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SURVEY

A Survey of Vehicle Localization: Performance Analysis and Challenges

XIAOYU SHAN, ADNANE CABANI, AND HOUCINE CHAFOUK, (Member, IEEE)
UNIROUEN, ESIGELEC, IRSEEM, Normandy University, 76000 Rouen, France

Corresponding author: Adnane Cabani (cabani@esigelec.fr)

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ABSTRACT Vehicle localization plays a crucial role in ensuring the safe operation of autonomous vehicles and the development of intelligent transportation systems (ITS). However, there is insufficient effort to compare the performance and challenges of different vehicle localization algorithms. This paper aims to address this gap by analyzing the comprehensive performance of existing advanced vehicle localization techniques and discussing their challenges. Firstly, we analyze the self-localization methods based on active and passive sensors. The results show that, the light detection and ranging (LiDAR) and vision-based localization techniques can reach high accuracy. However, they have high computational complexity. Only using the inertial measurement unit (IMU), global positioning system (GPS), radar, and ultrasonic sensors may not realize localization result with high accuracy. Then, we discuss V2X-based cooperative localization methods, analyze the multi-sensor based localization techniques and compare the comprehensive performance among all methods. Although the artificial intelligence (AI) techniques can effectively enhance the efficiency of vision-based localization algorithms, the high computational complexity still should be considered. In addition, since the IMU, GPS, radar, and ultrasonic sensors have good performance in terms of the availability, reliability, scalability, and cost-effectiveness, they can be used as auxiliary sensors to achieve good comprehensive performance through data fusion techniques. Finally, we propose the challenges of different techniques and look forward to future work.

INDEX TERMS Active sensor-based self-localization, cooperative localization, data fusion, ITS, localization, multi-sensors based vehicle localization, passive sensor-based self-localizaion, V2X based cooperative localization.

LIST OF ABBREVIATIONS

Abbreviations	Description
5G	5th generation mobile network.
6-DoF	Six degrees of freedom.
AI	Artificial intelligence.
A-SMGCS	Advanced-surface movement guidance and control system.
CL	Cooperative localization.
CIF	Covariance intersection filter.
CMAD	Cross mean absolute difference.
DMR	Drivable moving search region.
DOA	Direction-of-arrival.
DR	Dead reckoning.
EKF	Extended Kalman filter.
FRPDM	Free-resolution probability distributions map.
GNSS	Global navigation satellite system.
GPS	Global positioning system.
HD	High-definition.
IMU	Inertial measurement unit.
IoT	Internet of things.
IoV	Internet of vehicle.
ITS	Intelligent transportation system.
KF	Kalman filter.
LiDAR	Light detection and ranging.
MCL	Monte Carlo localization.
MSMV	Multi-sensor multi-vehicle.
NCC	Normalized cross-correlation.
NLOS	Non-line-of-sight.
OBU	Onboard unit.

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PF	Particle filter.
RAM	Random access memory.
RANSAC	Random sample consensus algorithm.
RMSE	Root mean square error.
RSSI	Received signal strength indication.
RSUs	Roadside units.
SBL	Sparse Bayesian learning.
SLAM	Simultaneous localization and mapping.
SCIF	Split covariance intersection filter.
TDOA	Time difference of arrival.
TPSM	Third party sparse maps.
UAV	Unmanned aerial vehicle.
UKF	Unscented Kalman filter.
V2I	Vehicle-to-infrastructure.
V2V	Vehicle-to-vehicle.
V2X	Vehicle-to-everything.
VANETs	Vehicular ad hoc networks.
vSLAM	Vision SLAM.

I. INTRODUCTION

The continuous increase in the number of vehicles has a negative impact on the people's daily lives. The large number of vehicles regularly causes traffic jams and slowdowns, leading to excessive energy consumption and significant emissions of greenhouse gases. These emissions directly impact air quality, contributing to an increase of the carbon footprint. In order to solve these kind of problems, the intelligent transportation systems (ITS) can be built. ITS takes cutting-edge techniques such as information communication, automatic and intelligently control technique, which can enable vehicles to run automatically according to the environment and their conditions by comprehensively managing vehicles. ITS has four layers: the physical layer, the communication layer, the operation layer, and the service layer. The physical layer comprises various sensors and information-receiving equipment in the system, primarily responsible for detecting systems' environment and collecting data. The communication layer has the function of realizing information sharing among vehicles and other devices in the system. Meanwhile, the operation layer formulates the running route of vehicles and controls their operating modes. Moreover, the service layer enables automatic and intelligent system operation.

Vehicle localization methods with high comprehensive performance is one of the key functions of the ITS, not only vehicle localization accuracy but also robustness and real-time performance during the localization process should be considered. Time delays can affect vehicle scheduling decisions and thus impact the system's efficiency. Although the global navigation satellite system (GNSS) [1], [2], [3], [4] is widely used in vehicle localization, they are susceptible to interferences from severe weather conditions and high buildings. Moreover, in some special environments with weak signals, named GNSS-denied environment [5], [6], [7], [8] (such as tunnels, underground parking lots, and forests), the accuracy of GNSS cannot be guaranteed. Therefore, it is necessary to use multiple sensors to achieve high precision localization. Multi-sensor-based localization methods use a variety of sensors (including active sensors and passive sensors) to collect diverse and effective data, which can make up for the shortcomings of using GNSS technique alone. By taking advantage of artificial intelligence (AI) [9], [10] [11], [12] and data fusion technique (such as Kalman filter (KF) [13], extended Kalman filter (EKF) [14], unscented Kalman filter (UKF) [15], [16], [17], particle filter (PF) [18], [19], [20], etc.), the data collected by various sensors (such as LiDAR and different types of cameras) can be processed, which improves the accuracy and robustness of vehicle localization.

Furthermore, the architecture of the data fusion process mainly includes three manners: the centralized, decentralized, and distributed. For centralized architecture, all collected data of each vehicle is transmitted to the central workstation where the localization process of each vehicle is accomplished. The centralized architecture can achieve real-time localization when the communication bandwidth and calculation ability of the central workstation is high enough. However, it is difficult to deploy this kind of system on a large scale in the real world since it requires huge economic expenses. Moreover, in the distributed architecture, there is no central workstation, each vehicle realizes the localization on their own processors. Compared with centralized architecture, the distributed manner requires lower communication bandwidth, which is more suitable to achieve high real-time performance localization.

Moreover, cooperative and collaborative localization methods can improve the efficiency of localization by using available information shared by other vehicles or infrastructures. With the improvement of the communication techniques, such as vehicle-to-vehicle (V2V) [21], vehicle-to-infrastructure (V2I) [22], and vehicle-to-everything (V2X) [23], [24] in the internet of things (IoT) [25] and internet of vehicle (IoV) [26] domain, data sharing among objects in the system becomes more convenient. Cooperative localization enhances the cooperation among vehicles and infrastructures by making full use of the information in the system.

A survey of vehicle localization based on visual and point cloud odometry methods has been proposed in [27]. Another related work for investigating the hardware architectures for camera and LiDAR SLAM is proposed in [28], and the authors develop the possible fusion approach for increasing the localization accuracy and robustness. At the same time, the authors of [29] propose the possible potentials and limitations for map-based vehicle localization method. However, the cooperative vehicle localization by using V2X communication is ignored in these papers. Moreover, although the vehicle accuracy as the most important performance of vehicle localization has been discussed in these papers, there is a lack of the comprehensive performance like the reliability, availability, scalability and real-time performance, which are also indispensable performances of robust vehicle positioning system.

Therefore, the aim of this paper is to survey the state-of-the-art localization techniques (including active and passive sensors based self-localization methods, V2X based cooperative vehicle localization methods, and so on.), analyze their comprehensive performances, and present the challenges in vehicle localization domain. We will comprehensively discuss the state-of-the-art vehicle localization methods in the following main criterion and co-criteria:

Main criterion: Accuracy. The definition of the vehicle localization accuracy can be regarded as 'how close' the estimated or measured position result is to the true position. The vehicle localization accuracy validating methods are proposed in [30]. In the 2-D vehicle localization scenario, the accuracy can be evaluated by calculating the mean along-track error E_{lat} and across-track error E_{long} (Lateral and longitudinal errors). As shown in equation (1).

$$E_{lat} = \frac{1}{N}\sum_{i=1}^{N}(x_i^t - x_i^e)$$
$$E_{long} = \frac{1}{N}\sum_{i=1}^{N}(y_i^t - y_i^e) \tag{1}$$

where the x_i^t and y_i^t are the true position of vehicle at time i on x and y coordinate, respectively. The x_i^e and y_i^e are the estimated position of vehicle at time i on x and y coordinate, respectively.

Moreover, the positioning mean error E_p can be represented by calculating the mean Euclidean distance between the true point (x_i^t, y_i^t) and the estimated or measured position result (x_i^e, y_i^e), as represented in equation (2). In addition, the root mean square error (RMSE) is also an indicator of localization accuracy, which can be calculated by the equation (3).

$$E_p = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(x_i^t - x_i^e)^2 + (y_i^t - y_i^e)^2} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[(x_i^t - x_i^e)^2 + (y_i^t - y_i^e)^2]} \tag{3}$$

Localization accuracy can be affected by the precision of the sensor data, which is affected by the environment, the distance between targets, the view angle and other factors. In addition, the standard of accuracy requirement for different vehicle localization system is different. For collision warning applications, the positioning accuracy of 1 meter can meet the basic application requirements. If the positioning accuracy can reach 0.5 meters, the application will have good accuracy performance [31]. Furthermore, since autonomous vehicles (AVs) require higher localization accuracy, a localization accuracy criterion for AVs in the United States is defined in [32]. Both the lateral and longitudinal errors should be less than 0.1 m at 95 percent confidence with the alert limit is 0.29 m in local street scenario. Additionally, another standard (The maximum positioning error is 0.3 m) is proposed by the 5G PPP (5G infrastructure public private partnership) in Europe. So, the state-of-the-art methods selected in our paper need to meet the localization accuracy standard in different applications.

