Pavement State Recognition Method Considering Slope

Xiuhao Xi¹, Jun Xiao*¹, Qiang Zhang¹ and Yanchao Wang¹

¹ School of Mechanical and Electronic Engineering, Wuhan University of Technology, Wuhan, Hubei, 430070, China
*Corresponding author’s e-mail: xjun@whut.edu.cn

Abstract. For the problem of road surface condition recognition, this paper proposes a real-time tracking method to estimate road surface slope and adhesion coefficient. Based on the fusion of dynamics and kinematics, the current road slope of the vehicle which correct vertical load is estimated. The effect of the noise from dynamic and kinematic methods on the estimation results is removed by designing a filter. The normalized longitudinal force and lateral force are calculated by Dugoff tire model, and the Jacobian matrix of the vector function of the process equation is obtained by combining the relevant theory of EKF algorithm. The road adhesion coefficient is estimated finally. The effectiveness of the algorithm is demonstrated by analyzing the results under different operating conditions, such as docking road and bisectional road, using a joint simulation of Matlab/Simulink and Carsim.

1. Introduction
As an import section of the human-vehicle-road control system, the road surface adhesion has a significant impact on driver safety and vehicle stability. The methods for estimating road adhesion coefficient are mainly divided into two categories: Cause-Based and Effect-Based[1-2]. The Effect-Based method uses the existing sensors on the vehicle to measure and estimate the changes in the dynamic response of the vehicle caused by the changes in the road adhesion conditions, and indirectly estimate the road adhesion coefficient[3]. The Cause-Based method directly measures the factors related to the road adhesion coefficient (such as road unevenness[4] and tire noise[5]) by installing corresponding sensors on the vehicle, and then calculates the road adhesion coefficient. However, the Effect-Based method relies on an accurate mathematical model, while the Cause-Based method requires the installation of additional sensors, which increases economic costs.

Slope, another key information of the road surface, is an important parameter that affects the longitudinal dynamics control of the vehicle. The estimation of road slope is mainly divided into two methods: kinematics and dynamics. The kinematics method uses GPS[6] and longitudinal acceleration sensor[7] to calculate the slope. However, the low frequency of GPS can cause large slope estimation errors, and the static error of the longitudinal acceleration sensor will also affect the accuracy of the estimation result. The dynamic method is based on the longitudinal dynamics model of the vehicle and uses methods such as least square method [8] and Kalman filter [9] to estimate the road slope. However, this method is affected by the change of measurement noise during the estimation process, and the estimation accuracy is reduced.

In this paper, we estimate the road slope based on the method of fusion of dynamics and kinematics, then revise the tire model and the vehicle model by the estimation results. The road adhesion coefficient in the current driving state of the vehicle in real time is estimated and revised by using the EKF algorithm.
Finally, we use the simulation to prove the effectiveness of the algorithm. The road surface recognition algorithm framework is shown in Figure 1.

![Figure 1. Pavement recognition algorithm framework](image)

2. Slope estimation based on the fusion method of dynamics and kinematics

2.1. Slope estimation method based on dynamics

It can be seen from Newton’s second law that when a vehicle moves longitudinally on a ramp, its dynamic equation is

\[
m\dot{\upsilon} = \frac{T_j i_g i_o \eta_f}{r} - mg \sin \theta - \frac{C_D A \rho \upsilon^2}{2} - mgf \cos \theta
\]  

(1)

Where \( m \) is the vehicle mass. \( \dot{\upsilon} \) is the longitudinal acceleration of the vehicle. \( T_j \) is the torque input from the engine to the gearbox. \( i_g \) is the transmission ratio of the gearbox. \( i_o \) is the transmission ratio of the main reducer. \( \eta_f \) is the mechanical efficiency of the drive train. \( r \) is the effective rolling radius of the wheel. \( g \) is the acceleration of gravity. \( \theta \) is the ramp angle. \( C_D \) is the air resistance coefficient. \( A \) is the windward area. \( \rho \) is the air density. \( \upsilon \) is the longitudinal speed of the vehicle. \( f \) is the rolling resistance coefficient.

