Estimation of Vehicle Status and Parameters Based on Nonlinear Kalman Filtering

Huang Yuhao
Jiangsu University of Technology, Changzhou
School of Electrical and Information Engineering
Changzhou, China
15150688985@163.com

2022 6th International Conference on Robotics and Automation Sciences (ICRAS) | 978-1-6654-6784-1/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICRAS55217.2022.9842063

***Abstract*—From the perspective of economy and engineering practicability, due to the existing mass-produced on-board sensor measurement accuracy is not high or difficult to measure at low cost, some car status parameters can not be obtained directly through the sensor, therefore, in order to accurately and real-time acquisition of vehicle motion state information, this paper is based on a nonlinear three-degree of freedom vehicle model, respectively, using the unscented Kalman filter algorithm and the extended Kalman filter algorithm to estimate longitudinal speed, centroid slip angle, swing angle velocity. Simulink and Carsim were used for co-simulation. The results show that the effect of the extended Kalman filter algorithm in estimating longitudinal speed and swing angle velocity is not much different from the unscented Kalman filter, and the unscented Kalman filtering algorithm could more accurately track the centroid slip angle of the vehicle.**

Keywords—unscented Kalman filtering, extended Kalman filtering, vehicle dynamics, parameter estimation

I. Introduction

In recent years, with the rapid development of China's automobile industry and the improvement of people's safety awareness, automobile safety issues have attracted more and more attention. People are also increasingly demanding the handling stability and active safety of cars. The wide application of advanced dynamic control systems for vehicles provides good handling performance for automobiles [1-2], which greatly avoids the occurrence of traffic accidents, and the implementation of accurate access to the driving state of the vehicle is the premise of active safety control of automobiles [3]. At present, the cost of vehicle speed sensors and gyroscopes is high, and parameters such as vehicle speed and centroid slip angle directly used to test the vehicle will increase the cost of the car, so a low-cost, high-precision way is needed to achieve the estimation of important state parameters of the vehicle. This is also the current research hotspot of active safety control of automobiles.

Existing parameter estimation methods include fuzzy logic estimation way [4-5], neural network method [6-7] and Kalman filter estimation method [8-9] etc. but the neural network method requires substantial training samples, the determination of the weighting coefficients of fuzzy logic estimation relies heavily on the experience of engineers, so the Kalman filter estimation method is the most used. With the application of classical Kalman filtering technology combined with automotive dynamic models in the automotive field, this method has also received the attention of a large amount of scholars. But classical Kalman only applies to estimation problems for linear systems. In practical studies, nonlinear models are often used in order to be able to more accurately describe the motion of the vehicle. To this end, the researchers introduced extended Kalman filtering (Extended Kalman Filter, EKF) and unscented Kalman filtering (Unscented Kalman Filter, UKF) techniques. However, because car is a strong nonlinear system, EKF introduces truncation error through first-order Taylor unfolding, and When the car is driving in non-linear conditions such as speed bumps and muddy roads, the estimation results are difficult to achieve high accuracy, and even lead to divergence of results. Unscented Kalman filtering can handle non-linear nonlinear functions because it does not need to calculate the Jacobi matrix of nonlinear functions, and the estimation accuracy is higher, so it is more suitable for estimating the parameters of nonlinear systems. Thus, the UKF estimation method is used to estimate the state parameters such as centroid slip angle, pendulum angle velocity and vehicle speed of the car, and use Matlab/Simulink for joint simulation with Carsim.

II. Vehicle Dynamic Model

A. Vehicle Dynamics Model

This article mainly studies motion characteristics of automobiles driving on flat roads. On the basis of linear two-degree-of-freedom vehicle model, one vehicle longitudinal motion degree of freedom is increased, and the other two degrees of freedom are constant in lateral motion and pendulum motion. The model of the vehicle is reflected in Fig. 1.

