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A Review of Dynamic State Estimation for the Neighborhood System of Connected Vehicles

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Abstract

Precise vehicle state and the surrounding traffic information are essential for decision-making and dynamic control of intelligent connected vehicles. Tremendous research efforts have been devoted to developing state estimation techniques. This work investigates the research progress in this field over recent years. To be able to describe the state of multiple traffic elements uniformly, the concept of a vehicle neighborhood system is proposed to describe the system composed of vehicles and their surrounding traffic elements and to distinguish it from the traditional macroscopic traffic research field. In this work, the vehicle neighborhood system consists of three main traffic elements: the host vehicle, the preceding vehicle, and the road. Therefore, a review of state estimation methods for the vehicle neighborhood system is presented around the three traffic objects mentioned earlier. This article performs a comprehensive analysis of these approaches and depicts their strengths and drawbacks. In addition, future research directions on the state estimation of the vehicle neighborhood system are further discussed.

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1. Introduction

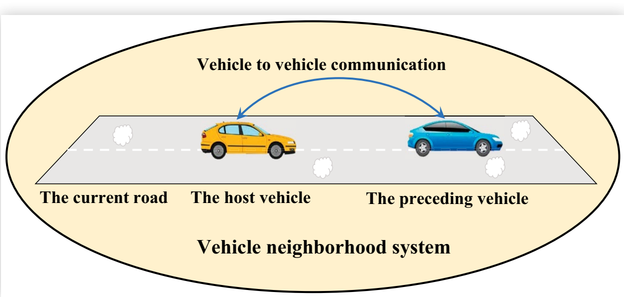
Traffic accidents are one of the main causes of human casualties [1]. Intelligent connected vehicles will provide a new possibility for the automotive industry to effectively solve safety and congestion problems due to their functions of intelligent decision-making and collaborative control. Some typical technologies include vehicle–road coordination systems, advanced driver assistance systems (ADAS), and the like. Some of the most representative technologies in ADAS include stability control systems [2, 3], braking control systems [4, 5, 6, 7], local path planning systems [8, 9], active suspension control systems [10, 11, 12], and the like. The prerequisite for these active safety systems to work effectively is to obtain accurate vehicle state and tire–road friction coefficient (TRFC) [1]. To describe these vehicle states and road surface information in a unified way, this work refers to the concept of "neighborhood system" in mathematics and calls the set composed of the host vehicle, the preceding vehicle, and the current road as the vehicle neighborhood system. As shown in Figure 1. The corresponding variables, such as vehicle sideslip angle, tire stiffness, and TRFC, constitute the key state parameters in the vehicle neighborhood system.

To further explain the vehicle neighborhood system, some definitions are first introduced.

- ***Definition 1***. The domain of discourse is the set of objects under discussion, which is predefined and does not require the scope of the relevant variables to be specified each time when further processed [13].
- ***Definition 2***. Let X be a domain of discourse and x be an object in X. A particular subset of X (which may not contain x) is said to be a neighborhood of x [14].
- ***Definition 3***. Let X be a domain of discourse and x be an object in X. The set of all neighborhoods of x is called a neighborhood system of object x. The union of all object neighborhood systems in the X is called the neighborhood system of X [14].

The local traffic environment usually mainly consists of vehicles, roads, pedestrians, traffic signs, and other objects, and the relevant objects belong to predefined. According to *Definition 1*, it is known that the local traffic environment is a domain of discourse. For the local traffic environment domain, the road is used as the object, and the surrounding roads are also a subset of the domain. The current and surrounding roads constitute a road neighborhood concerning *Definition 2*. Similarly, the host vehicle and the surrounding vehicles can form a vehicle neighborhood. Furthermore, suppose that the current road is the coupling object of the vehicle and only focuses on a certain road and the vehicles driving on the road. In this case, all vehicle neighborhoods will constitute a vehicle neighborhood system regarding *Definition 3*. Such a novel concept can describe a vehicle-centric generalized vehicle system, which can be distinguished from the research object of the macroscopic transportation system. In this article, we focus on the state estimation of the host vehicle, the preceding vehicle, and the TRFC in the vehicle neighborhood system.

FIGURE 1 The vehicle neighborhood system.



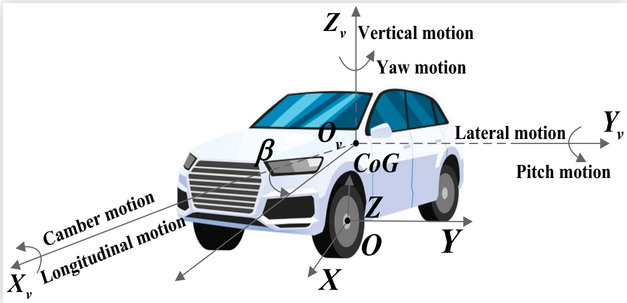
However, current onboard low-cost sensors cannot measure these states directly due to technical and cost reasons, thus many estimator- or observer-based methods have been proposed to obtain these states indirectly [15, 16]. From the perspective of the vehicle neighborhood system, its state mainly includes the dynamic state of the vehicle body and the interaction between the tire and the road surface. Although several comprehensive surveys on the vehicle state [17, 18, 19, 20, 21] and TRFC [22, 23, 24] have been reported, most of the previous studies focused on a particular aspect and did not provide a comprehensive review from a systemic perspective. In previous studies, host vehicle and preceding vehicle state estimation as well as TRFC identification are usually considered as two types of parameter identification problems. However, in this study, we try to define a new concept to describe a more macroscopic vehicle–road-coupled system. This will provide a new perspective to researchers in this field. Therefore, these different states or TRFC will become the internal states of this macroscopic system. This article systematically reviews the research progress of state estimation of the vehicle neighborhood system in recent years. It contains an analysis of existing methods and describes their advantages and disadvantages. Finally, future research directions are further discussed. This work will help researchers or vehicle engineers select appropriate estimation methods for intelligent vehicle decision-making and control.

To provide some specifics of the analysis, the remainder of the article is organized as follows. Section 2 presents the state estimation of the host vehicle and the preceding vehicle. The estimation of TRFC is shown in Section 3. The conclusion and some promising prospects are discussed in Section 4.

2. State Estimation of the Host Vehicle and the Preceding Vehicle

Vehicle state estimation usually includes vehicle body dynamic state estimation and model parameters identification. As shown in Figure 2, some typical states such as longitudinal

FIGURE 2 The vehicle coordinate systems.



and lateral speeds, tire forces, tire cornering stiffness, sideslip angle, the height of the center of gravity and vertical load, and the like. Accurate state information is essential for ADAS [25, 26, 27]. However, onboard sensors fail to directly obtain the theses information. Therefore, estimating these vehicle states using only onboard sensors is a hot topic of current research.

2.1. The Vehicle Dynamic Model

Observers-based, Kalman-based, and machine learning-based are commonly used methods to solve this problem. These different categories are shown in Figure 3. The first two approaches usually estimate vehicle states based on longitudinal or lateral dynamics models. The longitudinal model (see

FIGURE 3 The different estimation methods.

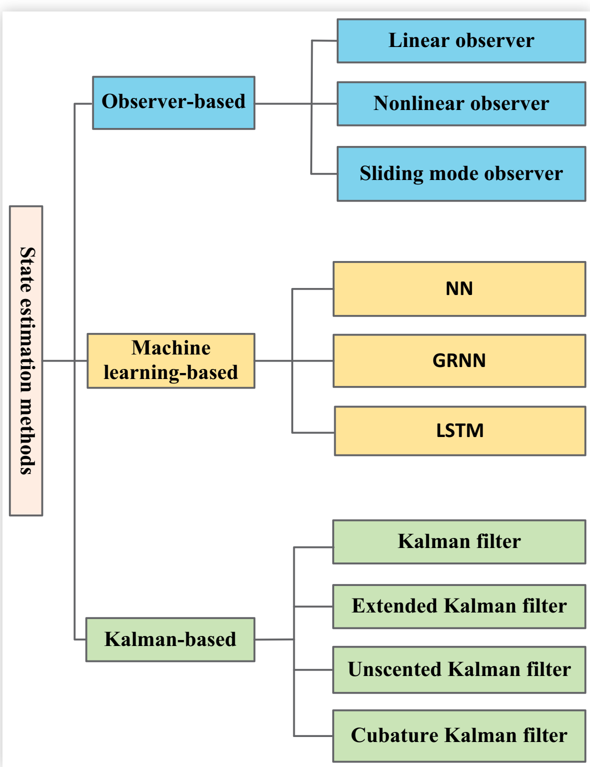


FIGURE 4 The longitudinal dynamics model.

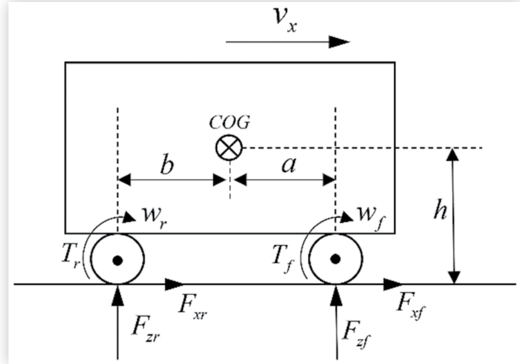


Figure 4) [28] depicts the vehicle dynamics response under the condition of braking and driving maneuvers.

$$F_{xf} = \left(T_f - J\omega_f\right)/R \qquad \text{Eq. (1)}$$

$$F_{xr} = \left(T_r - J\omega_r\right)/R \qquad \text{Eq. (2)}$$

$$ma_x = \left(F_{xf} + F_{xr}\right) - \frac{1}{2}C_D\rho A v_x^2 - mgf_{roll} \qquad \text{Eq. (3)}$$

$$F_{zf} = \frac{mgb - mha_x}{(a+b)} \qquad \text{Eq. (4)}$$

$$F_{zr} = \frac{mga + mha_x}{(a+b)} \qquad \text{Eq. (5)}$$

where F_{xf}, F_{xr} are front longitudinal tire force and rear longitudinal tire force, a and b are distances from the center of gravity (COG) to the front axle and rear axle, m is the vehicle mass, T_f and T_r are front and rear track driving torques, v_x is the longitudinal vehicle velocity, J is a moment of inertia, h is the height of COG, C_D is the air drag influence coefficient the wheel rotational speed, ρ is the air density, A is the windward area, C_D is the air drag influence coefficient the wheel rotational speed, f_{roll} is the rolling resistance coefficient, R is the wheel radius, F_{zf}, F_{zr} are vertical forces at front and rear wheels, a_x is the longitudinal acceleration, and w_f, w_r are front tire speed and rear tire speed.

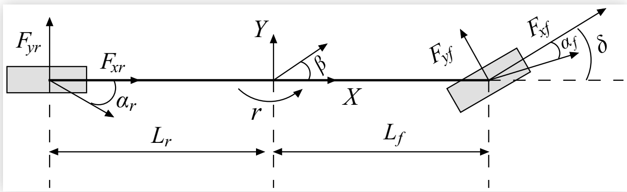
In contrast to the longitudinal model, the classic lateral dynamics model is a single-track model [29] (see Figure 5). In addition, the multi-degree-of-freedom model [30] and the roll dynamics model [31] are also common models.

$$\dot{\beta} = \frac{F_{yf}\cos\delta + F_{yr}}{mv_x} - r \qquad \text{Eq. (6)}$$

$$a_y = \frac{F_{yf}\cos\delta + F_{yr}}{m} \qquad \text{Eq. (7)}$$

$$\alpha_f = \delta - \beta - \frac{L_f r}{v_x} \qquad \text{Eq. (8)}$$

FIGURE 5 The lateral dynamics model.



$$\alpha_r = -\beta + \frac{L_r r}{v_x} \quad \text{Eq. (9)}$$

where F_{yf}, F_{yr} are front lateral tire force and rear lateral tire force. L_f and L_r are distances from the COG to the front axle and rear axle, β is the sideslip angle, δ is the front-wheel angle, α_f is the front-wheel sideslip angle, α_r are rear wheel sideslip angle, and a_y is the lateral acceleration.