From equation (1), the road ramp angle \( \theta_a \) calculated based on the dynamic method can be obtained as

\[
\theta_a = \arcsin \left( \frac{2 T_j i_g i_o \eta_f - C_D A \rho \upsilon^2 - 2 m g \dot{\upsilon} - 2 m g f}{2 m g \sqrt{1 + f^2}} \right) - \arcsin \left( \frac{f}{\sqrt{1 + f^2}} \right)
\]  

(2)

2.2. Slope estimation method based on kinematics

The value measured by the \( a_x \) longitudinal acceleration inertial sensor installed in the vehicle is affected by the actual acceleration and slope of the vehicle itself, and its value is

\[
a_x = \dot{\upsilon} + g \sin \theta
\]  

(3)

From equation (3), the road ramp angle \( \theta_b \) calculated based on kinematics method can be obtained as
2.3. Slope estimation method based on the fusion of dynamics and kinematics

During the driving process of the vehicle, the road slope can be regarded as consisting of high-frequency signals and low-frequency signals. The dynamics-based slope estimation method relies on an accurate vehicle model, and the parameters in the vehicle model are affected by high-frequency noise. Thus the high-frequency part of the method is filtered through a low-pass filter, and the low-frequency part is reserved. The $a_x$ heavily influenced by static bias is due to low frequency noise, so the low-frequency part of this method is filtered by a high-pass filter, and the high-frequency part is retained. From equations (2) and (4), the slope value $\theta$ calculated based on the fusion method of dynamics and kinematics is:

$$\theta = \arcsin\left(\frac{a_x - \dot{v}_x}{g}\right) = \arcsin\left(\frac{a_x - v_x(t) - v_x(t-1)}{\Delta t} \right)$$ (4)

$$\theta = \arcsin\left(\frac{a_x - \dot{v}_x}{g}\right)$$ (4)

$$\theta = \arcsin\left(\frac{a_x - v_x(t) - v_x(t-1)}{\Delta t} \right)$$ (4)

$$\theta = \arcsin\left(\frac{a_x - \dot{v}_x}{g}\right)$$ (4)

(5)

Where $T$ is the time constant.

When the frequency of the road gradient is low, the value is greatly affected by the calculation result of the dynamic method, and it can better reflect the road gradient value under steady-state conditions. When the frequency of the road slope changes relatively high, the value is greatly affected by the calculation results of the kinematics method, and it can quickly follow the transient changes of the road slope.

3. Estimation of pavement adhesion coefficient based on EKF

3.1. Nonlinear vehicle dynamics model

When establishing the dynamics model, the vehicle is simplified as follows:

- Assuming that the centre of vehicle' mass is the origin of the moving coordinate system.
- Assuming that the vehicle is moving parallel to the ground. The influence of suspension deformation on it is ignored.
- Ignoring the influence of the steering system and assuming a linear relationship between the steering wheel angle and the front wheel angle.
- The mechanical properties of the four tires of the vehicle are the same.

The simplified vehicle dynamics model is shown in Figure 2.

![Vehicle force analysis diagram](image)
Figure 2 shows that the longitudinal and lateral motion equations of the vehicle are
\[ ma_x = (F_{x_1} + F_{x_2}) \cos \delta + F_{x_3} + F_{x_4} - (F_{y_1} + F_{y_2}) \sin \delta - C_D \rho v^2 - mg \sin \theta - mgf \cos \theta \]
\[ ma_y = (F_{y_1} + F_{y_2}) \sin \delta + (F_{y_3} + F_{y_4}) \cos \delta + F_{y_3} + F_{y_4} \]  
(6)

Where \( a_x \), \( a_y \) are the longitudinal and lateral accelerations of the vehicle. \( F_{x_1}, F_{x_2}, F_{x_3}, F_{x_4} \) are the longitudinal forces of the four wheels. \( F_{y_1}, F_{y_2}, F_{y_3}, F_{y_4} \) are the lateral force of the four wheels. \( \delta \) is the front wheel turning angle. \( \theta \) is the road ramp angle, which can be calculated in Chapter 2.

3.2. Tire model

This paper uses Dugoff model to model and analyse the whole car tire. The force coordinate system of the whole car tire is shown in Figure 3.

