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Longitudinal vehicle state estimation using nonlinear and parameter-varying observers☆

Ehsan Hashemi[a,*], Saeid Khosravani[a], Amir Khajepour[a], Alireza Kasaiezadeh[b], Shih-Ken Chen[b], Bakhtiar Litkouhi[b]

[a] *Department of Mechanical and Mechatronics Engineering, University of Waterloo, ON, Canada*
[b] *R&D Department, General Motors Co., Warren, MI, USA*

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ABSTRACT

A corner-based velocity estimation approach is proposed which is used for vehicle's traction and stability control systems. This approach incorporates internal tire states within the vehicle kinematics and enables the velocity estimator to work for a wide range of maneuvers without road friction information. Tire models have not been widely implemented in velocity estimators because of uncertain road friction and varying tire parameters, but the current study utilizes a simplified LuGre model with the minimum number of tire parameters and estimates velocity robust to model uncertainties. The proposed observer uses longitudinal forces, updates the states by minimizing the longitudinal force estimation error, and provides accurate outcomes at each tire. The estimator structure is shown to be robust to road conditions and rejects disturbances and model uncertainties effectively. Taking into account the vehicle dynamics is time-varying, the stability of the observer for the linear parameter varying model is proved, time-varying observer gains are designed, and the performance is studied. Road test experiments have been conducted and the results are used to validate the proposed approach.

1. Introduction

Vehicle control systems require lateral and longitudinal states (velocities and forces) to control wheel slip, vehicle yaw rates, and side slip angles. Among these states, longitudinal state estimation makes major contributions into vehicle stability and traction control. Recent literature has adopted two fundamental approaches regarding longitudinal velocity estimation. One is the modified kinematic-based approach [1], which uses acceleration and the yaw rate measurements from an inertial measurement unit (IMU) and estimates the vehicle states employing stochastic estimators such as Kalman. This method does not employ a tire model, but instead usually utilizes GPS receiver to remove estimation bias. Bevly et al. proposed an estimation method in [2,3] using a single-antenna GPS and measurements from IMU. Integrating the yaw rate during turning, their method obtains the vehicle heading. The state estimation structure provided by Ryu and Gerdes in [4] is a practical approach for determining vehicle states in which integration of the inertial sensors is performed when GPS data is unavailable. A full description of the planar vehicle dynamics is also implemented in their work to estimate lateral states using the yaw angle obtained by a GPS. However, these tire-free approaches rely on accurate GPS data which may be lost. It also imposes additional high costs on production vehicles.

The other longitudinal velocity estimation method exploits an observer on vehicle's longitudinal dynamics with the tire model. The advantage of this method is that it considers the tire capacities, although it still needs road conditions and tire parameters, which may vary significantly in different driving conditions. Using a linear Kalman filter, together with the fuzzy logic approach, Kobayashi et al. proposed a state estimator in [5], which exhibits acceptable performance and low computational loads. To deal with the varying tire parameters and model uncertainties, tire slips are used to define a model scheduling in [6,7]. Nonlinear observers are studied on bicycle model in [8,9] for vehicle state estimation. An Extended Kalman filter (EKF) is employed for both longitudinal and lateral vehicle state estimation in [10,11]. EKF has also been used in [12,13] along with the Burckhardt model [14] to estimate the vehicle states and parameters of the tire model; an EKF with smooth variable structure is also utilized in [15]. Computational

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* Corresponding author.
E-mail addresses: ehashemi@uwaterloo.ca (E. Hashemi), saeid.khosravani.1@uwaterloo.ca (S. Khosravani), a.khajepour@uwaterloo.ca (A. Khajepour).

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complexities of the EKF justify using a reliable approach such as the unscented Kalman filter (UKF) [16,17] without any need for linearization in system dynamics. Nonlinear stochastic estimation capability of the UKF provides acceptable numerical efficiency compared with the EKF. Antonov et al. [18] employed an UKF for vehicle state estimation and provided a longitudinal/lateral velocity estimator at each corner. They utilized wheel torques, wheel speeds at each corner, and a simplified empirical Magic formula [19] as the tire model. However, this method needs the road condition and is sensitive to the effective tire rolling radius because it uses the slip ratio. Wielitzka et al. presented a method in [20] for the vehicle state estimation using UKF, but their approach employs tire model that needs road friction.

On the other hand, to tackle the unknown road condition issue, other approaches estimate vehicle states as well as the road friction [21]. A sliding-mode observer is proposed in [22] based on the LuGre dynamic friction model to estimate longitudinal velocity as well as the friction limit. However, concurrent estimation of the road friction for low excitation and low-slip regions is challenging. Li et al. used nonlinear observer and the Dugoff tire model in [23] for the vehicle state estimation, but their method necessitates steering torque measurement for identification of the tire model's friction parameter. A nonlinear model and a gain scheduling scheme is considered in [24] on the linear parameter-varying observer to cope with the road friction changes. Zhang et al. presented a different version of the sliding-mode observer in [25] to estimate velocities using wheel speed sensors, braking torques and longitudinal/lateral accelerometer measurements. Their approach utilizes a sliding-mode observer for the velocity estimation and an EKF for estimation of the Burckhardt tire model's friction parameter.

In real situations, a tire model is highly dependent on the presence of tire wear, variable tire parameters, inflation pressure, and uncertainties in road conditions. Therefore, developing an observer for the velocity estimation robust to road conditions and fairly insensitive to tire parameters is desirable. A time-varying Kalman observer is proposed in [26] for longitudinal force estimation using wheel dynamics as well as longitudinal speed estimation at each corner with known and stochastic initial conditions and without road friction information, but utilizes derivatives of the LuGre model's internal states.

