

MULTI-SOURCE INFORMATION-BASED STATE FUSION ESTIMATION FOR DISTRIBUTED ELECTRIC DRIVE VEHICLES

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Abstract

To enhance the accuracy and reliability of state estimation for distributed electric drive vehicles in GNSS-denied and complex terrain environments, this paper innovatively proposes a multi-source information-based state fusion estimation method. The core of the method is a dichotomy based hybrid model data state fusion framework designed to address dual uncertainties in both GNSS signal and terrain. First, a vehicle dynamics model based Cubature Kalman Filter (CKF) is designed. Second, to tackle model mismatch in complex terrain, a vehicle state estimation method based on a Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) network is proposed. In this approach, the CNN is responsible for terrain type recognition, while the LSTM serves as the backbone network to extract nonlinear correlated features from eight types of time series data and compute the model output. Then, to improve the reliability of the estimation algorithm and reduce errors from any single method, a physics-informed trend reference is introduced, which operates independently of absolute ground truth. Using dichotomy logic, the weights of the CKF-based estimate and the CNN-LSTM-based estimator are dynamically adjusted in real time by comparing their respective deviations from this reference. To validate the effectiveness of the proposed method, experiments under four operating conditions were carried out on an eight wheel distributed electric drive vehicle. The results demonstrate that the proposed method effectively improves the estimation accuracy of longitudinal velocity and sideslip angle, as well as the environmental adaptability of the vehicle.

Keywords: multi-source information, cubature Kalman filter, convolutional neural network, long short term memory, dichotomy, state fusion estimation.

1. Introduction

Distributed electric drive vehicles offer high control flexibility, a shortened driveline, compact design, and increased transmission efficiency [1]. Their unique structural layout and propulsion architecture enable significant technological innovations that enhance vehicle stability, increase drive efficiency, and simplify the chassis structure. This creates an ideal platform for advanced chassis-dynamics control systems such as anti-lock braking systems [2], acceleration slip regulation [3], and direct yaw-moment control [4]. Eight-wheel, distributed electric-drive vehicles, primarily

used for enemy reconnaissance, personnel transport, and logistical support, are required to possess robust dynamic control capabilities in complex terrains. Longitudinal velocity and sideslip angle are the most critical state variables for chassis dynamics control. Therefore, accurate and reliable measurement of these parameters is essential. However, in environments without *global navigation satellite system* (GNSS), accurate positional information is unavailable, making inertial navigation systems inadequate for precisely estimating longitudinal velocity and sideslip angle.

The commonly used vehicle state estimation methods can be categorized into dynamics model-based estimation methods [5–7], kinematics model-based estimation methods [8, 9], neural network-based estimation methods [10–12]. However, a single state estimation algorithm may encounter issues such as initial noise parameter uncertainty or mathematical model parameter uncertainty during actual estimation [13, 14].

To improve robustness, researchers have integrated diverse estimators to utilize algorithmic redundancy. Chen *et al.* [15] combined a dynamic-model-based strong-tracking filter with a kinematic-model-based ridge estimator through iterative error compensation to estimate velocity and sideslip angle. Wang *et al.* [16] introduced the *moving polynomial Kalman smoother* (MPKS) method, which combines the Savitzky-Golay filter with Kalman filtering to enhance signal conditioning and phase properties. Next, they proposed a hybrid sideslip estimator that combines a dynamic-model-based robust unscented Kalman filter and a kinematic-model-based extended Kalman filter. Liu *et al.* [17] used a genetic algorithm-optimized BP neural network to adaptively correct the global error of an unscented Kalman filter, reducing estimation anomalies. Li *et al.* [18] developed a physics-data hybrid sideslip estimator where a deep neural network approximates the nonlinear mappings not captured by the physical model, ensuring accurate and reliable estimation. Xia *et al.* [19] proposed an adaptive weighted fusion of dynamic and kinematic estimators for estimating the sideslip angle. Importantly, these fusion schemes mainly depend on mathematically similar models, increasing structural complexity, computational load, and issues related to algorithmic homogeneity.

On one hand, when lateral tire forces stay within their linear limits, model-based filters achieve high estimation accuracy. However, accuracy drops once the tire force moves into the nonlinear zone [20, 21]. Additionally, unknown biases in measured lateral acceleration can cause errors in loop and accumulation [22]. Conversely, kinematic-model-based filters avoid these problems, but the wheel speed signal affected by tire forces has an inherent delay, which prevents quick feedback of vehicle dynamics. Furthermore, distributed electric drive vehicles lack non-driven wheels and often experience wheel slip, making it impossible to determine the actual longitudinal velocity directly from wheel speed. As a result, during extreme manoeuvres or wheel slip events, the vehicle system and its components display significant time-varying nonlinearities and strong coupling, making both dynamic and kinematic approaches inadequate.

On the other hand, current deep learning-based state estimators fail to account for terrain influences and typically assume centralized vehicle architectures, making them unsuitable for distributed electric drive platforms [23]. Moreover, their reliance on limited training data often leads to overfitting, resulting in unstable or unreliable estimation results.

The special contributions of this paper are listed below:

- (i) To address the problem of model mismatch of distributed electric drive vehicles in GNSS-denied and complex terrain, we propose a *convolutional neural network - long short term memory* (CNN-LSTM) based state estimation method. The CNN is responsible for terrain type recognition, while the LSTM serves as the backbone network to extract nonlinear correlation features from eight types of time-series data and compute the model outputs.

Step 2: Generate cubature points

$$\chi_{i,k} = \widehat{\chi}_{k-1} + S_k \xi_i, \quad i = 1, 2, \dots, 2n_m, \quad (7)$$

where i is the sequence number of the cubature point, n_m is the dimension of the system model, S_k is obtained by performing Cholesky decomposition on $P_{k/k}$ with the condition $P_{k/k} = S_k S_k^T$, and ξ_i stands for the cubature point.

Step 3: Time update. The propagation of cubature points can be expressed as

$$\chi_{i,k+1|k} = f(\chi_{i,k}).$$

The one-step state prediction equation can be expressed as

$$\widehat{x}_{k+1|k} = \frac{1}{2n_m} \sum_{i=1}^{2n_m} \chi_{i,k+1|k}, \quad (8)$$

$$P_{k+1|k} = \frac{1}{2n_m} \sum_{i=1}^{2n_m} \chi_{i,k+1|k} \chi_{i,k+1|k}^T - \widehat{x}_{k+1|k} \widehat{x}_{k+1|k}^T + Q_k, \quad (9)$$

where Q_k represents the covariance matrix of the system noise.

