Estimation of Vehicle Longitudinal Speed Based on Improved Kalman Filter

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Abstract: Estimation of vehicle longitudinal acceleration is very important in vehicle active safety control system. In this paper, two driving conditions of a 4WD off-road vehicle are divided by vehicle signals such as steering angle. Under different working conditions, different estimation algorithms are adopted. In the straight driving condition, the longitudinal speed was estimated by adjusting the variance weight of acceleration Kalman observation noise based on kinematics method. For steering conditions, in order to obtain the longitudinal velocity at the center of mass, by dynamic method, a lateral state estimator was designed and tire sideslip dynamics was modeled. The CarSim-Simulink co-simulation results show that the proposed algorithm has high accuracy and strong practicability.

1. Introduction

Longitudinal speed is an important variable to calculate the wheel slip rate. Accurate reference speed is of key significance to optimize the control effect of ABS, TCS, ASR and other control systems. At present, kinematics and dynamics are the main models for longitudinal speed of vehicle[1]-[3]. The kinematics mainly uses the wheel speed information, inertial measurement unit, etc. To estimate the speed according to the kinematics formula and other operational methods, which requires high anti-interference performance of the sensor signal, and is only applicable to the conventional working conditions. Theoretical method of dynamics relies on the vehicle dynamics model and analyzes the force of the vehicle to realize the estimation of the vehicle longitudinal speed, which greatly increases the difficulty of calculation, and the simplified model will produce estimation errors.

In order to solve the above existing problems, this paper takes a 4WD off-road vehicle as the research object, adopts the hierarchical architecture estimation algorithm. Firstly, a variety of on-board sensors are used to identify vehicle driving conditions. Secondly, the difference of wheel speed was analyzed to obtain the pre-estimated speed, which was used as the measurement value of Kalman filtering algorithm. Finally, in the straight driving condition, the weight value of noise variance was determined by fusing the information of wheel speed and acceleration. In the steering condition, since neither the wheel speed nor the acceleration information can reflect the real longitudinal speed. Considering the influence of slip angle of tire on the longitudinal speed, this paper designed a lateral state estimator based on the 3-DOF dynamics model to model the tire sideslip dynamics and obtain the longitudinal velocity at the center of mass. The co-simulation model was established by CarSim-Simulink results show that the estimated vehicle longitudinal speed is consistent with the CarSim output reference vehicle speed, and the algorithm is simple, which is easy to implement in real vehicle ECU.
2. The general structure of the estimation algorithm

The structure of the speed estimation algorithm to be adopted in this paper is shown in figure 1, which consists of three parts: Driving Condition Recognition (DCR), Pre-Estimator of Speed (PES), Longitudinal Speed Calculator (LSC), and the descriptions below are abbreviated. In this paper, with the aid of layered architecture idea, the DCR module makes certain judgments on the current driving conditions according to the longitudinal/lateral acceleration $\alpha_x, \alpha_y$, front wheel steering angle $\delta$, four-wheel speed $\omega_{ij}$, throttle position $a_{tho}$, braking signal $s_{brake}$, ABS working signal $s_{ABS}$ and other on-board signals, and it is divided into two kinds of driving conditions: straight driving and steering. PES module analyzes the wheel speed in different working conditions and puts forward the corresponding algorithm to get the pre-estimated speed $v_{ij}$, which is close to the real speed. In the straight driving condition, the LSC module obtains the final estimated longitudinal speed through the vehicle dynamics model and the extended Kalman filter algorithm. Under steering conditions, LSC considers the influence of lateral state variables such as sideslip angle $\beta$ and yaw rate $\omega_r$ on longitudinal speed, and adds slip angle of tire $\alpha_f$ to make a certain degree of correction.