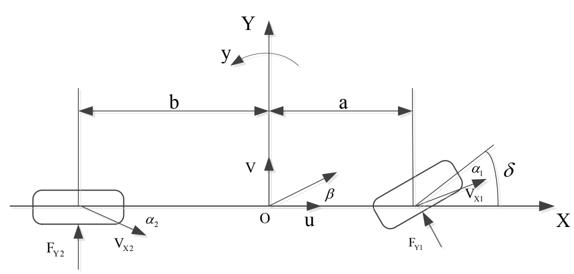

Fig. 1. Vehicle dynamics model

The equation of motion of the three-degree-of-freedom vehicle model obtained from Fig. 1 is as follows:

$$\begin{cases}\dot{v}_y = -v_x\gamma + \frac{d_1k_1-d_2k_2}{mv_x}\gamma + \frac{(k_1+k_2)v_x}{mv_y} - \frac{k_1}{m}\delta \\ \dot{v}_x = v_y\gamma + a_x \\ \dot{\gamma} = \frac{d_1^2k_1+d_2^2k_2}{I_zv_x}\gamma + \frac{d_1k_1-d_2k_2}{I_z}\beta - \frac{k_1}{m}\delta \\ \beta = \arctan(\frac{v_x}{v_y}) \\ a_y = \frac{d_1k_1-d_2k_2}{mv_x}\gamma + \frac{k_1+k_2}{m}\beta - \frac{k_1}{m}\delta\end{cases} \quad (1)$$

Thereinto, v_y is a lateral speed, v_x is longitudinal speed, γ is swing angle velocity, d_1 is the distance from the centroid to the anterior axis, d_2 is he distance from the centroid to the posterior axis, m is the whole vehicle quality, δ is front wheel corner, k_1 and k_2 are the sum of the lateral bias stiffnesses of the front and rear wheels, respectively, β is centroid slip angle, a_x is Longitudinal acceleration, a_y is Lateral acceleration, I_z is Moment of inertia around the z-axis.

B. *Tire Model*

To simplify the calculation and improve the computational efficiency, this paper uses magic tire model [10], the principle of the magic tire model is to use the combined formula of the trigonometric function to match the experimental tire data. The model has strong uniformity, could describe all the steady-state mechanical properties of the tire, simple and practical, and has high simulation accuracy.

The general expression of a magic formula is:

$$Y = y + S_V \quad (2)$$

$$y = D\sin(Carctan(Bx - E(Bx - \arctan(BX)))) \quad (3)$$

$$x = X + S_h \quad (4)$$

Thereinto, Y represents a lateral force, a longitudinal force, or a positive moment, X indicates the lateral declination or slip rate, D is the peak factor; C is the form factor; B is the stiffness factor; E is the curvature factor; S_h is the horizontal offset; S_V is the vertical offset.

The individual parameters of formula (2) -equation (4) are based on the Magic Tire Model parameters provided in the Carsim software. The coefficients B, C, and D in the formula are determined by the vertical load and camber of the tire in turn.

From the three-degree-of-freedom vehicle dynamics model, it is necessary to refer to the longitudinal and lateral forces of the tire when predicting the state of the vehicle. The input amounts used to calculate the tire side force and the side force are the tire side declination and, respectively. The longitudinal slip rate of the tire, the calculation formula of which can be derived from the vehicle model.

Longitudinal force:

$$\begin{cases}\alpha_{11,12} = \delta - \arctan[\frac{v+a\omega_r}{u\pm(\frac{L}{2})\omega_r}] \\ \alpha_{21,22} = -\arctan[\frac{v+b\omega_r}{u\pm(\frac{L}{2})\omega_r}]\end{cases} \quad (5)$$

$$\begin{cases}u_{11,12} = \sqrt{u^2+v^2} \pm \omega_r(\frac{h_f}{2} \pm a\beta) \\ u_{21,22} = \sqrt{u^2+v^2} \pm \omega_r(\frac{h_r}{2} \mp b\beta) \\ s_{ij} = \frac{r_e\omega_{ij}-u_{ij}}{u_{ij}}\end{cases} \quad (6)$$

In the equation, u_{ij} is the center speed of each wheel, The subscript ij indicates 11, 12, 21, 22, The same goes for below; ω_{ij} is the rotational angular velocity of each wheel; The s_{ij} is the longitudinal slip rate of each wheel, and the α_{ij} is the side declination angle of each wheel; the h_f is the front wheel track; the h_r is the rear wheel track; and the r_e is the wheel rolling radius.