The co-criteria include the availability, reliability, scalability, and real-time performance.

Availability [31]: Availability refers to the capacity of vehicle localization method can be realized in different environments (including the GNSS-denied environment, weather extremes, and so on.). In addition, in cooperative vehicle localization domain, the standard of information sharing is defined in the in-vehicle navigation systems–communications message set requirements standard (ISO 15075).

Reliability [31]: Reliability is an important factor for the safety of a localization system. The safety of the intended functionality standard (ISO 21448) provides the guidance on requirement of data collection. Moreover, the standard ISO/TR 21707 provides the quality requirement of data being shared in the system.

Scalability [33]: Scalability is the ability to realize localization in large-scale vehicles localization system. To evaluate the scalability performance, the economic expenses and overall system performance after the expansion of vehicle localization system should be considered. The ISO/DIS 23150 standard can provide a guidance for the communication among sensors and data fusion units when expanding the vehicle localization system in the future ITS.

Real-time Performance [34]: Real-time performance can be evaluated by the system response time or the time delay of the result refresh in the process. For the cooperative vehicle localization, the communication delay can affect the real-time performance, the standard of communication delay is defined in IEEE 802.11 p.

Based on the both main criterion and co-criteria, by using the reference selection method proposed in the appendix, the references with competitive results are determined to survey in our paper.

The process of vehicle localization is shown in figure 1. It mainly includes the data collection and processing stage, and the output result is the estimation of the vehicle's position and direction.

In addition, the coordinate system in the localization domain mainly includes earth-centred inertial (ECI) coordinate system, earth-centred earth-fixed (ECEF) coordinate system, and the geographical coordinate system.

The remaining sections of this paper are structured as follows: Section II discusses the active sensor-based vehicle localization algorithms. Section III describes the passive sensor-based methods. Section IV analyzes the V2X-based cooperative localization algorithms. Section V discusses the multi-sensor based methods. Section VI gives the comprehensive performance analysis of different methods and proposes their challenges. Finally, the conclusion and future work are presented in the last section.

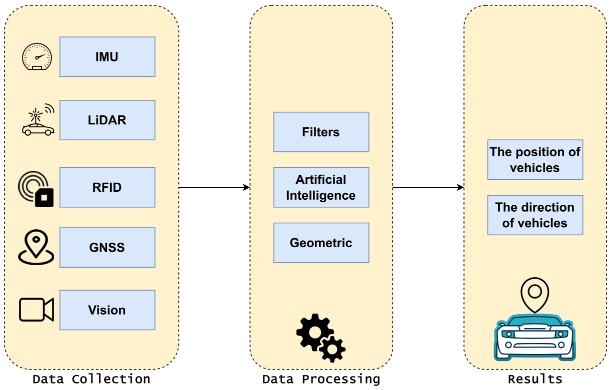

FIGURE 1. Vehicle localization process.

II. ACTIVE SENSOR-BASED SELF-LOCALIZATION

In this section, we analyze and compare the state-of-the-art vehicle self-localization methods which use the on-board active sensors in the data collection step. Active sensors, including LiDAR, radar, and ultrasonic sensors, they can emit energy to the environment and the data is collected by measuring the scattered or reflected signal. In the following sections, we illustrate the advantages and disadvantages of each data collection method. Additionally, we compare the economic cost of each sensor and analyze its latency, which affects the scalability and real-time performance during vehicle self-localization.Moreover, we discuss the advantages and disadvantages of each algorithm, further analyze the accuracy and other co-criteria performance of each technique. The current main methods for the vehicle self-localization algorithm will be described in detail in the following subsections.

A. LIDAR-BASED SELF-LOCALIZATION METHOD

Light detection and ranging (LiDAR) can collect emitted laser light and calculate the distance to the target based on the intensity and time of the received laser, which can provide accurate data for vehicle localization. By processing the data collected by LiDAR through the use of filters, mapping, artificial intelligence (AI), and multi-method techniques, the excellent accuracy performance can be achieved in the vehicle localization domain. For a LiDAR-based method, a map (including planar and point-cloud maps [35]) is generally required to match with the point cloud data collected by LiDAR. If there is no prior map, the simultaneous localization and mapping (SLAM) method can be used to create a real-time map. Then, the position of the vehicle can be determined by map matching methods.

To address the problem that the traditional map matching process is easily affected by the resolution, the authors of [36] proposed an algorithm based on a free-resolution probability distributions map (FRPDM) using 3D LiDAR. The FRPDM stores the probability distribution converted by the Gaussian mixture modeling (GMM) method, which effectively reduces space complexity. The size of the FRPDM is about 0.061 MB/km, which is smaller than the extended line map in [37] (0.134 MB/km), the binary grid map in [38] (0.901 MB/km), and the multi-resolution Gaussian mixture map in [39] (44.3 MB/km). The authors also proposed a data association method for the point-to-probability distribution scan matching method. The RMSE on the lateral and longitudinal directions are 0.057 m and 0.178 m, respectively. Although this method can reach an average map matching time in 37 ms, the extraction time is 146 ms, which results in a higher total data processing time (183 ms). Therefore, this method is not sufficient for applications that require high real-time performance. To increase the real-time performance, the authors of [40] proposed a localization method based on mapping and UKF techniques, using a distance-weight map (DWM) in an underground mine environment. The spatial localization error is 4 cm, and the processing time per frame is 60 ms. In order to further improve the availability of localization algorithms in mountainous rural environments, an algorithm exploiting multi-layer LiDAR was proposed in [41]. A 3D normal distribution map is built at first. Then, the normal distribution transform (NDT) scan matching method and the EKF technique are employed to estimate the position. The average absolute error on longitudinal and lateral are 0.38 m and 0.08 m with the average velocity 45 km/h, respectively. However, it is not reliable enough for autonomous driving because it may cause the traffic accident during demonstrations. Additionally, another work which can reach high accuracy localization is proposed in [42]. This method includes the mapping and localization phase. In the mapping phase, the pole detector is designed, and the pole landmarks are extracted by the pole detector from LiDAR scans. Then, the extracted pole landmarks are registered in a global map which is provided by the true trajectory. In the localization phase, the PF technique is implemented to realize position estimation by matching the pole landmarks provided by sensors with that in the map. The advantage of this algorithm is that the positioning RMSE is about 0.1 m, which can meet the accuracy requirement of AVs.

Furthermore, in recent years, the AI technique is employed in the localization domain to reach high real-time performance. The authors of [43] designed an improved lightweight deep neural network to realize the deep local feature extraction in day-night changed environment. A prior map is built by using aligned dense LiDAR point clouds and imagery provided by a portable camera-LiDAR sensor. Meanwhile, the ground truth point cloud dataset with 5 cm accuracy is employed to evaluate the localization accuracy and robustness in vision-changed conditions. The extraction speed of the feature in this method is 92 frames per second, and this work focus on the day-night changed environment, which has high availability performance. Another work was proposed in [44], the authors designed a siamese neural network-based algorithm by using a global prior map. The reduced dimension scan representations learned from neural networks are utilized to realize place recognition, and the global prior map is employed to determine the vehicles' position. The advantage of this algorithm is that the storage space for sensor data is reduced. Moreover, another work based on deep learning is proposed in [45]. In order to achieve fast and accurate information interaction during vehicle localization, only a few LiDAR points are used in the proposed framework. In addition, a clustering algorithm is employed to realize the non-semantic features extraction from the information collected by LiDAR and the data smoothing process occurs in the convolutional layers. In order to enhance the reliability of the algorithm, both the north campus long-term (NCLT) and Kitti dataset are used to evaluate the accuracy performance in the short and long term trajectory. Experimental results show that a reasonable accuracy (Mean positioning error is below 1 m) can be achieved.

In addition, a LiDAR-based road sign perception system using third-party sparse maps (TPSM) was proposed to improve the accuracy of traditional GNSS-based vehicle localization algorithms [46]. This system uses LiDAR to detect road and lane sign features and employs the PF technique to estimate the position of vehicle. This algorithm increases the accuracy by using TPSM road features (0.31 m for the constrained update). However, the TPSM is not suitable for all sensors, limiting its scalability. To address the issue that the traditional normalized cross-correlation (NCC) algorithm requires sufficient feature points, a cross means absolute difference (CMAD) algorithm based on known map information using 3D LiDAR is proposed in [47]. This method includes offline and online parts. In the offline part, the map is built, calibrated, and segmented. The 3D map is then transformed into a 2D grid map and feature extraction is performed. In the online part, the same procedure is used for LiDAR scanning. The mean energy and feature registration method are used to initialize location and orientation of the vehicle, and the drivable moving search region (DMR) method is designed during feature registration during the process. The RMSE is about 0.1-0.3 m in outdoor environments and it has good real-time performance.

B. RADAR-BASED SELF-LOCALIZATION METHOD

While the LiDAR-based and vision-based method can provide more precise data, radar-based methods cannot be easily replaced at the moment. Because radar is the only sensor capable of accurately measuring the speed of objects under long distance conditions, as supported by Zhou et al. [48]. Moreover, radar-based methods can offer good real-time performance due to their low latency during data collection, as highlighted by Lu et al. [34]. Additionally, radar-based methods are capable of functioning effectively in adverse weather conditions, further enhancing their reliability. There are some popular types of radar used in vehicle localization, including multiple-input multiple-output radar [49], millimeter wave automotive radar [50], and so on.

In order to enhance the availability of localization methods, the authors of [51] proposed an improved algorithm by using a 76 GHz omnidirectional millimeter-wave radar (MWR). They develop a novel error propagation model to calculate the unique noise characteristics of sensors operating in snowy environments. The process consists of four steps: image generation of objects, template matching, probability updating, and offset updating. The lateral RMSE with 0.25 m can be achieved, regardless of the presence or absence of snowfall. Since radar sensors have strong reliability and availability, especially in extreme weather conditions, the authors in [52] used ground penetrating radar to realize vehicle localization in inclement weathers. The positioning results show that the total mean positioning error (the sum of along-track and cross-track error) are 0.34 m, 0.39 m, and 0.77 m, in the clear, snow, and rain weather scenario, respectively. To improve the accuracy of radar based vehicle localization methods in urban environments, the accuracy that less than 0.5 m with 95-percentile is achieved in [53].