Based on the earlier discussed vehicle model, it is essential to obtain tire force in real-time. Therefore, some tire model is proposed to collect tire forces information, such as the Magic Formula model [32], the Unitire tire model [33], the Brush tire model [34], and so on. A combined longitudinal and lateral brushed tire model is used to describe the dynamic characteristic of tires. Some specific equations are as follows

$$F_{x,i} = \frac{C_x\left(\frac{s_i}{1+s_i}\right)}{f_i} F_i \quad \text{Eq. (10)}$$

$$F_i = \begin{cases} f_i - \frac{1}{3\mu_i^9 F_{z,i}} f_i^2 + \frac{1}{27\left(\mu_i^9\right)^2 F_{z,i}^2} f_i^3, & \text{if} \quad f_i \le 3\mu_i^9 F_{z,i} \\ \mu_i^9 F_{z,i} & \text{else} \end{cases} \quad \text{Eq. (11)}$$

$$f_i = \sqrt{C_x^2\left(\frac{s_i}{1+s_i}\right)^2 + C_y^2\left(\frac{\tan\alpha_i}{1+s_i}\right)^2} \quad \text{Eq. (12)}$$

where μ_i^9 is TRFC, C_x, C_y, $F_{z,i}$ are the tire longitudinal, lateral stiffness coefficients, vertical tire forces, s_i, α_i are the longitudinal slip ratio, wheel sideslip angle, $i = 1, 2, 3, 4$, which correspond to the left-front, right-front, left-rear, and right-rear wheels, respectively.

2.2. The Observer-Based Vehicle State Estimation

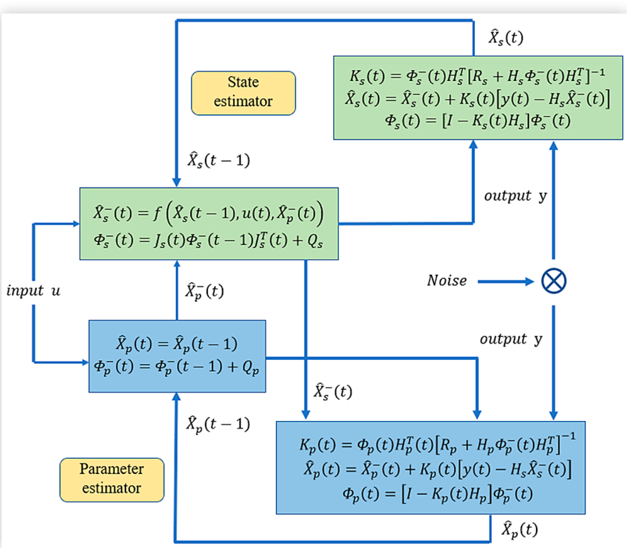
In recent years, several observers have been used to estimate the vehicle state, including linear observer, nonlinear observer sliding mode observer, and so on. State observer is a system that provides an estimate of the internal state of a given real system, from measurements of the input and output of the real system. For the linear observer, Stephant et al. [35] proposed the Luenberger observer to estimate sideslip angle, and real vehicle test results demonstrate that this observer has high estimation accuracy. Zhang et al. [36] developed an H-infinity observer to predict sideslip angle based on the front-wheel angle information. In addition, the controller output observer [37] was studied for estimating tire forces. A similar observer [38] was used for estimating tire traction forces. The advantage of the method is adaptive to model parameter uncertainties. The linear observer-based method usually works effectively in the case of a linear working area. Furthermore, some nonlinear observers were proposed to estimate vehicle state considering the nonlinear vehicle dynamics. In addition, nonlinear state observers were widely investigated with input state stability. Zhao et al. [39] made use of a nonlinear observer to estimate vehicle velocity. Some tests indicate that the performance of a nonlinear observer is better than a linear observer [40]. Grip et al. [41] designed a nonlinear observer for estimating sideslip angle. To improve the adaptive of the nonlinear observer, the high-gain nonlinear observer was proposed successively [42]. Moreover, Hashemi et al. [43] made use of a nonlinear observer to identify the road bank. Except for the above-mentioned observers, the sliding mode observer (SMO) is the popular method. SMO has been extensively applied to vehicle speed estimation due to its efficient application in terms of computational efficiency and its robustness to parameter variations and modeling uncertainties. The SMO was proposed to estimate vehicle velocity [44, 45], tire cornering stiffness [46], tire forces [47], and sideslip angle [48]. To further enhance the estimation performance of SMO, the second-order SMO [49], reduced-order SMO [50], and higher-order SMO [51] were designed to estimate vehicle state. In addition, some observers optimized based on other methods have also been reported. For example, Boada et al. [52] proposed an observer based on an adaptive neuro-fuzzy inference system to estimate the sideslip angle. The estimation performance of observer-based methods usually deeply relies on the accuracy of vehicle models. Unfortunately, accurate vehicle models are hard to obtain in practice. Therefore, the observer-based approach has some limitations in improving the estimation accuracy. An estimation method that is model-based but also robust to model mismatch is a better solution. Furthermore, Kalman filtering and its modifications are usually able to obtain minimum mean squared error estimates with Gaussian noise and are robust to model mismatches. Thus, Kalman-based methods are widely utilized for state estimation of vehicle systems.

2.3. The Kalman-Based Vehicle State Estimation

The Kalman filter (KF) can find the optimal solution and achieve fast convergence in noisy environments. Therefore, it is widely used for parameter and state estimation. As early as 1999, Venhovens et al. [53] proposed to use the KF to estimate vehicle state. Cho et al. [54] designed a random-walk KF to predict tire forces. Zhang et al. [55] proposed a Kalman-based estimator to estimate sideslip angle. To improve the estimation accuracy, some multi-sensor fusion methods based on KF were used to predict vehicle state, such as GPS [56, 57] and grade inertial sensor [58]. Usually, the earlier defined methods based on linear models to estimate the vehicle state are effective when the vehicle is in a linear working condition. However, when the vehicle enters the nonlinear working region, the vehicle model and the tire itself have strong nonlinearity, and the estimation accuracy based on the traditional KF is low, or even the filter is diverging. Therefore, KF works best only in problems that can be represented as linear systems. To address this limitation several advanced techniques have been investigated and developed, such as an extended KF (EKF). Wenzel et al. [59] first developed an EKF to estimate vehicle state and model parameters. Furthermore, tire forces are also essential for vehicle stability [60]. Baffet et al. [61] made use of EKF to predict sideslip angle and tire forces considering the change of TRFC. In addition, the dual EKF estimation method was utilized to estimate vehicle state [62]. The typical dual EKF framework is shown in Figure 6. Based on the three-degree-of-freedom vehicle model, EKF was used to estimate the vehicle state. Further, the Highway Safety Research Institute (HSRI) tire model is used to estimate tire–road friction using EKF. The two EKFs establish real-time communication to improve estimation accuracy.

To enhance the adaptability of the estimation algorithm, interacting multiple model EKF (IMMEKF) was used to predict vehicle state [63]. Furthermore, a variety of vehicle dynamics models have been used in the study of estimating sideslip angle based on the EKF. For example, the single-track vehicle model [64, 65, 66, 67, 68, 69, 70], the seven-degree-of-freedom (DOF) model [71], the four-DOF model [72], the eight-DOF model [73], and the like. To improve the noise adaptivity of the EKF, a fuzzy EKF is proposed to estimate the vehicle states [74]. In addition, vehicle sensors will inevitably

FIGURE 6 The EKF-based method.



lose measurement data due to aging and other issues. In this case, the fault-tolerant EKF is proposed for vehicle state estimation [75, 76]. Moreover, the inertial parameters of the vehicle will change during driving, and the extended H-infinity KF is designed to suppress the impact of model parameters perturbation on the estimation performance [77]. In addition, estimating mass and grade using EKF is also another important research field [78]. Since the EKF is only a first-order approximation of the nonlinear system, its estimation accuracy will decrease under some strong nonlinear conditions. In addition, when the filter is subjected to harsh conditions, the linearization of the system may not be effective, resulting in divergence of the filter. The unscented KF (UKF) is a filtering algorithm that avoids the linearization of the EKF.

To this end, UKF is also utilized for the state estimation of vehicles. Antonov et al. [79] proposed a UKF-based approach to estimate vehicle velocity with low-cost onboard sensors. Heidfeld et al. [80] developed a hybrid UKF to predict vehicle state. Furthermore, variable structure UKF [81] and weight fusion UKF [82] were presented to improve estimation performance. In addition, a variety of vehicle dynamics models have been used for estimating vehicle state based on the UKF. For example, the nine-DOF model [83], double-track vehicle model [84, 85], kinematics model [86], three-DOF model [87, 88], seven-DOF model [89, 90], and the like. In addition, some improved UKFs have been designed to enhance estimation accuracy. Strano et al. [91] considered the state constraints in the estimation process and designed a constrained UKF to estimate vehicle state. Zhang et al. [92] proposed an adaptive double-layer UKF to predict sideslip angle. To enhance the adaptive estimation algorithm, interacting multiple model UKF (IMMUKF) was used to predict vehicle state [93], and the framework is shown in Figure 7.

The IMMUKF consists of two vehicle dynamics models based on a linear tire model and a nonlinear tire model. The UKF is used to estimate the vehicle state based on the two different vehicle models separately. Finally, the two estimation results are fused to improve the estimation accuracy. UKF can effectively improve the estimation accuracy of the vehicle state, but its stability needs to be improved when facing some high-dimensional nonlinear systems. The cubature KF (CKF) is based on the numerical integration of a Gaussian filter and uses a three-degree spherical-radial cube rule to numerically compute the Gaussian-weighted integral. It is a derivative-free nonlinear filtering algorithm that improves over UKF in terms of estimation accuracy, numerical stability, and computational cost. Compared with the UKF, the cubature KF (CKF) [94] is a more effective filtering method and has been widely used for high-accuracy estimation of vehicle state. A standard CKF is employed to predict vehicle state [95].

Chen et al. [96] designed an adaptive square-root CKF to estimate vehicle state. The parameters of the square-root CKF can be adaptively adjusted according to the motion state of the vehicle. Song et al. [101] proposed an extended square-root CKF to combine measurements from different sensors to cope with the problem of vehicle state estimation in limit conditions. The estimation framework is shown in Figure 8. First,

FIGURE 7 The IMMUKF-based method.

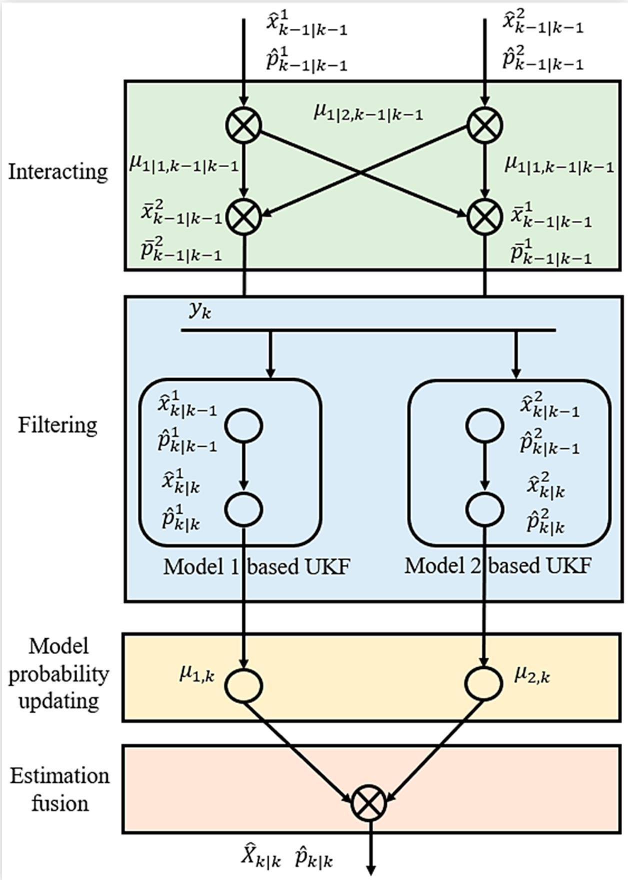
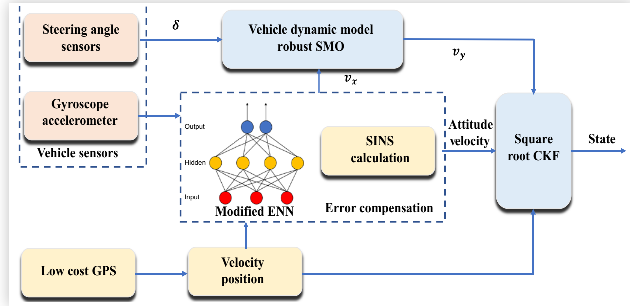


FIGURE 8 The extended square-root CKF.



the longitudinal velocity of the vehicle is estimated based on the onboard sensors. Then, a neural network is used to obtain the longitudinal velocity based on GPS. Finally, the CKF is used to estimate the vehicle state.