III. Kalman Filtering Algorithm

Classical Kalman filtering is used to address the problem of state estimation of linear systems at Gaussian noise, and it can be applied to any dynamic system containing uncertain information. At the same time, in order to make the Kalman filter suitable for nonlinear systems, it is proposed to use the Taylor series to expand system state, take the first order term, and realize the system approximate linearization, which is the extended Kalman filter (EKF) [11]. Because the extended Kalman filter only considers the first-order information and ignores the higher-order information, some scholars have proposed the uninvited transformation (UT), which obtains the estimated variable by finding the statistics of the transformation point, and realizes the second-order approximation of the system, so that the expression of the model is more accurate, which is the unscented Kalman filter (UKF).

A. *Extended Kalman Filtering Algorithm*

To figure out the problem of state estimation of nonlinear systems, extended Kalman filtering is based on the idea of linearization of nonlinear systems, and some local points of nonlinear systems are expanded by Taylor series, and higher-order scales are discarded to form first-order Taylor series, which realizes the local linearization of nonlinear systems. The linearized system can be evaluated using classical Kalman filtering.

1) *Local Linearization*

EKF is based on linear Kalman filtering, employing the local linearity characteristics of nonlinear functions to locally linearize the nonlinear model. Classical Kalman filtering is then applied to complete the filter estimation of the target.

Nonlinear state space model：

$$x(k+1) = f\big(k, x(k)\big) + w(k) \quad (7)$$

$$z(k) = h\big(k, x(k)\big) + v(k) \quad (8)$$

$$w(k) \sim N\big(0, Q(k)\big),\ \ v(k) \sim N(0, R(k)) \quad (9)$$

In the above equation: $w(k)$ is process noise, $v(k)$ is observation noise; Assuming that process noise $w(k)$ and observation noise $v(k)$ are Gaussian white noise with a mean of zero, the noise sequence is independent of each other.

For general nonlinear systems around filter values $x(k)$ Expand the nonlinear functions $f(*)$ and $h(*)$into Tayor series and omit terms above the second order, linearize the process noise $w(k)$ around $f(*)$ and the observational noise $v(k)$ around $h(*)$ to obtain an approximate linearization model:

A is the Jacobian matrix obtained after the partial derivative of the equation of state f to x:

$$A(k) = \frac{\partial f}{\partial x(k)}\bigg|_{x(k)=\hat{x}(k)} \tag{10}$$

W is the Jacobian matrix obtained after the partial derivative of the equation of state f to w:

$$W(k) = \frac{\partial f}{\partial w(k)}\bigg|_{x(k)=\hat{x}(k)} \tag{11}$$

H is the Jacobian matrix obtained after the partial derivative of the equation of state h to x:

$$H(k) = \frac{\partial f}{\partial x(k)}\bigg|_{x(k)=\hat{x}(k)} \tag{12}$$

V is the Jacobian matrix obtained after the partial derivative of the equation of state h to v:

$$V(k) = \frac{\partial f}{\partial v(k)}\bigg|_{x(k)=\hat{x}(k)} \tag{13}$$

2) Linear Kalman Filtering

In contrast to the basic equations of Kalman filtering, in the linearized system equations, the state transfer matrix, observation matrix, process noise matrix, and observation noise matrix are replaced by Jacobian matrices of f and h. Utilizing the basic equation of Kalman filtering to the linearized system state space model can obtain the extended Kalman filter recursive equation, and the extended Kalman filtering algorithm can be divided into two parts: prediction process and measurement update. The prediction process is to obtain a predictive estimate of the next moment based on the state of the system at the current moment; the correction process is to combine observations and prediction estimates to obtain the optimal estimate of the system.

