under real driving maneuvers. Sun et al. [7] proposes a switched nonlinear observer to estimate both TRFC and the vehicle velocity. Kiencke and Nielsen [1] and Hiemer et al. [8] linearize the estimator error dynamics then place the eigenvalues of the linear system on the left half plane. Oudghiri et al. [9] presents a robust estimation method using a fuzzy sliding mode observer. The extended Kalman filter (EKF) is employed

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to estimate vehicle states in [10,11]. However, EKF involves complex mathematical calculations during each iteration, which makes it difficult to be implemented in real-time.

In recent years, Regenerative braking (RB) control strategies have been widely studied. Many effective RB strategies have been proposed for hybrid EVs, plug-in hybrid EVs and four-wheel-independently-actuated electric vehicles (FWIA-EVs). The challenges of RB control systems are to distribute torques to the four wheels to improve the maneuverability of vehicles and improve RB energy recovery. Control allocation (CA) algorithms are designed in [12–14] to distribute the braking torques. The combination of off-line and on-line optimizations is employed in [12] to improve the maneuverability of vehicles and to save energy. The cost function consists of the yaw control offset, energy loss of the drive system, and barrier function. Nonlinear and non-convex optimization problems are solved by the Newton–Lagrange algorithm to transform the non-convex problem to a convex quadratic problem. In [13], an adaptive energy-efficient control allocation algorithm is proposed to distribute the braking torques of vehicles and the overall closed-loop system is guaranteed to be input-to-state stable. In [14], a novel method for constructing the state-dependent coefficient formulation of the RB system dynamics is proposed and an augmented penalty approach is suggested for handling the constraints on RB torques. Apart from control allocation algorithms, predictive control is also widely utilized to solve the braking torque distribution problem. Nonlinear model predictive control (NMPC) is employed in [15,16]. Since NMPC involves solving complicated optimization problems online when the vehicle dynamical model is complicated, the initial plane griding technique is employed in [15] to improve the computational efficiency of NMPC. In [17], the nonlinear RB system is converted to a linear time varying system and the problem can be viewed as a linear system during a short period of time. Then a model predictive controller is utilized to obtain optimal braking torques. In this way, the computational burden of the controller can be greatly relieved. In [18], an optimal predictive control law is designed to allocate the hydraulic and regenerative braking torque distributions. Uncertain parameters are taken into consideration in [18] and a robust control law is proposed to improve the performance of the optimal predictive control method. To the best of our knowledge, existing RB controller assumes that the vehicle states are available, which is not realistic.

Based on the above observation, an observer-based RB controller is proposed in this paper. The objective of the controller is to track the desired longitudinal velocity profiles and to improve the RB energy recovery. Firstly, a novel modular observer for vehicle velocity estimation is proposed to provide the longitudinal velocity information for the RB controller design. The longitudinal velocity observer is based on the estimation of longitudinal tire forces. Moreover, the convergence analysis of the modular observer is given. Then, the RB controller is designed based on the estimated vehicle states. The RB controller consists of an upper-layer controller and a lower-layer controller. A robust controller is designed as the upper-layer controller to track the velocity reference profiles. Then the lower-layer controller tracks the generalized torque obtained from the upper-layer controller and improves the RB energy recovery by allocating the braking torques among front and rear wheels.

This paper is organized in the following way. The bicycle model of vehicles and the tire friction model are developed in Section 2. In Section 3, the modular observer for the longitudinal velocity is designed and the convergence analysis are given. Then the RB controller is designed in Section 4. In Section 5, simulation results are presented to validate the performance of the observer and the controller. Conclusions are given in Section 6.

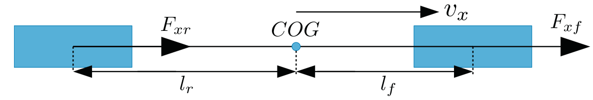

Fig. 1. Bicycle model of vehicle.

2. Vehicle model development

2.1. Bicycle model of vehicle

In this subsection, the model of vehicle is presented by analyzing the dynamic characteristics of vehicles. To promote further analysis, the following assumption is proposed.

Assumption 1. Under straight-line braking maneuvers, the left and right wheels at the front and rear side of FWIA-EVs are assumed to be completely identical.

Straight line maneuver is considered in this paper, therefore, the bicycle model is utilized, and the bicycle model is illustrated in Fig. 1. In Fig. 1, F_{xf} and F_{xr} are the longitudinal tire force of the front and rear wheel, respectively. The longitudinal velocity of the vehicle is denoted as v_x. The center of gravity is denoted as COG. By Assumption 1, the following dynamic equations can be obtained:

$$m\dot{v}_x = 2(F_{xf} + F_{xr}) - F_a \tag{1}$$

$$J_i\dot{\omega}_i = u_i - R_{eff}F_{xi}, \quad i \in \{f, r\} \tag{2}$$

$$F_a = C_a v_x^2 \tag{3}$$

where m is the vehicle mass, F_a is the aerodynamic drag force, J_i represents the moment of inertia of the i wheel, ω_i is the angular velocity of the i wheel, R_{eff} is the effective radius of wheel, C_a is the aerodynamic drag coefficient. The system input is the braking torque of the i wheel u_i.

By substituting (2), and (3) into (1), the following dynamic equation can be obtained:

$$\begin{aligned}\dot{v}_x &= [-\frac{C_a v_x^2}{m} - \frac{2J_\omega(\dot{\omega}_f + \dot{\omega}_r)}{mR_{eff}}] + \frac{2}{mR_{eff}}T_d \\ &= h(v_x) + bT_d\end{aligned} \tag{4}$$

where the required total torque T_d is expressed as follows:

$$T_d = Bu = \begin{bmatrix} 1 & 1 \end{bmatrix}\begin{bmatrix} u_f \\ u_r \end{bmatrix}. \tag{5}$$

In (4), b is defined as follows:

$$b \triangleq \frac{2}{mR_{eff}}. \tag{6}$$

2.2. Tire friction model

Forces from the road act on the four tires of the vehicle and highly influence the dynamics of the vehicle, hence an accurate tire model should be selected to describe the longitudinal tire forces. Many tire models have been proposed to describe the relationship between tire forces and vehicle states, such as the Pacjka Magic Formula, the Unitire model, the Lugre Model and so on. In this paper, the Dugoff's tire model is used to describe the longitudinal tire-road friction forces. The longitudinal tire forces can be expressed as follows [19]:

$$F_{xi} = C_{\sigma i}\frac{\sigma_i}{1 + \sigma_i}f(\lambda_i) \tag{7}$$

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