Similar studies have also been reported in [102, 103, 104]. To cope with the challenge of unknown noise in the estimation process, a robust CKF is proposed to improve estimation accuracy [100, 105, 107]. In addition, to improve the nonlinear fit of CKF, high-order CKF is used to predict the vehicle state [106]. Fuzzy logic [99] and multilayer perceptron [97] are also proven to enhance the estimation performance of CKF. Other scholars improve the estimation accuracy of vehicle state from the perspective of model adaptation. Hou et al. [98] designed an interactive multi-model CKF to fuse the estimation results of multiple vehicle models to improve the estimation accuracy. Table 1 presents a summary of Kalman-based methods for vehicle state estimation.

2.4. The Machine Learning-Based Vehicle State Estimation

In addition, state prediction based on machine learning has also proven to be an effective estimation method in recent years. Machine learning-based methods usually involve collecting a certain amount of vehicle input and output data. The model is trained based on a large number of samples and then deployed to the vehicle for state prediction [108]. The advantage of the machine learning-based approach is that it does not take into account the accuracy of the model and does not concern whether the vehicle is operating under nonlinear conditions. Artificial neural network (NN) is a common prediction method. Saadeddin et al. [109] developed a NN inference system to estimate vehicle velocity. Gwak et al. [110] designed a NN to estimate vehicle state. A similar study was also reported in [111]. Estimating the sideslip angle using NN was one of the effective methods. Melzi et al. [112] considered the dynamic characteristics of different pavements and designed NN to predict sideslip angle. Vargas et al. [113] developed a fusion method that combined the NN with KF to estimate roll angle. To further enhance the estimation performance of the NN-based method, multilayered perceptron NN [114] and progressive NN [115] were proposed successively. In addition, a general recurrent NN (GRNN) [116] was designed to optimize the training samples. Furthermore, a recurrent NN state estimation scheme is developed to estimate sideslip angles in real time [117]. Li et al. [118] proposed a brain-inspired ontology perception system based on deep learning to predict sideslip angle. Furthermore, backpropagation NNs [119, 120] and classification artificial NNs [121] are also used for sideslip angle estimation. In addition, the long–short-term memory network (LSTM) [122] is gaining attention because it can take advantage of the time series correlation of data to optimize estimation performance. An LSTM-based multilayer network estimator is presented to predict the sideslip angle, and experimental results show that the method has high estimation accuracy [123]. However, the machine learning-based methods depend heavily on the integrality data set. Hence, the estimation performance of the algorithm can be directly affected when the data is limited.

2.5. State Estimation of the Preceding Vehicle

Apart from obtaining the host vehicle state, ADAS usually needs to obtain the state of the preceding vehicle. For example, the adaptive cruise control system needs to get the preceding

TABLE 1 Summary of Kalman-based methods.

Number	Models	Methodology	References
1.	Simplified wheel dynamics model	KF	[54]
2.	Three-DOF model	KF	[55]
3.	GPS	KF	[56, 57]
4.	Grade inertial sensor/GPS	KF	[58]
5.	Four-wheel vehicle model	Dual EKF	[59]
6.	Single-track vehicle model	EKF	[60, 64, 65, 66, 67, 68, 69, 70]
7.	Five-DOF model	Dual EKF	[61]
8.	Three-DOF model	Dual EKF	[62]
9.	Single-track vehicle model	IMMEKF	[63]
10.	Seven-DOF model	EKF	[71]
11.	Four-DOF model	EKF	[72]
12.	Eight-DOF model	EKF	[73]
13.	Three-DOF model	Fuzzy EKF	[74]
14.	Four-wheel vehicle model	Fault-tolerant EKF	[75, 76]
15.	Three-DOF model	Extended H-infinity Kalman filter	[77]
16.	Kinematic model	EKF	[78]
17	Double-track vehicle model	UKF	[79, 80, 84, 85]
18	Double-track vehicle model	Variable structure UKF	[81]
19	Double-track vehicle model	Weight fusion UKF	[82]
20	Nine-DOF model	UKF	[83]
21.	Kinematics model	UKF	[86]
22.	Seven-DOF model	UKF	[89, 90]
23.	Three-DOF model	UKF	[87, 88]
24.	Seven-DOF model	Adaptive UKF	[92]
25.	Single-track vehicle model	Constrained UKF	[91]
26.	Seven-DOF model	IMM UKF	[93]
27.	Four-wheel vehicle model	Square-root CKF	[96]
28.	Sensor-based model	CKF	[97]
29.	Seven-DOF model	Interacting multiple model cubature Kalman	[98]
30.	Three-DOF model	Fuzzy CKF	[99]
31.	Three-DOF model	Robust CKF	[100]
32.	Three-DOF model	Square-root CKF	[101, 102]
33.	Seven-DOF model	Square-root CKF	[103, 104]
34.	Longitudinal dynamic model	Robust embedded cubature Kalman	[105]
35.	Three-DOF model	High-order CKF	[106]
36.	Three-DOF model	CKF	[95]
37.	Single-track vehicle model	Adaptive robust CKF	[107]

vehicle state to achieve better vehicle following. However, the preceding vehicle state is usually difficult to measure directly via the in-vehicle sensors of the host vehicle [124]. Therefore, it is a common method to use in-vehicle sensors of the host vehicle to obtain some motion information about the preceding vehicle and combine it with a complex vehicle model to estimate the preceding vehicle state.

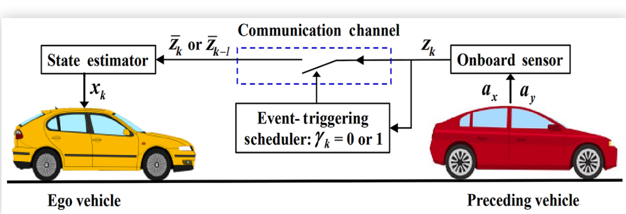
For estimating the longitudinal motion state, such as the velocity, the vehicle following model and its improvements [125, 126, 127, 128] are among the popular models. These methods usually require only the relative distance between the host vehicle and the preceding vehicle to estimate the preceding vehicle state. This type of model is usually capable of precisely describing the straight-line motion of a vehicle, but the accuracy decreases in the case of curves. Therefore, some curvilinear models are reported to fill the gap. For example, the constant turn rate and velocity model and the constant turn rate and acceleration (CTRA) model [129]. The earlier described two models assume that the vehicle velocity and yaw rate are unrelated. However, the vehicle velocity is usually highly coupled with the yaw rate, especially in the case of high velocity. To this end, some combined model is used to estimate the preceding vehicle state. Wang et al. [124] proposed a combined model-based estimation scheme. Unlike conventional models, the new model is constructed on the basis of the host vehicle and the preceding vehicle, as well as the road constraints. Accordingly, Liu et al. [130] proposed an integrated longitudinal and lateral state estimation algorithm, which exploited the coupled nonlinear properties of vehicle dynamics to enhance the accuracy of state estimation of the preceding vehicle. Furthermore, a CTRA model, a bicycle model, and a UKF are used to predict the motion state of the preceding vehicle [131]. Typically, these methods assume that some model-inherent parameters of the preceding vehicle are known. Unfortunately, these parameters are often difficult to measure with host vehicle sensors.

Vehicle-to-vehicle (V2V) makes it possible to exchange intrinsic parameters between vehicles [132]. As a result, the host vehicle is able to receive the preceding vehicle state directly through V2V communication, but the host vehicle cannot receive the preceding vehicle state during the sampling interval. Thus, it is impossible to directly use V2V communication to obtain the preceding vehicle state, and an additional estimator needs to be designed. Zhou et al. [133] utilized V2V communication to receive sensor data from the preceding vehicle and proposed a vehicle state estimation method. Schinke et al. [134] designed an estimation framework to predict the state of a lead and following vehicle simultaneously in a V2V communication environment.

In addition, many V2V communication systems transmit information periodically, which is typical of time-triggered systems. However, the periodic transmission might consume more network bandwidth, while event-triggered systems [135] are able to reduce the transmission of information while ensuring estimation performance. To this end, Wang et al. [136] first proposed an event-triggered framework for the state estimation of the preceding vehicle. The event-triggered scheme is shown in Figure 9. It will decide whether to send sensor information from the preceding vehicle to the host vehicle based on a specific threshold to achieve a balance between estimation accuracy and communication cost. Their test results show that the proposed method can effectively balance the communication rate and estimation accuracy.

Further, interactive multi-model event-triggered UKF considering the advantages of different models is also presented for state estimation of the preceding vehicle [137]. The earlier discussed studies fully considered the advantages of V2V communication but ignored the effect of data loss. To address this issue, Lv et al. [138] designed an event-triggered CKF considering data loss to estimate the preceding vehicle state in a connected vehicle environment. Simulation test results show that by properly adjusting the threshold, an ideal trade-off between transmission rate and estimation accuracy can be achieved, and the influence of packet loss is significantly reduced. Therefore, using V2V communication to predict the motion state of the preceding vehicle is the current mainstream research direction.

FIGURE 9 The event-triggered scheme.



3. Estimation of Tire–Road Friction Coefficient

In the vehicle neighborhood system, in addition to obtaining the vehicle state, we also need to get the TRFC. Studies have shown that traffic accidents are more likely to occur on roads with low friction coefficients. The magnitude of the longitudinal and lateral tire forces is related to the TRFC. Hence, the TRFC can indirectly affect vehicle stability [139]. However, the TRFC cannot be measured directly by onboard sensors. Thus, some estimation methods need to be utilized to solve the problem. Existing studies on TRFC estimation are mainly on the basis of data-based and model-based approaches. The variation of road texture affects the magnitude of TRFC [140] and different road textures are shown in Figure 10.

For this reason, researchers used cameras to acquire a lot of road images and estimate TRFC using a data-based approach. Holzmann et al. [141] made use of camera pictures to estimate the TRFC. Du et al. [142] presented a knowledge-based deep NN to predict TRFC based on road texture pictures. Leng et al. [143] proposed a fusion strategy to identify TRFC. Yu et al. [144] used a backpropagation NN to predict the TRFC. This kind of method has good estimation performance in high visibility environments, but their estimation accuracy may be decreased in a night driving environment. To address the problem, several approaches on the basis of mechanical response have been proposed successively. Singh et al. [145] presented a methodology to determine the TRFC utilizing tire vibration. Furthermore, the intelligent tire with advanced sensors was also used to identify TRFC [146, 147, 148]. Several other sensors are also used to estimate TRFC, such as ultrasonic sensors [149], laser profilometers [150], wireless piezoelectric tire sensors [151], and magnetometers [152].

FIGURE 10 The different road textures.

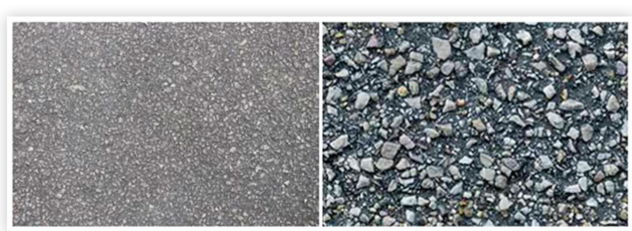


TABLE 2 Summary of longitudinal dynamics-based methods.