In addition, the authors of [54] proposed a machine learning-based algorithm by using mmWave radars operating in the frequency range of 77 GHz-81 GHz. This algorithm includes two steps: range estimation and angle estimation. For range estimation, unwanted clutter is removed based on the properties of mainlobe clutter and sidelobe clutter, followed by estimating the average range in a certain frame. To improve angle estimation accuracy, a polynomial regression model is proposed, achieving the RMSE with 2.56 degrees. Another work which utilizes artificial intelligence (AI) techniques was presented in [55]. The authors design a deep radar object detection network (RODNet) which uses range-azimuth frequency heatmaps (RAMaps). RODNet increases the availability by incorporating three architectures, namely 3D convolution deconvolution, 3D stacked hourglass, and 3D stacked hourglass with temporal inception. Additionally, a new method for learning step is proposed by leveraging cross-model supervision. The latency is less than 100 ms for real-time performance.

C. ULTRASONIC-BASED SELF-LOCALIZATION METHOD

Ultrasonic-based sensors are commonly used in low-cost curb detection and localization systems due to their affordability. Additionally, the ultrasonic sensor is widely used in indoor positioning algorithms [56]. Nevertheless, the limited detection range of ultrasonic sensors (approximately 3 m) makes them unsuitable for long distance measurement scenarios. In other words, the scalability performance is insufficient. To increase accuracy and real-time performance of ultrasonic-based localization methods, the authors of [57] designed a low-cost curb detection and localization system utilizing multiple ultrasonic sensors. Initially, a ground reflection elimination filter is proposed to eliminate obvious reflections caused by ground reflections. Subsequently, the reliability of the measurement data is calculated, and a distance estimation algorithm is proposed by analyzing the obtained reliability. The complexity of this algorithm is

$O(N^2)$, and when four ultrasonic sensors are implemented, the system achieves the accuracy with 13.5 cm on the RMSE.

Additionally, the execution time for processing raw sensor data (collected over 100 seconds) is 0.58 seconds, demonstrating good real-time performance. Another method with excellent real-time performance is reported in [58]. To enhance the availability of ultrasonic-based methods in GPS-denied environments, a navigation estimation system is designed. The raw data from the ultrasonic sensors is preprocessed to reduce the effects caused by sensor noise. The EKF technique is employed to estimate the vehicle's position. Moreover, the result refresh rate is 92 Hz, achieving excellent real-time performance.

D. DISCUSSION

Although LiDAR-based localization methods can provide high accuracy compared to other active sensor-based methods, they have higher computation requirements and economic expenses. In terms of 1D, 2D and 3D map matching method in LiDAR-based methods, the 3D map matching method can get the most accuracy and robustness localization result since the 3D maps have rich type of features, and it especially has good performance in complex scenarios. However, compared with 1D and 2D map-based methods, the storage requirement of map and the computation power increase dramatically compared with 1D and 2D map-based methods, which has bad influence on the performance of scalability. AI techniques can be employed to enhance the accuracy and real-time performance of 3D map matching methods [59], which could be beneficial for applications where accuracy and real-time performance are crucial, such as autonomous driving, in the future.

Furthermore, although radar-based localization methods may not always meet the accuracy requirements of autonomous driving or ITS, the radar still plays an irreplaceable role in the field of object detection [60]. On the one hand, the radar-based localization system has excellent performance in extreme weather scenarios. On the other hand, ultrasonic sensor-based methods offer excellent real-time performance, as reported in [58], which can serve as auxiliary sensors in certain scenarios.

III. PASSIVE SENSOR-BASED SELF-LOCALIZATION

For passive sensors, such as IMU, GPS, and vision-based sensors, only the radiation or emission in the nature or from the target can be detected. In this section, we analyze the accuracy, real-time performance, and complexity performance of self-localization methods based on passive sensors that utilize popular data processing techniques, such as filters, AI, and mapping methods.

A. IMU-BASED SELF-LOCALIZATION METHOD

IMU sensors are widely used for dead reckoning (DR) [61] and inertial navigation system (INS) [62]. However, a disadvantage of IMU sensors is that when they are applied to long-distance positioning system, the accumulated error can significantly decrease the accuracy of the final result. One approach which can mitigate this issue is to use multiple IMUs simultaneously to increase the accuracy of the localization system.

In [63], the authors proposed an algorithm based on multiple IMUs. They employ least-square and probabilistic marginalization methods to map measurements from all IMU sensors onto a virtual IMU, and the probabilistic estimators are used to estimate the location of the vehicle. This algorithm achieves a localization refresh time of about 10 ms, based on sensor measurement rates of 200 Hz. However, the RMSE of this approach is 0.6 m. Another multi-IMU based system called real-time multi-IMU visual-inertial navigation system (mi-VINS) was proposed in [64]. In this system, in order to enhance the real-time performance, a tightly-coupled EKF based estimation method is proposed to fuse asynchronous measurements from multiple sensors. Moreover, the propagation method of the joint covariance and state estimation of each IMU are defined. Furthermore, to ensure the consistency in the data fusion process, all the spatial and temporal calibration parameters are processed online for the calibration refinement of sensors, which can reduce the space complexity caused by offline steps. The RMSE of this approach is about 0.2 m with an average data processing time of 23 ms (43 Hz), and mi-VINS can increase the robustness in cases where one of the IMUs in the system does not work.

To further increase the robustness of IMU-based methods, the authors of [61] proposed an algorithm based on KF and deep neural networks. The deep neural networks are utilized to optimize and provide noise estimates during the KF algorithm. The raw data of the IMU is refreshed at a rate of 100 Hz, and the translational error is about 1.1 percent. Additionally, in certain special environments, such as GPS-denied environments, IMU can play a crucial role in the localization system.Another work based on solely the commercial-of-the-shelf (COTS) IMU in GPS-denied environment is proposed in [65]. In this work, a new developed Bayesian filter is proposed which can achieve the position error of less than 0.5 m.

B. GPS-BASED SELF-LOCALIZATION METHOD

GNSS, including GPS [66], Beidou [67], and Galileo [68], can provide convenient and low-cost global localization services by using four or more satellites. The accuracy of GPS is about from a few meters to twenty meters [35]. In order to increase the accuracy of GPS, various techniques such as real-time kinematic (RTK) [69], have been proposed. However, the accuracy of GPS is easily affected by factors such as obstacles, atmospheric conditions and signal blockage. And GPS signals are easily lost in many scenarios in real-world. So, the vehicle localization in GPS-denied environment is a popular research topic [70], [71].

In order to improve the accuracy of GPS-based localization by GNSS signal reception state detection, the authors of

[72] designed a multi-path detection system based on support vector machines (SVM). To enhance the effectiveness of the map-matching method, the authors of [73] proposed a spatio-temporal-based matching algorithm (STD matching) which considers the spatial features of roads (including road topology and detailed road information), vehicle speed constraints on different roads, and real-time vehicle movement during low-sampling rate GPS trajectories. Furthermore, the authors employ GPS clustering, GPS smoothing, and A^* algorithms to reduce the computational costs and improve the accuracy. The experimental results, obtained from a road network comprising 200,236 vertices and 90,709 road segments, indicate a matching accuracy of over 80%, which is higher and more stable than the results obtained by the HMM-RCM algorithm proposed in [74]. However, the running time when there are 3-10 candidate points is about 11 seconds, under low-sampling rate conditions.

Furthermore, to enhance the scalability of GPS-based localization methods, the authors of [75] designed a system which is intended for global-scale deployment. This system involves an offline map building step and an online query step. In the offline map building step, they design a structure-from-motion model and congas descriptors. The structure and appearance compression methods are employed to reduce data storage space, and the data is stored using a tiled model. In the online query step, congas extraction and projection, 2D-3D matching and voting, pose recovery, and pose refinement are included. The query latency of this system is about 200 ms, demonstrating excellent real-time performance. Additionally, this system is robust compared to previous methods, as it delivers significantly stable results. Unlike previous methods, aiming at improving the GPS localization accuracy in non-line of sight (NLOS) scenario, the authors of [76] employed 3D mapping techniques to improve the conventional ranging-based GNSS localization methods. Specifically, they utilize terrain height-aiding techniques to achieve additional virtual ranging measurements, and the NLOS reception is predicted by using 3D city models.

C. VISION-BASED SELF-LOCALIZATION METHOD

Vision-based data collection methods capture target images through vision devices such as monocular cameras [77], binocular cameras [78], or panoramic thermal cameras [79]. Then, the effective feature data can be extracted from the images. The SLAM algorithms [80], [81], [82], [83], which are a basic vehicle localization algorithm using vision sensors, are widely implemented in urban environment. SLAM algorithms include visual SLAM (vSLAM) [84], centralized collaborative monocular SLAM [85], and so on.

The vSLAM technique is widely used in vehicle localization and it mainly includes three modules: initialization, tracking, and mapping [86]. The initialization module is responsible for establishing the coordinate system, and the tracking and mapping modules have the function of building and updating the map. The authors of [87] proposed a method which utilizes the LiDAR-based map, which can achieve the real-time performance with 0.06 s and the RMSE is about 0.1 m. In order to further enhance the real-time performance, a topview system based on real-time capable image processing pipeline is designed in [88], the estimation of position is realized by processing data collected by four fisheye cameras. The accuracy of this algorithm is about 0.33 m on the worst condition, and the result refresh time is 0.04 s. Furthermore, another work with high accuracy and real-time performance based on visual sensor is proposed in [89]. In the developed method, the back lane markings registry (BLMR) and data matching method with light-weigh are used. The visual lane marking is detected by sensors and matched with map, for the purpose of estimating the position of vehicle in the map reference. Additionally, the proposed algorithm has high reliability and availability, which can realize data processing and positioning even if the lane markings can not be observed by a short distance detection. The positioning mean error of this method is 0.06 m, for the real-time performance, the result refresh time is 7.66 ms.