Applying the Kalman filter basic equation to the linearized model yields the extended Kalman filter recursive equation as below:

$$\hat{X}(k|k+1) = f(\hat{X}(k|k)) \tag{14}$$

$$P(k+1|k) = \Phi(k+1|k)P(k|k)\Phi^T (k+1|k) + Q(k+1) \tag{15}$$

$$K(k+1) = P(k+1|k)H^T(k+1) [H(k+1)P(k+1|k)H^T(k+1) + R(k+1)]^{-1} \tag{16}$$

$$\hat{X}(k+1|k+1) = \hat{X}(k+1|k) + K(k+1) [Z(k+1) - h(\hat{X}(k+1|k))]^{-1} \tag{17}$$

$$P(k+1) = [I - K(k+1)H(k+1)]P(k+1|k) \tag{18}$$

In the above formula, the initial values of the filtering initial value and the filter error variance matrix are:

$$X(0) = E[X(0)],\ P(0) = var[X(0)] \tag{19}$$

B. Traceless Kalman Filtering Algorithm

Compared with the EKF algorithm, the UKF algorithm [12] abandons the method of linearization of nonlinear systems, based on the standard unselected transformation, the rule of the unsolicited transformation is in the original set of points distributed in the state (also known as sigma points), using the principle of similar distribution, using a rule to select some sampling points, to ensure that the average and covariance of the selected points are equal to the average and covariance of the original state point set, and introduce it into the nonlinear system, through the change of these point sets, and then find the mean and covariance. Finally, the sample point is calculated by transforming the result and the corresponding weight to calculate the Gaussian distribution to obtain the estimated variable. For the following nonlinear discrete systems:

$$\begin{cases} x(k+1) = f\big(x(k)\big) + w(k) \\ z(k) = h\big(x(k)\big) + v(k) \end{cases} \tag{20}$$

The sample points are constructed as follows:

$$x_i = \begin{cases} \bar{x}, & i = 0 \\ \bar{x} + (\sqrt{(n+\lambda)P_x})_i, & i = 1,2,\cdots,n \\ \bar{x} - \left(\sqrt{(n+\lambda)P_x}\right)_i, & i = n+1, n+2, \cdots 2n \end{cases} \tag{21}$$

where X is the n-dimensional state variable; $\hat{x}$ and P_x are the mean and variance of x, respectively.

The weights for each point are:

$$w_i{}^{(m)} = \begin{cases} \frac{\lambda}{n+\lambda}, & i = 0 \\ \frac{1}{2(n+\lambda)}, & i = 1,2,\cdots,2n \end{cases} \tag{22}$$

In the above equation, n is the state vector dimension to be estimated, the superscript m is the mean, and λ is the scale factor, which can be used to reduce the total prediction error;

Assuming that the state estimate and the variance array at the previous moment are $\hat{x}(k-1)$ and $P_k(k-1)$, respectively, the specific steps for filtering the nonlinear system (20) using UKF are as below:

- Set the Initial Value.

$$\begin{cases} \hat{x}(0) = E[x(0)] \\ P(0) = E\{[x(0) - \hat{x}(0)][x(0) - \hat{x}(0)]^T\} \end{cases} \tag{23}$$

- Update Time.

When $k > 1$, press equation (21) to construct $2n+1$ sample points, namely:

$$X(k-1) = \left\{\hat{x}(k-1), \hat{x}(k-1) + \left(\sqrt{(n+\lambda)P_x(k-1)}\right)_i, \hat{x}(k-1) - \left(\sqrt{(n+\lambda)P_x(k-1)}\right)_i\right\} \quad (i = 1,2,\cdots,n) \qquad (24)$$

The average and variance of the predicted sample points are then calculated, namely:

$$\begin{cases} \hat{x}^-(k) = \sum_{i=0}^{2n} W_i^{(m)} x_i^-(k) \\ P_x^-(k) = \sum_{i=0}^{2n} W_i^{(m)} [x_i^-(k) - \hat{x}^-(k)] \cdot [x_i^-(k) - \hat{x}^-(k)]^T + Q(k) \end{cases} \qquad (25)$$

where Q is the process noise covariance matrix.

- Update the Measurement.