Number	Models	Methodology	References
1	Magic formula model	Kalman filter	[158, 159]
2	Magic formula model	Reduced-order observer	[160, 161]
3	Magic formula model	RLS	[162, 163]
4	LuGre dynamic model	State observer	[164, 165]
5	Pseudostatic LuGre model	Sliding mode observer	[166]
6	Burckhardt model	Nonlinear curve fitting technique	[167, 168]
7	Burckhardt model	Sliding mode observer	[169]
8	Modified Burckhardt tire model	Nonlinear estimator	[170]
9	Magic formula model	Improved nonlinear observer	[171]
10	Single-wheel model	RLS	[172]
11	Six DOF vehicle model	RLS	[173]
12	Four-wheel vehicle model	Fuzzy logic and Kalman filter	[175]

In recent years, other data-driven approaches have been proposed. It is also a common method to use a NN to describe vehicle dynamic behavior, and then use a genetic algorithm to optimize the NN to identify TRFC. Zhang et al. [153] established a mapping method to predict TRFC by a regressive NN. Ribeiro et al. [154] used a time-delay NN to predict the TRFC. Furthermore, other NNs have also been reported, such as LSTM NN [155], gated recurrent unit network [156], deep neural network [157], and the like. In general, data-driven approaches are gaining more and more attention as the computing power of onboard processors increases. However, the estimation accuracy of such methods depends on the completeness of the dataset. Meanwhile, this data-driven approach needs to first obtain vehicle operating data before identifying TRFC. However, if the method is transplanted to another vehicle, the original identification method may fail. Therefore, this data-driven method is currently difficult to be deployed on vehicle chassis control systems.

Model-based estimation methods usually identify TRFC based on the dynamic response of the vehicle. For the same slip rate, the slope of the curve is different for different TRFCs. Thus, according to this physical phenomenon, we can estimate TRFC. Gustafsson et al. [158] first developed a new method to identify TRFC utilizing the longitudinal slip slope. Similarly, some research supplied more experimental data to demonstrate the efficiency of the algorithm [159, 160, 161]. Furthermore, Rajamani et al. [162, 163] further enhance the applicability of the type of method using GPS signals. Although the earlier estimation method requires few sensors and the prediction accuracy is within acceptable limits, its robustness is an issue that needs to be addressed. Therefore, estimating TRFC using tire force is another research direction. The state observer and RLS are two commonly available methods. Various model-based estimation methods have been proposed, such as LuGre dynamic model [164, 165, 166], the Burckhardt model [167, 168, 169, 170], the Magic Formula model [171], the single-wheel model [172], and the six-DOF vehicle model [173]. These parameters of tire models usually need to be identified dynamically to improve the model's accuracy [174].

In addition, Castillo et al. [175] developed a fuzzy logic system to estimate the TRFC. Based on the real-time information on motor torque and speed of four-wheel electric vehicles, Xia et al. [170] designed a TRFC estimation algorithm by using the Lyapunov stability theory. This longitudinal dynamics-based approach allows the TRFC to be estimated directly from onboard sensor information and different estimation method is shown in Table 2. The downside is that longitudinal dynamics-based estimation methods usually require larger excitation, while lateral dynamics-based methods also have high estimation accuracy when the excitation is relatively small. Yamazaki et al. [176] made use of lateral acceleration information to estimate TRFC. To improve the adaptive of the estimation method, cornering stiffness coefficient [177], yaw rate [178], and aligning torque [179] were also used for TRFC estimation. To make full use of the information from multiple sensors, a fusion estimation method is proposed to estimate the TRFC [180, 181]. Jin et al. [182] proposed a method combining machine vision and vehicle dynamics to predict TRFC. Furthermore, Shao et al. [183] proposed an adaptive observer to estimate TRFC using steering torque information. Other observers are also commonly used in methods, such as extended Luenberger observer [184], online gradient descent algorithm [185], nonlinear observer [186, 187], high-order SMO [188], and the like. Considering the measurement noise of the sensor, the EKF [189] and UKF [190] are used for the identification of the TRFC. In addition, the particle filter is also used to identify TRFC [191]. The different estimation method is shown in Table 3.

The aforementioned research is only based on longitudinal or lateral vehicle models, which may lead to serious estimation errors. For this reason, some scholars have proposed hybrid estimation methods. The hybrid estimation framework is shown in Figure 11. The hybrid estimation approaches optimize the estimation results by dynamically adjusting the weights of different estimation algorithms, which greatly improves the estimation accuracy. Specifically, this hybrid estimation method usually designs some integration algorithms for the weighted fusion of longitudinal and lateral TRFCs to improve the estimation accuracy.

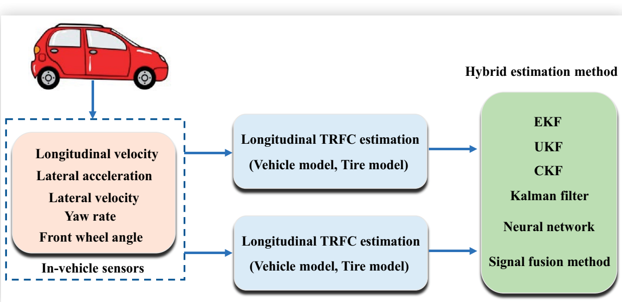
TABLE 3 Summary of lateral dynamics-based methods.

Number	Models	Methodology	References
1	Brush model	Analytical model	[176]
2	Single-track vehicle model	Analytical model	[177, 178]
3	Hypothetical brush model	Direct model inversion	[179]
4	Seven-DOF vehicle model	The multi-sensor signal fusion method	[180, 181, 182]
5	Single-track vehicle model	Nonlinear adaptive observer	[183]
6	Random-walk model	Extended Luenberger observer	[184]
7	Seven-DOF vehicle model	Online gradient descent algorithm	[185]
8	Single-track vehicle model	Nonlinear observer	[186, 187]
9	Single-track vehicle model	High-order sliding mode differentiator	[188]
10	Three-DOF vehicle model	EKF	[189]
11	Single-track vehicle model	UKF	[190]
12	Single-track vehicle model	Particle filter	[191]

Ren et al. [192] designed a hybrid estimator considering longitudinal, lateral, and yaw motions to improve estimation accuracy. Feng et al. [193] proposed a moving sliding window estimation strategy. The estimation algorithm can fully consider the constraints of the estimator under the actual physical conditions without relying on the initial estimation information. However, the estimation performance of the time domain-based fusion method will degrade under small acceleration conditions. Therefore, a frequency domain-based is proposed to estimate TRFC [194].

Furthermore, using recursive least squares [195] to predict TRFC dynamically based on longitudinal and lateral tire forces is another common method. To further improve the estimation performance, Qi et al. [196] designed an EKF method to estimate TRFC based on tire forces. In order to decrease the impact of old sensor data on the estimation accuracy in the EKF, a limited memory adaptive EKF [197] is presented to solve this issue. Furthermore, a UKF has also been utilized for TRFC estimation in recent years. Subsequently, Wang et al. [198] proposed a strong tracking UKF to identify TRFC. Similar studies have been reported in [199]. The more advanced CKF has also received the attention of relevant scholars in recent years. Yin et al. [200] proposed a new adaptive CKF to estimate TRFC. Experimental results show that the estimation performance of the proposed method is better than that of the traditional CKF. Particle filtering has also been shown to be an effective method [201]. Each of these estimation methods has different innovations in terms of vehicle dynamics models or estimation algorithms. To make it clearer for the reader to understand the discrepancies between the different methods, some details are presented in Table 4.

FIGURE 11 The hybrid estimation method.



4. Summary and Perspectives

In this article, we review and compare the state-of-the-art methods for state estimation of the vehicle neighborhood system. The latest estimation methods for different traffic elements are systematically evaluated and summarized in three broad aspects. Although many valuable research results have been achieved, the problem of state estimation of the vehicle neighborhood system is still challenging. The measurement performance and noise statistics of onboard sensors are time-varying due to aging or other driving environments such as high temperatures. Most current estimation methods assume that the noise follows a Gaussian distribution but the noise of vehicle sensors in real driving environments may not satisfy the Gaussian distribution. How to evaluate the performance of onboard sensors online and design estimation methods under non-Gaussian distribution is an urgent problem to be solved. Especially for autonomous vehicles, their driving decisions completely rely on correct sensor information, and wrong or low-quality measurement information may lead to wrong decisions or even traffic accidents. Some non-Gaussian noise filtering algorithms can be employed to estimate the vehicle neighborhood state such as particle filtering or some advanced Kalman combined with machine learning algorithms.

State estimation of vehicle neighborhood systems requires consideration of the effects of severe coupling problems. The mechanical interaction between the various physical components of the vehicle body and the mechanical response of the

TABLE 4 Summary of hybrid estimation methods.

Number	Models	Methodology	References
1	Three-DOF model	Hybrid estimator	[192]
2	Three-DOF model	Moving sliding window method	[193]
3	Active front steering model	Frequency domain method	[194]
4	Sensor-based model	Recursive least squares	[195]
5	Four-DOF model	EKF	[196]
6	Three-DOF model	Adaptive EKF	[197]
7	Brush tire model	Strong tracking UKF	[198, 199]
8	Four-wheel model	Adaptive CKF	[200]
9	Three-DOF model	Particle filtering	[201]

tires to the road causes the state variables of the system to be strongly coupled. In addition, the signals measured by the sensors on board belong to different subsystems. Therefore, additional state and parameter information is usually required in advance to estimate the system state. Considering this coupling problem, designing a distributed modular estimation architecture is an effective approach to address this type of problem.

The model-based estimation method can be applied to normal driving conditions, but it may lead to a decrease in estimation accuracy in some extreme conditions. In addition, the simplification of mathematical modeling inevitably reduces the accuracy of the vehicle dynamic model. The data-based prediction method can get rid of the dependence on the model but requires the data set to be as comprehensive as possible, and its generalization performance needs to be improved. How to make full use of the advantages of the two types of methods and design a reasonable fusion strategy to improve the state estimation of the vehicle neighborhood system is also an interesting research direction. Based on the above problem, designing a multi-model fusion algorithm based on probability distribution is a promising solution.

In addition to improving the accuracy of state estimation, the real-time performance of the algorithm is essential for decision-making. The control cycle of a typical onboard electronic control unit is about 20 ms, which imposes specific real-time requirements on the vehicle dynamic state estimation. Furthermore, the computational performance of onboard controllers is usually much lower than that of computer processors. Considering the above-mentioned issues, using a simple structured nonlinear observer, and deploying Field-Programmable Gate Array is an effective solution.

The current traffic state information may not be good enough for autonomous vehicles to obtain real-time decisions, since future traffic information is also critical for them. Most of the existing research methods are only able to estimate the state of the system at the current moment. How to use machine learning methods to achieve online prediction of the vehicle's motion state and TRFC in the future, which will greatly increase the fault tolerance and rationality of autonomous vehicle decision-making. Obtaining road traffic information ahead using V2X and designing advanced filtering algorithms that take into account the time series of information is the key to solving this type of problem. Accordingly, this will be the mainstream research direction of the state prediction problem for vehicle neighborhood systems.

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References

1. Wang, Y., Hu, J., Wang, F.A., Dong, H. et al., "Tire Road Friction Coefficient Estimation: Review and Research Perspectives," *Chinese Journal of Mechanical Engineering* 335, no. 6 (2022): 1-11.
2. Li, S.E., Chen, H., Li, R., Liu, Z. et al., "Predictive Lateral Control to Stabilise Highly Automated Vehicles at Tire-Road Friction Limits," *Vehicle System Dynamics* 58, no. 5 (2020): 768-786.
3. Hu, Z., Liao, Y., Liu, J., and Xu, H., "Investigation of Vehicle Stability by Integration of Active Suspension, Torque Vectoring, and Direct Yaw Control," *SAE Int. J. Veh. Dyn., Stab., and NVH* 6, no. 4 (2022): 441-459, doi:https://doi.org/10.4271/10-06-04-0029.
4. He, L., Ye, W., He, Z., Song, K. et al., "A Combining Sliding Mode Control Approach for Electric Motor Anti-Lock Braking System of Battery Electric Vehicle," *Control Engineering Practice* 102 (2020): 104520.
5. Chen, X., Wei, L., Wang, X., Li, L. et al., "Hierarchical Cooperative Control of Anti-Lock Braking and Energy Regeneration for Electromechanical Brake-by-Wire System," *Mechanical Systems and Signal Processing* 159 (2021): 107796.