Step 4: Measurement update. The covariance matrix of the measurement prediction results and the cross-covariance matrix can be respectively expressed as

$$P_{z,k+1|k} = \frac{1}{2n_m} \sum_{i=1}^{2n_m} y_{i,k+1|k} y_{i,k+1|k}^T - \widehat{y}_{k+1|k} \widehat{y}_{k+1|k}^T + R_k, \quad (10)$$

$$P_{xz,k+1|k} = \frac{1}{2n_m} \sum_{i=1}^{2n_m} \widehat{x}_{i,k+1|k} y_{i,k+1|k}^T - \widehat{x}_{k+1|k} \widehat{y}_{k+1|k}^T, \quad (11)$$

where R_k represents the covariance matrix of measurement noise, $P_{k+1|k}$ represents the Cholesky decomposition, $\widehat{\chi}_{i,k+1|k}$ represents the cubature points, $y_{i,k+1|k}$ and $\widehat{y}_{k+1|k}$ represent the propagation and predicted measurement of cubature points. The prediction error of $\varepsilon_{k+1|k} = y_{k+1} - \widehat{y}_{k+1|k}$ can be obtained by calculating the difference between the actual measurement value and the predicted measurement value, where y_{k+1} represents the actual measurement value at the $k+1$ sampling instant, $\widehat{y}_{k+1|k}$ is the predicted measurement value at the $k+1$ sampling instant.

The Kalman gain is given by $K_{k+1} = P_{xz,k+1|k} P_{z,k+1|k}^{-1}$. The estimated vehicle state vector is given by $\widehat{x}_{k+1} = \widehat{x}_{k+1|k} + K_{k+1} (y_{k+1} - \widehat{y}_{k+1|k})$. The error-covariance matrix of the state estimate is expressed as $P_{k+1} = P_{k+1|k} - K_{k+1} P_{z,k+1|k} K_{k+1}^T$.

Although distributed electric drive eight-wheel vehicles exhibit complex multi-axle coupling and nonlinear dynamic characteristics, a simplified model is employed here based on the following considerations:

- (i) The model provides a computationally efficient and physically interpretable baseline for state estimation.
- (ii) Complex dynamics not captured by this model will be compensated and learned by the subsequently proposed CNN-LSTM-based state estimator.

Based on the 2-DOF vehicle dynamics model, the discrete-time state equation is formulated as

$$\begin{cases} \beta_{k+1} = \beta_k + \left(-\frac{\sum_{i=1}^4 K_i}{mv_x} \beta_k - \left(\frac{\sum_{i=1}^4 L_i K_i}{mv_x^2} + 1 \right) \gamma_k + \frac{K_1}{mv_x} \delta_{1,k} + \frac{K_2}{mv_x} \delta_{2,k} \right) T + w_k \\ \gamma_{k+1} = \gamma_k + \left(-\frac{\sum_{i=1}^4 L_i K_i}{I_z} \beta_k - \frac{\sum_{i=1}^4 L^2_i K_i}{I_z v_x} \gamma_k + \frac{L_1 K_1}{I_z} \delta_{1,k} + \frac{L_2 K_2}{I_z} \delta_{2,k} \right) T + w_k \\ v_{x,k+1} = v_{x,k} + (a_{x,k} + \gamma_k \beta_k v_{x,k}) T + w_k \end{cases}, \quad (12)$$

where T represents the sampling period of the Kalman filter.

For distributed electric drive vehicles, where each wheel serves as an independently torque-controlled driving unit, the propensity for drive slip is notably high, causing wheel speed measurements to deviate substantially from the actual vehicle velocity. Under such conditions, wheel speeds cannot be relied upon as a valid observable for characterizing the vehicle's overall motion state. Even when tire forces enter the nonlinear region, the lateral acceleration acquired from an inertial measurement unit, though subject to an unknown bias, can be processed through a filtering approach to obtain a reliable estimate [26]. Therefore, to ensure the robustness of the observer under both tire nonlinear and wheel slip conditions, lateral acceleration is selected as the observation input to the dynamic model.

The discretized form of the measurement update equation for the dynamic model estimator can be expressed as

$$a_y = \dot{v}_y + v_x \gamma = \beta v_x + v_x \gamma = -\frac{\sum_{i=1}^4 K_i}{m} \beta - \frac{\sum_{i=1}^4 L_i K_i}{mv_x} \gamma + \frac{K_1}{m} \delta_1 + \frac{K_2}{m} \delta_2 + v_k, \quad (13)$$

where $\mathbf{x}_{k+1} = [\beta_{k+1} \quad \gamma_{k+1} \quad v_{x,k+1}]^T$ represents the state vector, $\mathbf{y}_k = [a_{y,k}]$ represents the measurement vector, $\mathbf{u}_k = [\delta_{f,k} \quad a_{x,k}]^T$ represents the known input vector.

The linear tire model used in the CKF estimator is intended to ensure a stable and observable system structure for state estimation. This simplification prioritizes real-time performance, parametric robustness, and baseline effectiveness under normal conditions, but it does not become a performance bottleneck for the proposed framework. Hence, a CNN-LSTM-based state estimation is introduced which operates independently of specific tire model assumptions. It is capable of directly learning the full-vehicle dynamic mapping from historical operational data.

3. CNN-LSTM-based state estimation

3.1. Model framework

Although joint estimation of vehicle states and road tire friction has been shown to improve accuracy [27, 28], its convergence exhibits a noticeable delay during transient manoeuvres, failing to meet real-time requirements. To address this issue, we innovatively introduce a prior road-surface perception mechanism that combines real-time forward-looking terrain features, aiming to improve both the dynamic response and the estimation accuracy of the state estimation system.

Vehicle dynamic states are inherently temporal sequences. As a variation of a recurrent neural network, the LSTM is specifically designed for sequential data. It not only offers strong nonlinear modelling capabilities but also mitigates the vanishing and exploding gradient problems found

in traditional *recurrent neural networks* (RNNs) [29]. These features make LSTM particularly suitable for modelling dynamics under various adhesion conditions. Therefore, it serves as the primary architecture for state-parameter estimation in this study.

We have innovatively proposed a CNN-LSTM-based state estimation framework, as shown in Fig. 3. The operation process of this framework is divided into three stages. First, forward-looking road images captured by on-board vision sensors are processed by a CNN for feature extraction and classification, yielding a real-time terrain-type label. Second, a temporal feature vector is constructed by concatenating the current and the preceding three-time steps of vehicle dynamic observations with the corresponding terrain label. This vector is then fed into an LSTM. Finally, an encoder-decoder LSTM structure is designed to model temporal dependencies, enabling the accurate estimation of the vehicle's sideslip angle and longitudinal velocity.