Figure 1. Structure diagram of speed estimation algorithm

3. DCR and PES module

In the process of vehicle driving, the external environment (such as road changes, etc.), and the driver’s intention of irregular changes, will lead to a certain difference in four-wheel wheel speed[3]. In order to better obtain the pre-estimated speed close to the real speed, it is necessary to fuse the on-board multi-sensor signals to recognize the vehicle driving conditions in real time. In addition, under the steering condition, the vehicle will produce the roll force couple moment, which will change the wheel load and affect the wheel speed. Therefore, the driving conditions are divided into two categories: steering and straight driving. The threshold method is adopted to identify the current driving state, and the judgment logic is shown in formula 1.

$$
\begin{align*}
&\text{Steering} \begin{cases} 
\text{Normal steering} \\
|\delta| > \varepsilon_1 \\
\text{Abnormal steering} \\
\text{Rapid acceleration} \end{cases} & w_{ij} < e_2 \& a_{tho} < e_3 & |\alpha| < e_4, F = 1 \\
& w_{ij} > e_2 \& (a_{tho} > e_3 \& |\alpha| > e_4), F = 2 \\
& a_{tho} > e_5 \& |\alpha| > e_6, F = 3 \\
& w_{ij} < e_7 \& |\alpha| < e_8, F = 4
\end{align*}
$$

$$
\begin{align*}
&\text{Straight} \begin{cases} 
\text{Normal acceleration/constant speed} \\
|\delta| < \varepsilon_1 \\
\text{Normal deceleration} \\
\text{Sharp deceleration} \end{cases} & w_{ij} < e_9 \& |\alpha| < e_9 \& s_{brake} = 1, F = 5 \\
& a_{\alpha} < -e_9 \& s_{ABS} = 1 \& s_{brake} = 1, F = 6
\end{align*}
$$

Where $F$ is the mark bit defined by the working condition; $\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, \varepsilon_5$ are respectively the front wheel rotation angle, absolute value of wheel speed difference, throttle position, average speed of four wheels and acceleration logic threshold.

According to the different working conditions and the difference of wheel speed, the estimated speed can be obtained through the maximum wheel speed method, minimum wheel speed method, etc.[1], which can be used as the key variable of the estimation algorithm below.
4. LSC module

4.1 Longitudinal Speed estimation of straight driving conditions

4.1.1 Derivation and design of Kalman filter

Under conventional driving conditions, the pre-estimated vehicle speed can be directly used as the estimated value of vehicle speed because the wheel does not slip significantly. However, in unconventional conditions, the deviation of the pre-estimated vehicle speed is large, so it is necessary to introduce acceleration information correction. In this paper, the weight of the estimated vehicle speed and acceleration is changed by adjusting the measurement noise covariance value, so as to adjust the vehicle speed value.

The ideal radius of the wheel without load is $R_0$. In the case of load, the wheel will deform and the radius will change, denoted as $R_a$[4]. However, in general, the wheel speed is calculated according to the ideal radius $R_0$. Here, the offset of wheel radius is defined as $\varepsilon$. That is:

$$\varepsilon = \frac{R_0 - R_a}{R_0}$$  \hspace{1cm} (2)

Therefore, the real speed of the vehicle can be expressed as:

$$v_r = v_w (1 + \varepsilon)$$  \hspace{1cm} (3)

The pre-estimated speed is composed of the measured noise of the calculated value of the speed, namely:

$$v_m = v_w + \sigma_v$$  \hspace{1cm} (4)

$$a_m = a_t + \sigma_a$$  \hspace{1cm} (5)

Where $v_r$ is the real speed of the vehicle; $v_w$ is the estimated value of ideal speed; $v_m$ is the speed measurement; $a_m$, $a_t$ are respectively body measurement and real longitudinal acceleration; $\sigma_v$, $\sigma_a$ is the observation noise of velocity and acceleration.

Due to the influence of vehicle vibration and environment, the measured data of the sensor has a certain error, so $\sigma_v$, $\sigma_a$ is assumed to be Gaussian white noise with an average value of 0.