6. Zhao, Q., Zheng, H., Kaku, C., Cheng, F. et al., "Safety Spacing Control of Truck Platoon Based on Emergency Braking under Different Road Conditions," *SAE Int. J. Veh. Dyn., Stab., and NVH* 7, no. 1 (2023): 69-81, doi:https://doi.org/10.4271/10-07-01-0005.
7. Rajendran, S., Spurgeon, S.K., Tsampardoukas, G., and Hampson, R., "Estimation of Road Frictional Force and Wheel Slip for Effective Antilock Braking System (ABS) Control," *International Journal of Robust and Nonlinear Control* 29, no. 3 (2019): 736-765.
8. Wang, Z., Duan, Y., Wu, J., and Zhang, Y., "Cooperative Game Approach to Merging Sequence and Optimal Trajectory Planning of Connected and Automated Vehicles at Unsignalized Intersections," SAE Technical Paper 2022-01-0295, 2022, doi:https://doi.org/10.4271/2022-01-0295.
9. Wang, Y., Yin, G., Li, Y. et al., "Self-Learning Control for Coordinated Collision Avoidance of Automated Vehicles," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* 235, no. 4 (2021): 1149-1163.
10. Sande, T.P., Merks, M.H.M., Lindeman, E., and Nijmeijer, H., "Rule-Based Control of a Semi-Active Suspension System for Road Holding Using Limited Sensor Information: Design and Experiments," *Vehicle System Dynamics* 60, no. 12 (2022): 4226-4244.
11. He, X., Chen, J., Tang, D., Peng, S. et al., "Using an Inerter-Based Suspension to Reduce Carbody Flexible Vibration and Improve Riding-Comfort," *SAE Int. J. Veh. Dyn., Stab., and NVH* 7, no. 2 (2023): 137-151, doi:https://doi.org/10.4271/10-07-02-0009.
12. Aghasizade, S., Mirzaei, M., and Rafatnia, S., "The Effect of Road Quality on Integrated Control of Active Suspension and Anti-Lock Braking Systems," *AUT Journal of Mechanical Engineering* 3, no. 1 (2019): 123-135.
13. Gauker, C., "Domain of Discourse," *Mind* 106, no. 421 (1997): 1-32.
14. Yao, Y., "Neighborhood Systems and Approximate Retrieval," *Information Sciences* 176, no. 23 (2006): 3431-3452.
15. Rajasekharan, A. and Subramaniam, S., "Enhancing Ride Comfort and Stability of a Large Van Using an Improved Semi-active Stability Augmentation System," *SAE Int. J. Veh. Dyn., Stab., and NVH* 6, no. 4 (2022): 385-403, doi:https://doi.org/10.4271/10-06-04-0026.
16. Hashemi, E., Pirani, M., Khajepour, A., Fidan, B. et al., "Fault Tolerant Consensus for Vehicle State Estimation: A Cyber-Physical Approach," *IEEE Transactions on Industrial Informatics* 15, no. 9 (2019): 5129-5138.
17. Zhuoping, Y.U. and Xiaojie, G.A.O., "Review of Vehicle State Estimation Problem under Driving Situation," *Journal of Mechanical Engineering* 45, no. 5 (2009): 20-33.
18. Tin Leung, K., Whidborne, J.F., Purdy, D. et al., "A Review of Ground Vehicle Dynamic State Estimations Utilizing GPS/INS," *Vehicle System Dynamics* 49, no. 1-2 (2011): 29-58.
19. Guo, H., Cao, D., Chen, H. et al., "Vehicle Dynamic State Estimation: State of the Art Schemes and Perspectives," *IEEE/CAA Journal of Automatica Sinica* 5, no. 2 (2018): 418-431.
20. Singh, K.B., Arat, M.A., and Taheri, S., "Literature Review and Fundamental Approaches for Vehicle and Tire State Estimation," *Vehicle System Dynamics* 57, no. 11 (2019): 1643-1665.
21. Jin, X., Yin, G., and Chen, N., "Advanced Estimation Techniques for Vehicle System Dynamic State: A Survey," *Sensors* 19, no. 19 (2019): 4289.
22. Li, L., Wang, F., and Zhou, Q., "Integrated Longitudinal and Lateral Tire/Road Friction Modeling and Monitoring for Vehicle Motion Control," *IEEE Transactions on Intelligent Transportation Systems* 7, no. 1 (2006): 1-19.
23. Acosta, M., Kanarachos, S., and Blundell, M., "Road Friction Virtual Sensing: A Review of Estimation Techniques with Emphasis on Low Excitation Approaches," *Applied Sciences-Basel* 7, no. 12 (2017): 1-47.
24. Khaleghian, S., Emami, A., and Taheri, S., "A Technical Survey on Tire-Road Friction Estimation," *Friction* 5, no. 2 (2017): 123-146.
25. Alquran, M. and Mayyas, A., "Design of a Nonlinear Stability Controller for Ground Vehicles Subjected to a Tire Blowout Using Double-Integral Sliding-Mode Controller," *SAE Int. J. Veh. Dyn., Stab., and NVH* 5, no. 3 (2021): 291-305, doi:https://doi.org/10.4271/10-05-03-0020.
26. Hu, Y. and Wang, H., "Robust Tracking Control for Vehicle Electronic Throttle Using Adaptive Dynamic Sliding Mode and Extended State Observer," *Mechanical Systems and Signal Processing* 135 (2020): 106375.
27. Lin, F., Wang, S., Zhao, Y., and Cai, Y., "Research on Autonomous Vehicle Path Tracking Control Considering Roll Stability," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* 235, no. 1 (2021): 199-210.
28. Li, Z., Wang, P., Liu, H., Hu, Y. et al., "Coordinated Longitudinal and Lateral Vehicle Stability Control Based on the Combined-Slip Tire Model in the MPC Framework," *Mechanical Systems and Signal Processing* 161 (2021): 107947.
29. Peng, H. and Chen, X., "Active Safety Control of X-by-Wire Electric Vehicles: A Survey," *SAE Int. J. Veh. Dyn., Stab., and NVH* 6, no. 2 (2022): 115-133, doi:https://doi.org/10.4271/10-06-02-0008.
30. Lu, X., Shi, Q., Li, Y., Xu, K. et al., "Road Adhesion Coefficient Identification Method Based on Vehicle Dynamics Model and Multi-Algorithm Fusion," SAE Technical Paper 2022-01-0908, 2022, doi:https://doi.org/10.4271/2022-01-0908.
31. Nam, K., Oh, S., Fujimoto, H., and Hori, Y., "Estimation of Sideslip and Roll Angles of Electric Vehicles Using Lateral Tire Force Sensors through RLS and Kalman Filter Approaches," *IEEE Transactions on Industrial Electronics* 60 (2012): 988-1000.
32. Besselink, I.J.M., Schmeitz, A.J.C., and Pacejka, H.B., "An Improved Magic Formula/Swift Tyre Model That Can Handle Inflation Pressure Changes," *Vehicle System Dynamics* 48, no. S1 (2010): 337-352.

33. Xu, N., Zhou, J., Li, X., and Li, F., "Analysis of the Effect of Inflation Pressure on Vehicle Handling and Stability under Combined Slip Conditions Based on the UniTire Model," *SAE Int. J. Veh. Dyn., Stab., and NVH* 5, no. 3 (2021): 259-277, doi:https://doi.org/10.4271/10-05-03-0018.
34. Choi, M., Oh, J.J., and Choi, S.B., "Linearized Recursive Least Squares Methods for Real-Time Identification of Tire–Road Friction Coefficient," *IEEE Transactions on Vehicular Technology* 62, no. 7 (2013): 2906-2918.
35. Stephant, J., Charara, A., and Meizel, D., "Linear Observers for Vehicle Sideslip Angle: Experimental Validation," in *Proceedings of IEEE International Symposium on Industrial Electronics*, Ajaccio, France, 341-346, May 2004.
36. Zhang, H., Zhang, G., and Wang, J., "Sideslip Angle Estimation of an Electric Ground Vehicle via Finite-Frequency H∞ Approach," *IEEE Transactions on Transportation Electrification* 2 (2015): 200-209.
37. Ozkan, B., Margolis, D., and Pengov, M., "The Controller Output Observer: Estimation of Vehicle Tire Cornering and Normal Forces," *Journal of Dynamic Systems, Measurement, and Control-ASME* 130 (2008): 061002.
38. Hsiao, T., "Robust Estimation and Control of Tire Traction Forces," *IEEE Transactions on Vehicular Technology.* 62 (2012): 1378-1383.
39. Zhao, L.H., Liu, Z.Y., and Chen, H., "Design of a Nonlinear Observer for Vehicle Velocity Estimation and Experiments," *IEEE Transactions on Control Systems Technology* 19 (2010): 664-672.
40. Guo, H., Chen, H., Cao, D., and Jin, W., "Design of a Reduced-Order Non-Linear Observer for Vehicle Velocities Estimation," *IET Control Theory Applications* 7 (2013): 2056-2068.
41. Grip, H.F., Imsland, L., Johansen, T.A., Fossen, T.I. et al., "Nonlinear Vehicle Side-Slip Estimation with Friction Adaptation," *Automatica* 44 (2008): 611-622.
42. Gao, X., Yu, Z., Neubeck, J., and Wiedemann, J., "Sideslip Angle Estimation Based on Input-Output Linearisation with Tire-Road Friction Adaptation," *Vehicle System Dynamics* 48 (2010): 217-234.
43. Hashemi, E., Zarringhalam, R., Khajepour, A., Melek, W. et al., "Real-Time Estimation of the Road Bank and Grade Angles with Unknown Input Observers," *Vehicle System Dynamics* 55 (2017): 648-667.
44. Li, B., Du, H., Li, W., and Zhang, B., "Non-Linear Tyre Model–Based Non-Singular Terminal Sliding Mode Observer for Vehicle Velocity and Side-Slip Angle Estimation," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* 233, no. 1 (2019): 38-54.
45. Tanelli, M., Ferrara, A., and Giani, P., "Combined Vehicle Velocity and Tire-Road Friction Estimation via Sliding Mode Observers," in *Proceedings of the IEEE International Conference on Control Applications*, Dubrovnik, Croatia, 130-135, 2012.
46. Fouka, M., Nehaoua, L., and Arioui, H., "Motorcycle State Estimation and Tire Cornering Stiffness Identification Applied to Road Safety: Using Observer-Based Identifiers," *IEEE Transactions on Intelligent Transportation Systems* 23, no. 7 (2022): 7017-7027.
47. Cadiou, J.C., El Hadri, A., and Chikhi, F., "Non-Linear Tyre Forces Estimation Based on Vehicle Dynamics Observation in a Finite Time," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* 218 (2004): 1379-1392.
48. Song, Z.B., Zweiri, Y.H., Seneviratne, L.D., and Althoefer, K., "Non-linear Observer for Slip Estimation of Tracked Vehicles," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* 222 (2008): 515-533.
49. M'Sirdi, N.K., Rabhi, A., Fridman, L. et al., "Second Order Sliding-Mode Observer for Estimation of Vehicle Dynamic Parameters," *International Journal of Vehicle Design* 48, no. 3-4 (2008): 190-207.
50. Chen, Y., Ji, Y., and Guo, K., "A Reduced-Order Nonlinear Sliding Mode Observer for Vehicle Slip Angle and Tyre Forces," *Vehicle System Dynamics* 52 (2014): 1716-1728.
51. Imine, H., Benallegue, A., Madani, T., and Srairi, S., "Rollover Risk Prediction of Heavy Vehicle Using High-Order Sliding-Mode Observer: Experimental Results," *IEEE Transactions on Vehicular Technology* 63 (2013): 2533-2543.
52. Boada, B.L., Boada, M.J.L., and Diaz, V., "Vehicle Sideslip Angle Measurement Based on Sensor Data Fusion Using an Integrated ANFIS and an Unscented Kalman Filter Algorithm," *Mechanical Systems and Signal Processing* 72 (2016): 832-845.
53. Venhovens, P.J.T. and Naab, K., "Vehicle Dynamics Estimation Using Kalman Filters," *Vehicle System Dynamics* 32 (1999): 171-184.
54. Cho, W., Yoon, J., Yim, S., Koo, B. et al., "Estimation of Tire Forces for Application to Vehicle Stability Control," *IEEE Transactions on Vehicular Technology* 59 (2009): 638-649.
55. Zheng, H., Miao, Y., and Li, B., "A Heavy Tractor Semi-Trailer Stability Control Strategy Based on Electronic Pneumatic Braking System HIL Test," *SAE Int. J. Veh. Dyn., Stab., and NVH* 3, no. 3 (2019): 237-249, doi:https://doi.org/10.4271/10-03-03-0016.
56. Anderson, R. and Bevly, D.M., "Using GPS with a Model-Based Estimator to Estimate Critical Vehicle States," *Vehicle System Dynamics* 48 (2010): 1413-1438.
57. Lee, S., Nakano, K., and Ohori, M., "On-Board Identification of Tyre Cornering Stiffness Using Dual Kalman Filter and GPS," *Vehicle System Dynamics.* 53 (2015): 437-448.
58. Ryu, J. and Gerdes, J.C., "Integrating Inertial Sensors with Global Positioning System (GPS) for Vehicle Dynamics Control," *Journal of Dynamic Systems Measurement and Control-Transactions of the ASME* 126 (2004): 243-254.
59. Wenzel, T.A., Burnham, K.J., Blundell, M.V., and Williams, R.A., "Dual Extended Kalman Filter for Vehicle State and Parameter Estimation," *Vehicle System Dynamics* 44 (2006): 153-171.
60. Swami, A., Liu, C., Kubenz, J., Prokop, G. et al., "Experimental Study on Tire Contact Patch Characteristics

for Vehicle Handling with Enhanced Optical Measuring System," *SAE Int. J. Veh. Dyn., Stab., and NVH* 5 (2021): 333-350, doi:https://doi.org/10.4271/10-05-03-0023.