Meanwhile, another work called high-speed pavement visual odometry (HSP-VO) method based on two cameras is proposed in [90]. The data collected by the lateral camera is used to match with the sparse visual map (noting that the sparse visual map is created in the offline step), which includes GPS coordinates, visual features, and the 3D information. Another down-view high-speed camera is used to increase the efficiency of feature extraction during the vehicle's movement at high speed. Moreover, the KF technique is employed to fuse the data provided by the two cameras. The accuracy of this method is 0.19 m on mean error. In addition, the mean time consumption of the feature extraction and matching process by using raw images is about 14.1 ms, which is an excellent real-time performance.

D. DISCUSSION

Although passive sensors can achieve low-cost localization, their accuracy, robustness, and availability may not meet the high-performance requirements of ITS applications. The accuracy of GPS positioning is easily affected by the NLOS and multi-path effect, and the GPS is completely ineffective in signal-denied environments. Nowadays, a more popular approach is to use GPS as an aid equipment, combining it with other sensors through data fusion methods to achieve higher-performance localization. For example, in low-cost sensor localization systems with excellent scalability performance, GPS receivers are important sensors. Additionally, only using an IMU sensor cannot achieve accurate result because the cumulative error grows rapidly over time. However, it can achieve localization with excellent real-time performance, as shown in [63]. Moreover, vision sensors play an irreplaceable role in the positioning domain, particularly in SLAM algorithms, and reasonable accuracy can be achieved. However, vision sensors depend on light intensity and weather conditions. In order to increase real-time performance, a graphics processing unit (GPU) with high-performance should be equipped, which increases economic expenses. Furthermore, vision sensor-based methods using maps require additional computation power to process and store the maps. With the development of AI techniques in the field of image processing, applying AI techniques to vision-based methods has great potential to enhance accuracy and real-time performance. AI techniques for localization and mapping have recently been reported in [91].

IV. V2X BASED COOPERATIVE LOCALIZATION

Unlike self-vehicle localization methods, cooperative or collaborative vehicle localization methods use the V2X technique to share their state data (such as velocity, heading, location, and environment information) among vehicles or infrastructures, achieving the purpose of enhancing the localization efficiency through data sharing. V2X technique enables the data communication capability among vehicles and other objects (such as base stations) [92]. It includes V2V, V2I, vehicle-to-cloud (V2C), vehicle-to-road-signs (V2RS), vehicle-to-network (V2N), and vehicle-to-pedestrian (V2P). The V2X standards are DSRC (IEEE 802.11p) and C-V2X (3GPP LTE/5G NR) [93]. The 802.11p band is 5.9 GHz (5.85-5.925 GHz) [94]. The details of cellular-based V2X communications are in [95]. Combining main communication techniques such as UWB (802.15.4a) [96], Wi-Fi (IEEE 802.11) [97], RFID [98], and cellular-based (5G) [99] with AOA [100], TDOA [101], and RSS [102], [103] methods, the range estimation and cooperative vehicle localization can be achieved. In this section, we analyze the state-of-the-art vehicle localization based on V2V and V2I communication techniques.

A. V2V-BASED LOCALIZATION METHOD

The V2V-based localization method refers to the method which utilizes the data shared between connected vehicles. By using the shared state of other vehicles, such as their speed, position, and orientation angle data in V2V networks, vehicles in the system can achieve localization with reasonable accuracy [104]. The main protocol of V2V is IEEE 802.11p, and the communication data mainly includes three kinds of messages: cooperative awareness messages (CAMs), decentralized environmental notification messages (DENMs), and service announcement messages (SAMs) [35]. One work based on V2V communication technique named implicit cooperative positioning with data association (ICPDA) is proposed in [105]. Two algorithms named ICP-DA-PF and ICP-DA-LC are proposed for vehicle localization in urban environment. Additionally, a new distributed Bayesian framework is designed and a belief propagation algorithm is proposed to solve the data association problem over the framework in a distribute way. Considering the communication/processing overhead in the cooperative vehicle system, the distributed KF is employed to solve the trade-off between positioning accuracy and algorithm complexity. The experiment results show that the RMSE of vehicle localization in real urban scenario is about 0.8 m.

Meanwhile, the authors of [106] proposed an algorithm which uses the chain branch leaf (CBL) clustering method in VAENTs, which can improve the adaptability to different data transfer rates during the V2V communication process. Additionally, they propose the multi-point relaying technique to reduce time delay and optimize network routing. Experimental results show that in real scenarios, the latency is less than 250 ms, and the average time delay is about 180 ms, which has good real-time performance. In the real world, radio-based cooperative vehicle localization methods are susceptible to the influence of multi-path signals provided by different types of objects in the process of information transmission, thereby reducing the accuracy of positioning. A work on mitigating the effects of multi-path signals on localization accuracy is proposed in [107]. Firstly, in order to make better use of the localization information provided by different objects, a radio map is established to store the number of objects, object type, and object state. Then, the probability hypothesis density filter and a map fusion routine are proposed to integrate the available information provided by multi-path signals to enhance the accuracy of vehicle localization. The RMSE of localization result is less than 0.3 m, which shows that this method can effectively utilize information generated from different types of objects and the high reliability. However, map matching based localization methods need to create and maintain a large-scale map which causes expensive calculation and data storage cost.

B. V2I-BASED LOCALIZATION METHOD

The V2I technique can realize data sharing and communication between vehicles and roadside units (RSUs)/ base stations (BSs), and the protocol for V2I is IEEE 802.11p. Compared to V2V-based methods, V2I-based methods have more effective information (such as the position of fixed RSUs and BSs). To increase the accuracy by making full use of the position of fixed BSs, the authors of [108] and [109] proposed the V2I-based method by using data-fusion technique to realize vehicle localization in the IoV system, and the GPS data correction technique is also employed. In the system model, the RSU is equipped with a GPS receiver that can provide the difference of received GPS data from the real position, which is utilized to correct the real-time position collected by on-board GPS receivers. In the data processing stage, a data fusion system consisting of KF and EKF techniques is designed to fuse the corrected GPS data and IMU data to obtain the position of the vehicle. The advantage of this algorithm is that only one single RSU is used to collect data from multiple vehicles, making the economic expense low. When the vehicle passes the toll gate ramp, the error is less than 0.1 m, which is accurate. However, if the GPS signal is not available or has high time delay during transmission, the real-time performance and accuracy will be seriously affected. To improve the accuracy when the GPS

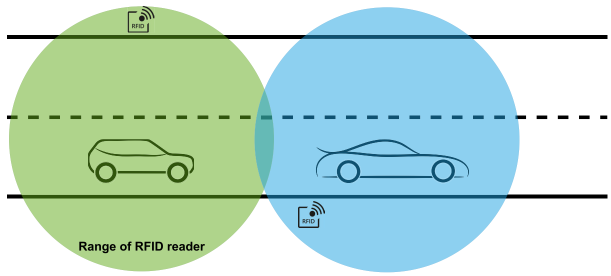

FIGURE 2. **Model based on RFID.**

signal strength is insufficient, the authors of [110] proposed a DOA and V2I technique-based algorithm. The system model consists of three cooperating BSs, and the sparse Bayesian learning (SBL) robust technique is used to enhance the stability and effectiveness of DOA data. Finally, the vehicle position is estimated by processing the location data of BSs and DOA measurement data generated in different situations. The advantage of this algorithm is its high robustness, and it can be used in non-uniform noise scenes. The disadvantage is that it requires high hardware facilities (three BSs are required), and it is difficult to realize vehicle localization in an environment with insufficient BSs in the real world.

The radio frequency identification (RFID) technique is commonly used for indoor localization, where the tag reader reads data on the tag through radio signals to collect data. The communication diameter of the tag reader is shown in Figure 2. Tags are deployed on the roadside, and the tag reader is equipped on the vehicle. When the distance between tags and the car is less than the communication range, the reader can get the information provided by the tags. The international standards organization (ISO) has three standards for RFID: ISO 14443, ISO 15693, and ISO 18000. Tags include active tags and passive tags. The authors of [111] utilized ultrahigh frequency (UHF) RFID to achieve accurate localization in a GPS-less environment. They use the robust Chinese remainder theorem (CRT) and the levenberg-mlarquardt (LM) method to estimate the position of the vehicle. The frequency band of the reader is between 902.75 and 927.75 MHz, and the protocol is ISO/IEC 18000-6C Class1 Gen2. The error is less than 0.27 m with 90% probability. Since this method has excellent real-time performance, the error caused by the time delay is less than 0.1 m. Moreover, this algorithm's complexity is made up of two parts: CRT ($O(nN^2)$) and LM ($O(Kk^3)$), where n and N are the number of tags and signal frequencies, respectively, and K and k are the number of iterations of the LM method and the dimensions of the matrix, respectively.

Furthermore, related work concerning unmanned aerial vehicle (UAV) accurate localization, a system which realizes six degrees of freedom (6-DoF) localization is proposed in [112]. Each UAV is equipped with three or more RFID tags, and the Bayesian filter method is implemented to estimate the location of the UAVs. The mean error and orientation estimation result is 0.04 m and 2.5 degrees, respectively. Meanwhile, for the purpose of enhancing the real-time performance, the authors of [113] designed a real-time localization system (RTLS) based on RFID and UWB technique. This system includes the real-time data acquisition layer, the data processing layer, the holographic workshop map layer, and the application service layer. The response time is less than 0.5 s, the average accuracy of RFID and UWB based localization method are 0.39 m and 0.18 m, respectively.

