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Open-source dataset of vehicle state for an electric vehicle on a low-adhesion road

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This study demonstrates and opens for academic research six sets of electric vehicle data collected during experiments on a low-adhesion road. The 11-dimensional data were collected from a small, single-motor SUV with front-wheel drive.

Experimental data collected for vehicles on low-adhesion roads are crucial for research on system dynamics modeling, stability control system design, and vehicle state estimation. Indeed, all vehicle control systems must be validated on low-adhesion roads, including vehicle models, control algorithms, and state estimation algorithms. It is very difficult to organize real vehicle experiments, considering experimental equipment, site selection, and cost. Therefore, it is impossible for most researchers to verify their algorithms using real vehicle experiments. One alternative solution is validation against existing data. Furthermore, in spite of the abundance of vehicle research, few scholars publish their original data, especially the data from low-adhesion roads.

The experimental data in this study are collected on compacted snow roads. Two kinds of experiments are included: double lane change and slalom. The data are stored in .mat format and can be directly read and processed in MATLAB software.

The 11 dimensions of experimental data are listed in Figure 1(a). δ_{sw}, ω_{FL}, ω_{FR}, ω_{RL}, ω_{RR}, a_x, a_y and r are measured by the original sensors on the experimental vehicle. δ is calculated by δ_{sw} according to the steering ratio 15.65, which is calculated from steering experimental data. υ_x and υ_y are measured by the additional high-precision combined inertial navigation system, RT3002, produced by Oxford Technical Solutions Ltd. The sampling resolution of the data is 0.01 s. The basic parameters of the vehicle are listed in Figure 1(b).

The experimental data can be used in the development and verification of vehicle state estimation algorithms, such as tire-road friction coefficient, vehicle sideslip angle, and vehicle longitudinal and lateral velocities. Some noise in the measurement signals is difficult to describe with mathematical models, and the experimental data contains some nonlinear response of the vehicle. Therefore, these data can be used to verify the robustness of the estimation method of measuring noise and unmodeled dynamics; this verification is typically difficult to accomplish through the use of simulation data. By using these experimental data from a real vehicle, the effectiveness of the estimation method on the actual vehicle can be quickly verified, greatly shortening the development cycle for estimation methods. Moreover, the experimental data have the potential to be utilized for vehicle dynamics modeling and control system design and validation.

Usage. In this study, a nonlinear observer is proposed to estimate the longitudinal and lateral velocities of the vehicle, and the estimation method is verified against experimental data.

The relationship between vehicle velocity, acceleration, and yaw rate is as follows:

$$\dot{\upsilon}_x = a_x + r\upsilon_y, \quad \dot{\upsilon}_y = a_y - r\upsilon_x. \tag{1}$$

If a_x, a_y, and r are completely accurate, then υ_x and υ_y can be obtained by directly integrating according to (1). However, there is measurement noise in measurement signals a_x, a_y, and r, especially bias noise, causing the estimation results to diverge. Therefore, the following nonlinear observer is designed to solve this problem by applying corrections:

$$\begin{aligned}\dot{\hat{\upsilon}}_x &= r\hat{\upsilon}_y + a_x + k_x\left(\frac{F_x(\hat{\upsilon}_x,\hat{\upsilon}_y)}{m} - a_x\right),\\ \dot{\hat{\upsilon}}_y &= -r\hat{\upsilon}_x + a_y + k_y\left(\frac{F_y(\hat{\upsilon}_x,\hat{\upsilon}_y)}{m} - a_y\right),\end{aligned}$$

where $\hat{\upsilon}_x$ and $\hat{\upsilon}_y$ represent the respective estimated velocities, F_x and F_y are the longitudinal and lateral forces of the vehicle calculated from the vehicle model and the tire