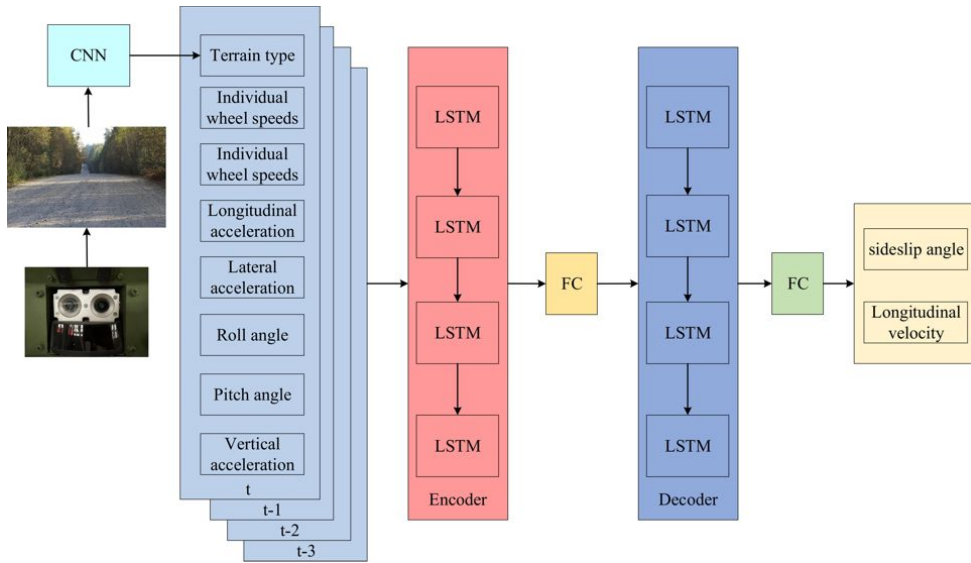


Fig. 3. CNN-LSTM-based state estimation architecture.

3.2. CNN-based terrain type classification

As shown in Table 1, distinct terrain types exhibit specific relationships with friction coefficients and road roughness classes [30]. The friction coefficient range for terrain types is referenced from [31], which reports typical values under various tire-road conditions. In this study, terrain type is identified through on-board vision sensors, which naturally incorporate the effects of both adhesion and roughness into the LSTM. This approach enables the network to effectively understand how different road characteristics influence vehicle dynamic responses.

As a deep-learning architecture, CNN outperforms traditional image-recognition methods by automatically extracting distinctive features from raw images through layered convolution and pooling operations. At the same time, its parameters are refined iteratively via back-propagation. Additionally, sparse connectivity and weight sharing among neurons significantly decrease computational demands. As a result, this study develops a CNN to classify four types of terrain with the identification process shown in Fig. 4. The CNN architecture includes thirteen convolutional layers, five pooling layers, three fully connected layers, and a Softmax output layer.

Table 1. Terrain type correspondence to friction coefficient and road roughness level.

Terrain Type	Friction coefficients	Road roughness classes
Dry asphalt	0.7–1.0	A, B, C, D
Wet asphalt	0.3–0.5	A, B, C, D
Gravel	0.4–0.7	D, E
Grass	0.3–0.5	C, D

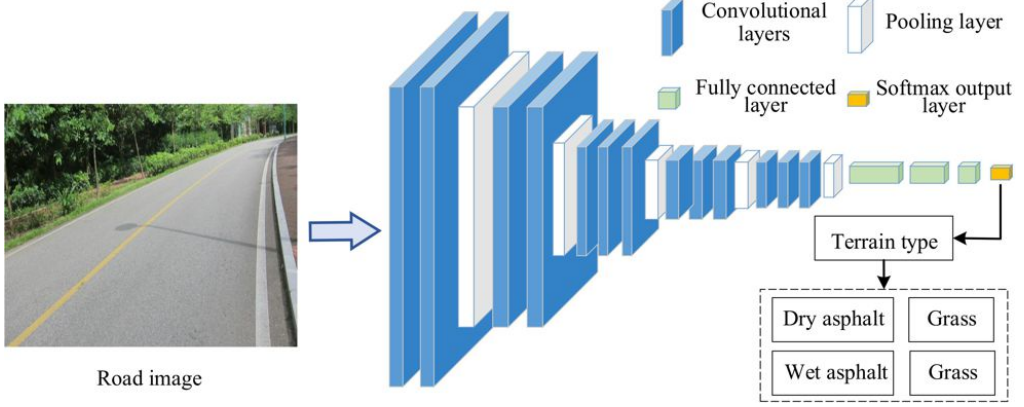


Fig. 4. Terrain type identification pipeline.

To mitigate state estimation inaccuracies arising from terrain transitions, an image s^t is acquired from the on-board camera for each spatial location (x^t, y^t) at time step t . Consequently, the set $S^t = \{s^t, 0 < t < T_{obs}\}$ is fed into the CNN to encode terrain-type information over a temporal window and is subsequently concatenated with available vehicle measurements to construct a sequential feature vector.

3.3. Vehicle state estimation method

Based on the vehicle dynamic and kinematic models, the functional relationships between the sideslip angle, longitudinal velocity, and measurable quantities can be expressed as

$$[\beta, v_x] = f[\delta_1, n_{ij}, a_x, a_y], \quad (14)$$

where n_{ij} is the wheel-speed information for each wheel.

As the terrain-type classification result does not incorporate road-elevation variations, relying solely on this label together with the relationship expressed in (14) inevitably compromises state estimation accuracy when the vehicle traverses complex topographies such as puddles, haystacks, uphill/downhill sections, or side slopes. To address this limitation, the study exploits all available multi-source measurements by incorporating roll angle, pitch angle, and vertical acceleration into a refined estimation model, yielding

$$[\beta, v_x] = f[\delta_1, n_{ij}, a_x, a_y, \psi, \theta, z_a, \varepsilon], \quad (15)$$

where ψ is roll angle, θ is pitch angle, z_a is vertical acceleration, and ε is terrain type.

The state estimation module uses an encoder–decoder dual-LSTM setup that works on three levels. First, the encoder LSTM compresses the sequences of terrain-type features, extracted by the CNN, along with the vehicle’s past observable states into a fixed-size context vector that keeps long-term memory. Next, this context vector goes through a nonlinear spatial transformation via a fully-connected layer to produce a high-dimensional feature set. Finally, the decoder LSTM picks out the important information from the context vector and provides precise estimates of key vehicle states through a regression output layer. This multi-level structure allows for effective fusion of environmental and vehicle dynamic features over space and time.

The model computation proceeds as follows:

$$\left\{ \begin{array}{l} r_t = [\delta_1, n_{ij}, a_x, a_y, \psi, \theta, z_a, \varepsilon]_t \\ R_t = \{X_t, \dots, X_{t-4}\} \\ o_1 = F_{\text{LSTM1}} \left(\mathbf{W}_{\text{LSTM1}}^T, \mathbf{b}_{\text{LSTM1}}, R_t \right) \\ o_2 = \mathbf{W}_{\text{FC1}}^T o_1 + \mathbf{b}_{\text{FC1}} \\ o_3 = F_{\text{LSTM2}} \left(\mathbf{W}_{\text{LSTM2}}^T, \mathbf{b}_{\text{LSTM2}}, o_2 \right) \\ \begin{bmatrix} \beta \\ v_x \end{bmatrix} = \mathbf{W}_{\text{FC2}}^T o_3 + \mathbf{b}_{\text{FC2}} \end{array} \right., \quad (16)$$

where r_t is the concatenated vector of observable vehicle states and terrain-type features, R_t represents the data sequence across multiple consecutive time steps, $\mathbf{W}_{\text{LSTM1,2}} \in (w_i, w_f, w_g, w_o)$ and $\mathbf{W}_{\text{LSTM1,2}} \in (w_i, w_f, w_g, w_o)$ are the gate coefficients for the two LSTM layers, $\mathbf{W}_{\text{FC1,2}}$ and $\mathbf{b}_{\text{FC1,2}}$ are the weight matrices of the two fully-connected layers, o_1 , o_2 , and o_3 are the outputs of the respective network layers, F_{LSTM} is the LSTM cell function.