![Tire force coordinate system](image)

The wheel dynamic equation is
\[ J_i \ddot{\omega}_i = T_d - T_b - fF_{m_i} r - F_{m_i} r \]  
(7)

Where \( J_i \) (i=1, 2, 3, 4) is the rotational inertia of the four wheels. \( \dot{\omega}_i \) is the angular acceleration of the four wheels. \( T_d, T_b \) is the driving and braking torque of the four wheels.

The vertical load of four wheels are
\[ F_{z_1,2} = \frac{m}{2L} (gb \cos \theta - h_g a_x - h_g g \sin \theta) \mp \frac{ma h_g}{B_f} \]  
\[ F_{z_3,4} = \frac{m}{2L} (ga \cos \theta + h_g a_x + h_g g \sin \theta) \mp \frac{ma h_g}{B_f} \]  
(8)

Where \( L \) is the wheelbase. \( a \) and \( b \) are the distances from the centre of mass to the front and rear axles. \( h_g \) is the height of the centre of mass. \( B_f \) and \( B_r \) are the length of the front and rear wheels.

For a single wheel, its force equation are
\[ F_x = \mu F_C \frac{s}{1-s} f(\lambda) \]
\[ F_y = \mu F_C \frac{\tan \alpha}{1-s} f(\lambda) \]  
(9)

Where
$$f(\lambda) = \begin{cases} 
\lambda(2-\lambda), & \lambda < 1 \\
1, & \lambda \geq 1 
\end{cases}$$

$$\lambda = \frac{1-s}{2\sqrt{C_s^2 s^2 + C_a^2 \tan^2 \alpha}} (1-\varepsilon v, \sqrt{s^2 + \tan^2 \alpha})$$  \hspace{1cm} (10)

Where $\mu$ is the road surface adhesion coefficient. $F_z$ is the vertical load of the wheel. $C_s$ and $C_a$ are the tire longitudinal slip and cornering stiffness. $s$ is the slip rate. $\alpha$ is the cornering angle. $\varepsilon$ is the speed influence factor.

According to the expression form of the Dugoff tire model, it can be normalized to

$$F_s = \mu_0 F_z C_s \frac{s}{1-s} f(L) = \mu_0 \overline{F_s}$$

$$F_y = \mu_0 F_z C_a \tan \alpha \frac{1-s}{1-s} f(L) = \mu_0 \overline{F_y}$$

In the equation, $\overline{F_s}$ and $\overline{F_y}$ are the normalized longitudinal and lateral forces, which have nothing to do with the road adhesion coefficient. The equation (6)-(7) can be reduced to

$$a_x = \mu_1 \frac{\overline{F_s}}{m} \frac{\cos \delta}{m} - \frac{C_D A \rho v^2}{m} - g \sin \theta - gf \cos \theta$$

$$a_y = \mu_1 \frac{\overline{F_y}}{m} \frac{\sin \delta}{m} + \mu_2 \frac{\overline{F_s}}{m} \frac{\cos \delta}{m} + \mu_3 \frac{\overline{F_y}}{m} \frac{\sin \delta}{m} + \mu_4 \frac{\overline{F_s}}{m}$$

$$\dot{\omega}_i = -\mu_1 \overline{F_s} r + T_{di} - T_{bi} - fF_s r$$

3.3. Implementation of EKF algorithm

3.3.1. Establishment of system state equation and measurement equation. For the vehicle nonlinear system, the state space expression established by EKF filtering is

$$\dot{x}(t) = f(x(t), u(t), w(t))$$

$$z(t) = h(x(t), u(t), v(t))$$

Where $x(t)$ is the system state variable that needs to be estimated. $z(t)$ is the measurement output variable. $u(t)$ is the control input variable. $w(t)$ and $v(t)$ are Gaussian interference signals with a covariance of $R(t)$, representing process noise and measurement noise, respectively.

