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An improved estimation method for vehicle velocity of distributed drive electric vehicle

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Abstract:In this paper, Simulink and Carsim are combined to study the velocity estimation of distributed drive electric vehicles. Firstly, the minimum co-simulation system is established to complete the design and debugging of the algorithm. Then, a new algorithm combining unscented Kalman filter and strong tracking filter is proposed based on the vehicle estimation model. The accuracy and real-time performance of the velocity estimation algorithm are validated by simulation under snake-shaped driving conditions with different road adhesion coefficients. Finally, an experimental test is carried out to verify the effectiveness of the proposed algorithm in estimating vehicle velocity.

Keywords: distributed drive electric vehicle; velocity estimation; unscented Kalman filter; strong tracking filter; real vehicle experiment

1. Introduction

The advanced electronic control systems such as electronic stability program (ESP) and acceleration slip regulation (ASR) have been widely used in modern vehicles. One of the necessary conditions for the effective operation of these systems is the state signals of vehicles could be acquired in real-time during driving [1-2]. Therefore, how to evaluate the vehicle state parameters accurately and in real-time, including the longitudinal vehicle velocity and lateral velocity, has become a research hotspot [3]. Especially, the development of distributed drive electric vehicles (DDEVs) provides a good convenience for vehicle state parameters estimation.

The methods of vehicle state parameter observation include kinematics-based methods and dynamics-based methods. In kinematics-based methods, the target state variables could be calculated through kinematics relationships between some signals acquired by on-board sensors. In [4-5], the authors extracted the linear speed of wheels directly from the wheel speed sensors, and obtained the estimated value of longitudinal velocity after noise removal. In [6-8], the estimated value of lateral velocity was obtained from the relationship between yaw rate and the change rate of lateral velocity. Such methods do not depend on the vehicle models, but require high accuracy of sensors. In addition, the estimation errors are easily affected by wheel slip ratio and road conditions.

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The dynamics-based methods describe the vehicle state through some dynamic models, and then use estimation algorithm to estimate target state variables. Kalman filter theory has been widely used in estimation algorithm. In [9-11], the single-track and dual-track vehicle models were used as state estimation models. The dual-track vehicle model has high accuracy because it considers the effect of longitudinal driving force on the basis of the single-track model, but its estimation effects are limited by the accuracy of the model of tire forces. In [12], the estimation of velocity was realized by the unscented kalman filter (UKF) based on the three-degree-of-freedom(3-DOF) vehicle model. In [13], the dugoff tire model was added to the vehicle model, and then the extended kalman filter (EKF) was used to estimate the state parameters. Guo et al.[14] proposed an EKF method based on field programmable gate array (FPGA), which improved the estimation accuracy of longitudinal velocity. The effects of these methods depend on the accuracy of vehicle model. Moreover, the real-time tracking ability of the estimation algorithm needs to be improved in the process of drastic velocity change, such as double line-shifting condition and serpentine condition.

In view of improving the accuracy and real-time tracking ability of the velocity estimation method, a combination of strong tracking filter algorithm and UKF is designed based on a simulink/Carsim co-simulation platform for DDEVs. The overall structure of the observation method is shown in Figure 1. Then, a seven-degree-of-freedom dynamic model and HSRI tire model are established to calculate the observed state variables, which are then transferred to the velocity estimation algorithm to complete the velocity estimation. Finally, the simulation and experimental tests are carried out to verify the estimation accuracy and real-time tracking performance of the proposed algorithm. Table 1 shows the specifications of the variables and parameters used for the simulations and experimental test.

Figure 1. The overall structure of the observation method

2. The minimum co-simulation system

In this paper, Carsim and Simulink are combined to establish the minimum simulation system for velocity estimation. In Carsim the driver model can be directly set to analyze the influence of different driving behaviour on vehicle. At the same time, it can reflect the vehicle's response to different road conditions and air conditions in real time, and reflect the driving state of vehicle [15-17]. However, the electric vehicle models have

not yet been developed in Carsim , so it is necessary to add the in-wheel motors to its vehicle models.

2.1 Model of the in-wheel motor

In [18], the voltage balance equation of in-wheel motor is:

Table 1. Specifications of the variables and parameters used in this paper.

Symbol	Description	Unit	Symbol	Description	Unit
m	Total mass of vehicle	kg	R	Wheel radius	m
v_x	Longitudinal vehicle velocity	m/s	J	Moment of inertia of the wheel	kg m ²
v_y	Lateral vehicle velocity	m/s	ω	Wheel angular velocity	rad/s
γ	Yaw rate	rad/s	λ_s	Wheel slip ratio	-
F_{xi}	Longitudinal forces of four tires	N	α	Side-slip angle	rad
F_{yi}	Lateral forces of four tires	N	F_z	Vertical load of tire	N
δ	Front steering wheel angle	rad	g	The acceleration of gravity	m/s ²
a	Distance from COG to the front axle	m	h_g	Height of COG	m
b	Distance from COG to the rear axle	m	a_x	Longitudinal acceleration of wheel	m/s ²
d	Track width	m	a_y	lateral acceleration of wheel	m/s ²
T_i	Driving torques of four wheels	N m	L	wheelbase	m

$$\begin{bmatrix} u_A \\ u_B \\ u_C \end{bmatrix} = \begin{bmatrix} R_A & 0 & 0 \\ 0 & R_B & 0 \\ 0 & 0 & R_C \end{bmatrix} \times \begin{bmatrix} i_A \\ i_B \\ i_C \end{bmatrix} + \begin{bmatrix} L_A & L_{AB} & L_{AC} \\ L_{BA} & L_B & L_{BC} \\ L_{CA} & L_{CB} & L_C \end{bmatrix} P \begin{bmatrix} i_A \\ i_B \\ i_C \end{bmatrix} + \begin{bmatrix} e_A \\ e_B \\ e_C \end{bmatrix} + \begin{bmatrix} U_n \\ U_n \\ U_n \end{bmatrix} \quad (1)$$

where u_A, u_B, u_C represent the voltages of three phase stators respectively, R_A, R_B, R_C are the phase resistances of three-phase stator windings respectively, i_A, i_B, i_C are three-phase currents, L_A, L_B, L_C represent the self-inductances of three phase stators, $L_{AB}, L_{AC}, L_{BA}, L_{BC}, L_{CA}, L_{CB}$ are the mutual inductances between the three-phase stator windings, P represents differential operator, e_A, e_B, e_C represent induction electromotive forces of three phase stators respectively, U_n is the neutral-point voltage.

$$L_A = L_B = L_C = L \quad (2)$$

$$L_{AB} = L_{AC} = L_{BA} = L_{BC} = L_{CA} = L_{CB} = M \quad (3)$$

The neutral-point voltage equation is [19]:

$$U_n = (u_A + u_B + u_C)/3 - (e_A + e_B + e_C)/3 \quad (4)$$

The electromagnetic torque equation is:

$$T_e = (e_A i_A + e_B i_B + e_C i_C)/\omega \quad (5)$$

The equation of motion is:

$$T_e - T_L = B\omega_m + J_m \frac{d\omega_m}{dt} \quad (6)$$

where: ω_m is the angular velocity of in-wheel motor, J_m is the moment of inertia, T_L is the load torque. B is viscous friction coefficient

2.2 Vehicle velocity tracking model

In order to observe the velocity of DDEVs, a velocity tracking model is designed, as shown in Figure 2. In this model, a PID controller is applied. The input of the controller is the difference between the target velocity V_c and the current velocity V_s . The output signal of the controller is u_c . Then the constraints are added to u_c to prevent the driving torque from exceeding the maximum torque provided by motor, so, u_c is converted to u'_c . The control voltage of in-wheel motor, U_c , is a function of u'_c . The function can be obtained by calibrating the motor. Then, U_c is applied to the Simulink model of in-wheel motor to obtain the driving torque of the Carsim vehicle model.

Figure 2. Principle of vehicle velocity tracking model

2.3 The combination of simulation software

In order to realize the distributed driving, the torque signals of the four in-wheel motors are used as inputs to the vehicle model, and its outputs are the state parameters such as the steering wheel angle, the wheel speed and yaw rate, which will be used in the estimation algorithm. The S-Function module of Simulink is used to realize the communication between the Carsim and the vehicle model.

3. Vehicle Dynamics Modeling

3.1 7-DOF Vehicle Dynamics Model

During the modeling process, the roll motion and pitch motion of the vehicle are ignored, the front track width is considered to be equal to the rear, and the vertical motion of the suspension system is also not considered. Then, the 7-DOF vehicle model [5] shown in Figure 3 is constructed, and its 7-DOF include longitudinal motion, lateral motion and yaw motion, as well as four wheel rotations.

Figure 3. 7-DOF vehicle model

The dynamic equations of longitudinal motion, lateral motion and yaw motion are as follows:

$$m(\dot{v}_x - v_y \gamma) = (F_{x1} + F_{x2}) \cos \delta - (F_{y1} + F_{y2}) \sin \delta + F_{x3} + F_{x4} \quad (7)$$

$$m(\dot{v}_y + v_x \gamma) = (F_{x1} + F_{x2}) \sin \delta + (F_{y1} + F_{y2}) \cos \delta + F_{y3} + F_{y4} \quad (8)$$

$$I\dot{\gamma} = (F_{x2} \cos \delta - F_{y2} \sin \delta - F_{x1} \cos \delta + F_{y1} \sin \delta) \frac{d}{2} + (F_{x1} \sin \delta + F_{y1} \cos \delta + F_{x2} \sin \delta + F_{y2} \cos \delta) a + (F_{x4} - F_{x3}) \frac{d}{2} - (F_{y3} + F_{y4}) b \quad (9)$$

The dynamic equation of wheel rotation is as follows:

$$T_i - F_{xi} R = J\dot{\omega} \quad (10)$$

where $F_{xi} (i = 1, 2, 3, 4)$ represent the longitudinal forces of the left front wheel, the right front wheel, the left rear wheel and the right rear wheel respectively, $F_{yi} (i = 1, 2, 3, 4)$ represent the lateral forces of those wheels.

3.2 HSRI tire model

The Institute of Highway Safety, Michigan University, USA, has conducted a large number of experiments on the nonlinear characteristics of the tires during vehicle driving, and obtained a semi-empirical tire model with high fitting precision, which is usually called the HSRI tire model.[20] Compared with the magic formula tire model,[21] the calculation amount of this model is less. The expressions are as follows:

$$\mu = \mu_{peak} (1 - A_s R \omega \sqrt{\lambda_s^2 + \tan^2 \alpha}) \quad (11)$$

$$H = \left[\left(\frac{\lambda_s}{1 - \lambda_s} \frac{C_1}{\mu F_z} \right)^2 + \left(\frac{1}{1 - \lambda_s} \frac{C_2}{\mu F_z} \tan \alpha \right)^2 \right]^{\frac{1}{2}} \quad (12)$$

$$F_x = \begin{cases} \frac{\lambda_s C_1}{1 - \lambda_s} & H < \frac{1}{2} \\ \frac{\lambda_s C_1}{1 - \lambda_s} \left(\frac{1}{H} - \frac{1}{4H^2} \right) & H \geq \frac{1}{2} \end{cases} \quad (13)$$

$$F_y = \begin{cases} \frac{C_2 \tan \alpha}{1 - \lambda_s} & H < \frac{1}{2} \\ \frac{C_2 \tan \alpha}{1 - \lambda_s} \left(\frac{1}{H} - \frac{1}{4H^2} \right) & H \geq \frac{1}{2} \end{cases} \quad (14)$$

where μ 、 μ_{peak} are the adhesion coefficient and peak adhesion coefficient, A_s is the shape coefficient of tire, C_1 is the longitudinal stiffness of tire, C_2 is the lateral stiffness of tire, H is a function between parameters.

There is a hysteresis effect in the generation of the lateral force, so the relaxation length τ is introduced to describe the transient characteristics.[22] Then the tire dynamic lateral force can be expressed by the following formula:

$$\dot{F}_y = \frac{v_y}{\tau} [-F_y + \bar{F}_y(\alpha, F_z)] \quad (15)$$

where $\bar{F}_y(\alpha, F_z)$ is the lateral force of the tire model under quasi-static condition.

The construction of the HSRI tire model requires the motion parameters such as α 、 λ_s 、 F_z . The calculation formula of α in [23] are as follows:

$$\alpha_1 = \arctan \frac{v_y + a\gamma}{v_x - \frac{d}{2}\gamma} - \delta \quad (16)$$

$$\alpha_2 = \arctan \frac{v_y + a\gamma}{v_x + \frac{d}{2}\gamma} - \delta \quad (17)$$

$$\alpha_3 = \arctan \frac{v_y - b\gamma}{v_x - \frac{d}{2}\gamma} \quad (18)$$

$$\alpha_4 = \arctan \frac{v_y - b\gamma}{v_x + \frac{d}{2}\gamma} \quad (19)$$

The vertical loads of each wheel are affected by the longitudinal acceleration, the lateral acceleration and the height of COG. The calculation formula is:

$$F_{z1} = \frac{m}{L} \left(\frac{gb}{2} - \frac{a_x h_g}{2} - \frac{a_y h_g b}{d} \right) \quad (20)$$

$$F_{z2} = \frac{m}{L} \left(\frac{gb}{2} - \frac{a_x h_g}{2} + \frac{a_y h_g b}{d} \right) \quad (21)$$

$$F_{z3} = \frac{m}{L} \left(\frac{ga}{2} + \frac{a_x h_g}{2} - \frac{a_y h_g a}{d} \right) \quad (22)$$

$$F_{z4} = \frac{m}{L} \left(\frac{ga}{2} + \frac{a_x h_g}{2} + \frac{a_y h_g a}{d} \right) \quad (23)$$

The wheel slip ratio during driving is as follows:

$$\lambda_s = \frac{\omega R - v_x}{\omega R} \quad (24)$$

4. Parameters Estimation Method Combining Strong Tracking Filter with UKF

4.1 velocity Estimation Principle

The dynamic system of vehicle is a nonlinear dynamic Gaussian system. The state equations of the system can be expressed as follows:

$$\begin{aligned} x(t+1) &= f(x(t), v(t)) + W(t) \\ y(t+1) &= h(x(t), v(t)) + v(t) \end{aligned} \quad (25)$$

where f represents the function of the state equation, h is the observation equation function of the dynamic system, $W(t)$ is the process excitation noise, and it is a Gaussian white noise.

When implementing unscented transformation for Equation (24), the following result can be obtained:

$$x(t) = \begin{bmatrix} v_x \\ v_y \\ \gamma \\ a_x \\ a_y \\ T_z \end{bmatrix}_t = \begin{bmatrix} \bullet \\ v_x \times \Delta t \\ \bullet \\ v_y \times \Delta t \\ \bullet \\ \gamma \times \Delta t \\ 0 \\ 0 \\ 0 \end{bmatrix}_{t-1} + \begin{bmatrix} v_x \\ v_y \\ \gamma \\ a_x \\ a_y \\ T_z \end{bmatrix}_{t-1} + \omega(t) \quad (26)$$

where Δt is the sampling time interval.

In the velocity estimation of DDEV, the state equation and observation equation of the dynamic system as shown in Equations (26) and (27), can be derived from the 7DOF dynamic model and HRSI tire model.

$$\dot{x}(t) = f(x(t), u(t), \omega(t)) = \begin{bmatrix} 0 & \frac{\gamma}{2} & \frac{v_y}{2} \\ -\frac{\gamma}{2} & 0 & \frac{v_x}{2} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} v_x \\ v_y \\ \gamma \end{bmatrix} + \begin{bmatrix} -\frac{F_{y1} + F_{y2}}{m} \\ \frac{F_{x1} + F_{x2}}{m} \\ \frac{a}{I_z}(F_{x1} + F_{x2}) + \frac{d}{2I_z}(F_{y1} - F_{y2}) \end{bmatrix} \delta + \quad (27)$$

$$\begin{bmatrix} \frac{F_{x1} + F_{x2} + F_{x3} + F_{x4}}{m} \\ \frac{F_{y1} + F_{y2} + F_{y3} + F_{y4}}{m} \\ \frac{a(F_{y1} + F_{y2}) - b(F_{y3} + F_{y4})}{I_z} - \frac{d(F_{x1} - F_{x2}) - d(F_{x3} - F_{x4})}{2I_z} \end{bmatrix} + \omega(t) \quad (28)$$

$$y(t) = h(x(t), t) + v(t) = [a_y \quad \gamma]^T + \Gamma(t)$$

The state variables observed by the observer are longitudinal velocity, lateral velocity, lateral force of four wheels and yaw rate. The state variables measured by the observer are longitudinal acceleration, lateral acceleration and yaw rate. Therefore, q and w can be used to represent the observed state variables and the measured state variables respectively in the velocity estimation method. Their expressions are as follows:

$$q = [v_x \quad v_y \quad \gamma \quad F_{y1} \quad F_{y2} \quad F_{y3} \quad F_{y4}]^T = [q_1 \quad q_2 \quad q_3 \quad q_4 \quad q_5 \quad q_6 \quad q_7]^T \quad (29a)$$

$$w = [a_x \quad a_y \quad \gamma]^T = [w_1 \quad w_2 \quad w_3]^T \quad (29b)$$

In the velocity estimation method, the driving torque, motor speed and front wheel angle can be easily measured. Therefore, the input variables are defined as u , and its expression is as follows:

$$u = [\delta \quad \omega_1 \quad \omega_2 \quad \omega_3 \quad \omega_4 \quad T_1 \quad T_2 \quad T_3 \quad T_4]^T = [u_1 \quad u_2 \quad u_3 \quad u_4 \quad u_5 \quad u_6 \quad u_7 \quad u_8 \quad u_9]^T \quad (30)$$

The above formula is simplified by the vehicle estimation model (7 DOF model and HSRI tire model), which results in:

$$\begin{cases} \dot{q}_1 = [u_2 \cos(u_1) - q_4 \sin(u_1) + u_3 \cos(u_1) - q_5 \sin(u_1) + u_4 + u_5] / m + q_3 q_2 \\ \dot{q}_2 = [u_2 \sin(u_1) - q_4 \cos(u_1) + u_3 \sin(u_1) - q_5 \cos(u_1) + q_6 + q_7] / m - q_3 q_1 \\ \dot{q}_3 = \left\{ a[u_2 \sin(u_1) + q_4 \cos(u_1) + u_3 \sin(u_1) - q_5 \cos(u_1)] - \frac{d}{2}[u_3 \cos(u_1) - q_5 \sin(u_1) \right. \\ \quad \left. - u_2 \cos(u_1) + q_4 \sin(u_1)] - b(q_6 + q_7) + \frac{d}{2}(u_5 - u_4) \right\} I_z \\ \dot{q}_4 = \frac{v_y}{\tau_1} [-q_4 + \bar{F}_{y1}(\alpha_1, F_{z1})] \\ \dot{q}_5 = \frac{v_y}{\tau_2} [-q_5 + \bar{F}_{y2}(\alpha_2, F_{z2})] \\ \dot{q}_6 = \frac{v_y}{\tau_3} [-q_6 + \bar{F}_{y3}(\alpha_3, F_{z3})] \\ \dot{q}_7 = \frac{v_y}{\tau_4} [-q_7 + \bar{F}_{y4}(\alpha_4, F_{z4})] \\ \begin{cases} w_1 = \gamma = q_3 \\ w_2 = a_x = u_2 \cos(u_1) - q_4 \sin(u_1) + u_3 \cos(u_1) - q_5 \sin(u_1) + u_4 + u_5 \\ w_3 = a_y = u_2 \sin(u_1) - q_4 \cos(u_1) + u_3 \sin(u_1) - q_5 \cos(u_1) + q_6 + q_7 \end{cases} \end{cases} \quad (31)$$

$$\begin{cases} w_1 = \gamma = q_3 \\ w_2 = a_x = u_2 \cos(u_1) - q_4 \sin(u_1) + u_3 \cos(u_1) - q_5 \sin(u_1) + u_4 + u_5 \\ w_3 = a_y = u_2 \sin(u_1) - q_4 \cos(u_1) + u_3 \sin(u_1) - q_5 \cos(u_1) + q_6 + q_7 \end{cases} \quad (32)$$

The traditional UKF method has the problems of insufficient adaptive ability and poor robustness when the vehicle state changes sharply and the system model mismatches.[24] Therefore, the strong tracking filtering(STF) theory[25,26]is introduced to UKF to improve the performance of the estimation algorithm.

4.2 Algorithm steps

Step 1: Selection of sampling points and initialization of the mean and covariance.

a). Selecting $2n+1$ sampling points to form a sigma point set, and letting $\bar{X}$ 、 P respectively represent the mean and covariance of the sampling points.

$$\bar{X}_0 = E[x_0] \quad \bar{P}_0 = E[(x_0 - \bar{X}_0)(x_0 - \bar{X}_0)^T] \quad (33)$$

$$\begin{cases} X^{(0)} = \bar{X}_i, \quad i = 0 \\ X^{(i)} = \bar{X}_i + (\sqrt{(n + \lambda)P})_i, \quad i = 1 \sim n \\ X^{(i)} = \bar{X}_i - (\sqrt{(n + \lambda)P})_i, \quad i = n + 1 \sim 2n \end{cases} \quad (34)$$

where n represents the dimension of the sampling points, λ is the scaling parameter of the sampling point set, $\lambda = \varepsilon^2(n + \kappa) - n$, ε denotes the distribution state parameter of the sampling points, κ is the parameter to be selected.

b). Calculating the weights of each sample point in the sigma point set:

$$\begin{cases} N_m^{(0)} = \frac{\lambda}{n + \lambda}, & i = 0 \\ N_c^{(0)} = \frac{\lambda}{n + \lambda} + (1 - \varepsilon^2 + \beta), & i = 0 \\ N_m^{(i)} = N_c^{(i)} = \frac{\lambda}{2(n + \lambda)}, & i = 1 \sim 2n \end{cases} \quad (35)$$

where N_m represent the weights of each sampling point, N_c denote the covariance weights of each sampling point, β is the weight coefficient.

c). Calculating the Sigma point set:

$$X^{(i)}(t|t) = \begin{bmatrix} \hat{X}(t|t) & \hat{X}(t|t) + \sqrt{(n + \lambda) p(t|t)} & \hat{X}(t|t) - \sqrt{(n + \lambda) p(t|t)} \end{bmatrix} \quad (36)$$

Step 2: Calculation of the predicted values of mean and covariance.

a). Calculating the one-step predictions of $2n+1$ Sigma point set.

$$X^{(i)}(t+1|t) = f[t, X^{(i)}(t|t)] \quad (37)$$

b). The one-step predictions of the system state vector can be obtained by weighting the Equation (37).

$$\hat{X}(t+1|t) = \sum_{i=0}^{2n} (N_m^{(i)} X^{(i)}(t+1|t)) \quad (38)$$

$$\hat{P}(t+1|t) = \sum_{i=0}^{2n} N_c^{(i)} [\hat{X}(t+1|t) - X^{(i)}(t+1|t)] [\hat{X}(t+1|t) - X^{(i)}(t+1|t)]^T + Q \quad (39)$$

c). Constructing a new sigma point set.

$$X^{(i)}(t+1|t) = \begin{bmatrix} \hat{X}(t+1|t) & \hat{X}(t+1|t) + \sqrt{(n + \lambda) p(t+1|t)} & \hat{X}(t+1|t) - \sqrt{(n + \lambda) p(t+1|t)} \end{bmatrix} \quad (40)$$

d). By substituting Equation (40) into Equation (27), The predictions of observations will be obtained.

$$Z^{(i)}(t+1|t) = h[X^{(i)}(t+1|t)] \quad (41)$$

e). The predictions of mean and covariance can be obtained by summing the weighted Equation (41).

$$\bar{Z}(t+1|t) = \sum_{i=0}^{2n} (N_m^{(i)} Z^{(i)}(t+1|t)) \quad (42)$$

$$P_{z_{t+1}z_{t+1}} = \sum_{i=0}^{2n} N_c^{(i)} [Z^{(i)}(t+1|t) - \bar{Z}(t+1|t)] [Z^{(i)}(t+1|t) - \bar{Z}(t+1|t)]^T + R \quad (43)$$

$$P_{x_{t+1}z_{t+1}} = \sum_{i=0}^{2n} N_c^{(i)} [X^{(i)}(t+1|t) - \bar{Z}(t+1|t)] [Z^{(i)}(t+1|t) - \bar{Z}(t+1|t)]^T \quad (44)$$

Step 3: Combination of STF and UKF

a) Updating the predictions of mean and covariance by introducing multiple fading sub-optimal factors.

$$\bar{Z}(t+1|t) = \lambda i(t) \sum_{i=0}^{2n} N_m^{(i)} Z^{(i)}(t+1|t) \quad (45)$$

$$P_{x(t+1)z(t+1)} = \lambda i(t) \sum_{i=0}^{2n} N_c^{(i)} [X^{(i)}(t+1|t) - \bar{Z}(t+1|t)] [Z^{(i)}(t+1|t) - \bar{Z}(t+1|t)]^T \quad (46)$$

where $\lambda i(t)$ are the multiple fading sub-optimal factors.

$$\lambda i(t) = \text{diag}[\lambda 1(t), \lambda 2(t), \dots, \lambda n(t)], \lambda i(t) \geq 1. \quad (47)$$

b). By calculating the errors of the predictions of mean and covariance, and the following result can be obtained.

$$\Delta \hat{Z}(t+1) = Z(t+1|t) - \hat{Z}(t+1|t) \quad (48)$$

$$\Delta \hat{P}_{x(t+1)z(t+1)} = P_{x(t+1)z(t+1)} - \hat{P}_{x(t+1)z(t+1)} \quad (49)$$

Step 4: Calculation of the predicted error matrix

a). The predictions of mean error matrix and covariance error matrix are shown in equations (49) and (50) respectively.

$$U_{1(t+1)} = \begin{cases} \Delta \hat{Z}(t+1) \bullet \Delta \hat{Z}^T(t+1) & t = 0 \\ \frac{\rho \Delta \hat{Z}(t)}{1 + \rho} + \frac{\Delta \hat{Z}(t+1) \bullet \Delta \hat{Z}^T(t+1)}{1 + \rho} & t \geq 1 \end{cases} \quad (50)$$

$$U_{2(t+1)} = \begin{cases} \Delta \hat{P}_{x(t+1)z(t+1)} \bullet \Delta \hat{P}_{x(t+1)z(t+1)}^T & t = 0 \\ \frac{\rho \Delta \hat{P}_{x(t)z(t)}}{1 + \rho} + \frac{\Delta \hat{P}_{x(t+1)z(t+1)} \bullet \Delta \hat{P}_{x(t+1)z(t+1)}^T}{1 + \rho} & t \geq 1 \end{cases} \quad (51)$$

where ρ is the forgetting factor, $\rho \in (0, 1]$

b). By calculating the predictions of mean and covariance based on the STF and UKF, and the following equations can be obtained.

$$\bar{Z}_{-(t+1|t)} = \lambda i(t) \sum_{i=0}^{2n} N_m^{(i)} U_{1(t+1)} \quad (52)$$

$$P_{-x(t+1)z(t+1)} = \lambda i(t) \sum_{i=0}^{2n} N_c^{(i)} U_{2(t+1)} \quad (53)$$

Step 5: Calculation of the gain matrix and update of the system status

a). The Kalman filter gain matrix can be expressed as :

$$K(t+1) = P_{x_k z_k} P_{z_k z_k}^{-1} \quad (54)$$

b). The state update and the covariance update are shown in Equations (54) and (55).

$$\hat{X}(t+1|t+1) = \hat{X}(t+1|t) + K(k+1)[Z(k+1) - \hat{Z}(k+1|k)] \quad (55)$$

$$\hat{P}(t+1|t+1) = \hat{P}(t+1|t) - K(k+1)P_{z_k z_k} K^T(k+1) \quad (56)$$

4.3 Simulation and Analysis

In order to evaluate the proposed estimation method, the strong tracking filtering algorithm (UKF+STF in figures) and the unscented kalman filter algorithm (UKF in figures) are simulated under different road adhesion coefficients. The ‘actual value’ in figures represent the variable values output by Carsim. Table 2 shows the values of the vehicle used for the simulations and experimental test.

Table 2. Specifications of the vehicle.

Symbol	value	Unit
m	830	kg
L	2.36	m
a	1.109	m
b	1.251	m

h_g	0.54	m
d	1.405	m
I_z	1110.9	kg m ²
R	0.33	m
μ_{peak}	0.7	-

The simulation tests for the snake-shaped driving are carried out, in which the vehicle speed is constant at 50km/h and the road adhesion coefficients are set to 0.3 and 0.8 respectively. Figure 4 and Figure 5 show the simulation results of longitudinal velocity and lateral velocity under high and low adhesion coefficients respectively.

Figure 4. The simulation results under high-attachment snake-shaped driving condition

Figure 5. The simulation results under low-attachment snake-shaped driving condition

It can be seen from the above figures that when the vehicle is driving on the road surface with adhesion coefficient of 0.8 at 50 km/h, the maximum and minimum values of the actual lateral velocity are 1.63 km/h and -1.62 km/h. The values estimated by UKF are 1.78 km/h and -1.77 km/h, while the values estimated by the proposed method are 1.68 km/h and -1.66 km/h, which reduces the errors by 0.1 km/h and 0.11 km/h

respectively. In addition, the UKF method fluctuates sharply during the period of 6.5s~7.0s, 8.0s~8.7s, 8.9s~9.8s. The reason is that the UKF method cannot track the change of vehicle velocity in real time during steering. After introducing STF into estimation method, the estimation of lateral velocity remains stable and the estimation error is kept within 3%; In the estimation of longitudinal velocity, the fluctuation period of UKF method is 5.67s~8.34s, and the maximum error is 0.06km/h. However, the STF method has maintained good tracking ability, and kept the error within 0.02 km/h.

When the vehicle is driving on the road surface with adhesion coefficient of 0.3, the maximum and minimum values of the actual lateral velocity are 0.45 km/h and -0.47 km/h. The values estimated by UKF are 0.49km/h and -0.52 km/h, while the values estimated by the proposed method are 0.47 km/h and -0.48 km/h, which reduces the errors by 0.02 km/h and 0.04 km/h respectively. In addition, the UKF method fluctuates sharply during the period of 7.85s~8.47s. The estimated lateral velocity of the STF method follows the actual value closely, and the error is controlled within 0.015 km/h. The longitudinal velocity estimated by UKF method fluctuates sharply from 4.23s to 8.57s, and the maximum error is 0.07 km/h in this phase, which indicates that this method is not stable enough in estimating the velocity under the low-adherence road. However, the proposed estimation method has excellent performance and the error has been kept within 0.02km/h.

The simulation results show that the proposed method can track the change of vehicle velocity in real time under different road adhesion conditions, and the accuracy and anti-interference ability of this method are better than UKF method.

5. Experimental test

5.1 Test Platform Structure

The test prototype car was refitted into distributed electric drive form. Motor parameters are shown in Table 3.

Table 3. Motor parameters

Name	Value	Unit
Rated power	5	kw
Peak power	7.5	kw
Rated Torque/Current	100/45	(N m)/A
Peak Torque/Current	150/65	(N m)/A
Rated speed	480	r/min

The HC'12.MPC0555 control panel that supports the automatic generation of Simulink code is used as the vehicle controller. The steering angle of the vehicle is measured by the steering parameter measuring instrument (Figure 6-a). The current required to control the motor is measured by the signal collection device (Figure 6-b).

The four-wheel speed signals are obtained by four wheel speed sensors mounted at the wheel (Figure 6-c).

As shown in Figure 6-d, the state parameters such as longitudinal velocity and lateral velocity during vehicle driving are measured by the attitude orientation navigator (model: XW-ADU5630), which are used as the actual value and compared with the estimated velocity of the algorithm to verify the validity and accuracy of the vehicle velocity observer.

Figure 6. Signal collection device and its installation form

5.2 Validation process

The test site is dry asphalt pavement (adhesion coefficient is 0.8). Considering the limitation of site size and safety, the test path is set to S-shaped and the vehicle speed is controlled at about 50 km/h. The validity of the vehicle velocity observer is verified by comparing the estimated value of the velocity observer with the actual value measured by the state measurement system.

Figure 7 shows the steering wheel angle signal of the experimental vehicle. The current signals of four in-wheel motors are shown in Figure 8. Figure 9-a and Figure 9-b show the comparisons between the estimated value and actual value of the longitudinal velocity and lateral velocity.

Figure 7. The front wheel angle signal of the experimental vehicle

Figure 8. The current signals of four in-wheel motors

(a) The actual value and estimated value of the longitudinal velocity

(b) The actual value and estimated value of the lateral velocity

Figure 9. The comparisons of longitudinal velocity and lateral velocity

5.3 Results analysis

It is clear that the actual value of longitudinal velocity is 49.98 km/h on average, while the average longitudinal velocity estimated by the velocity observer is 50.02 km/h. The average error during the whole process is 0.024km/h, and the maximum error is 0.03km/h; In the lateral velocity estimation, the average error is 0.016km/h, and the

maximum error is 0.022km/h. Apparently, the estimations of the longitudinal velocity and lateral velocity are much closer to the actual values extracted from the state measurement system, which indicates that the velocity observer has a high estimation accuracy and shows that the observer has real-time tracking ability for the process of frequent direction change of vehicle. In addition, the errors at the peak in the figures are relatively large, which is due to the non-linear tire characteristics during vehicle steering, resulting in the deviation of the velocity estimation model in calculating tire force.

6. Conclusion

Based on the minimum co-simulation system, this paper proposes an algorithm combining UKF and STF to estimate the velocity of DDEVs, which takes the 7-DOF dynamic model and HSRI tire model as estimation models. Compared with the UKF method, the experimental and simulation results illustrate the accuracy and robustness of the proposed algorithm.

The vehicle estimation model contains the vehicle dynamics model and the tire force calculation model, which means that it is difficult to distinguish their contributions to the estimation error. It is recommended that the data-driven intelligent tire model be further developed in order to estimate vehicle parameters more accurately.

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Availability of data and materials

The data used to support the findings of this study are available from the corresponding author upon request.

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Authors' contributions

QS was responsible for the entire trial; QS wrote the manuscript; QS, ZL, and GL assisted with experiments and data analysis. All authors read and approved the final manuscript.

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Competing interests

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Figures

Figure 1

The overall structure of the observation method

Figure 2

Principle of vehicle velocity tracking model

Figure 3

7-DOF vehicle model

Figure 4

The simulation results under high-attachment snake-shaped driving condition

Figure 5

The simulation results under low-attachment snake-shaped driving condition

(a) Steering parameter measuring instrument

(b) Signal collection device

(c) Wheel speed sensor

(d) Attitude orientation navigator

Figure 6

Signal collection device and its installation form

Figure 7

The front wheel angle signal of the experimental vehicle

Figure 8

The current signals of four in-wheel motors

(a) The actual value and estimated value of the longitudinal velocity

(b) The actual value and estimated value of the lateral velocity

Figure 9

The comparisons of longitudinal velocity and lateral velocity