To enhance estimation accuracy and prevent overfitting, the encoder and decoder in the state-estimation output module each employ a four-layer stacked LSTM-4 architecture, with a 0.2 dropout rate between layers and 128 hidden units per layer. The Adam optimizer is adopted, with an initial learning rate $\alpha = 0.001$ and a decay factor of 0.9.

To reduce training complexity and accelerate convergence, both the CNN and the CNN-LSTM models adopt the L2 loss function, formulated as

$$L = \frac{1}{N} \sum_{i=1}^N (Y_i - f(r_t))^2. \quad (17)$$

In the expression, N is the size of the training dataset. Within the CNN, Y_i represents the ground-truth terrain class, whereas $f(r_t)$ is the network-predicted terrain class. In the CNN-LSTM network, Y_i are the ground-truth values of sideslip angle and longitudinal velocity, and $f(r_t)$ are the corresponding model-predicted values.

3.4. Model training

Dynamic data were collected from the eight-wheel distributed electric drive unmanned ground vehicle under differential-GNSS conditions on four terrain types. Pitch, roll, vertical, longitudinal, and lateral accelerations, together with the ground-truth longitudinal velocity, were obtained from an integrated inertial navigation system; individual wheel speeds were measured by wheel encoders, and front-wheel steering angles by steering-wheel sensors. The vehicle network and bus architecture are illustrated in Fig. 5.

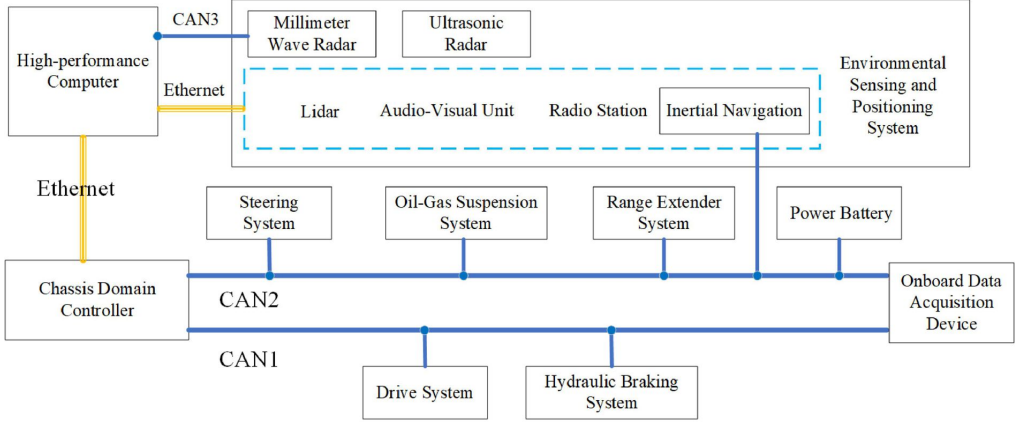


Fig. 5. Vehicle network and bus architecture.

The ground-truth vehicle sideslip angle is computed as

$$\beta = \arctan \frac{v_{\text{real}_y}}{v_{\text{real}_x}}, \quad (18)$$

where $V_X = v_{\text{real}_x} \cos \rho - v_{\text{real}_y} \sin \rho$ and $V_Y = v_{\text{real}_x} \sin \rho + v_{\text{real}_y} \cos \rho$ are the east and north velocity components provided by the integrated inertial navigation system, v_{real_x} and v_{real_y} represent the ground-truth longitudinal and lateral vehicle velocities after coordinate transformation, v_{real_y} is the vehicle yaw angle.

Dry concrete, wet concrete, grass, and gravel roads were selected as test surfaces. To simulate the complex longitudinal-lateral coupled motion in real driving, the operating conditions were categorized into three modes based on longitudinal speed profiles: acceleration, deceleration, and acceleration followed by deceleration. In the turning scenarios, different front-wheel steering angles were applied while coupling the aforementioned three longitudinal speed change patterns, thereby covering combined dynamics such as accelerating or decelerating during a turn, as shown in Table 2.

Table 2. Training samples.

Driving condition	Longitudinal velocity (km/h)		
	Uniform acceleration	Uniform deceleration	Variable acceleration/deceleration
Straight-line driving	0–70	70–0	0–70–0
Cornering manoeuvre	0–70	70–0	0–70–0

We collected 300 independent driving sequences for each road surface, each corresponding to a complete scenario. To prevent temporal data leakage and ensure rigorous evaluation of generalization, the dataset was partitioned at the sequence level rather than by individual samples. Specifically, 210 sequences (70%) were used for training, 60 sequences (20%) for validation, and the remaining 30 sequences (10%) were reserved for testing. As shown in Fig. 6, the loss function stabilizes at approximately 7 after 5,000 iterations, indicating favourable convergence behaviour. Meanwhile, the accuracy on the test set progressively converges to 98.8% as training progresses, demonstrating the model's strong feature learning capability and satisfactory generalization performance on previously unseen driving sequences.

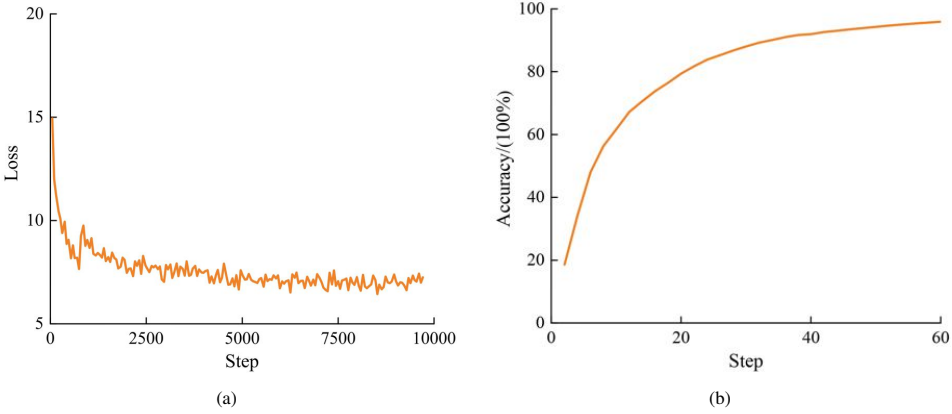


Fig. 6. Loss a) and accuracy b) curves.