The state transition equation and observation equation of the system are as follows:

$$x(k+1) = f(x_k, w_k) = A(k)x(k) + B(k)w(k)$$  \hspace{1cm} (6)

$$z(k) = h(x_k, n_k) = Hx(k) + n(k)$$  \hspace{1cm} (7)

$w_1, w_2, w_3$ is defined as process noise. The vector and matrix are defined as follows:

$$x(k) = \begin{bmatrix} a_t(k) \\ v_w(k) \\ \varepsilon(k) \end{bmatrix}, \quad w(k) = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}, \quad z(k) = \begin{bmatrix} a_m(k) \\ v_m(k) \end{bmatrix}, \quad n(k) = \begin{bmatrix} \sigma_a(k) \\ \sigma_v(k) \end{bmatrix}$$  \hspace{1cm} (8)

$$A(k) = \begin{bmatrix} 1 & 0 & 0 \\ t & 1 & -ta_m(k) \\ 0 & 0 & 1 \end{bmatrix}, B(k) = \begin{bmatrix} t & 0 & 0 \\ -\frac{1}{2}t^2 & t & \frac{1}{2}t^2a_m(k) \\ 0 & 0 & t \end{bmatrix}$$  \hspace{1cm} (9)

According to Kalman filtering principle[5], it can be obtained:

$$\hat{x}(k|k-1) = A(k-1)x(k-1|k-1)$$  \hspace{1cm} (10)

$$P(k|k-1) = A(k-1)P(k-1|k-1)A^T(k-1) + Q(k-1)$$  \hspace{1cm} (11)

$$K(k) = P(k|k-1)H^T(k)[H(k)P(k|k-1)H^T(k) + R(k)]^{-1}$$  \hspace{1cm} (12)

$$\hat{x}(k|k) = \hat{x}(k|k-1) + K(k)[z(k) - H(k)\hat{x}(k|k-1)]$$  \hspace{1cm} (13)

$$P(k|k) = [I - K(k)H(k)]P(k|k-1)$$  \hspace{1cm} (14)

4.1.2 Parameter confirmation of Kalman algorithm

Although the fixed observation noise can achieve the filtering effect well, when the vehicle is in the unusual condition and the wheel skids or is locked, the Kalman filter with fixed parameters cannot reflect the real speed[6]. Therefore, according to the different working conditions, this paper changes the measurement noise $R$ in real time, changes the weight of the pre-estimated speed and acceleration, and then revises the estimated speed of the vehicle.
In engineering practice, when the acceleration signal is small and the signal-to-noise ratio of the signal is low, its credibility will be reduced. Therefore, too much trust in the acceleration signal will reduce the authenticity of longitudinal speed. Therefore, the weight of the estimated speed should be appropriately increased, such as in conventional conditions. Similarly, when the acceleration is large and the accuracy of the system dynamics model decreases, the kinematics method should be selected and the weight of the acceleration signal should be appropriately increased, such as the conditions of easy skid such as rapid acceleration and rapid braking. That is:

\[
\begin{align*}
R_A^\uparrow, R_V^\downarrow & \quad \text{Unconventional condition} \\
R_A^\downarrow, R_V^\uparrow & \quad \text{Conventional condition}
\end{align*}
\] (15)

4.2 Longitudinal speed estimation in steering condition

4.2.1 Vehicle model

Vehicle is a nonlinear system with high complexity, and its related parameters are difficult to calculate. Therefore, this paper grasps the most critical factors, simplifies the model to the greatest extent, and saves calculation time. A 3-DOF vehicle model including longitudinal, lateral and yaw was established, as shown in figure 2.

![3-DOF vehicle model](image)

In this model: \( F_{xyij} \) is the reaction force of four wheels by the ground; \( \delta \) is the front wheel rotation angle; \( w_r \) is yaw rate; \( v_{Gx}, v_{Gy} \) are respectively the longitudinal and lateral velocity at the center of mass; \( a, b \) are the distance between the center of mass of the vehicle and the front and rear axles; \( T_f, T_r \) is the front and rear wheelbase; \( \alpha_f, \alpha_r \) is the slip angle of front and rear tires.