C. V2V AND V2I-BASED LOCALIZATION METHOD

For a localization method that takes advantage of both V2V and V2I communication techniques, the authors in [114] designed a generic stochastic localization framework which can process different type of data collected by sensors. A PF based algorithm is designed to fuse the relative positioning provided by neighbor vehicles, which can achieve a reasonable localization error with about 1 m. However, the data transmission delay and the relative data association is not considered, which may have a bad influence on the real-time performance.

Moreover, in order to realize vehicle localization in weak GPS signal environments, the authors of [115] designed an error-cognitive localization system that uses both the V2V and V2I technique. This system includes a tag-reading model, a tag deployment model, and a position correction model, etc. The roadside tag deployment method is obtained through matrix analysis, and data such as vehicle speed, tag distance, and correction parameters are used to increase the accuracy. This algorithm can realize vehicle localization in scenarios where there is no GPS signal or the GPS signal is weak, and the proposed tag deployment method reduces the number of tags utilized in the system, further reducing economic expenses. Additionally, the RMSE is less than 0.5 m. At the same time, the authors of [116] proposed a cooperative localization algorithm by using GPS pseudorange errors in the V2X network. V2V and V2I communication techniques are employed to share positions, pseudorange estimated errors, and DR data, while set inversion and constraint propagation (CP) techniques are used to design the distributed estimation algorithm. Highly reliable confidence domains can be calculated without the need for direct range measurements, and the latency is less than 0.1 s.

D. DISCUSSION

The V2X-based vehicle localization method can enhance the cooperative interaction ability of the whole system by realizing information sharing, thereby further enhancing the information utilization effectiveness in the system. In addition, fault detection and exclusion methods can also enhance the efficiency, which can also benefit from V2X communication techniques [117]. With the development of the 5G, the communication efficiency can be further enhanced, which can enhance the performance of V2X-based methods. Compared to V2I-based methods, the V2V-based method has better scalability performance since it does not require infrastructure deployment, such as base stations. However, the V2I-based localization can increase accuracy since the position of infrastructure is fixed, which can realize the correction of positioning errors. The disadvantages of V2X-based methods include the need of communication resources and time delay during communication process, especially in the large number vehicles scenarios. So, the time delay during data transmission should be considered in order to increase the accuracy. Additionally, the RFID-based method can provide excellent positioning performance in special application scenarios, such as highway toll gates or parking lots. In summary, V2X-based localization has excellent potential for high-precision vehicle positioning applications (such as autonomous driving).

V. MULTI-SENSORS BASED VEHICLE LOCALIZATION

From the above discussion, no single sensor can meet the availability, scalability, computational complexity, economic expenses, accuracy and real-time performances at the same time. So, taking advantages of multiple sensors has the substantial potential to achieve vehicle localization with more comprehensive performance. In this section, we analyze the multi-sensor based localization methods.

A. MAP-BASED MULTI-SENSOR LOCALIZATION

The authors of [118] proposed a method based on an improved Monte Carlo localization (MCL) technique that utilizes both GNSS and LiDAR data to achieve robust localization in different environments. The GNSS data increases accuracy in feature-poor scenarios, and the LiDAR data can enhance accuracy in feature-rich scenarios. This method can achieve high accuracy in complex environments (0.566 m position mean without GNSS and 0.3895 m on average position mean with GNSS). However, the sensor cost is high, which hinders large-scale implementation. Another algorithm that uses radar and camera is proposed in [119].

Meanwhile, to enhance the real-time performance of multi-sensor-based consistent localization methods using mapping, the authors of [120] proposed a global map based algorithm which achieves a result refresh rate of 25 Hz with an average error which is less than 0.1 m. To get the position of vehicle in underground parking lots, a method based on Wi-Fi and computer vision techniques is proposed in [121]. This algorithm uses dead-reckoning (DR), the random sample consensus (RANSAC) method, and complementary filter to realize data fusion and correct errors in offline maps, achieving the accuracy of less than 1 meter. The advantage of this algorithm is that it can achieve reasonable accuracy when GPS is unavailable, but the requirements for the various modules of the localization system can lead to high complexity. In addition, another map based multi-sensor data fusion vehicle localization method is proposed in [122]. The authors use images sequence and wheel-inertial ego-motion data to create a semantic local map at first. The position estimated by camera data is provided by matching the local map with the online map database. The map matching process is simplified by using the developed supervised neural network, which can reduce computational overhead. The mean absolute errors of positioning result are 0.04 m and 0.17 m in the lateral and longitudinal directions, respectively. However, the map matching process requires online map, which may cause positioning time delay.

B. DATA FUSION-BASED MULTI-SENSOR LOCALIZATION

The authors of [123] proposed an algorithm named fuzzy adaptive Kalman filter, which can increase the performance of the conventional UKF by verifying and correcting the real-time noise of sensors. The proposed fuzzy adaptive Kalman filter can increase the accuracy by about 40 percent compared to the conventional UKF.

In order to increase the localization real-time performance and accuracy of AVs, the authors in [16] proposed a real-time localization method based on UKF and PF. The main contribution of this paper is that both the real-time performance and the accuracy is balanced by the proposed optimization method. The data collected by IMU, LiDAR, and GPS is fused to estimate the position. The result refresh time is about 8.2 ms, with the localization error that is less than 0.3 m. However, the computational complexity is not considered since the PF method has high complexity when the number of particles is large.

Furthermore, to further improve the accuracy, the authors of [124] proposed an IMM-UKF-GNN (grey neural network) algorithm, where the IMM method can achieve a soft switching among three different UKFs (noting that these UKFs have different noise). In this work, the GNN is employed to further increase the accuracy by training. Moreover, the bio-inspired technique has been implemented in data fusion methods. For example, the authors of [125] proposed an integrated robot localization method named particle swarm optimization enhanced particle filter (POF) based on PF and PSO techniques. The pose tracking of robots is realized by the particle set update, evolutionary search and normalization, and re-sampling steps. The mean error of the result is less than 0.05 m, and the position refresh rate is 96 ms. In addition, another work considering low-cost multiple sensors (gyroscopes, acceleration, magnetic, and mileage sensors) data fusion method is proposed in [126]. For the purpose of reducing the error of result outputted by the EKF, the authors propose an adaptive error correction EKF algorithm that uses the evolutionary iteration mechanism of genetic methods to optimize the noise covariances in the traditional EKF.

Focusing on the vehicle localization in GPS-denied environment, the authors of [127] propose an adaptive continuum shape constraint analysis (ACSCA) method. First of all, one novel identifiable specific target named icosahedron target is defined and detected by LiDAR sensor along the vehicle moving trajectories. The ACSCA algorithm can recognize the icosahedron target and get the relative position data for calculating the position of vehicle automatically. The RMSE of the localization result is less than 0.05 m. However, the time and economic requirements for preparation, data processing and data postprocessing is high. At the same time, another work focusing on both real-time and accuracy performance is proposed in [128]. This method includes two parts, at the first part, the wheel odometry, IMU, and tightly coupled visual-inertial odometry are employed to collect data. And the data fusion of these different kinds of data is realized by EKF technique. At the second part, the dense 3D point cloud mapping is implemented, which can process data in real-time based on a standard CPU. The average RMSE of the positioning based on six different experiment scenarios is less than 0.3 m. Moreover, these two algorithms have good performance in GPS-denied environments, which increases the reliability of the localization system. To increase real-time performance, a data fusion-based multi-sensor algorithm is proposed in [129], which has an excellent result refresh time (3 ms).

Additionally, another algorithm based on deep learning and PF is proposed in [119]. A deep learning-based scoring mechanism is designed to detect the position of the rear corner of the vehicle at first. Then, the authors use the PF to output the estimated vehicle position, and the output data is fused with the radar data to obtain the final position of vehicle, which can achieving an accuracy of 0.18 m. The advantage of this algorithm is that this system is robust. However, the requirements for the first-acquainted vehicle picture are strict because the picture needs to be applied to extract the rear corner location information, and the final result will be inaccurate if the radar data is inaccurate. At the same time, the authors of [130] utilize the graded KF technique to fuse the data collected by IMU and GPS. This algorithm satisfies the advanced-surface movement guidance and control system (A-SMGCS) standard, and it can achieve comprehensive utilization of sensor data. However, the performance of the result is not analyzed when the vehicle is moving in a non-linear motion, and the impact of changes in road conditions on the accuracy needs to be further considered.

In addition, another algorithm based on multi-sensor data fusion is proposed in [131]. The sensors in the data collection stage include GPS and camera. The geographic information databases are employed to reduce the impact of accumulated errors on the accuracy due to time change. The error correction process depends on geography information database, if the data information in the database cannot be obtained or the information has big errors, the accuracy performance will be affected. Another work is proposed in [132], which uses the data collected by camera, GPS, and inertial navigation system to achieve lane-level vehicle localization. The authors utilize the information collected by the camera to match the high-definition (HD) map. And they propose the method based on the iterative closest point (ICP) to deal with errors. The advantage of this algorithm is that it can achieve lane-level localization and does not employ expensive sensors (such as LiDAR), which is conducive to large-scale promotion.

C. DATA FUSION-BASED MULTI-SENSOR COOPERATIVE LOCALIZATION

V2V communication technique can realize data sharing in the IoV, which can enhance the positioning performance through a cooperative or collaborative way. The authors of [133] propose a mathematical framework for cooperative vehicle localization by using GNSS, IMU, and UWB sensors. This framework can work in the centralized and distributed manner. The positioning error in both centralized and distributed manner are less than 0.08 m. In addition, based on the conclusion of this paper, we can conclude that compared with the centralized manner, the distributed manner has higher scalability and reliability. Because each vehicle in the system can realize data processing in an independent way. However, the accuracy is lower than that in the centralized manner, since the more precise computation of correlations among the states of vehicles can be processed in the data fusion center.