In the establishment of this model, the selected state variable is the four-wheel road adhesion coefficient $\mu_i$, then the system state variable $x(t) = [\mu_1, \mu_2, \mu_3, \mu_4]^T$, the selected observed variables are the vehicle longitudinal acceleration $a_x$, lateral acceleration $a_y$ and four-wheel angular acceleration $\beta_i$, then the system observes the variable $z(t) = [a_x, a_y, \dot{\omega}_i, \dot{\omega}_2, \dot{\omega}_3, \dot{\omega}_4]^T$. The control input variable is expressed as

$$u(t) = [\delta, \theta, T_{di}, F_{zi}, \overline{F_{si}}, \overline{F_{yi}}]^T$$

$$z(t) = H(t)x(t) + y(t) + v(t)$$  \hspace{1cm} (15)
Where $H(t)$ is the Jacobian matrix of the nonlinear function. $h(x(t), u(t), v(t))$ is the parameter to obtain partial derivatives of each parameter and its expression is

$$H(t) = \begin{bmatrix}
\frac{\partial h_1}{\partial x_1} & \frac{\partial h_1}{\partial x_2} & \cdots & \frac{\partial h_1}{\partial x_n} \\
\frac{\partial h_2}{\partial x_1} & \frac{\partial h_2}{\partial x_2} & \cdots & \frac{\partial h_2}{\partial x_n} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial h_n}{\partial x_1} & \frac{\partial h_n}{\partial x_2} & \cdots & \frac{\partial h_n}{\partial x_n}
\end{bmatrix}$$

(16)

By equation (12) can be seen

$$H(t) = \begin{bmatrix}
\frac{F_{x_1} \cos \delta - F_{x_3} \sin \delta}{m} & \frac{F_{x_2} \cos \delta - F_{x_3} \sin \delta}{m} & \frac{F_{x_3}}{m} & \frac{F_{x_4}}{m} \\
\frac{F_{x_1} \sin \delta + F_{x_3} \cos \delta}{m} & \frac{F_{x_2} \sin \delta + F_{x_3} \cos \delta}{m} & \frac{F_{x_3}}{m} & \frac{F_{x_4}}{m} \\
\frac{m}{m} & 0 & 0 & 0 \\
0 & \frac{-F_{x_1}}{m} & 0 & 0 \\
0 & 0 & \frac{-F_{x_3}}{m} & 0 \\
0 & 0 & 0 & \frac{-F_{x_4}}{m}
\end{bmatrix}$$

(17)

3.3.3. Initial value of filter to realize recursive algorithm. The specific workflow of the EKF filtering algorithm is shown in Figure 4. In the figure, Q and R are the covariance matrices of process noise and measurement noise. Among them, the process noise covariance matrix $Q = I_4$, and the measurement noise covariance matrix $R = I_6 \times 0.1$. The initial value of the error covariance matrix $P(t_0) = I_4$, and the initial value of the system state variable $\hat{x}(t_0) = [1,1,1,1]^T$.

4. Simulation verification

The above algorithm for pavement gradient estimation of joints and adhesion coefficients was certified by Carsim/Simulink simulation. The E-class four-wheel drive SUV in the Carsim database is used as the vehicle model, and the relevant parameters are shown in Table 1.
Table 1. Vehicle parameters

| Name                        | Symbol | Value     | Name                        | Symbol | Value     |
|-----------------------------|--------|-----------|-----------------------------|--------|-----------|
| weight                      | m      | 1860kg    | Centroid height             | h_c   | 0.72m     |
| Centroid distance of F axle | a      | 1.18m     | Effective tire rolling radius | r      | 0.393m    |
| Centroid distance of R axle | b      | 1.77m     | Coefficient of air resistance | C_d   | 0.3       |
| Wheelbase                   | L      | 2.95m     | Frontal area                | A      | 3 m²      |
| The distance of the F wheel | B_f   | 1.575m    | Air density                 | ρ      | 1.206 kg/m³ |
| The distance of the R wheel | B_r   | 1.575m    | Rolling resistance coefficient | f     | 0.01      |

4.1. Simulation verification of single road adhesion coefficient
Considering the high and the low adhesion coefficient of the influence of the traveling state of the vehicle, two single-road driving conditions provided with CarSim are shown as follows: 1) adhesion coefficient is 0.8 and the driver keeps a straight line at a constant speed of 60km/h; 2) adhesion coefficient is 0.3, and the speed is maintained at a constant speed of 30km/h. The road slope of the two working conditions is set to 15%. The EKF algorithm's recognition of the road adhesion coefficients is shown in Figure 5-6.

