Estimation and Simulation Analysis of the Sideslip Angle of Intelligent Vehicle under Unstructured Road Environment

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Abstract. Vehicle sideslip angle is one of the important variables to describe the vehicle's lateral motion state, and it is also difficult to estimate accurately. In order to solve the difficult problem of direct measurement of intelligent vehicle sideslip angle in unstructured road environment, a 3-DOF vehicle Dynamics model was established, Carsim and Matlab were also used to construct the parametric model of vehicle. Based on the extended Kalman filter (EKF) algorithm, the State observer was used to estimate the sideslip angle of the intelligent vehicle. In the case of emergency shift, the estimation effect of State observer is verified by joint simulation. The simulation results show that the proposed method can accurately estimate the sideslip angle of the intelligent vehicle.

Introduction

Roads are divided into two parts, the structured road and unstructured road. In view of the complexity of unstructured road environment, it is of great significance to study the active control of intelligent vehicle under the unstructured road environment [1].

The active safety control of intelligent vehicle is the main development direction of its stability control, and the sideslip angle is the key parameter of the active safety control process. Therefore, it is the key of active safety control of intelligent vehicle to select the appropriate estimation method of the sideslip angle and to establish the corresponding State observer.

At present, there are 4 methods of the sideslip angle observation. The first method is to use the kinematic relationship between the lateral velocity, the lateral acceleration and the angular velocity of the transverse pendulum to get the lateral velocity of the vehicle by integral, and then calculate the sideslip angle. This method results in the cumulative error of the estimated result due to simultaneous integral operation of the noise of the sensor signal [2-4]. The 2nd method is to use the input and output of the vehicle Dynamics model to estimate, and the accuracy of the estimation results depends on the vehicle parameters, and the nonlinear characteristics of the vehicle severely limit the estimation accuracy of the method in the nonlinear segment [5]. The 3rd is based on the neural network model estimation method, which uses the experimental value to establish the mapping relation between the sideslip angle, the yaw velocity and the lateral acceleration [6]. The fourth method is to synthesize the advantages of the 1th and 2nd methods [7].

Models

This paper considers the lateral motion, yaw motion and roll motion of the vehicle, and establishes a 3-DOF vehicle Dynamics model [8-9], the dynamic equation of the model is as follows.

\[
\begin{align*}
mu(\dot{\beta} + \alpha) - m_s h \dot{\phi} &= K_f \alpha_f + K_s \alpha_s, \\
I \dot{\omega} &= aK_f \alpha_f - bK_s \alpha_s, \\
I \dot{\phi} - m_s h u(\dot{\beta} + \alpha) &= -C_{\phi} \dot{\phi} - (K_{\phi} - m_s g h_s) \phi.
\end{align*}
\]

The specific meanings and units in the model are shown as follows.

\[
\begin{align*}
m & \quad \text{Whole vehicle Quality kg} \\
m_s & \quad \text{Spring Load Quality kg} \\
u & \quad \text{Longitudinal speed m/s}
\end{align*}
\]
\[ \begin{align*}
\beta & \quad \text{Sideslip Angle rad} \\
\omega_r & \quad \text{Yaw rate rad/s} \\
\alpha_f, \alpha_r & \quad \text{Front and rear tyre sideslip angle} \\
I_x, I_z & \quad \text{Moment of inertia around the x,z axis kg \cdot m^2} \\
\varphi & \quad \text{Vehicle roll angle rad} \\
\dot{\varphi} & \quad \text{Vehicle roll rate rad/s} \\
\ddot{\varphi} & \quad \text{Vehicle roll acceleration rad/s}^2 \\
a, b & \quad \text{The distance between the centroid and the front and rear axes m} \\
K_{\varphi} & \quad \text{Total lateral roll stiffness of front and rear suspension N \cdot m/rad} \\
k_f, k_r & \quad \text{Front and rear tire side deflection stiffness N/rad} \\
C_{\varphi} & \quad \text{Total lateral tilt damping of front and rear suspension N \cdot m \cdot s/rad} \\
\omega_{\dot{r}} & \quad \text{Vehicle yaw rate acceleration rad/s}^2 \\
\\end{align*} \]