61. Baffet, G., Charara, A., and Dherbomez, G., "An Observer of Tire-Road Forces and Friction for Active Security Vehicle Systems," *IEEE/ASME Transactions on Mechatronics* 12 (2007): 651-661.
62. Zong, C., Hu, D., and Zheng, H., "Dual Extended Kalman Filter for Combined Estimation of Vehicle State and Road Friction," *Chinese Journal of Mechanical Engineering* 26 (2013): 313-324.
63. Tsunashima, H., Murakami, M., and Miyataa, J., "Vehicle, and Road State Estimation Using Interacting Multiple Model Approach," *Vehicle System Dynamics* 44 (2006): 750-758.
64. Hang, P., Chen, X., Fang, S., and Luo, F., "Robust Control for Four-Wheel-Independent-Steering Electric Vehicle with Steer-by-Wire System," *International Journal of Automotive Technology* 18, no. 5 (2017): 785-797.
65. Naets, F., van Aalst, S., Boulkroune, B., El Ghouti, N., Desmet, W., Design and Experimental Validation of a Stable Two-Stage Estimator for Automotive Sideslip Angle and Tire Parameters. *IEEE Transactions on Vehicular Technology*, 66(11):9727-9742, 2017.
66. Xia, X., Xiong, L., Lin, X., and Yu, Z., "Vehicle Sideslip Angle Estimation Considering the Tire Pneumatic Trail Variation," SAE Technical Paper 2018-01-0571, 2018, doi:https://doi.org/10.4271/2018-01-0571.
67. Hu, C., Wang, Z., Taghavifar, H., Na, J. et al., "MME-EKF-Based Path-Tracking Control of Autonomous Vehicles Considering Input Saturation," *IEEE Transactions on Vehicular Technology* 68, no. 6 (2019): 5246-5259.
68. Di Biase, F., Lenzo, B., and Timpone, F., "Vehicle Sideslip Angle Estimation for a Heavy-Duty Vehicle via Extended Kalman Filter Using a Rational Tyre Model," *IEEE Access* 8 (2020): 142120-142130.
69. Li, X., Xu, N., Li, Q., Guo, K. et al., "A Fusion Methodology for Sideslip Angle Estimation on the Basis of Kinematics-Based and Model-Based Approaches," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* 234, no. 7 (2020): 1930-1943.
70. Sun, W., Wang, Z., Wang, J., Wang, X. et al., "Research on a Real-Time Estimation Method of Vehicle Sideslip Angle Based on EKF," *Sensors* 22, no. 9 (2022): 3386.
71. Lu, H., Liu, Q., Shi, Y., and Yu, F., "Estimation of Vehicle Sideslip Angle and Individual Tyre-Road Forces Based on Tyre Friction Circle Concept," *International Journal of Vehicle Autonomous Systems* 13, no. 4 (2017): 274-305.
72. Jiang, G., Liu, L., Guo, C., Chen, J. et al., "A Novel Fusion Algorithm for Estimation of the Side-Slip Angle and the Roll Angle of a Vehicle with Optimized Key Parameters," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* 231, no. 2 (2017): 161-174.
73. Zhou, C., Liu, X.H., and Xu, F.X., "Intervention Criterion and Control Strategy of Active Front Steering System for Emergency Rescue Vehicle," *Mechanical Systems and Signal Processing* 148 (2021): 107160.
74. Wang, Y., Wei, M., Zhao, W., Zhang, F. et al., "Vehicle State Estimation Based on Combined RLS and FAEKF," *China Mechanical Engineering* 28, no. 06 (2017): 750.
75. Wang, Y., Xu, L., Zhang, F., Dong, H. et al., "An Adaptive Fault-Tolerant EKF for Vehicle State Estimation with Partial Missing Measurements," *IEEE/ASME Transactions on Mechatronics* 26, no. 3 (2021): 1318-1327.
76. Yuan, H. and Song, X., "A Modified EKF for Vehicle State Estimation with Partial Missing Measurements," *IEEE Signal Processing Letters* 29 (2022): 1594-1598.
77. Zhang, F., Wang, Y., Hu, J., Yin, G. et al., "A Novel Comprehensive Scheme for Vehicle State Estimation Using Dual Extended H-Infinity Kalman Filter," *Electronics* 10, no. 13 (2021): 1526.
78. Kidambi, N., Pietron, G., Boesch, M., Fujii, Y. et al., "Accuracy and Robustness of Parallel Vehicle Mass and Road Grade Estimation," *SAE Int. J. Veh. Dyn., Stab., and NVH* 1 (2017): 317-325, doi:https://doi.org/10.4271/2017-01-1586.
79. Antonov, S., Fehn, A., and Kugi, A., "Unscented Kalman Filter for Vehicle State Estimation," *Vehicle System Dynamics* 49 (2011): 1497-1520.
80. Heidfeld, H. and Schünemann, M., "Optimization-Based Tuning of a Hybrid UKF State Estimator with Tire Model Adaption for an All Wheel Drive Electric Vehicle," *Energies* 14, no. 5 (2021): 1396.
81. Chen, J., Song, J., Li, L., Jia, G. et al., "UKF-Based Adaptive Variable Structure Observer for Vehicle Sideslip with Dynamic Correction," *IET Control Theory Applications* 10 (2016): 1641-1652.
82. Chen, L., Bian, M., Luo, Y., and Li, K., "Real-Time Identification of the Tyre-Road Friction Coefficient Using an Unscented Kalman Filter and mean-square-error-Weighted Fusion," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* 230 (2016): 788-802.
83. Wang, Z., Qin, Y., Gu, L., and Dong, M., "Vehicle System State Estimation Based on Adaptive Unscented Kalman Filtering Combing with Road Classification," *IEEE Access* 5 (2017): 27786-27799.
84. Villano, E., Lenzo, B., and Sakhnevych, A., "Cross-Combined UKF for Vehicle Sideslip Angle Estimation with a Modified Dugoff Tire Model: Design and Experimental Results," *Meccanica* 56, no. 11 (2021): 2653-2668.
85. Mazzilli, V., Ivone, D., De Pinto, S., Pascali, L. et al., "On the Benefit of Smart Tyre Technology on Vehicle State Estimation," *Vehicle System Dynamics* 1-26 (2021).
86. Kim, D., Kim, G., Choi, S., and Huh, K., "An Integrated Deep Ensemble-Unscented Kalman Filter for Sideslip Angle Estimation with Sensor Filtering Network," *IEEE Access* 9 (2021): 149681-149689.
87. Wu, X., Zhou, B., Wen, G., Long, L. et al., "Intervention Criterion and Control Research for Active Front Steering with Consideration of Road Adhesion," *Vehicle System Dynamics* 56, no. 4 (2018): 553-578.

88. Wang, P., Pang, H., Xu, Z., and Jin, J., "On Co-estimation and Validation of Vehicle Driving States by a UKF-Based Approach," *Mechanical Sciences* 12, no. 1 (2021): 19-30.

89. Song, Y., Shu, H., and Chen, X., "Chassis Integrated Control for 4WIS Distributed Drive EVs with Model Predictive Control Based on the UKF Observer," *Science China Technological Sciences* 63, no. 3 (2020): 397-409.

90. Liu, Y.J., Dou, C.H., Shen, F., and Sun, Q.Y., "Vehicle State Estimation Based on Unscented Kalman Filtering and a Genetic-Particle Swarm Algorithm," *Journal of the Institution of Engineers* 102, no. 2 (2021): 447-469.

91. Strano, S. and Terzo, M., "Constrained Nonlinear Filter for Vehicle Sideslip Angle Estimation with No A Priori Knowledge of Tyre Characteristics," *Control Engineering Practice* 71 (2018): 10-17.

92. Zhang, Z., Chu, L., Zhang, J., Guo, C. et al., "Design of Vehicle Stability Controller Based on Fuzzy Radial Basis Neural Network Sliding Mode Theory with Sideslip Angle Estimation," *Applied Sciences* 11, no. 3 (2021): 1231.

93. Jin, X. and Yin, G., "Estimation of Lateral Tire-Road Forces and Sideslip Angle for Electric Vehicles Using Interacting Multiple Model Filter Approach," *Journal of the Franklin Institute* 352 (2015): 686-707.

94. Arasaratnam, I. and Haykin, S., "Cubature Kalman Filters," *IEEE Transactions on Automatic Control* 54, no. 6 (2009): 1254-1269.

95. Xin, X., Chen, J., and Zou, J., "Vehicle State Estimation Using Cubature Kalman Filter," in *2014 IEEE 17th International Conference on Computational Science and Engineering*, Chengdu, China, 44-48, 2014.

96. Cheng, S., Li, L., and Chen, J., "Fusion Algorithm Design Based on Adaptive SCKF and Integral Correction for Side-Slip Angle Observation," *IEEE Transactions on Industrial Electronics* 65, no. 7 (2017): 5754-5763.

97. Shen, C., Zhang, Y., Tang, J., Cao, H. et al., "Dual-Optimization for a MEMS-INS/GPS System during GPS Outages Based on the Cubature Kalman Filter and Neural Networks," *Mechanical Systems and Signal Processing* 133 (2019): 106222.

98. Hou, S., Xu, W., and Liu, G., "Design of an Interacting Multiple Model-Cubature Kalman Filter Approach for Vehicle Sideslip Angle and Tire Forces Estimation," *Mathematical Problems in Engineering* (2019): 1-13.

99. Xiong, H., Liu, J., Zhang, R., Zhu, X. et al., "An Accurate Vehicle and Road Condition Estimation Algorithm for Vehicle Networking Applications," *IEEE Access* 7 (2019): 17705-17715.

100. Wang, Y., Zhang, F., Geng, K., Zhuang, W. et al., "Estimation of Vehicle State Using Robust Cubature Kalman Filter," in *IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*, 1024-1029, 2020.

101. Song, R. and Fang, Y., "Vehicle State Estimation for INS/GPS Aided by Sensors Fusion and SCKF-Based Algorithm," *Mechanical Systems and Signal Processing* 150 (2021): 107315.

102. Wenkang, W., Jingan, F., Bao, S., and Xin, L., "Vehicle State Estimation Using Interacting Multiple Model Based on Square Root Cubature Kalman Filter," *Applied Sciences* 11, no. 22 (2021): 10772.

103. Cheng, S., Li, C.F., Chen, X., Li, L. et al., "A Hierarchical Estimation Scheme of Tire-Force Based on Random-Walk SCKF for Vehicle Dynamics Control," *Journal of the Franklin Institute* 357, no. 18 (2020): 13964-13985.

104. Chen, X., Li, S., Li, L., Zhao, W. et al., "Longitudinal-Lateral-Cooperative Estimation Algorithm for Vehicle Dynamics States Based on Adaptive-Square-Root-Cubature-Kalman-Filter and Similarity-Principle," *Mechanical Systems and Signal Processing* 176 (2022): 109162.

105. Zhang, Z., Yin, G., and Wu, Z., "Joint Estimation of Mass and Center of Gravity Position for Distributed Drive Electric Vehicles Using Dual Robust Embedded Cubature Kalman Filter," *Sensors* 22, no. 24 (2022): 10018.