Moreover, the authors of [134] proposed a cooperative localization method based on GPS receiver and radar by using DSRC technique. The multiple pieces of information are fused by KF technique. When more than three neighbor vehicles communicate with the ego-vehicle, the RMSE is less than 0.5 m. Additionally, another work based on data fusion for cooperative vehicle localization is proposed in [135]. An adaptive ant colony optimization PF (AACOPF) method is proposed, which does not need any prior information. This method includes six steps: particles initialization, importance sampling, adaptive cooperative localization, update weights, ant colony optimization resampling, and output state estimation. Furthermore, the particle propagation model is designed and the weight updating method is developed by analysing range data provided by UWB sensors. The positioning error is about 0.66 m.

For data fusion for non-linear systems with multiple sensors with correlated noise, the authors of [136] use the adaptive and robust UKF (ARUKF) to design a two-layer data fusion structure named ARUKF-MSIF (multi-sensor information filters). In the first layer, the redundant measurement noise covariance estimation (RMNCE) method is employed to process the unknown noise at each time at first. Then, the chi-square test and indicator calculation and the proposed Q-adaption algorithm are used to further reduce the error. Finally, the final estimation is determined in the fusion center in the second layer. In addition, the author of [137] proposed a data fusion method named covariance intersection (CI), which can solve the data fusion problem with unknown correlation between input data and yield consistent estimates. However, the CI method has pessimistic estimate results since the source data is treated as totally correlated, and the independent part is not considered. Therefore, the author of

[138] proposed the split covariance intersection filter (SCIF), which can estimate the source data in both correlated and independent parts. Moreover, the authors of [139] use the SCIF to fuse the data from GNSS, camera, LiDAR, and HD maps, which achieves an accuracy with an RMSE of 0.27 m.

D. DISCUSSION

The analysis above shows that multi-sensor-based vehicle localization methods have a good performances since they combine the advantages of different sensors and communication methods. However, in order to obtain better algorithm performance, there are still many factors that need to be considered. The first factor is the independence of the data to be fused. When each input information source can be expressed as a random variable with a known mean, covariance, and cross-correlation with the other sources, rigorous estimate results can be achieved by traditional KF, EKF, UKF, and PF. However, the fusion result is not consistent when there is correlation between input estimates. Meanwhile, the CIF can yield consistent fusion results even when facing an unknown degree of source estimate correlation, but it neglects the independent information, which yields pessimistic estimate results. The SCIF can increase the accuracy of the estimated result because both known independent information and unknown correlated information in source data are considered. The second factor is the redundancy of the input data, and the constraint propagation techniques on interval can realize a reliable result when facing redundant data. Moreover, the authenticity of the input data should also be considered. Since a large number of sensors are used in large-scale vehicle localization systems, fault detection and identification techniques need to be utilized to increase the robustness of the system. For an efficient data fusion structure, since the two-layer structure is easily affected by communication delay, high-efficiency data fusion algorithms for error correlation should be developed.

VI. LOCALIZATION METHODS PERFORMANCE ANALYSIS AND CHALLENGES

A. METHODS PERFORMANCE ANALYSIS

In this section, we analyze the comprehensive performance proposed in the introduction and identify the challenges of state-of-the-art vehicle localization methods. We present the characteristics of different data collection methods in table 1, including their deployment strategy, the precision of collected data, ability to work without light, ability to capture color information, cost of the sensors, and ability to work in bad weather conditions. We analyze and compare the comprehensive performance of different localization algorithms, as illustrated in table 2. The data is based on the details of traditional active and passive sensors based methods, as shown in table 3, the details of cooperative localization method, as illustrated in table 4, and the details of multi-sensor based algorithms, as shown in table 5.

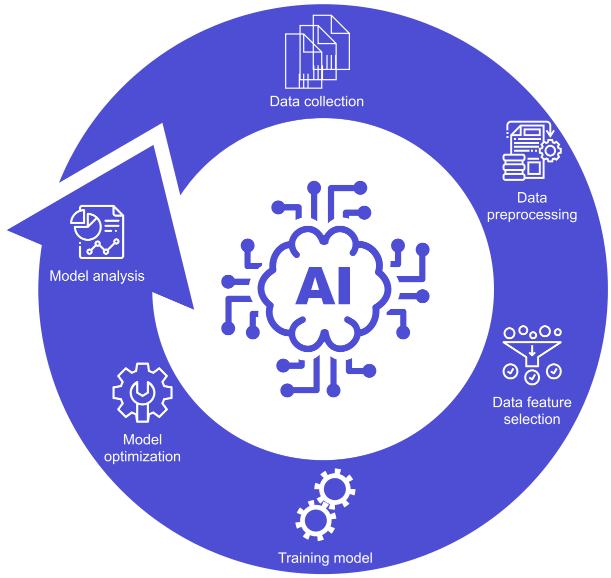

FIGURE 3. The flow chart of AI.

The LiDAR can provide the distance and angle data that between the vehicle and the object by receiving information such as the intensity and angle of the reflected light wave after the laser reaches the object. The data collected by LiDAR has high accuracy, strong stability, which is very suitable for applications with high localization accuracy requirements. The disadvantage is that it is susceptible to interference from natural weather such as rain, snow, and fog, and its accuracy will decrease under severe weather conditions. Meanwhile, the vision sensors can provide precise data for localization by processing images and extracting feature points. However, the quality of collected data can be impacted by the light intensity. Based on the precise collected data, the LiDAR-based and vision-based methods can achieve reasonable accuracy with high reliability because the high precision collected data. However, they have high computational complexity, the reason is that the picture and map generated by LiDAR (especially 3D maps) need large amount of computing and storage resources. One of the effective solution is that applying AI technique to vehicle localization [72], [140], which has great potential since the AI technique has outstanding performance in image processing domain. The flowchart of AI technique is shown in Figure 3. It mainly includes the data collection, data preprocessing, data features selection, model training, optimization and analysis steps. In addition, the LiDAR-based and vision-based methods have low scalability, because their high economic expenses.

Although GPS-based, IMU-based, radar-based, and ultrasonic-based methods cannot meet the high accuracy requirement, these sensors play a key role in the data fusion system, especially in low-cost data fusion systems, because they have high scalability and availability. Moreover, these sensors can also effectively collect data in extreme weather

TABLE 1. The comparison of different sensor-based localization methods.

Characteristics	LiDAR-based	Radar-based	Ultrasonic-based	GPS-based	IMU-based	Vision-based	V2X-based
Deployment	Easy	Easy	Easy	Easy	Easy	Easy	Hard
Data Precision	High	Middle	Low	Middle	Low	High	High
Without Light	Yes	Yes	Yes	Yes	Yes	No	Yes
Color	No	No	No	No	No	Yes	No
Price	Expensive	Middle	Middle	Middle	Middle	Middle	Middle
Work in bad weather	No	Yes	Yes	Yes	Yes	No	Yes

TABLE 2. Performances of different methods.

Performances	Low	Middle	High
Accuracy	Ultrasonic-, GPS-, IMU-	Radar-, V2V-, V2I-	LiDAR-, Vision-, Data Fusion-
Availability	Vision-, LiDAR-, V2I-	Data Fusion-, V2V-	GPS-, Ultrasonic-, Radar-, IMU-
Scalability	LiDAR-, Vision-, V2I-	V2V-, Data Fusion-	Ultrasonic-, Radar-, GPS-, IMU-
Reliability	IMU-, Ultrasonic-, GPS-	Radar-, V2V-, V2I-	Vision-, LiDAR-, Data Fusion-
Real-time performance	V2I-,V2V-, Data Fusion-	LiDAR-, Vision-, GPS-	Radar-, Ultrasonic-, IMU-

while vision-based and LiDAR-based methods may not work well. For instance, compared to other data collection methods like LiDAR, the IMU sensor has better cost-saving performance and stronger anti-interference ability. Additionally, the data collected by the IMU is relatively stable and has strong continuity for different weather and environmental conditions. However, the disadvantage is that the localization data error accumulates with time, affecting the accuracy of localization, and it is not suitable for scenes requiring high vehicle localization accuracy and localization applications with long time and distance requirements. As for GPS technique, its advantages include low economic cost, easy deployment, and wide coverage of GPS signals. Therefore, as an auxiliary sensor, GPS is suitable for most localization scenarios since it is not easily affected by bad weather or light. Furthermore, data fusion-based methods can also achieve highly accurate localization results by making full use of resources collected by various sensors. By using certain optimization criteria, to obtain a reasonable fusion result [141], [142], [143]. Popular filter techniques include KF, EKF, UKF, PF, etc., and compared with LiDAR-based and vision-based methods, the data fusion-based method has better scalability, reliability, and computational complexity performance. Multiple sensors can provide more options for realizing vehicle localization, thereby increasing the robustness of localization system.

Moreover, the V2I and V2V based methods can reach a middle accuracy. And the V2X communication technique also plays an irreplaceable role in cooperative localization because it can realize data sharing in the IoV system. Compared with V2V-based methods, the V2I-based has a better performance on accuracy and reliability. The reason is that the position of infrastructure is fixed while the position of other vehicles has a certain error. For example, the RFID technique uses tags and readers to cooperate with each other to realize data transmission and collection. Generally speaking, in the process of vehicle localization, the reader is equipped on the vehicle, and the tags are equipped on the roadside or buildings with obvious signs to provide location information or other data. The advantages of this technique for data collection can realize fast data reading speed, which can efficiently collect data. Moreover, the RFID tag is small in size and its deployment is not easily restricted by environmental conditions. However, its communication distance is limited, and if the distance between the reader and the tag is too long, it will affect the efficiency and accuracy of data collection seriously. Compared with the V2I, the V2V has the better performance on the scalability and availability, since the deployment of the infrastructure will cause additional economic costs. However, the V2X-based methods have higher computational complexity than data fusion-based methods. Because the time delay during data transmission in both V2I and V2V can not be neglected. In addition, by utilizing the distance measurement methods (TOA, TDOA, RSSI), the location of vehicles can be calculated by geometric method (The trilateration algorithm) [144], [145], [146], [147].

In addition, compared to vehicle localization methods that are not based on cooperation, the advantage of the cooperative vehicle localization algorithm is the utilization of information interaction and data sharing between vehicles and infrastructures, which enhances the data and resources (such as data storage, data computing, and communication resources) utilization rates. Moreover, most cooperative localization algorithms have distributed data processing capabilities, which greatly increases the parallelism of the localization process, reduces the centralized data processing burden on the server, and improves data processing efficiency. However, if there are a large number of vehicles in the ITS or the amount of collected sensor data is massive, the data transmission process may cause system channel congestion, resulting in additional time delays and affecting vehicle localization efficiency. Additionally, the computing power of the vehicle is limited, and if the data requires high computing power, the data processing efficiency may decrease.

B. CHALLENGES

We propose challenges for vehicle localization in the data collection and data processing steps. The challenges for data collection are illustrated in Figure 4. The main challenges faced in the data collection stage of vehicle localization in ITS are three aspects: sensor selection, deployment method,

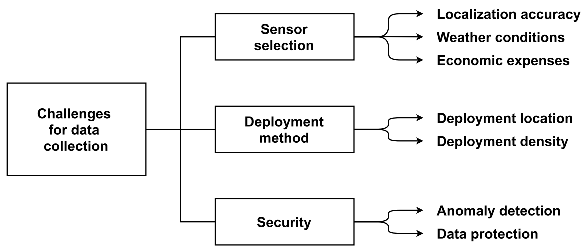

FIGURE 4. Challenges for data collection.

and security. For the sensor selection problem, it is necessary to consider the comprehensive performance (analyzed in the last section) of different sensors. For example, The LiDAR collects data with the highest accuracy, the IMU is suitable for data collection in extreme weather, and the LiDAR has high economic costs. Moreover, the environment should also be considered, such as GPS-denied environments [148]. For the deployment method, it is necessary to comprehensively consider the deployment method and density of the sensor. The IMU, LiDAR, GPS receiver, and some cameras belong to the onboard equipment, and their deployment method is simple. However, RFID requires the deployment of tags on the road or in the external environment, so it is necessary to make a decision on the deployment method based on economic costs and data collection efficiency factors. For the security of sensor data collection, it is necessary to consider two aspects: anomaly detection and data protection. Anomaly detection techniques can ensure the safety, effectively operate sensors and avoid malicious node intrusion. Data protection techniques can ensure data integrity and security and prevent data leakage.

The challenges at present of data processing method are shown in figure 5. For the data fusion technique, the challenges are seven aspects: coordinate system selection, kinematics model establishment, observation model establishment, system state estimate, independence analysis, noise processing, and data incest problem during data fusion. For coordinate system selection, especially in relative position estimation, the coordinate system transformation must be implemented. Moreover, the vehicle kinematics model should be determined. For example, the IMM filter technique can realize high accuracy localization since it considers the interaction among different models. And for the observation model establishment, we should consider the conversion of partial observation. At the same time, the influence of noise on the observations should also be considered. And regarding the system state estimation, not only a priori estimate is required, but also a posteriori estimation should be calculated. So, reducing algorithm complexity brought by the matrix inversion calculation is also a challenge. And the process has a certain time delay, it is also necessary to consider the influence of the time delay on the subsequent system state estimate results to obtain the best estimation value. Furthermore, the independence analysis is a key step during data fusion, the CIF, SCIF has excellent performance when facing the uncertain independence between input data. For noise processing, the unbiased estimation and biased estimation technique should be selected reasonable. Finally, the data incest problem can not be ignored especially in multi-sensor multi-vehicle localization system, the constraint propagation on intervals technique can be implemented to solve this kind of problem.

Moreover, using AI techniques to achieve vehicle localization can improve the utilization rate of data during the localization process and enhance the accuracy of localization results, especially in applications that require high localization accuracy, such as autonomous driving. Exploiting AI techniques such as neural networks and deep learning can obtain precise localization results and improve the robustness of the system. For example, in a certain period when the data collected by sensors is lost or the data is inaccurate due to data transmission errors, the performance of traditional algorithms will inevitably be affected because their decision-making is very dependent on the accuracy of data collected by sensors. However, compared with traditional algorithms, AI techniques require a larger amount of different types of data, which increases the pressure in the data collection process. In terms of computational cost, the time and energy costs are greater than that in traditional algorithms, because it requires more time for data training, and regarding the neural network technique, its computational cost is affected by the depth of the neural network designed. Therefore, in the process of constructing a neural network, we not only need to consider its impact on the accuracy of the output result but also its complexity. For AI techniques, the challenges of applying them to vehicle localization are the establishment of mathematical model representative data selection, data feature selection, model training and optimization, and model diagnosis and fusion.

First of all, for the mathematical model establishment, the problem and expected result should be divided and determined based on the existing data, and the field such as clustering or regression should be determined because it takes a lot of time to realize a certain function through AI techniques. Therefore, it is very important to determine the appropriate mathematical model. Then the representative data selection step is considered, because the amount of data that needs to be processed is huge. If all the data is processed, not only a lot of time and computing resources are wasted, but also the redundancy or wrong data in the data set will cause a bad influence on the results. So, it is necessary to select representative data for analysis and processing. And the possible solution to this type of problem is to evaluate the magnitude of the data in advance and use existing computing resources to estimate it. If the amount of data is too large and the existing computing resources cannot support its calculations, the dimensionality reduction method should be employed or the calculation method should be changed, such as using distributed computing instead of centralized computing or improving the complexity performance of

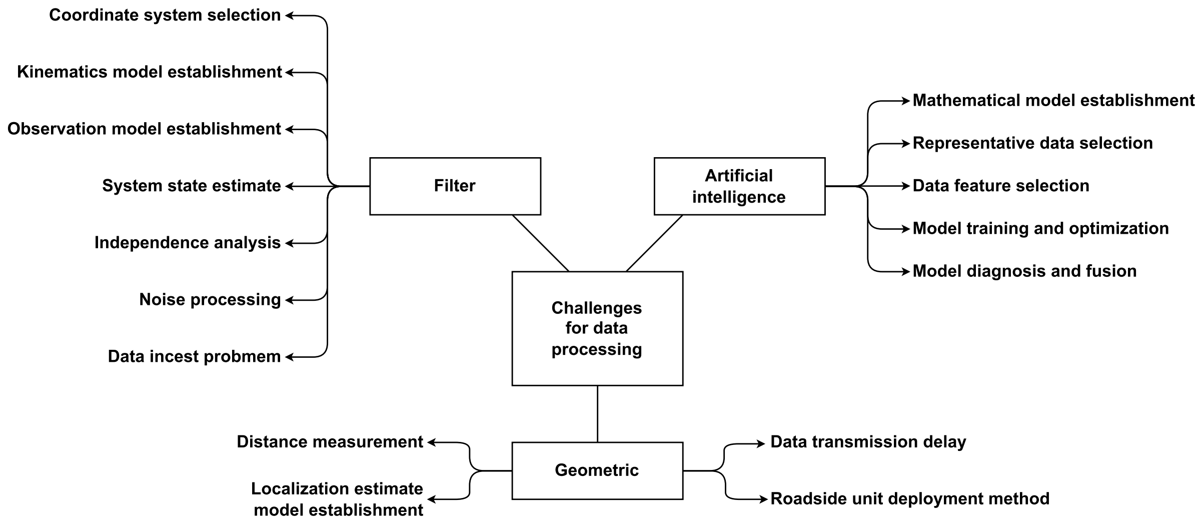

FIGURE 5. **Challenges for data processing method.**

the algorithm. Therefore, the representative data selection method can achieve the effect of enhancing the efficiency of the algorithm and reducing the computational burden.

For data feature selection, the main function of this step is to reduce the bad influence caused by erroneous or redundant data. This process requires feature preprocessing and validity analysis of the data. For data feature preprocessing, the effective methods are the removal of collinearity and normalization, etc. For feature validity analysis, the main methods includes the Chi-square test and correlation coefficient calculation. An effective data feature selection method can enhance the credibility of the results and reduce the waste of computing resources. For the model training and optimization stage, the main problem is that the parameter tuning problem. Excellent parameters are a necessary factor to enhance the efficiency of the algorithm, and therefore, it is necessary to have a deeper understanding of the algorithm and more attempts to discover the inherent laws. For model diagnosis and fusion, the first step is to perform the error analysis method on the output results, in order to obtain the reasons for the error such as model selection or parameter selection error, and then using cross-validation or other methods to diagnose the model. In addition, if the model is overfitted, the eliminate overfitting techniques should be developed. The recent work for AI-based localization has been reported in [149].

In addition, the algorithm that takes advantage of geometric methods to achieve vehicle localization exploits data such as the position data, angle data, and communication time on a two-dimensional plane. The advantages of this type of algorithm are that the complexity is low. The disadvantage of this type of algorithm is that the accuracy of vehicle localization is lower than that of using AI technique and data fusion-based technique. And the time delay in the data transmission process, which is not conducive to real-time vehicle localization. The challenges of using geometric methods to process data are the distance measurement, the localization estimate model establishment, the data transmission delay, and the roadside unit deployment method. For distance measurement, such as wireless communication scenarios, using TOA, TDOA, and RSSI methods to calculate distance, the challenge is that the influence caused by time delay and noise interference on distance accuracy during data transmission. And the solution is to implement the noise reduction method on the signal and optimize the transmission time delay to obtain a more accurate distance measurement result. For localization estimate model establishment, it is necessary to comprehensively consider the influence of various data on location results, and establishing an effective mathematical model to operate on the data. Furthermore, its computational complexity and parameter optimization are also factors that must be considered. For data transmission delay, the solution is to increase the channel bandwidth and optimize the channel method used for data transmission. Finally, with regard to the roadside unit deployment method, it is necessary to comprehensively consider the impact of roadside deployment location and density on the localization results, and also to determine the optimal deployment method based on economic cost.