According to the principle of Kalman algorithm, the state transition equation and observation equation of the 3-DOF vehicle model are determined[7].

\[
\begin{align*}
\dot{w}_r &= \frac{a^2 k_1 + b^2 k_2}{l_x v_x} w_r + \frac{a k_1 - b k_2}{l_x} \beta = \frac{a k_1}{l_x} \\
\dot{\beta} &= \left(\frac{a k_1 - b k_2}{mv_x} - 1\right) w_r + \frac{k_1 + k_2}{mv_x} \beta - \frac{k_1}{mv_x} \delta \\
\dot{v}_x &= w_r \beta v_x + a_x \\
\dot{w}_m &= \frac{a k_1 - b k_2}{mv_x} w_r + \frac{k_1 + k_2}{m} \beta - \frac{k_1}{m} \delta
\end{align*}
\] (16)

It is obtained by referring to equations (6) - (14) after the Kalman algorithm derivation process, which will not be repeated here.

4.2.2 Tyre sideslip dynamics

Under the steering condition, the tire sideslip and the body lateral movement will greatly reduce the accuracy of longitudinal velocity estimation, and the information of wheel speed and acceleration cannot reflect the change of vehicle speed well[8]. In order to solve this problem, this paper first uses a 3-DOF vehicle model to obtain the yaw rate and sideslip angle of mass center by EKF algorithm, then analyzes the sideslip dynamics of the tire and yaw motion of the vehicle body, and deduces the formula of longitudinal velocity estimation.
The sideslip angle of the two front / rear left and right wheels is regarded as the same, and the wheel speed is the component of the absolute wheel speed, and its relation is as follows:

\[
\begin{align*}
\alpha_f &= \hat{\beta} + \frac{a}{v_{gx}} w_r - \delta \\
\alpha_r &= \hat{\beta} - \frac{a}{v_{gx}} w_r
\end{align*}
\]

\[
\begin{align*}
v_{L1} &= u_{L1}/\cos\alpha_f \\
v_{R1} &= u_{R1}/\cos\alpha_f \\
v_{L2} &= u_{L2}/\cos\alpha_r \\
v_{R2} &= u_{R2}/\cos\alpha_r
\end{align*}
\]

Where \( \hat{\beta} \) is the estimated sideslip angle of the center of mass.

Considering the lateral yaw movement of the car body, the absolute speed of the wheel still cannot be taken as the longitudinal speed, which needs to be converted to the center of mass of the vehicle. The conversion formula is as follows:

\[
\begin{align*}
v_{g^\wedge xL1} &= \sqrt{v_{L1}^2 - (v_{gy}^\wedge + w_r a)^2 + w_r T_f / 2} \\
v_{g^\wedge xR1} &= \sqrt{v_{R1}^2 - (v_{gy}^\wedge + w_r a)^2 - w_r T_f / 2} \\
v_{g^\wedge xL2} &= \sqrt{v_{L2}^2 - (v_{gy}^\wedge + w_r b)^2 + w_r T_r / 2} \\
v_{g^\wedge xR2} &= \sqrt{v_{R2}^2 - (v_{gy}^\wedge + w_r b)^2 - w_r T_r / 2}
\end{align*}
\]

Where \( v_{gx}^\wedge \) is the longitudinal velocity at the center of mass estimated from the four-wheel speed; \( v_{gy}^\wedge \) is the lateral velocity estimation at the center of mass.