4. Dichotomy-based vehicle state fusion estimation

To counteract the transient accuracy drift inherent in single-estimator schemes, this study proposes a dichotomy-based fusion framework illustrated in Fig. 1. The architecture consists of two parallel estimators: a model-driven estimator based on the CKF and a data-driven estimator built on the CNN-LSTM. Each estimator independently provides state variables which are then compared against a theoretically derived reference trend from vehicle dynamics. Specifically, the deviation between each estimate and the trend baseline value is calculated, and the dichotomy is used to convert the relative deviation ratios into dynamic weighting coefficients in real time. This adaptive weight-allocation mechanism continuously adjusts the contribution of each estimator based on its current performance, effectively reducing transient errors and significantly improving the robustness of the overall estimation system.

4.1. Construction and validity analysis of trend baseline values

The dichotomous weight allocation mechanism adjusts weights based on the deviation between the output of each estimation algorithm and the baseline value. Therefore, the benchmark value must accurately represent the true trend of the state parameters [32]. The state trend baseline value derived from vehicle dynamics theory offers the following advantages: (i) it can accurately reflect the theoretical evolution pattern of the state parameter, and (ii) it is unaffected by uncertainties in model parameters and has a definite mathematical formulation. Consequently, this study selects the trend baseline value based on vehicle dynamics as the reference baseline for the dichotomous method.

The a_x and a_y measured by the IMU undergo low-pass filtering and bias compensation [23], resulting in pre-processed signals $\tilde{a}_x$ and $\tilde{a}_y$.

The reference values for longitudinal velocity and sideslip angle are expressed as

$$v_x = v_0 + \int a_x dt, \quad \beta = \beta_0 + \int \left(\frac{a_y}{v_x} - \dot{\omega}_r \right) dt. \quad (19)$$

At discrete time step k , (32) is discretized to obtain:

$$v_x(k) = v_x(k-1) + \tilde{a}_x \Delta t, \quad \beta(k) = \beta(k-1) + \frac{\tilde{a}_y \Delta t}{v_x(k)} - \frac{\omega_r(k) - \omega_r(k-1)}{\Delta t}. \quad (20)$$

Over short durations and in non-extreme terrain, acceleration bias components induced by road inclination are predominantly slowly-varying or approximately constant. The error introduced by integrating such a constant bias leads to a systematic offset when computing the deviation of each estimator from the same baseline. Because this offset is identical for both estimators, its influence is largely cancelled when comparing which estimator is closer to the baseline in relative terms. Hence, the absolute accuracy of the baseline is not critical to the fusion strategy; rather, physical consistency and its property as a common reference for both estimators are the keys to the effectiveness of the weighting logic. This design makes the fusion strategy robust to errors in the absolute reference value.

4.2. Dichotomous weight allocation mechanism

The schematic of the dichotomy-based fusion estimator is depicted in Fig. 7. At any discrete time step k , let $e_1(k)$ denote the error between Method 1 and the reference value, and $e_2(k)$ the corresponding error for Method 2.

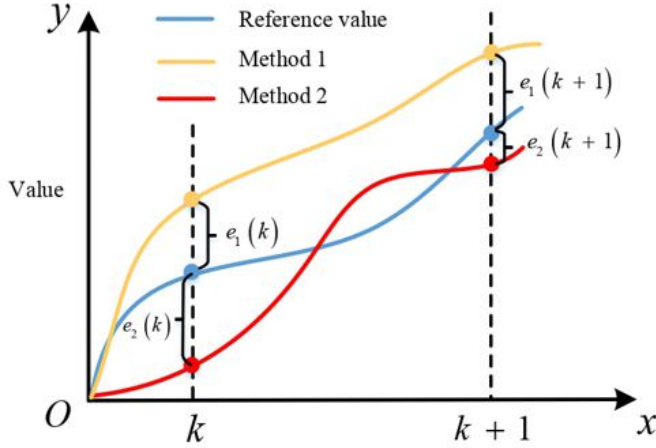


Fig. 7. Schematic of algorithmic fusion estimation based on the dichotomy method.

The dichotomy method is applied to determine the ratio between $e_1(k)$ and $e_2(k)$. This ratio is then converted into weighting coefficients that are assigned to individual estimators, and the current estimate is updated accordingly. The detailed procedure is as follows:

- (i) We obtain the target estimates and the corresponding reference values and calculate the deviation $e_i(k)$ between each estimate and the reference.

$$\begin{cases} e_1(k) = |x_r(k) - \hat{x}_{r1}(k)| \\ e_2(k) = |x_r(k) - \hat{x}_{r2}(k)| \end{cases}, \quad (21)$$

where $x_r(k)$ is the reference value, $\hat{x}_{r1}(k)$ is the estimate from Method 1, $\hat{x}_{r2}(k)$ is the estimate from Method 2.

- (ii) Specify the weight-accuracy tolerance $\uparrow$, initialize the search interval $[a_1, b_1]$ for the weight, and set the midpoint $[a_1, b_1]$, with $c_1 = \frac{a_1 + b_1}{2}$.

- (iii) When the search interval precision satisfies $|a_i - b_i| > \downarrow$, the dichotomy search method is initiated. This process is repeated until the weight accuracy reaches the prescribed tolerance, and output the weight assigned to the algorithm exhibiting the larger estimation error at that instant. The search flowchart is illustrated in Fig. 8.

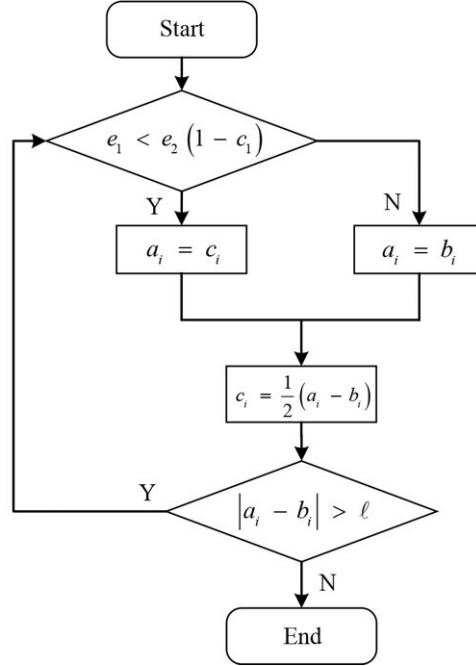


Fig. 8. Dichotomy-search flowchart.

Suppose that at time step k the deviation between Method 1 and the reference exceeds that of Method 2. The weight expressions for the respective estimators are formulated as

$$\begin{cases} \gamma(k) = \lim_{|a_i - b_i| \rightarrow \downarrow} \frac{|x_r(k) - \hat{x}_{r2}(k)|}{|x_r(k) - \hat{x}_{r1}(k)|} \\ \sigma(k) = 1 - \gamma(k) \end{cases} \quad (22)$$

The fused estimate is given by

$$y(k) = \gamma(k)\hat{x}_{r1}(k) + \hat{x}_{r2}(k)\sigma(k), \quad (23)$$

where $y(k)$ is the final estimate at time step k .