This study thus focuses on a method that treats the road condition and acceleration measurement noises as uncertainties. Its observations are also based on tire forces, which are accessible based on wheel dynamics using an unknown input observer [27] or a Kalman-based estimation [28] whenever measured (or estimated) effective torque is available. The proposed velocity estimator in this article uses a parameter-varying observer which can address high-slip conditions in different speed.

This article has been divided into five sections. A longitudinal force estimator is proposed in Section 2, which includes corner-based force estimation methodology using UKF. Suggested observer and stability analysis of the linear parameter-varying (LPV) error dynamics is provided in Section 3. Section 4 contains simulation and experimental results used to verify the approach in various maneuvers and road conditions with high and low longitudinal excitations. Finally, conclusions are provided in Section 5.

2. Longitudinal force estimation

Longitudinal force estimation significantly contributes to vehicle stability control in the model-based velocity estimator and tire capacity identifier. Estimation of longitudinal forces independent from the road condition may be classified on the basis of wheel dynamics into the Kalman-based estimation [26,28,29] and the nonlinear observers [27,30,31].

2.1. Force estimation with the unscented Kalman filter

The following describes the proposed UKF implementation for longitudinal tire force estimation. Julier et al. [16] proposed a deterministic sampling approach, namely UKF, for state and parameter estimation in discrete-time nonlinear systems and to overcome the linearization problem of the extended Kalman filter. Their method was modified later with augmented states in [32]. Proper capturing of nonlinearities contributed to the unscented transformation that defines the sample vectors $\bar{P} \in \mathbb{R}^{N\times 2N+1}$ around states where N is the length of the state vector. With some minor changes, UKF can also be employed for the parameter estimation instead of state estimation as provided in [33,34] for the vehicle parameter identification and in [28] for the longitudinal force estimation. The wheel dynamics at each corner yields:

$$\bar{T} - R_e F_x - C_b\omega + \Omega_F = I_w\dot{\omega}, \tag{1}$$

where R_e is the wheel effective radius, F_x is the longitudinal tire force, ω is the wheel rotational velocity, I_w is the wheel's moment of inertia, C_b shows the wheel bearing's linear viscous damping, and Ω_F represents uncertainties in the system including wheel torques, effective radius, and forces. The total effective torque on the wheels is shown by $\bar{T} = T_{tr} - T_{br}$, whereas traction and braking torques are denoted by T_{tr} and T_{br} correspondingly. For the proposed UKF-based force estimation, the effective torque T_t provides input; the wheel speed ω is available and assumed to be the measurement y_k, and the longitudinal force $\hat{F}_x$ is treated as the parameter $\hat{p}$. The discrete-time parameter estimation problem then can be expressed as:

$$\begin{aligned} p_{k+1} &= p_k + \varrho_k^p \\ y_k &= \mathcal{G}(x_k, p_k) + \varrho_k^m, \end{aligned} \tag{2}$$

where y_k corresponds to nonlinear observation on p_k and ϱ_k^p, ϱ_k^m represent process and measurement noises respectively. The estimated mean is updated as $\hat{p}_{mk} = \hat{p}_{k-1}$ and initialized by $\hat{p}_0 = \mathbb{E}[p]$. The sample points $\bar{P}_{k|k-1} = [\hat{p}_{mk} \quad \hat{p}_{mk} + \varsigma\sqrt{\bar{\Gamma}_{p_k}} \quad \hat{p}_{mk} - \varsigma\sqrt{\bar{\Gamma}_{p_k}}]$ are generated around the estimated mean $\hat{p}_{mk}$ of the parameters as in [32]. The square root factorization of the covariance matrix $\bar{\Gamma}_{p_k}$ can be obtained by Cholesky decomposition at each time step k. The error covariance matrix of the estimated parameter is initialized with Γ_{p_0} and updated by $\bar{\Gamma}_{p_k} = \Gamma_{p_{k-1}} + \rho_{k-1}^p$ with incorporation of the process noise covariance ρ_{k-1}^p. Furthermore, $\varsigma = \sqrt{N+\eta_1}$ is a scalar and represents the spread of sample points far from the mean values of random variables, where η_1 is the compound scaling parameter as $\eta_1 = \epsilon^2 N - N$ and $\epsilon = \sqrt{3/N}$. Afterward, $\eta_2 = 2$ is introduced to employ the prior information on the Gaussian distribution of the state/parameter. Generated sample points are supposed to be propagated within the system (wheel dynamics) as the function output $\mathcal{Y}_{k|k-1} = \mathcal{G}(x_k, \bar{P}_{k|k-1})$ with the conventional unscented transformation pattern. The output $\hat{y}_k$ is achievable from the expected value [35]:

$$\hat{y}_k = \sum_{i=0}^{2N} W_i^m \mathcal{Y}_{i,k|k-1}. \tag{3}$$

The weighting coefficients are also defined by $W_i^c = W_i^m = \frac{1}{2}(N + \eta_1)$ for all sets $i \in \{1, 2, \ldots, 2N\}$. These coefficients are $W_0^c = \frac{\eta_1}{N+\eta_1} + 1 - \epsilon^2 + \eta_2$ and $W_0^m = \frac{\eta_1}{N+\eta_1}$ for $i = 0$. The estimated function output $\hat{y}_k$ from (3) is then employed in the updated covariance matrices $\Gamma_{y_k y_k}, \Gamma_{p_k y_k}$ as follows using the measurement noise covariance ρ_k^m: