Estimation of Vehicle State and Road Coefficient for Electric Vehicle through Extended Kalman Filter and RLS Approaches

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Abstract. Estimation of vehicle state (e.g., vehicle velocity and sideslip angle) and road friction coefficient is essential for electric vehicle stability control. This article proposes a novel real-time model-based vehicle estimator, which can be used for estimation of vehicle state and road friction coefficient for the distributed driven electric vehicle. The estimator is realized using the extended Kalman filter (EKF) and the recursive least squares (RLS) technique. The proposed estimation algorithm is evaluated through simulation and experimental test. Results to data indicate that the proposed approach is effective and it has the ability to provide with reliable information for vehicle active safety control.

Introduction

Active safety technologies include anti-lock braking system, traction control system and stability control system. They can prevent the risky situation which may require the information about the vehicle dynamic states as well as road condition. [1-2] Due to the technical infeasibility and economic reason, some states are immeasurable in real time. They are required to be obtained by estimation. This has spurred a lot of research activity devoted to the estimation, resulting in many kinds of algorithm to estimate the vehicle dynamic states and the road condition [3-4].

The electric vehicle (EV) is driven by electric motor. The Real-time motor torque and speed can be transmitting to the controller as feedback. The wheel's driving force can be calculated based on the above information [5]. This article aims to develop a real-time estimation of vehicle state and road surface based on the distributed driven electric vehicle. In vehicle state estimation, extended Kalman filter algorithm is utilized based on a four-wheel vehicle model and the information obtained from the sensors and CAN-BUS. In road friction estimation, a recursive least square algorithm is utilized. Simulation results, obtained with the CarSim program demonstrate a good performance of the EKF algorithm. The test results show that the RLS algorithm is able to accurately identify road surface.

Vehicle model

Nonlinear vehicle model[6]

Ignoring air resistance and slope angle, a nonlinear model with four wheels is selected. This model is used to estimate the vehicle dynamic state. The model is presented in Figure 1.

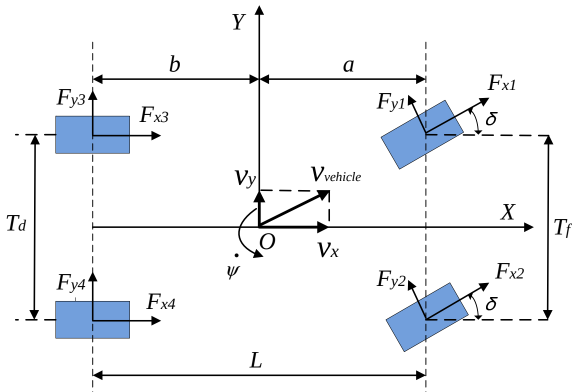


Figure.1 Four tires vehicle dynamic model

The equations of the motion nonlinear four tires vehicle dynamic model are as follows:

$$\begin{cases} \dot{V}_x = 1/m\cdot((F_{x1}+F_{x2})\cdot\cos\delta-(F_{y1}+F_{y2})\cdot\sin\delta+(F_{x3}+F_{x4})\cdot\cos\beta+(F_{y3}+F_{y4})\cdot\sin\beta)+V_y\cdot\dot{\psi} \\ \dot{V}_y = 1/m\cdot((F_{y1}+F_{y2})\cdot\cos\delta+(F_{y3}+F_{y4})\cdot\cos\beta+(F_{x1}+F_{x2})\cdot\sin\delta-(F_{x3}+F_{x4})\cdot\sin\beta)-V_x\cdot\dot{\psi} \\ \ddot{\psi} = 1/I_z\cdot(a\cdot(F_{x1}+F_{x2})\cdot\sin\delta+a\cdot(F_{y1}+F_{y2})\cdot\cos\delta-b\cdot(F_{y3}+F_{y4})+0.5\cdot t_f\cdot(F_{x2}-F_{x1})\cdot\cos\delta \\ \quad +0.5\cdot t_d\cdot(F_{x4}-F_{x3})-0.5\cdot t_f\cdot(F_{y2}-F_{y1})\cdot\sin\delta) \end{cases} \tag{1}$$

Longitudinal and vertical forces at each tire are as follows:

$$\begin{cases} F_{z1,2} = (0.5\cdot m\cdot g\mp m\cdot a_y\cdot h/t_d)\cdot b/L-0.5\cdot m\cdot a_x\cdot h/L \\ F_{z3,4} = (0.5\cdot m\cdot g\mp m\cdot a_y\cdot h/t_d)\cdot a/L+0.5\cdot m\cdot a_x\cdot h/L \\ F_{x1,2} = 1/r\cdot(T_{x1,2}-J\cdot\dot{\omega}_{x1,2}) \\ \beta = \arctan(V_y/V_x) \\ \mu_i = \dfrac{F_{xi}}{F_{zi}}(i=1,2,3,4) \end{cases} \tag{2}$$

where ω is the angular speed of the wheel, T_i is the driving torque,, F_x is the longitudinal tire–road contact force, F_y is the lateral tire–road contact force, F_z is the vertical tire–road contact force, r is the wheel radius, μ is the road friction coefficient. b is the distance between cog and rear axle, h_g is the height of the vehicle center of gravity, a is the distance between front axle and front axle.

Semi-empirical tire model[6]

As for the road friction vector μ, we employ a widely used model known as the Burckhardt model.

$$\mu(\lambda) = C_1(1-e^{-\lambda C_2})-C_3\lambda \tag{3}$$

The value C_2 of the equation (3) cannot be recognized using the below method. The improved tire formula as follow:

$$\mu(\lambda)=C_1-A_1e^{-23.99\lambda}-A_2e^{-33.82\lambda}-A_3e^{-94.13\lambda}-A_4e^{-306.39\lambda}-C_3\lambda \tag{4}$$

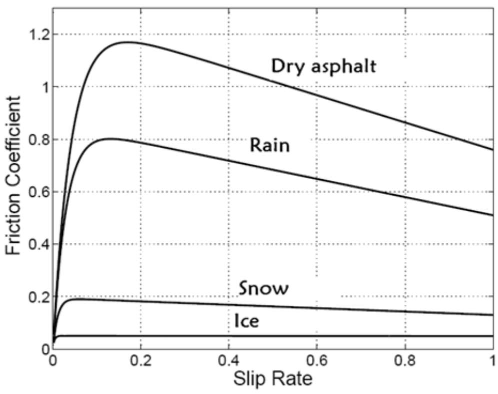


Figure.2 The friction coefficient in different road condition

Vehicle state estimation and road friction estimation

Vehicle state estimation

The EKF algorithm is a powerful extension of the standard Kalman filter [7].It is designed as estimation for non-linear system. The vehicle state estimator in this article is based on the EKF. The nonlinear discrete-time system as follow:

$$\begin{cases} x_{k+1} = f(x_k,u_k,w_k) \\ Z_k = h(x_k,v_k) \end{cases} \tag{5}$$

The nonlinear vehicle model can be transformed into standard state-space form.

State vector: $x=[V_x\ V_y\ \dot{\psi}\ F_{xi}\ F_{zi}\ \beta\ \mu_i]^T{}_{(i=1,2,3,4)}$

Input vector: $u=[\delta\ \omega_i]_{(i=1,2,3,4)}$

Road friction estimation

Least squares identification algorithm is a classical estimation method. It has a wide range of application. However, it is unsuitable for online identification[8,9]. The recursive least squares algorithm can reduce the amount of computation and memory usage. It has better instant communication. In this paper, this algorithm is as the road identification method [10].

When vehicle is traveling on varied roads, the slip-adhesion coefficient curves are different. Assuming that the slip-friction coefficient curves of the four kind's road (dry asphalt, rain, snow, ice) are available. When the vehicle is traveling on the road, which kind of road conditions is unknown. According to the above equation (3) we can obtain the slip-friction coefficient curve of this kind of road. The Burckhardt model is nonlinear because of the c_2. As an alternative, the improved Burckhardt model is approximated using a linear regression. The RLS methods can be directly applied to test against four different friction curves. The type of road condition can be identified.

Real vehicle experimental tests

Experimental equipment and experimental methods

The test car used for the experiments described in this work is a distributed driven electric vehicle. Test drives have been carried out on two different road conditions, i.e. dry asphalt and ice-road. When the vehicle travelling on the straight line, the state vectors were estimated by EKF algorithm. The curve map of tire slipping rate-road coefficient could be draw up. The above estimation algorithm was used to identify the road condition and the maximum road coefficient was estimated.

Figure.3 Research instrument and experimental road

Estimation result

Figure (4) show the measurement parameters obtained from the sensor. Figure (5) show the estimation result of the vehicle state vectors. Compared with the actual value, we can conclude that these vectors are well estimated. The estimation error is very small; this enables us to conclude that the estimation results are good. The tire slipping rate-friction coefficient curves are show in Figure (6): (a) for dry asphalt road and (b) for ice road. These diagrams are drawn based on the experimental measured samples.