5. Experimental validation on real vehicle

We conducted experiments with three typical operational scenarios using an eight-wheel distributed electric drive unmanned vehicle: a low-speed double-lane-change on off-road terrain, a high-speed double-lane-change on dry asphalt, and a medium-speed double-lane-change on wet asphalt, as illustrated in Fig. 9. Three state estimation methods are benchmarked: the CKF-based estimator (denoted as CKF), the CNN-LSTM-based estimator (denoted as CNN-LSTM), and the proposed fusion estimator (denoted as Proposed). Key vehicle parameters are listed in Table 3.

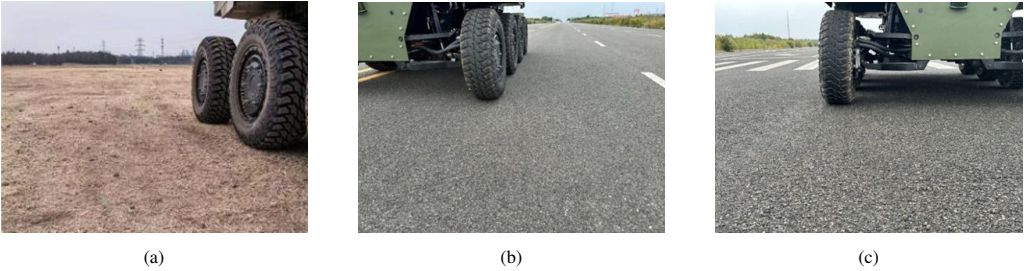


Fig. 9. Driving conditions: a) off-road terrain, b) dry asphalt, c) wet asphalt.

Table 3. Key vehicle parameters.

Parameters	Value
Total mass (kg)	4130
Track width (m)	2.15
Tire radius (m)	0.41
Yaw moment of inertia around the z-axis (kg·m ²)	5935

5.1. Low-speed double-lane-change on off-road terrain

Figure 10 presents experimental results on off-road terrain and Table 4 contains vehicle state parameter errors. It can be observed that during the period of 0–2.6 s, in response to the fluctuation in the estimated sideslip angle caused by acceleration noise in CKF at low speeds, the algorithm rapidly adjusts the weight of CNN-LSTM from the initial 0.5 to 0.8, effectively suppressing the early estimation error. During 7.3–8.2 s, when CNN-LSTM deviates due to inputs exceeding the training set range, the weight decreases sensitively to 0.6, thereby increasing the contribution of the CKF to avoid following erroneous estimates. From 9 to 11 s, when the drastic changes in lateral and longitudinal accelerations lead to a mismatch in the sideslip stiffness model of CKF, the weight further increases to 0.88, reinforcing the dominant role of the CNN-LSTM. The proposed fusion method reduces the root-mean-square error of sideslip angle estimation by 55.10% compared to CKF and by 40.54% compared to CNN-LSTM, while longitudinal velocity accuracy is enhanced by 66.90% and 56.94%.

Table 4. Vehicle state parameter errors.

Vehicle state parameters	Estimation method	Root-mean-square error
Sideslip angle (rad)	CKF	0.0049
	CNN-LSTM	0.0037
	Proposed	0.0022
Longitudinal velocity (km/h)	CKF	0.8102
	CNN-LSTM	0.5332
	Proposed	0.3488

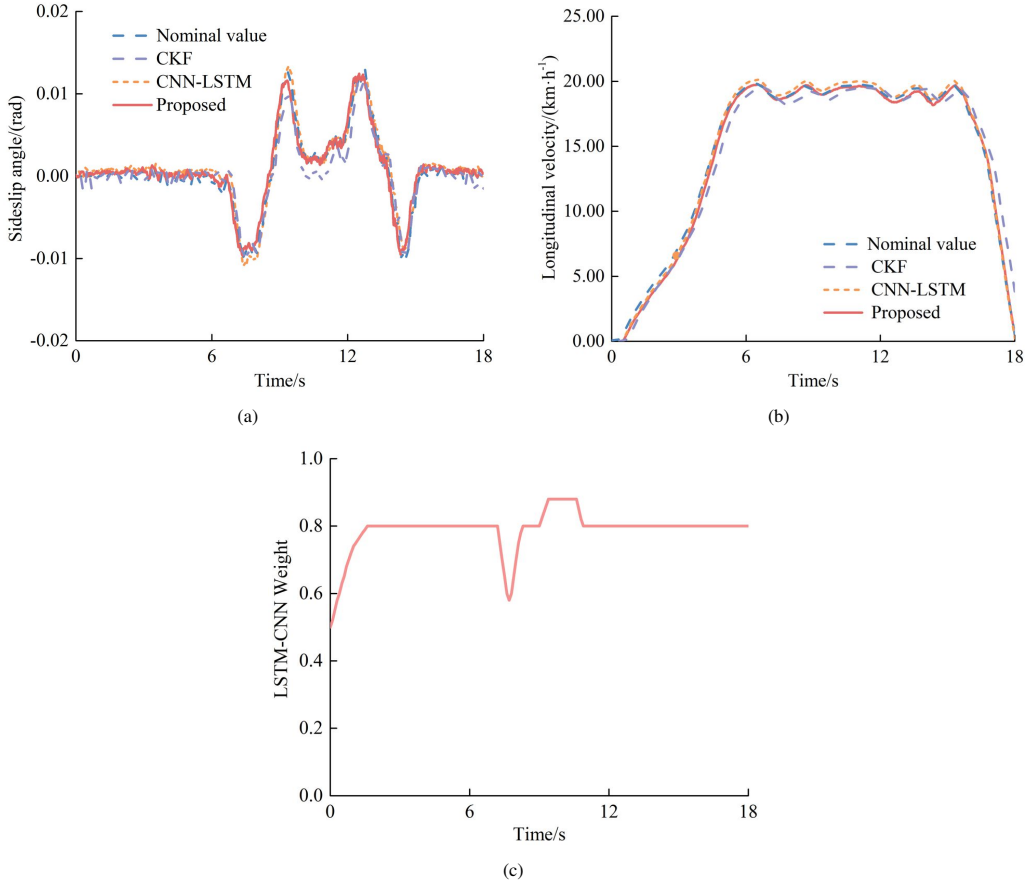


Fig. 10. Experimental results: a) sideslip angle, b) longitudinal velocity, c) CNN-LSTM weight.

5.2. High-speed double-lane-change on dry asphalt

Figure 11 presents experimental results on dry asphalt and Table 5 contains vehicle state parameter errors. CKF yields estimates with considerable deviations which stem from its fixed filtering parameters that lack adaptability to diverse operating conditions. The estimates of CNN-LSTM exhibit relatively large errors during the intervals 2.9–3.2 s and 3.8–4.5 s, owing to the absence of steering manoeuvres at the corresponding speeds in the training dataset. Consequently, the model is not well acquainted with the vehicle's dynamic behaviour under such speed conditions. The dichotomy-based fusion strategy responds sensitively by reducing the weighting factors to 0.72 and 0.75, respectively, thereby appropriately increasing the contribution of CKF to compensate for the transient inadequacy of the data-driven model. In terms of root-mean-square error, compared with CKF and CNN-LSTM, the proposed method improves the estimation accuracy of the sideslip angle by 91.04 % and 38.71 %, respectively, and that of the longitudinal velocity by 67.73 % and 44.09 %, respectively.