Since there is no driven wheel in the four-wheel-drive vehicle, the longitudinal velocity of the vehicle is defined as the average estimated speed of four wheels. That is:

\[
v_{gx} = \frac{v_{g^\wedge xL1} + v_{g^\wedge xR1} + v_{g^\wedge xL2} + v_{g^\wedge xR2}}{4}
\]

5. Simulation verification and analysis

The research object adopted in this paper is a four-wheel-drive off-road vehicle. Firstly, the vehicle model is established by CarSim, and its main parameters are shown in table 1. Then, the vehicle speed estimation system model is established by MATLAB/Simulink, and the CarSim-Simulink co-simulation model is built to prove the effectiveness of the proposed algorithm[9]. The adhesion coefficient of the road is uniformly set at 0.8, which is consistent with the common asphalt pavement.

The actual speed is based on the CarSim output reference speed. The road adhesion coefficient is uniformly set at 0.7, which is consistent with common asphalt pavement.

| Table 1 Partial parameters of the vehicle |
|------------------------------------------|
| Parameter | Value of parameter |
| vehicle mass | m/kg | 3590 |
| distance from front axis to center of mass | a/m | 1.18 |
| distance from rear axis to center of mass | b/m | 1.77 |
| front track | T_f/m | 1.80 |
| rear track | T_r/m | 1.80 |
| front wheel side stiffness | k_1/(N/rad) | -50484 |
| rear wheel side stiffness | k_2/(N/rad) | -50484 |
| radius of the tire | R/m | 0.39 |
| the moment of inertia of the body about the Z axis | I_z/kg ∙ m^2 | 2687.1 |

Due to the pre-estimated speed can better simulate the real speed under normal working conditions, the simulation part will not elaborate too much.
5.1 Rapid acceleration/Sharp deceleration condition
Rapid acceleration condition setting: the initial speed of the vehicle is set to 0, and the throttle opening reaches and keeps the maximum value at 0.1s.

Sharp deceleration condition setting: the initial speed of the vehicle is 100km/h, and the braking pressure is linearly increased to the maximum 20MPa between 0-2s, and the maximum is maintained until the vehicle stops.

The simulation results show that, according to figure 3, under the condition of rapid acceleration, all four wheels will slip to a certain extent at the starting stage. In addition, in the four-wheel drive mode, the wheel speed will also be slightly greater than the vehicle speed under the condition of vehicle stability, which cannot reflect the real longitudinal speed. By increasing the weight of the added speed of the Kalman filter, the relation between the speed and the wheel speed was reduced. Due to the presence of the integral error, the maximum absolute error of the estimated longitudinal speed was 0.126m/s, which was greatly improved compared with the conventional kinematics estimation method.

Similarly, according to figure 4, the maximum absolute error of the estimated longitudinal speed was 0.25m/s.

![Figure 3. Comparison of longitudinal speed estimation under rapid acceleration conditions](image1)
![Figure 4. Comparison of longitudinal speed estimation in sharp deceleration conditions](image2)

5.2 Abnormal steering condition
Driving condition setting: the vehicle runs at a continuous target speed of 100km/h and the steering wheel turns left at 720°. During the period of 1.5s-3.5s, the steering wheel returns to zero at a uniform speed.

![Figure 5. Estimation comparison of abnormal steering conditions](image3)

(a) Side slip angle of mass center
(b) The vehicle longitudinal speed
The simulation results show that: according to figure 5, the maximum absolute error of the estimated sideslip angle of mass center is 0.0064. Due to the wheel side angle is large at high speed and large rotation angle, although the accuracy of the established 3-DOF model is reduced, the actual vehicle speed can still be well tracked by adjusting the weights of process noise and observation noise. The absolute error of vehicle speed estimation is 0.46 m/s.

6 Conclusion
In this paper, different estimation methods are selected by identifying different working conditions. The kinematics method was used to adjust the weight value of noise according to the driving state of the vehicle in the straight driving condition, and the Kalman method was used to estimate the transverse state of the vehicle in the dynamic steering condition, so as to obtain the longitudinal velocity at the center of mass. These methods are simple to implement and practical. According to the results of CarSim-Simulink co-simulation test, it can be seen that the estimated longitudinal speed is in good agreement with CarSim output reference speed under various working conditions.

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