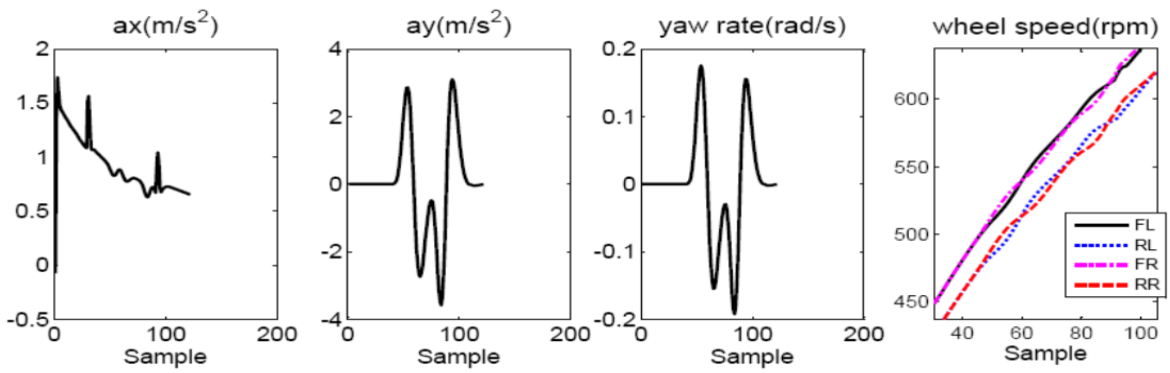


Figure.4 Measured parameters

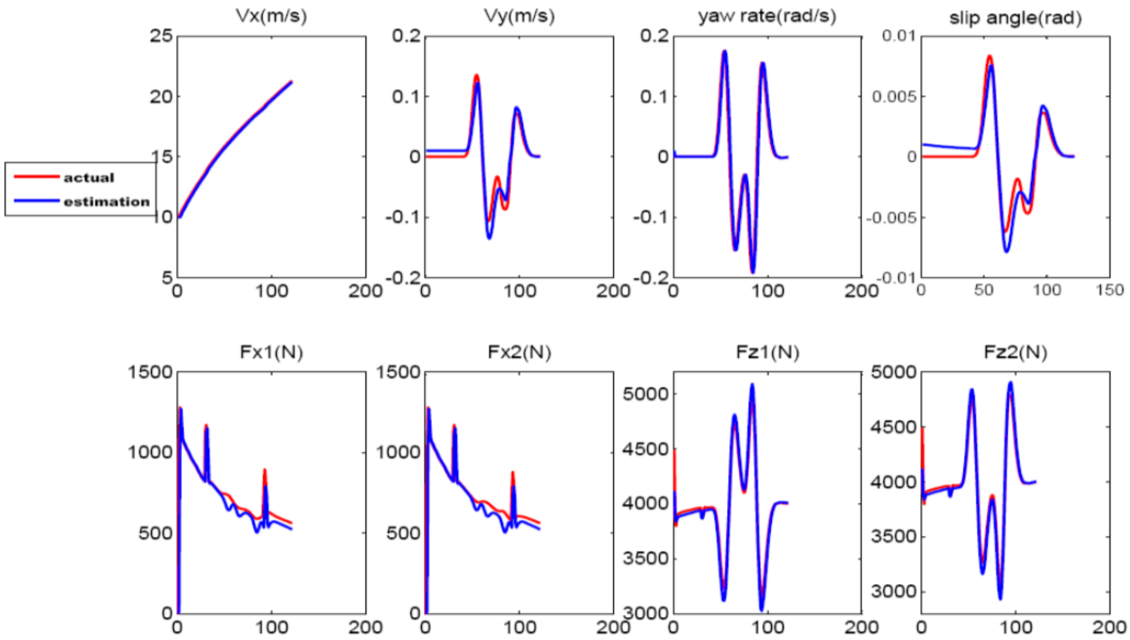
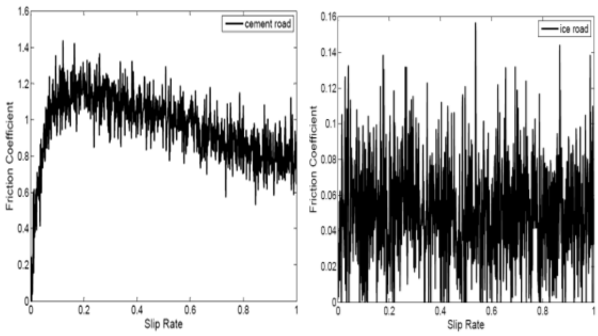
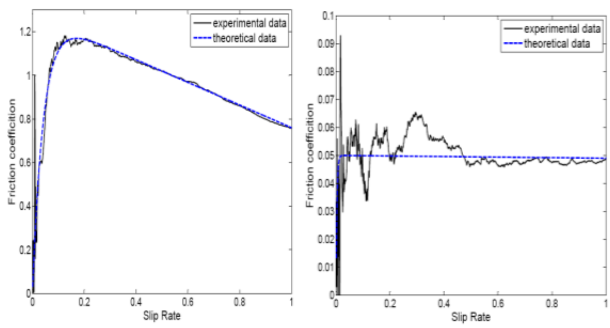


Figure.5 Estimation and actual vehicle states



(a) dry asphalt road (b) ice road

Figure.6 Test data of the friction coefficient



(a) dry asphalt road (b) ice road

Figure.7 Curve fitting results with RLS

Conclusions

This paper develops a real-time estimation of vehicle state and road surface based on the distributed driven electric vehicle. The extended Kalman filter and RLS algorithm were used in estimator design. The estimation results have been compared to real measurements collected with sensors. The estimation result of vehicle dynamic vector obtained by use the EKF observer. One can conclude that these vectors are well estimated. The method based on recursive least square with forgetting factor is used for road identification. This research shows that the algorithm is able to identification two surfaces: dry asphalt and ice. The proposed approach has several advantages such as accurate, effective, short cycle and low cost. Also, they have the ability to provide with reliable information for vehicle active safety control.

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