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Data list

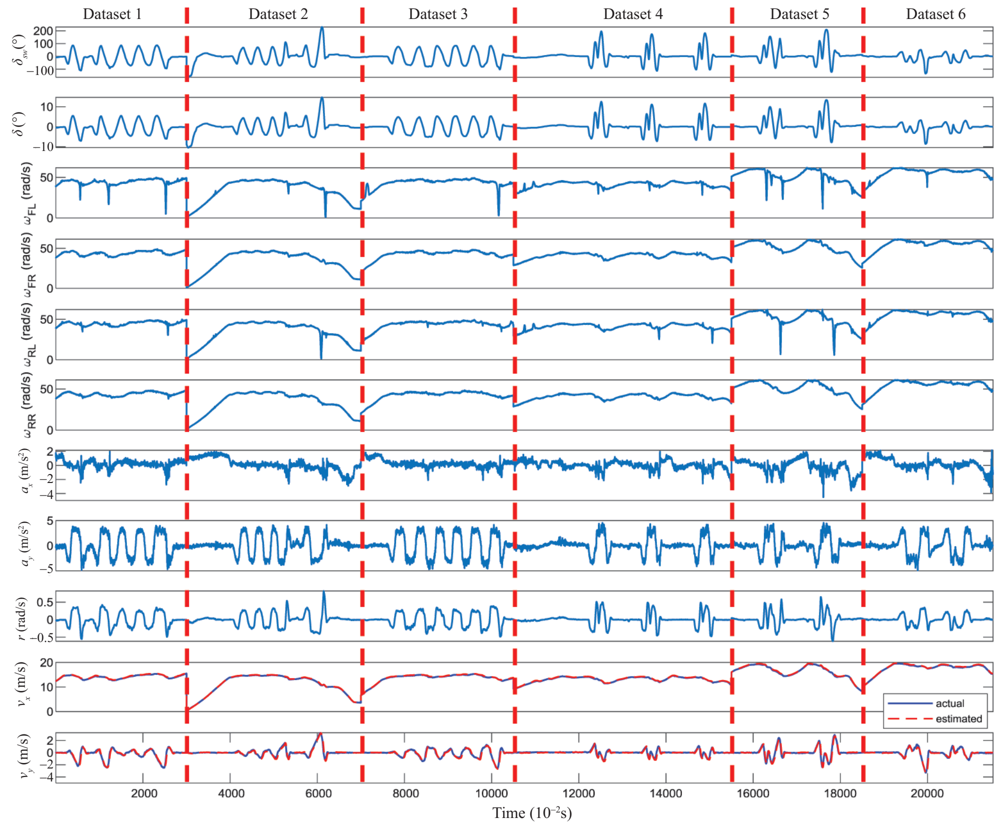
Symbol	Description	Unit
δ_{sw}	Steering wheel angle	°
δ	Front wheel angle	°
ω_{FL}	Angular velocity of front left wheel	rad/s
ω_{FR}	Angular velocity of front right wheel	rad/s
ω_{RL}	Angular velocity of rear left wheel	rad/s
ω_{RR}	Angular velocity of rear right wheel	rad/s
a_x	Longitudinal acceleration	m/s^2
a_y	Lateral acceleration	m/s^2
r	Yaw angular velocity	rad/s
v_x	Longitudinal velocity	m/s
v_y	Lateral velocity	m/s

(a)

Basic parameters of the vehicle

Parameter	Value	Unit
Mass	1669	kg
Moment of inertia	2337.14	$kg{\cdot}m^2$
Wheelbase	2.56	m
Distance from center of mass to front axle	1.153	m
Effective rolling radius of tire	0.3231	m
Front track	1.61	m
Rear track	1.612	m
Height of center of mass	0.601	m
Maximum road-tire friction coefficient	0.4	–

(b)



(c)

Figure 1 (Color online) (a) Data list; (b) basic parameters of the vehicle; (c) the experimental data and the estimated results.

model, m is the mass of the vehicle, and k_x and k_y are the coefficients of the correction term. When selecting $k_x > 0$ and $k_y > 0$, the error dynamics system of this observer are input-to-state stable for the measurement signal noise and the vehicle model errors. For the experimental data in this study, $k_x = 0.5, k_y = 0.2$ are selected. The maximum estimation error of longitudinal velocity is 1.2 m/s, and the maximum estimation error of lateral velocity is 0.52 m/s. The estimated effect is good, as shown in Figure 1(c).

Access methods. The experimental data can be download from the web[1)].

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1) https://download.csdn.net/download/Monster_21/12205315.