When a new measurement $\mathrm{z}(k)$ is obtained, the state mean and variance are updated, namely:

$$\begin{cases} \hat{x}(k) = \hat{x}^-(k) + K[z(k) - \hat{z}^-(k)] \\ P_x(k) = P_x^-(k) - KP_z(k)K^T \\ K = P_{xz}(k)P_z^{-1}(k) \end{cases} \qquad (26)$$

$$\begin{cases} \hat{z}^-(k) = \sum_{i=0}^{2n} W_i^{(m)} h(x_i^-(k)) \\ P_z(k) = \sum_{i=0}^{2n} W_i^{(m)} \left[h(x_i^-(k)) - \hat{z}^-(k)\right] \cdot \left[h(x_i^-(k) - \hat{z}^-(k))\right]^T + R(k) \\ P_{xz}(k) = \sum_{i=0}^{2n} W_i^{(m)} [x_i^-(k) - \hat{x}^-(k)] \cdot \left[h(x_i^-(k) - \hat{x}^-(k))\right]^T \end{cases} \qquad (27)$$

where $R(k)$ is the covariance matrix for measuring noise.

IV. Vehicle State Estimation Based on Nonlinear Kalman Filtering Algorithm

In order to accurately estimate the state change of the vehicle during driving, this paper uses the centroid slip angle, the lateral swing angle speed and the longitudinal speed as the state variables. That is $x = [\gamma, \beta, v_x]$;Use longitudinal acceleration and front wheel angle as system input control variables, namely, $u = [\delta, a_x]$;Employ the lateral acceleration as the output variable, namely, $y = a_y$, Combining the kinetic equations, the structural diagram of the joint simulation using Simulink and Carsim software is shown in Fig. 2.

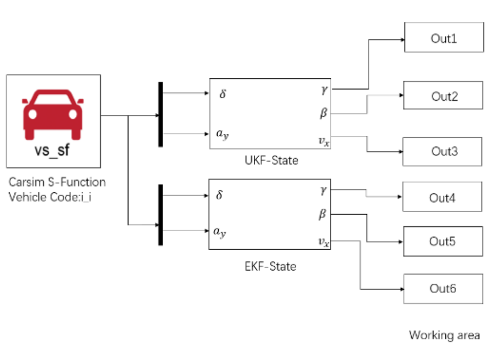

Fig. 2. Simulink simulation structure for estimating state of the car

The effects of the extended Kalman filter algorithm and the unscented Kalman filter algorithm are compared with the reference state of the dynamic model output using the steering wheel input angle step condition and the sine condition. The simulation parameters are obtained by the Carsim software, and the specific values are shown in Table I.

TABLE I. Vehicle Parameters

Vehicle Parameters	*Numeric Value*
The quality of the whole vehicle	1765kg
Distance from the center of mass to the front axis	1.2m
Distance from the center of mass to the rear axis	1.4m
The inertia of the z-axis of the whole vehicle	2700kg.m^2
The equivalent side stiffness of the front wheel	-101200N/rad
The equivalent side stiffness of the rear wheel	-133500N/rad
Steering wheel to front wheel angle transmission ratio	20

Set the pavement adhesion coefficient to 1 in Matlab/simulink, The sampling period is 0.01s, The original value of the error covariance matrix is $P_0 = 0.1I_{3\times3}$, System noise covariance matrix $Q = 0.1I_{3\times3}$, Observe the original value of the noise covariance matrix $R_0 = 1$.

Working Condition 1: The initial speed of the Carsim simulation is set to $5m/s$, Accelerate from $5m/s$ to $20m/s$ and make angular step input on the steering wheel after reaching $20m/s$,that is initial state $X(0) = [0,0, 20/3.6]$, The input amplitude is 1rad, The angular step input is shown in Fig. 3. The kalman filtered estimated vehicle speed, swing angle velocity, and centroid slip angle are shown in Fig. 4., Fig. 5. and Fig. 6.

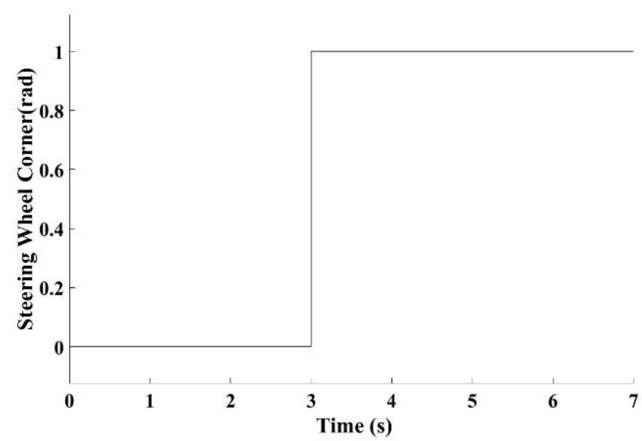

Fig. 3. Change of front wheel angle over time

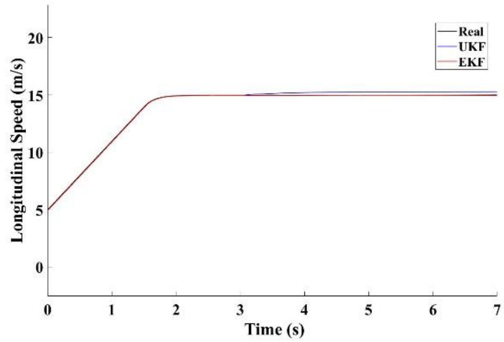

Fig. 4. Longitudinal speed estimation

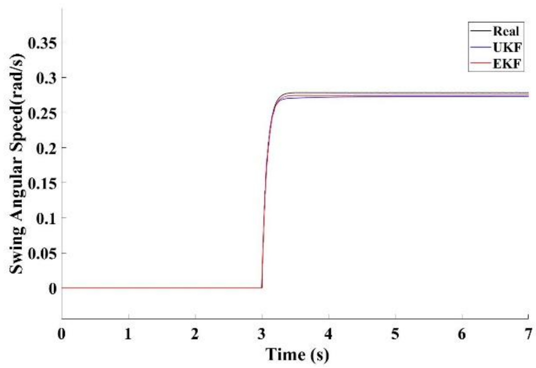

Fig. 5. Oscillating angle velocity estimation

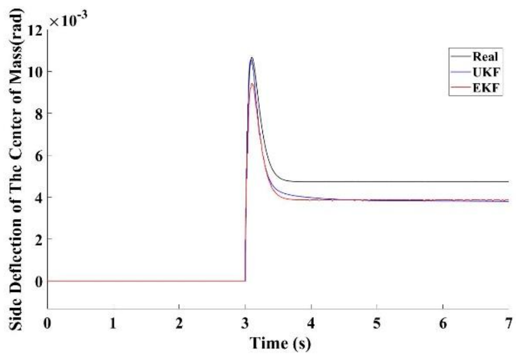

Fig. 6. Centroid slip angle estimation

Comparison is made by the estimate of the unscented Kalman filter and the extended Kalman filter with the actual value of the vehicle model output. As can be observed from Fig. 4. When the angular step input is applied to the steering wheel, the driving state of the car changes, the speed estimate of EKF is more ideal, in the lateral swing angle velocity estimation under the angular step working condition of Fig. 5. The extended Kalman filtering method at the inflection point is 0.5% higher than the unscented Kalman filtering accuracy, negligible, and then gradually converge. Nevertheless, in the estimation of the centroid slip angle in Fig. 6. The estimation accuracy of UKF at the peak is about 2% higher than that of EKF.

Work condition 2: The initial state remains the same, and the steering wheel corner input is changed to a sinusoidal input, as shown in Fig. 7. Estimates of vehicle speed, lateral swing angle velocity, and centroid slip angle are shown in Fig. 8., Fig. 9. and Fig. 10.

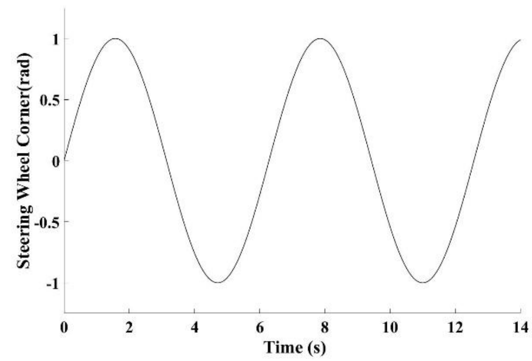

Fig. 7. Change of front wheel angle over time

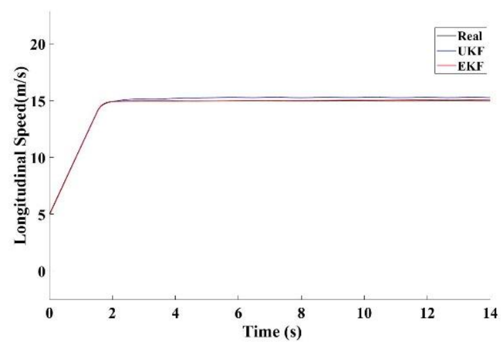

Fig. 8. Longitudinal speed estimation

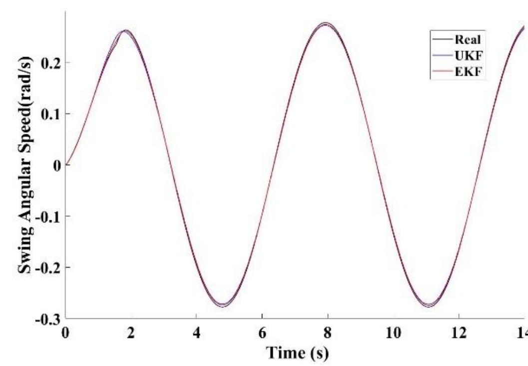

Fig. 9. Oscillating angle velocity estimation

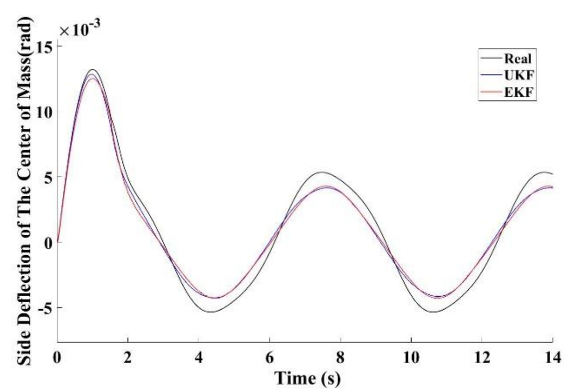

Fig. 10. Centroid slip angle estimation

Fig. 8. and Fig. 9. compare the actual values of longitudinal speed and pendulum angular velocity with the nonlinear Kalman filter estimates under the front wheel angle sinusoidal input, respectively, and it can be seen that the maximum error of the estimated values is less than 1%, and the overall accuracy is higher and the stability is better. Fig. 10. shows the actual value of the centroid measurement declination and the estimated value of the two algorithms, which can be seen that due to the sudden change in the steering wheel angle, the impact is more obvious, especially at the second peak. The estimation effect of the two methods is not much different, and the relative error is controlled within 1%.

V. CONCLUSION

This paper is based on a nonlinear three-degree-of-freedom vehicle dynamics model, unscented Kalman filter calculations and extended Kalman filtering algorithm were used respectively, the parameters that are easy to measure directly are selected as input signals, including steering wheel angle, longitudinal and lateral acceleration, and the state parameters such as centroid slip angle and pendulum angle velocity of the automobile are estimated. The results show that the state parameters of the vehicle tracked by the two algorithms have certain accuracy and real-time under the two working conditions of steering wheel angle step input and sinusoidal input. In estimating longitudinal speed and swing angle velocity, extended Kalman filtering is slightly more accurate than unscented Kalman filtering. In terms of swing velocity estimation, unscented Kalman filtering is better.

The three-degree-of-freedom dynamic model in this paper is relatively simple, and the automotive dynamics model of 7 degrees of freedom or 14 degrees of freedom can be selected for future studies, so that the estimated state parameters will be more and more accurate. This makes the car's control system more stable, reliable and safe.

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