The front and rear wheel tire side angle can be expressed as:

\[
\begin{align*}
\alpha_f &= \beta + \frac{a}{u} \omega_r - \delta - R_f \varphi.
\alpha_r &= \beta - \frac{b}{u} \omega_r - R_r \varphi.
\end{align*}
\]

In the formula, \( R_f, R_r \) is the front and rear wheel side roll deflection coefficient; \( \delta \) is the car front wheel angle, units are rad.

**Methodology**

**Estimation Method**

The classic Kalman filter form is as follows:

\[
\begin{align*}
\dot{x} &= f(x(t), u(t)) + \omega(t).
y &= h(x(t), u(t)) + v(t).
\end{align*}
\]

The accuracy of the optimal estimation depends on whether the selection of the correction coefficient array conforms to the optimal criterion, i.e. the minimum variance criterion, it is as follows:

\[
P(t) = E\left[\left( X(t) - \tilde{X}(t) \right)\left( X(t) - \tilde{X}(t) \right)^T \right] = \text{min}
\]

We can prove that \( P(t) \) is the solution of the following equation:

\[
\dot{P}(t) = \tilde{F}(t)P(t) + P(t)\tilde{F}^T(t) - P(t)\tilde{H}^T(t)R^{-1}(t)\tilde{H}(t)P(t) + Q(t)
\]

Thus, the recursive equation of the continuous system can be written as:

\[
\begin{align*}
K(t) &= P(t)\tilde{H}^T(t)R^{-1}(t).
\dot{x}(t) &= f(\tilde{x}(t), u(t)) + K(t)(y(t) - h(\tilde{x}(t)))\dot{P}(t).
\dot{P}(t) &= \tilde{F}(t)P(t) + P(t)\tilde{F}^T(t) - P(t)\tilde{H}^T(t)R^{-1}(t)\tilde{H}(t)P(t) + Q(t).
\end{align*}
\]

In the formula, \( K(t) \) is Kalman feedback gain; \( P(t) \) is covariance of estimated errors; \( R(t) \) is the covariance of measured noise; \( Q(t) \) is covariance of system noise; \( \tilde{x}(t) \) is estimated value; \( F(t) \) and \( H(t) \) are Jacobian matrices of system equations and observation equations respectively; “” is average value; “” is estimated value.

When the dimensions of the system are \( n \) and have \( m \) measurement variables, the equation of
system $F(t)$ and the equations of observation $H(t)$ are as follows:

$$
\dot{F}(t) = \frac{\partial f(x,u)}{\partial x} \bigg|_{x=x_0} = \begin{bmatrix}
\frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \ldots & \frac{\partial f_1}{\partial x_n} \\
\frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \ldots & \frac{\partial f_2}{\partial x_n} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial f_n}{\partial x_1} & \frac{\partial f_n}{\partial x_2} & \ldots & \frac{\partial f_n}{\partial x_n}
\end{bmatrix}
$$

(7)

$$
\dot{H}(t) = \frac{\partial h(x,\mu)}{\partial x} \bigg|_{x=x_0} = \begin{bmatrix}
\frac{\partial h_1}{\partial x_1} & \frac{\partial h_1}{\partial x_2} & \ldots & \frac{\partial h_1}{\partial x_n} \\
\frac{\partial h_2}{\partial x_1} & \frac{\partial h_2}{\partial x_2} & \ldots & \frac{\partial h_2}{\partial x_n} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial h_m}{\partial x_1} & \frac{\partial h_m}{\partial x_2} & \ldots & \frac{\partial h_m}{\partial x_n}
\end{bmatrix}
$$

(8)

From the above, the larger the noise, the more the Kalman filter relies on the prediction of the model, and the higher the system noise, the more the Kalman filter relies on the measurement feedback correction [10-11].