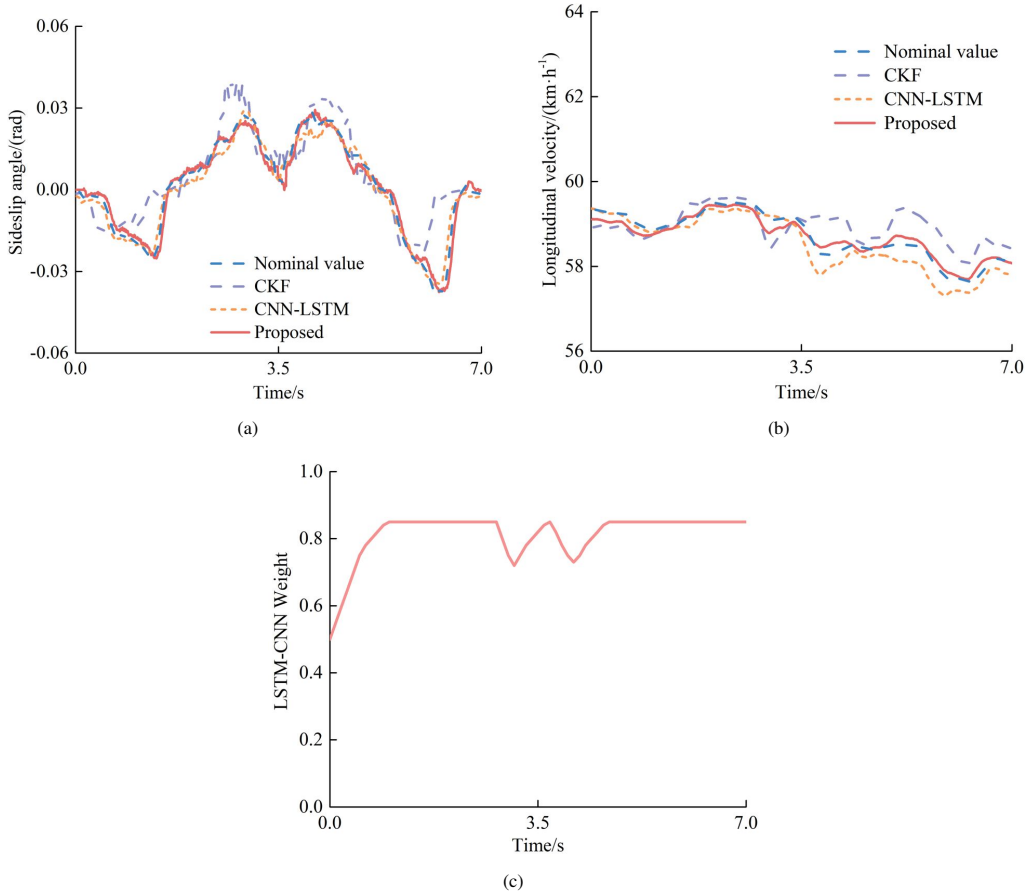


Fig. 11. Experimental results: a) sideslip angle, b) longitudinal velocity, c) CNN-LSTM weight.

Table 5. Vehicle state parameter errors.

Vehicle state parameters	Estimation method	Root-mean-square error
Sideslip angle (rad)	CKF	0.0212
	CNN-LSTM	0.0031
	Proposed	0.0019
Longitudinal velocity (km/h)	CKF	1.2444
	CNN-LSTM	0.7183
	Proposed	0.4016

5.3. Medium-speed double-lane-change on wet asphalt

Figure 12 shows that CKF accurately estimates the sideslip angle and longitudinal velocity during the 0-5.8 s interval. Thereafter, the rising vehicle nonlinearities degrade its performance, and the physics-based model fails to capture the evolving trends of the two states. CNN-LSTM

gradually improves its accuracy over time, maintaining low estimation errors between 5.8 s and 12 s. According to Table 6, the proposed method improves the sideslip angle estimation accuracy by 64.71% and 25.00% compared with CKF and CNN-LSTM, respectively, and the longitudinal velocity estimation accuracy by 65.93% and 44.90% in terms of root-mean-square error.

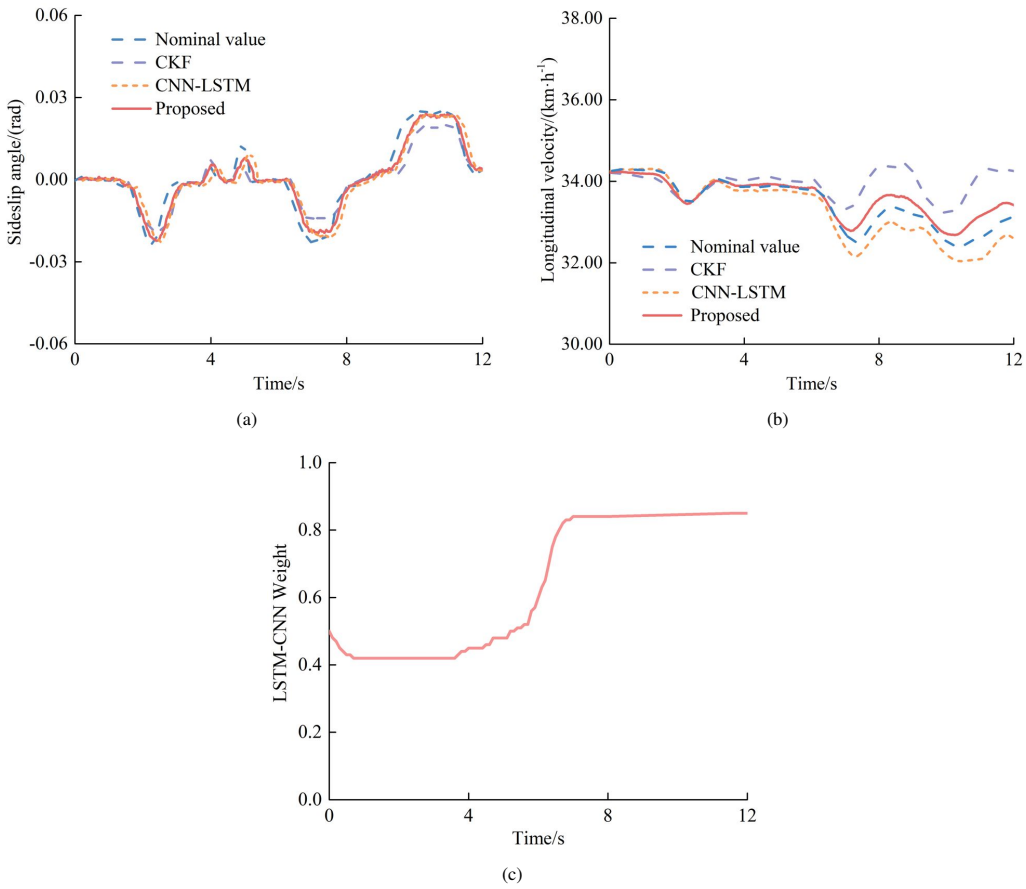


Fig. 12. Experimental results: a) sideslip angle, b) longitudinal velocity, c) CNN-LSTM weight.