106. Yaming, L., Rongyun, Z., Peicheng, S., Linfeng, Z. et al., "Distributed Electric Vehicle State Parameter Estimation Based on the ASO-SRGHCKF Algorithm," *IEEE Sensors Journal* 22, no. 19 (2022): 18780-18792.

107. Wang, Y., Geng, K., Xu, L., Ren, Y. et al., "Estimation of Sideslip Angle and Tire Cornering Stiffness Using Fuzzy Adaptive Robust Cubature Kalman Filter," *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 52, no. 3 (2022): 1451-1462.

108. Zhang, J., Wang, F.Y., Wang, K., Lin, W.H. et al., "Data-Driven Intelligent Transportation Systems: A Survey," *IEEE Transactions on Intelligent Transportation Systems* 12 (2011): 1624-1639.

109. Saadeddin, K., Abdel-Hafez, M.F., Jaradat, M.A., and Jarrah, M.A., "Performance Enhancement of Low-Cost, High-Accuracy, State Estimation for Vehicle Collision Prevention System Using ANFIS," *Mechanical Systems and Signal Processing* 41 (2013): 239-253.

110. Gwak, M., Jo, K., and Sunwoo, M., "Neural-Network Multiple Models Filter (NMM)-Based Position Estimation System for Autonomous Vehicles," *International Journal of Automotive Technology* 14 (2013): 265-274.

111. Vargas-Melendez, L., Boada, B., Boada, M., Gauchia, A. et al., "Sensor Fusion Based on an Integrated Neural Network and Probability Density Function (PDF) Dual Kalman Filter for On-Line Estimation of Vehicle Parameters and States," *Sensors* 17 (2017): 987.

112. Melzi, S. and Sabbioni, E., "On the Vehicle Sideslip Angle Estimation through Neural Networks: Numerical and Experimental Results," *Mechanical Systems and Signal Processing* 25 (2011): 2005-2019.

113. Vargas-Meléndez, L., Boada, B., Boada, M., Gauchía, A. et al., "A Sensor Fusion Method Based on an Integrated Neural Network and Kalman Filter for Vehicle Roll Angle Estimation," *Sensors* 16 (2016): 1400.

114. Taghavifar, H. and Mardani, A., "Use of Artificial Neural Networks for Estimation of Agricultural Wheel Traction Force in Soil Bin," *Neural Computing and Applications* 24 (2014): 1249-1258.

115. Xu, D., Yap, F.F., Han, X., and Wen, G.L., "Identification of Spring-Force Factors of Suspension Systems Using

Progressive Neural Network on a Validated Computer Model," *Inverse Problems in Science and Engineering* 11 (2003): 55-74.

116. Wei, W., Bei, S., Zhang, L., Zhu, K. et al., "Vehicle Sideslip Angle Estimation Based on General Regression Neural Network," *Mathematical Problems in Engineering* (2016): 1-7.
117. Gräber, T., Lupberger, S., Unterreiner, M., and Schramm, D., "A Hybrid Approach to Side-Slip Angle Estimation with Recurrent Neural Networks and Kinematic Vehicle Models," *IEEE Transactions on Intelligent Vehicles* 4, no. 1 (2018): 39-47.
118. Li, Y., Yin, G., Zhuang, W. et al., "Compensating Delays and Noises in Motion Control of Autonomous Electric Vehicles by Using Deep Learning and Unscented Kalman Predictor," *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 50, no. 11 (2018): 4326-4338.
119. Novi, T., Capitani, R., and Annicchiarico, C., "An Integrated Artificial Neural Network–Unscented Kalman Filter Vehicle Sideslip Angle Estimation Based on Inertial Measurement Unit Measurements," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* 233, no. 7 (2019): 1864-1878.
120. González, L.P., Sánchez, S.S., Garcia-Guzman, J., Boada, M.J.L. et al., "Simultaneous Estimation of Vehicle Roll and Sideslip Angles through a Deep Learning Approach," *Sensors* 20, no. 13 (2020): 3679.
121. Bonfitto, A., Feraco, S., Tonoli, A., and Amati, N., "Combined Regression and Classification Artificial Neural Networks for Sideslip Angle Estimation and Road Condition Identification," *Vehicle System Dynamics* 58, no. 11 (2020): 1766-1787.
122. Ghosh, J., Tonoli, A., and Amati, N., "A Deep Learning Based Virtual Sensor for Vehicle Sideslip Angle Estimation: Experimental Results," SAE Technical Paper 2018-01-1089, 2018, doi:https://doi.org/10.4271/2018-01-1089.
123. Kim, D., Min, K., Kim, H., and Huh, K., "Vehicle Sideslip Angle Estimation Using Deep Ensemble-Based Adaptive Kalman Filter," *Mechanical Systems and Signal Processing* 144 (2020): 106862.
124. Wang, Y., Zhou, Z., Wei, C. et al., "Host–Target Vehicle Model-Based Lateral State Estimation for Preceding Target Vehicles Considering Measurement Delay," *IEEE Transactions on Industrial Informatics* 14, no. 9 (2018): 4190-4199.
125. Asaithambi, G., Kanagaraj, V., Srinivasan, K.K., and Sivanandan, R., "Study of Traffic Flow Characteristics Using Different Vehicle-Following Models under Mixed Traffic Conditions," *Transportation Letters* 10, no. 2 (2018): 92-103.
126. Anand, P.A., Atmakuri, P., Anne, V.S.R., Asaithambi, G. et al., "Calibration of Vehicle-Following Model Parameters Using Mixed Traffic Trajectory Data," *Transportation in Developing Economies* 5, no. 2 (2019): 1-11.
127. Vegamoor, V.K., Darbha, S., and Rajagopal, K.R., "A Review of Automatic Vehicle Following Systems," *Journal of the Indian Institute of Science* 99, no. 4 (2019): 567-587.
128. Raju, N., Arkatkar, S., and Joshi, G., "Evaluating Performance of Selected Vehicle Following Models Using Trajectory Data under Mixed Traffic Conditions," *Journal of Intelligent Transportation Systems* 24, no. 6 (2020): 617-634.
129. Schubert, R., Richter, E., and Wanielik, G., "Comparison and Evaluation of Advanced Motion Models for Vehicle Tracking," in *2008 11th International Conference on Information Fusion*, Cologne, Germany, IEEE, 1-6, 2008.
130. Liu, H., Wang, P., Lin, J. et al., "Real-Time Longitudinal and Lateral State Estimation of Preceding Vehicle Based on Moving Horizon Estimation," *IEEE Transactions on Vehicular Technology* 70, no. 9 (2021): 8755-8768.
131. Zhou, Z., Zhou, G., Wang, Y. et al., "PTV Longitudinal-Lateral State Estimation Considering Unknown Control Inputs and Uncertain Model Parameters," *IEEE Transactions on Vehicular Technology* 70, no. 5 (2021): 4366-4376.
132. Shieh, Y., Hsu, J., Lin, H. et al., "Investigation of Vehicle Positioning by Infrared Signal-Direction Discrimination for Short-Range Vehicle-to-Vehicle Communications," *IEEE Transactions on Vehicular Technology* 67, no. 12 (2018): 11563-11574.
133. Zhou, Z., Wang, Y., Du, H., Ji, Q. et al., "Sub-full Model-Based Heterogeneous Sensor Fusion for Lateral State Estimation of Preceding Target Vehicles," *IEEE/ASME Transactions on Mechatronicsics* 25, no. 3 (2020): 1335-1345.
134. Schinkel, W., Sande, T., and Nijmeijer, H., "State Estimation for Cooperative Lateral Vehicle Following Using Vehicle-to-Vehicle Communication," *Electronics* 10, no. 6 (2021): 1-28.
135. Kooshkbaghi, M. and Marquez, H.J., "Event-Triggered Discrete-Time Cubature Kalman Filter for Nonlinear Dynamical Systems with Packet Dropout," *IEEE Transactions on Automatic Control* 65, no. 5 (2019): 2278-2285.
136. Wang, Y., Yan, Y., Shen, T., Bai, S. et al., "An Event-Triggered Scheme for State Estimation of Preceding Vehicles under Connected Vehicle Environment," *IEEE Transactions on Intelligent Vehicles* 8, no. 1 (Jan. 2023): 583-593.
137. Wang, Y., Hu, Z., Lou, S., and Lv, C., "Interacting Multiple Model-Based ETUKF for Efficient State Estimation of Connected Vehicles with V2V Communication," *Green Energy and Intelligent Transportation* 2 (2022): 100044.
138. Wang, Y., Yin, G., Lv, C., Zhang, Z. et al., "Event-Triggered State Estimation for Connected Vehicles with Packet Losses," in *2022 6th CAA International Conference on Vehicular Control and Intelligence (CVCI)*, Nanjing, China, 1-6, 2022.
139. Ahn, C., Peng, H., and Tseng, H.E., "Robust Estimation of Road Friction Coefficient Using Lateral and Longitudinal Vehicle Dynamics," *Vehicle System Dynamics* 50, no. 6 (2012): 961-985.
140. Mahboob, M., Kuosmanen, A., and Pellinen, T.K., "Macro- and Micro-Texture Evolution of Road Pavements and Correlation with Friction," *International Journal of Pavement Engineering* 16, no. 2 (2015): 168-179.
141. Holzmann, F., Bellino, M., Siegwart, R. et al., "Predictive Estimation of the Road-Tire Friction Coefficient," in *2006 IEEE International Conference on Control Applications*, Munich, Germany, IEEE, 885-890,2006.
142. Du, Y., Liu, C., Song, Y., Li, Y. et al., "Rapid Estimation of Road Friction for Anti-Skid Autonomous Driving," *IEEE*

Transactions on Intelligent Transportation Systems 21, no. 6 (2019): 2461-2470.