**Sideslip Angle State Observer Design**

By selecting a state variable $X(t) = [\beta \omega_r \phi \dot{\phi}]^T$, input variable $U(t) = (\delta)$ and output variable $Y(t) = [\omega_r \dot{\phi}]^T$, the observation equation of the vehicle sideslip angle State observer can be obtained:

$$
\begin{align*}
\dot{X}(t) &= E^{-1}AX(t) + E^{-1}BU(t), \\
Y(t) &= CX(t) + DU(t).
\end{align*}
$$

(9)

In the formula, each coefficient matrix is as follows:

$$
A = \begin{bmatrix}
K_f + K_r & \frac{aK_f - bK_r}{u} & -mu & -K_fR_f - K_RR_f & 0 \\
\frac{aK_f - bK_r}{u} & a^2K_f + b^2K_r & -aK_fR_f + bK_RR_f & 0 \\
0 & m_jh_ju & -K_x + m_jgh_j & -C_{\phi} \\
0 & 0 & 0 & 0 & 1
\end{bmatrix}
$$

$$
B = \begin{bmatrix}
-K_f & -aK_f & 0 & 0
\end{bmatrix}^T
$$

$$
C = \begin{bmatrix}
0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
$$

$$
D = [0 \ 0]^T
$$

$$
E = \begin{bmatrix}
mu & 0 & 0 & -m_jh_j \\
0 & I_z & 0 & 0 \\
-m_jh_ju & 0 & 0 & I_x \\
0 & 1 & 0 & 0
\end{bmatrix}
$$

Then the sideslip angle of the corresponding operating conditions can be calculated.

**Test and Results**

The main simulation parameters of the intelligent vehicle used in this paper are shown as follows.

**parameters and values**

| Parameters                  | Values      |
|-----------------------------|-------------|
| Whole vehicle Quality/kg    | 1070        |
| Centroid Height/m           | .51         |
| Tread/m                     | 1.42        |
| Centroid to front axle distance/m | 1.15    |
Tyre radius/m 0.277  
Centroid to rear axle distance/m 1.45  
Wheelbase/m 2.6  
Side Arm/m 0.52  
Inertia of the whole vehicle to the z-axis/kgm$^2$ 3879  
Inertia of the whole vehicle to the x-axis/kgm$^2$ 635

The initial speed of the vehicle is 100 km/h, the adhesion coefficient of the pavement is 0.8, and the simulation time is 10s. The Carsim simulation results under the same parameters are compared with the results of this method to verify the accuracy of this algorithm. Model steering wheel input as shown in Figure 1, the Carsim model output of the yaw rate curve, the side inclination rate curve as shown in Figure 2 and Figure 3, Carsim and the method of the sideslip angle of view of the value of the estimate pair, as shown in Figure 4.

![Figure 1. Steering wheel angle change.](image1.png)  
![Figure 2. Yaw rate change.](image2.png)  
![Figure 3. Side slope rate change.](image3.png)  
![Figure 4. Comparison of sideslip estimates.](image4.png)

From the simulation results, it can be seen that the estimated value of the design of the intelligent vehicle sideslip angle State observer output and the output value of the Carsim vehicle parametric model have some deviations in the curve crest and trough, but the trend is basically the same, and the estimation precision is high, which achieves the expected target.

**Conclusions**

Based on vehicle Dynamics model and Kalman filter algorithm, a state observer for the sideslip angle of the intelligent vehicle was designed. By using the emergency double-shift line condition, the estimation effect and the actual value of the intelligent vehicle sideslip angle State observer are compared and simulated. The simulation results show that the estimated value of the design of the intelligent vehicle sideslip angle State observer output and the output value of the Carsim vehicle parametric model have some deviations in the curve crest and trough, but the trend is basically the same, and the estimation precision is high, which achieves the expected target.

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