Table 6. Vehicle state parameter errors.

Vehicle state parameters	Estimation method	Root-mean-square error
Sideslip angle (rad)	CKF	0.0051
	CNN-LSTM	0.0024
	Proposed	0.0018
Longitudinal velocity (km/h)	CKF	1.0127
	CNN-LSTM	0.6263
	Proposed	0.3451

5.4. 20-degree slope

Figure 13 presents experimental results with a 20-degree slope and Table 7 contains vehicle state parameter errors. The proposed fusion method demonstrates significant advantages. In terms of root-mean-square error, CKF, which does not incorporate slope compensation, yields a longitudinal velocity as high as 22.1534 km/h and a sideslip angle of 0.0422 rad. Although trained on data, CNN-LSTM still suffers from lag and noise, resulting in a longitudinal velocity of 1.6813 km/h and a sideslip angle of 0.0072 rad. In contrast, the proposed fusion method utilizes a bisection-based adaptive weighting strategy, adjusting the CNN-LSTM weight to 0.82 within 2 seconds. This approach effectively suppresses the systematic bias inherent in CKF and the high-frequency noise present in CNN-LSTM. Consequently, it achieves a longitudinal velocity of 1.4547 km/h and a sideslip angle of 0.0061 rad, which represents a 15.3% improvement over CNN-LSTM.

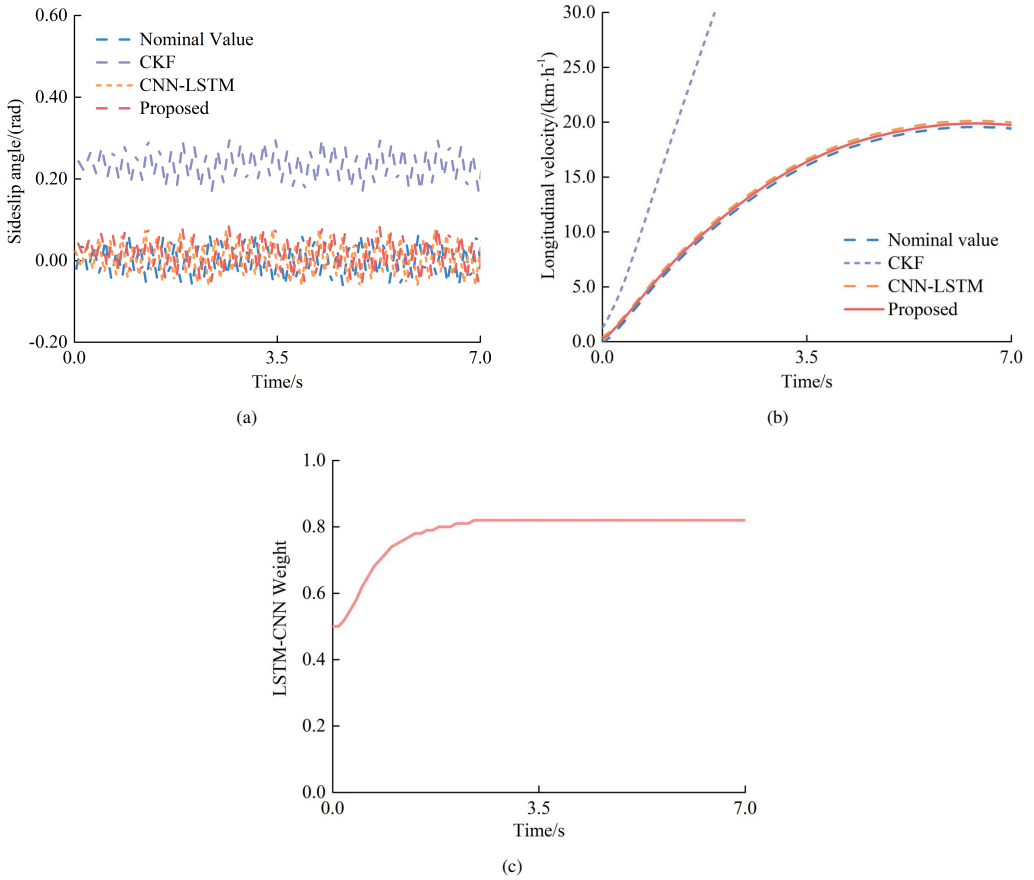


Fig. 13. Experimental results: a) sideslip angle, b) longitudinal velocity, c) CNN-LSTM weight.

Table 7. Vehicle state parameter errors.

Vehicle state parameters	Estimation method	Root-mean-square error
Sideslip angle (rad)	CKF	0.0422
	CNN-LSTM	0.0072
	Proposed	0.0061
Longitudinal velocity (km/h)	CKF	22.1534
	CNN-LSTM	1.6813
	Proposed	1.4547

6. Discussion

Quantitative comparisons confirm that the dichotomous adaptive fusion framework outperforms single CKF and CNN-LSTM methods. A mechanistic comparison is made with the current mainstream method, IMM-CKF [33].

- (i) IMM-CKF approximates complex dynamics using a predefined discrete set of models, with transitions governed by a Markov chain and posterior probabilities weighting the fused results. However, enumerating all precise physical models in advance is difficult. Hence, the proposed method uses a basic 2-DOF vehicle model plus a data-driven black-box compensator to learn unmodeled dynamics.
- (ii) IMM-CKF requires extensive prior knowledge, *i.e.*, designers must predefine a model set and a Markov transition matrix. The proposed method only needs a basic interpretable vehicle model and historical data to train the CNN-LSTM estimator; key parameters in the dichotomous fusion logic have clear physical meanings. This reduces deployment difficulty in environments lacking prior model knowledge.

7. Conclusions

This paper focuses on distributed electric drive vehicles and designs a multi-source information-based vehicle state fusion estimation method. The following distinctive contributions are achieved:

1. This study innovatively proposes a dichotomy-based model-data hybrid state estimation fusion framework which dynamically integrates the strengths of model-driven and data-driven approaches with high robustness and interpretability.
2. Real-vehicle experiments were conducted under four operating conditions. In terms of root mean square error, the proposed method improves sideslip angle estimation accuracy by at least 25.00% and up to 91.04% across the four conditions, while longitudinal velocity estimation accuracy is improved by at least 44.09% and up to 67.73%.

Future work will focus on a systematic quantitative comparison of the proposed fusion framework with representative hybrid estimation baselines, under consistent experimental conditions.

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