4.2. Simulation verification of docking road adhesion coefficient
Considering the driving situation of the docking road, the adhesion coefficient of the road set in CarSim is changed from 0.8 to 0.3, and the road gradient is 3%. The vehicle keeps the speed of 40km/h and travels in a straight line.

The model is simulated, and the relationship between the calculated value of the road adhesion coefficient and the set value is shown in Figure 7. It can be seen from the simulation results that the calculated road adhesion coefficients of the four tires tend to set high value in 0.3s. When the road adhesion coefficient suddenly drops, the algorithm can quickly calculate the low adhesion state at this time.
4.3. Simulation verification of bisectional road adhesion coefficient

The vehicle is set to drive on opposite roads. The left front wheel and the left rear wheel are on the high road surface, and the road adhesion coefficient is 0.8. The right front wheel and right rear wheel are on the low-attachment road, and the road adhesion coefficient is 0.3. The vehicle drives at the speed of 60km/h, and the road gradient is 3%. Figure 8 shows the results of the simulation on the bisectional road.

From the simulation results, the adhesion coefficient is set to 0.8 for the left wheel and 0.3 for the right wheel in CarSim. For the two wheels on the left, although there were slight fluctuations before 0.3 seconds, it did not affect the subsequent convergence results and the effectiveness of the estimation algorithm. For the two wheels on the right, it can quickly converge to around 0.8 in 0.1 second, which means that the estimation algorithm can estimate the road adhesion coefficient of the four wheels very well when the vehicle is driving on the bisectional road, which fully proves the algorithm’s effectiveness.

5. Conclusion

- In view of the influence of slope on the road surface recognition accuracy, the slope is recognized by the method based on kinematics, dynamics and the fusion of kinematics and dynamics, and the recognition result is used as the input of the road adhesion coefficient recognition model to eliminate the influence of slope.
- Combined with Dugoff tire model and EKF algorithm, the state equation, measurement equation and Jacobian matrix of vehicles under different conditions are established, and finally the road adhesion coefficient of vehicles under different conditions is identified.
- The simulation verifies the recognition of the adhesion coefficient of the algorithm on the low-attached road, high-attached road, butt road, and off road. The simulation data reflects that the algorithm can accurately calculate the state and changes of the road surface under various driving conditions.

References

[1] MEYER W E, WALTER J D. Frictional interaction of tire and pavement[M]. Philadelphia: ASTM International, 1983.
[2] KHALEGHIAN S, EMAMI A, TAHERI S. A technical survey on tire-road friction estimation[J]. Friction, 2017, 5(2): 123-146.
[3] KHALEGHIAN S. The application of intelligent tires and model based estimation algorithms in tire-road contact characterization[D]. Blacksburg: Virginia Polytechnic Institute and State University, 2017.
[4] Brgeson J. Sensor data fusion based estimation of tire-road friction to enhance collision avoidanc-e. Tampere University of Technology, 2010.
[5] EICHHORN U, ROTH J. Prediction and monitoring of tyre/road friction[J]. Proceedings Fisita, 1992: 67-74.

[6] SILVA A L D, CRUZ Z J J D, Fuzzy adaptive extended Kalman filter for UAV INS/GPS data fusion[J]. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 2016, 38(6): 1-18.

[7] MASSEL T, DING E L, ARNDT M. Investigation of different techniques for determining the road uphill gradient and the pitch angle of vehicles[C]//American Control Conference. Boston, Massach-usetts: [s, n.], 2014

[8] Winstead V, Kolmanovsky I V. Estimation of road grade and vehicle mass via model predictive control [C] //Proceedings of 2005 IEEE Conference on Control Applications, 2005: 1588-1593.

[9] LEI Yulong, FU Yao, LIU Ke. Vehicle quality androad gradientestimation based on extended Kalman filter [J]. Journal of Agricultural Machinery, 2014, 11( 11): 13-18. (in Chinese)

[10] DUGOFF H. Tire performance characteristics affecting vehicle response to steering and braking control inputs. Final report[R]. Washington D. C. : National Bureau of Standards, 1969.