143. Leng, B., Jin, D., Xiong, L., Yang, X. et al., "Estimation of Tire-Road Peak Adhesion Coefficient for Intelligent Electric Vehicles Based on Camera and Tire Dynamics Information Fusion," *Mechanical Systems and Signal Processing* 150 (2021): 107275.
144. Yu, M., Xu, X., Wu, C., Li, S. et al., "Research on the Prediction Model of the Friction Coefficient of Asphalt Pavement Based on Tire-Pavement Coupling," *Advances in Materials Science and Engineering* (2021): 1-10.
145. Singh, K.B., Arat, M.A., and Taheri, S., "An Intelligent Tire Based Tire-Road Friction Estimation Technique and Adaptive Wheel Slip Controller for Antilock Brake System," *Journal of Dynamic Systems Measurement and Control-Transactions of the ASME* 135, no. 3 (2013): 31002-31002.
146. Zou, Z., Zhang, X., Zou, Y., and Lenzo, B., "Tire-Road Friction Coefficient Estimation Method Design for Intelligent Tires Equipped with Three-Axis Accelerometer," *SAE Int. J. Veh. Dyn., Stab., and NVH* 5, no. 3 (2021): 249-258, doi:https://doi.org/10.4271/10-05-03-0017.
147. Hong, S., Erdogan, G., Hedrick, K., and Borrelli, F., "Tyre-Road Friction Coefficient Estimation Based on Tyre Sensors and Lateral Tyre Deflection: Modeling, Simulations, and Experiments," *Vehicle System Dynamics* 51, no. 5 (2013): 627-647.
148. Niskanen, A. and Tuononen, A.J., "Three Three-Axis IEPE Accelerometers on the Inner Liner of a Tire for Finding the Tire-Road Friction Potential Indicators," *Sensors* 15, no. 8 (2015): 19251-19263.
149. Kim, M.H., Park, J., and Choi, S., "Road Type Identification Ahead of the Tire Using D-CNN and Reflected Ultrasonic Signals," *International Journal of Automotive Technology* 22, no. 1 (2021): 47-54.
150. Ergun, M., Iyinam, S., and Iyinam, A.F., "Prediction of Road Surface Friction Coefficient Using Only Macro- and Microtexture Measurements," *Journal of Transportation Engineering-ASCE* 131, no. 4 (2005): 311-319.
151. Erdogan, G., Alexander, L., and Rajamani, R., "Estimation of Tire-Road Friction Coefficient Using a Novel Wireless Piezoelectric Tire Sensor," *IEEE Sensors Journal* 11, no. 2 (2011): 267-279.
152. Yoon, J.H., Li, S.E., and Ahn, C., "Estimation of Vehicle Sideslip Angle and Tire-Road Friction Coefficient Based on Magnetometer with GPS," *International Journal of Automotive Technology* 17, no. 3 (2016): 427-435.
153. Zhang, X. and Göhlich, D., "A Hierarchical Estimator Development for Estimation of Tire-Road Friction Coefficient," *PLoS ONE* 12, no. 2 (2017): 0171085.
154. Ribeiro, M., Moutinho, A., Fioravanti, R. et al., "Estimation of Tire–Road Friction for Road Vehicles: A Time Delay Neural Network Approach," *Journal of the Brazilian Society of Mechanical Sciences and Engineering* 42, no. 1 (2020): 1-12.
155. Pu, Z., Liu, C., Shi, X. et al., "Road Surface Friction Prediction Using Long Short-Term Memory Neural Network Based on Historical Data," *Journal of Intelligent Transportation Systems* 26, no. 1 (2020): 1-12.
156. Pu, Z., Cui, Z., Wang, S. et al., "Time-Aware Gated Recurrent Unit Networks for Forecasting Road Surface Friction Using Historical Data with Missing Values," *IET Intelligent Transport Systems* 14, no. 4 (2020): 213-219.
157. Šabanovič, E., Žuraulis, V., Prentkovskis, O. et al., "Identification of Road-Surface Type Using Deep Neural Networks for Friction Coefficient Estimation," *Sensors* 20, no. 3 (2020): 612.
158. Gustafsson, F., "Slip-Based Tire Road Friction Estimation," *Automatica* 33, no. 6 (1997): 1087-1099.
159. Gustafsson, F., "Monitoring Tire-Road Friction Using the Wheel Slip," *IEEE Control Systems Magazine* 18, no. 4 (1998): 42-49.
160. Yi, K. and Jeong, T., "Observer Based Estimation of Tire-Road Friction for Collision Warning Algorithm Adaptation," *Jsme International Journal Series C-Mechanical Systems Machine Elements and Manufacturing* 41, no. 1 (1998): 116-124.
161. Yi, K., Hedrick, K., and Lee, S.C., "Estimation of Tire-Road Friction Using Observer Based Identifiers," *Vehicle System Dynamics* 31, no. 4 (1999): 233-261.
162. Wang, J.M., Alexander, L., and Rajamani, R., "Friction Estimation on Highway Vehicles Using Longitudinal Measurements," *Journal of Dynamic Systems Measurement and Control-Transactions of the ASME* 126, no. 2 (2004): 265-275.
163. Rajamani, R., Piyabongkarn, D., Lew, J.Y. et al., "Tire-Road Friction-Coefficient Estimation," *IEEE Control Systems Magazine* 30, no. 4 (2010): 54-69.
164. Yi, J.G., Alvarez, L., Claeys, C. et al., "Emergency Braking Control with an Observer-Based Dynamic Tire/Road Friction Model and Wheel Angular Velocity Measurement," *Vehicle System Dynamics* 39, no. 2 (2003): 81-97.
165. Alvarez, L., Yi, J.G., Horowitz, R. et al., "Dynamic Friction Model-Based Tire-Road Friction Estimation and Emergency Braking Control," *Journal of Dynamic Systems Measurement and Control-Transactions of the ASME* 127, no. 1 (2005): 22-32.
166. Patel, N., Edwards, C., and Spurgeon, S.K., "Tyre-Road Friction Estimation—A Comparative Study," *Proceedings of the Institution of Mechanical Engineers Part D-Journal of Automobile Engineering* 222, no. 12 (2008): 2337-2351.
167. De Castro, R., Araujo, R., and Freitas, D., "Optimal Linear Parameterization for On-Line Estimation of Tire-Road Friction," *IFAC Proceedings Volumes* 44, no. 1 (2011): 8409-8414.
168. Ding, N.G., Yu, G.Z., and Wang, W.D., "Estimation of Brake Pressure and Tyre-Road Friction during ABS Activation," *International Journal of Vehicle Design* 58, no. 1 (2012): 33-45.
169. Zhang, X.W., Xu, Y., Pan, M., and Ren, F.H., "A Vehicle ABS Adaptive Sliding-Mode Control Algorithm Based on the Vehicle Velocity Estimation and Tyre/Road Friction Coefficient Estimations," *Vehicle System Dynamics* 52, no. 4 (2014): 475-503.

170. Xia, X., Xiong, L., Sun, K. et al., "Estimation of Maximum Road Friction Coefficient Based on Lyapunov Method," *International Journal of Automotive Technology* 17, no. 6 (2016): 991-1002.

171. Li, B.Y., Du, H.P., Li, W.H. et al., "Comparative Study of Vehicle Tyre-Road Friction Coefficient Estimation with a Novel Cost-Effective Method," *Vehicle System Dynamics* 52, 8 (2014): 1066-1098.

172. Zhao, Y.Q., Li, H.Q., Lin, F. et al., "Estimation of Road Friction Coefficient in Different Road Conditions Based on Vehicle Braking Dynamics," *Chinese Journal of Mechanical Engineering* 30, no. 4 (2017): 982-990.

173. Guan, H., Wang, B., Lu, P.P. et al., "Identification of Maximum Road Friction Coefficient and Optimal Slip Ratio Based on Road Type Recognition," *Chinese Journal of Mechanical Engineering* 27, no. 5 (2014): 1018-1026.

174. Zhang, K., Zhang, Y., and Xu, P., "An Algorithm for Parameter Identification of Semi-Empirical Tire Model," *SAE Int. J. Veh. Dyn., Stab., and NVH* 5, no. 3 (2021): 379-396, doi:https://doi.org/10.4271/10-05-03-0026.

175. Castillo, J.J., Cabrera, J.A., Guerra, A.J. et al., "A Novel Electrohydraulic Brake System with Tire–Road Friction Estimation and Continuous Brake Pressure Control," *IEEE Transactions on Industrial Electronics* 63, no. 3 (2015): 1863-1875.

176. Yamazaki, S., Furukawa, O., and Suzuki, T., "Study on Real Time Estimation of Tire to Road Friction," *Vehicle System Dynamics* 27 (1997): 225-233.

177. Wang, R.R. and Wang, J.M., "Tire-Road Friction Coefficient and Tire Cornering Stiffness Estimation Based on Longitudinal Tire Force Difference Generation," *Control Engineering Practice* 21, no. 1 (2013): 65-75.

178. Wakamatsu, K., Akuta, Y., Ikegaya, M. et al., "Adaptive Yaw Rate Feedback 4WS with Tire/Road Friction Coefficient Estimator," *Vehicle System Dynamics* 27, no. 5-6 (1997): 305-326.

179. Beal, C.E., "Rapid Road Friction Estimation Using Independent Left/Right Steering Torque Measurements," *Vehicle System Dynamics* 58, no. 3 (2020): 377-403.

180. Li, L., Li, H.Z., Song, J. et al., "Road Friction Estimation under Complicated Maneuver Conditions for Active Yaw Control," *Chinese Journal of Mechanical Engineering* 22, no. 4 (2009): 514-520.

181. Li, L., Song, J., Li, H.Z. et al., "Comprehensive Prediction Method of Road Friction for Vehicle Dynamics Control," *Proceedings of the Institution of Mechanical Engineers Part D-Journal of Automobile Engineering* 223, no. D8 (2009): 987-1002.

182. Jin, D., Leng, B., Yang, X. et al., "Road Friction Estimation Method Based on Fusion of Machine Vision and Vehicle Dynamics," in *2020 IEEE Intelligent Vehicles Symposium (IV)*, IEEE, 2020, 1771-1776.

183. Shao, L., Jin, C., Lex, C. et al., "Robust Road Friction Estimation during Vehicle Steering," *Vehicle System Dynamics* 57, no. 4 (2019): 493-519.

184. Ding, N.G., Chen, W., Zhang, Y.P. et al., "An Extended Luenberger Observer for Estimation of Vehicle Sideslip Angle and Road Friction," *International Journal of Vehicle Design* 66, no. 4 (2014): 385-414.

185. Chen, W.W., Tan, D.K., and Zhao, L.F., "Vehicle Sideslip Angle and Road Friction Estimation Using Online Gradient Descent Algorithm," *IEEE Transactions on Vehicular Technology* 67, no. 12 (2018): 11475-11485.

186. Gao, L.T., Xiong, L., Lin, X.F., Xia, X. et al., "Multi-Sensor Fusion Road Friction Coefficient Estimation during Steering with Lyapunov Method," *Sensors* 19, no. 18 (2019): 1-17.

187. Shao, L., Jin, C., Eichberger, A. et al., "Grid Search Based Tire-Road Friction Estimation," *IEEE Access* 8 (2020): 81506-81525.

188. Etienne, L., Lua, C.A., Di Gennaro, S., and Barbot, J.P., "A Super-Twisting Controller for Active Control of Ground Vehicles with Lateral Tire-Road Friction Estimation and CarSim Validation," *International Journal of Control Automation and Systems* 18, no. 5 (2020): 1177-1189.

189. Xu, Y., Chen, B.Y., and Chi, C., "Estimation of Road Friction Coefficient and Vehicle States by 3-DOF Dynamic Model and HSRI Model Based on Information Fusion," *Asian Journal of Control* 20, no. 3 (2018): 1067-1076.

190. Hu, J.Q., Rakheja, S., and Zhang, Y.M., "Real-Time Estimation of Tire-Road Friction Coefficient Based on Lateral Vehicle Dynamics," *Proceedings of the Institution of Mechanical Engineers Part D-Journal of Automobile Engineering* 234, no. 10-11 (2020): 2444-2457.

191. Liu, Y.H., Li, T., Yang, Y.Y. et al., "Estimation of Tire-Road Friction Coefficient Based on Combined APF-IEKF and Iteration Algorithm," *Mechanical Systems and Signal Processing* 88 (2017): 25-35.

192. Ren, H., Chen, S., Shim, T. et al., "Effective Assessment of Tyre–Road Friction Coefficient Using a Hybrid Estimator," *Vehicle System Dynamics* 52, no. 8 (2014): 1047-1065.

193. Feng, Y., Chen, H., Zhao, H. et al., "Road Tire Friction Coefficient Estimation for Four Wheel Drive Electric Vehicle Based on Moving Optimal Estimation Strategy," *Mechanical Systems and Signal Processing* 139 (2020): 106416.

194. Chen, L., Luo, Y., Bian, M. et al., "Estimation of Tire-Road Friction Coefficient Based on Frequency Domain Data Fusion," *Mechanical Systems and Signal Processing* 85 (2017): 177-192.

195. Madhusudhanan, A.K., Corno, M., Arat, M.A. et al., "Load Sensing Bearing Based Road-Tyre Friction Estimation Considering Combined Tyre Slip," *Mechatronics* 39 (2016): 136-146.

196. Qi, Z., Taheri, S., Wang, B. et al., "Estimation of the Tyre–Road Maximum Friction Coefficient and Slip Slope Based on a Novel Tyre Model," *Vehicle System Dynamics* 53, no. 4 (2015): 506-525.

197. Huang, B., Fu, X., Wu, S. et al., "Calculation Algorithm of Tire-Road Friction Coefficient Based on Limited-Memory

Adaptive Extended Kalman Filter," *Mathematical Problems in Engineering* 1 (2019): 1-14.

198. Wang, Y., Lv, C., Yan, Y., Peng, P. et al., "An Integrated Scheme for Coefficient Estimation of Tire Road Friction with Mass Parameter Mismatch under Complex Driving Scenarios," *IEEE Transactions on Industrial Electronics* 69, no. 12 (2022): 133337-113347.

199. Ping, X., Cheng, S., Yue, W. et al., "Adaptive Estimations of Tyre–Road Friction Coefficient and Body's Sideslip Angle Based on Strong Tracking and Interactive Multiple Model Theories," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering* 234, no. 14 (2020): 3224-3238.

200. Wang, Y., Yin, G., and Dong, H., "A Novel Approach for Tire-Road Friction Coefficient Estimation Using Adaptive Cubature Kalman Filter," in *2020 4th CAA International Conference on Vehicular Control and Intelligence (CVCI)*, 30-34,2020.

201. Zhang, L., Guo, P., Wang, Z., and Ding, X., "An Enabling Tire-Road Friction Estimation Method for Four-in-Wheel-Motor-Drive Electric Vehicles," *IEEE Transactions on Transportation Electrification*, Early Access, 2022.