Furthermore, the challenges for vehicle cooperative localization mainly includes three aspects: network selection, algorithm design, and software design, as illustrated in Figure 6. For network selection, the main communication methods are the V2V and V2I, and the challenges are similar, namely data transmission, quality of service, and security issues. For the data transmission process, if the number of vehicles and sensors in the communication range is large or the amount of data that needs to be exchanged is huge, it is easy to cause the channel congestion and data backlog, which can have a negative impact on the quality of service

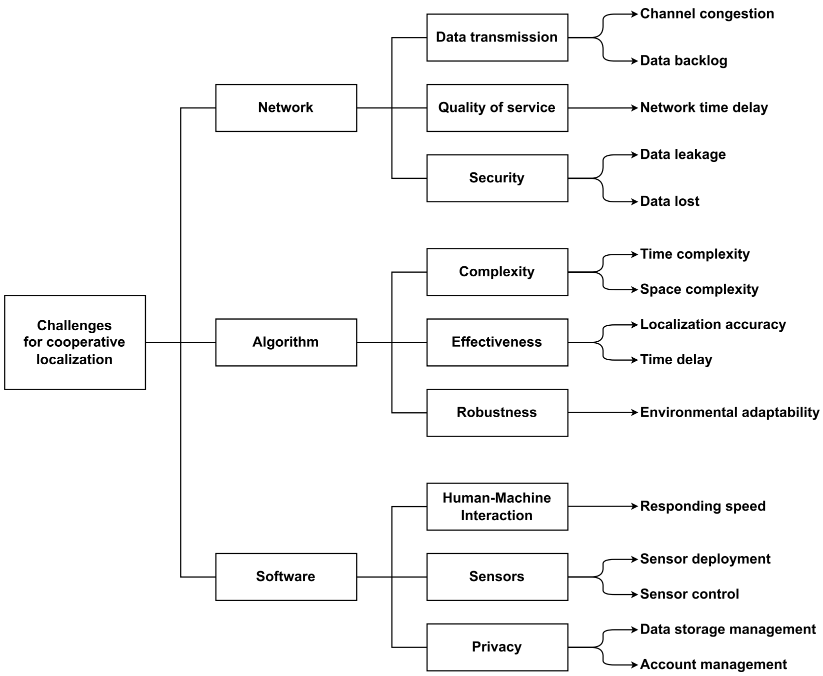

FIGURE 6. **Challenges for cooperative localization.**

and network time delays. This issue can also affect the efficiency of data transmission and processing. Furthermore, network security issues can not be ignored too. Due to the openness of the network, when nodes or vehicles frequently exchange data by the network, they may give malicious programs the opportunity to implant and cause the data leakage. In addition, attacks on data storage databases are also an important reason for data leakage and loss. Possible solutions include improving and strengthening the identity authentication technique, effectively managing the nodes and vehicles that utilize the network, and reducing the possibility of malicious nodes joining the network. Recent encryption techniques can also be used to encrypt and save data in the database, and the key can be changed regularly to prevent the database from being used maliciously and to ensure the confidentiality, integrity, and authenticity of the data. Finally, the fault detection method [150] can be employed to increase the robustness of the multi-sensor multi-vehicle cooperative localization system.

Moreover, the algorithm design mainly includes three aspects: algorithm complexity, algorithm efficiency, and robustness. Algorithm complexity mainly includes time complexity and space complexity, which together determine the efficiency of the algorithm. The time complexity of the algorithm mainly depends on the running time of the algorithm, and the space complexity is limited by the random access memory (RAM) requirements of the algorithm. When the localization algorithm is applied to a large-scale system, the data calculation time can be reduced and the algorithm efficiency can be enhanced by sacrificing the space complexity to reduce the algorithm time complexity, because the RAM and hardware in large-scale system are sufficient to meet the algorithm data processing requirements, and large-scale system has higher requirements for time performance and algorithm efficiency than small-scale system. For a small-scale system, the RAM and hardware in the system can be reduced by sacrificing the time complexity of the algorithm to achieve the purpose of reducing economic expenses. For algorithm efficiency, the main challenge in localization is accuracy and time delay performance. Additionally, the real-time performance mainly depends on the selection of the communication model and channel width, and the proper communication scheduling can also reduce the time delay. The recent work for real time performance analysis has been reported in [34]. For the robustness performance of the algorithm, since there will be sudden changes caused by the change of environment, such as weather and road conditions, the implementation of the localization algorithm should consider the response strategy for emergencies, to avoid the occurrence of invalid localization result due to external factors.

In addition, in terms of software design, the challenges facing the implementation of localization algorithms are human-machine interaction, sensor management, and software privacy protection. For the needs of human-computer interaction, the software augmented reality function should be considered. The user customization technique can be implemented since it bases on user needs which can minimize economic expenses. Moreover, the augmented reality function can better enhance the users' feeling of

TABLE 3. Details of traditional algorithms.

Ref	Sensor(s)	Data processing method	Accuracy	Real-time Performance	Advantages	Scenarios
[36]	3D LiDAR	Map matching	lat.=0.057 m long.=0.178 m	183 ms (Processing time)	FRPDM can reduce the space complexity significantly	Urban
[40]	3D LiDAR	DWM and UKF	4 cm	60 ms/frame	High accuracy	Underground mine
[41]	Multi-layer LiDAR	NDT and EKF	lat.=0.38 m, long.=0.08 m	NA	Can be implemented in mountainous rural environments	Public road
[43]	Camera-LiDAR sensor	Lightweight deep neural network	NA	92 frames/s	High reliability	Day-night changed
[47]	3D LiDAR	CMAD	0.1-0.3 m	NA	The traditional NCC method is improved	Real-world
[51]	76GHz MWR	Error propagation model	lat. 0.25 m on RMSE	NA	High availability	Snowfall weather
[54]	mmWave radars	polynomial regression model	2.56 degrees on RMSE	NA	Low complexity	Ground and aerial
[57]	Multiple ultrasonic sensors	Ground reflection elimination filter	13.5 cm on RMSE	Processing time is 0.58 s	Good real-time performance	Real-world
[63]	Multiple IMUs	Least-square and probabilistic marginalization methods	0.6 m on RMSE	Result refresh time is 10 ms	High availability	Real-world
[64]	Multiple IMUs	tightly-coupled EKF	0.2 m on RMSE	Result refresh time is 23 ms	Space complexity is reduced	Real-world
[87]	Vision sensor	Mapping	0.1 m on RMSE	Result refresh time 0.06 s	High accuracy	Urban
[88]	Four fisheye cameras	Filter	0.33 m	Result refresh time 0.04 s	Excellent real-time performance	Parking scenario
[90]	Vision sensor	Mapping	0.19 m on mean error	Mean time consumption is about 14.1 ms	High scalability	Campus road

TABLE 4. Details of cooperative algorithms.

Ref	Communication technique	Data processing method	Accuracy	Real-time Performance	Advantages	Scenarios
[151]	V2V	ICPDA	The RMSE is 0.8 m	NA	High scalability	Urban
[107]	V2V	PHD filter	RMSE is less than 0.3 m	NA	High Reliability	Real-world
[108]	V2I	KF and EKF	0.1 m on RMSE	NA	High accuracy	Highway
[112]	V2I	Bayesian filter	Mean error is 0.04 m	NA	High accuracy	Indoor
[113]	V2I	Map matching	Mean error is about 0.3 m	The response time is less than 0.5 s	Good real-time performance	Manufacturing workshop
[113]	V2V and V2I	PF	Mean error is 1 m	NA	High reliability	Real -world
[115]	V2V and V2I	Error-cognitive	RMSE is less than 0.5 m	NA	High scalability	GPS weak
[116]	V2V and V2I	CP	NA	The latency is less than 0.1 s	High Robustness	Real-world

utilizing the software and enhance the human-computer interaction. In addition, methods based on knowledge-driven and embedded computation to enhance computing power should be used to enhance the practicability of the software. For sensor management, it includes sensor deployment and sensor control methods. Sensor deployment methods

TABLE 5. Details of multi-sensor based algorithms.

Ref	Sensors	Data processing method	Accuracy	Real-time Performance	Advantages	Scenarios
[118]	GNSS and LiDAR	Mapping	Mean error is about 0.5 m	NA	High Robustness	Urban canyons
[120]	GNSS, LiDAR	Mapping	Mean error is less than 0.1 m	Result refresh rate of 25 Hz	High reliability	Real-world
[122]	Vision sensors	Mapping	Mean errors are 0.04 m and 0.17 m in the lat. and long. directions.	NA	Low complexity	Real-world
[16]	GPS, IMU, LiDAR	PF and UKF	Mean error is less than 0.3 m	Result refresh time is 8.2 ms	Good real-time performance	Real-world
[127]	IMU, LiDAR	ACSCA	RMSE is less than 0.05 m	NA	High accuracy	GPS-denied
[128]	IMU, vision sensor	EKF	RMSE is less than 0.3 m	NA	High reliability	GPS-denied
[133]	GNSS, UWB sensor	Math framework	Mean error is less than 0.08 m	NA	Low cost	Real-world
[134]	Radar, GPS	KF	RMSE is less than 0.5 m	NA	High scalability	Real-world
[139]	GNSS, camera, LiDAR	SCIF	RMSE is 0.27 m	NA	High accuracy and robustness	Real-world

include the selection of sensor deployment locations and the deployment density required by the system. Efficient sensor deployment methods can effectively provide the data required for localization and appropriately reduce economic costs. Sensor control methods include sensor data collection time and frequency control, and a reasonable sensor control method can enhance the interaction between sensors and vehicles, while can effectively collect data and increase the accuracy of localization while enhancing the robustness of the system. For software privacy protection, it mainly includes two aspects: data storage management and account management. For data management, the current challenges are database security and data access security, because if the database and data access process is maliciously invaded, it will affect the privacy of the software. In order to response to this problem, possible countermeasures include updating the software operating system in real-time, reducing software vulnerabilities, and making the system more secure can be employed. At the same time, implementing encrypted passwords method can reduce the possibility of malicious users damage the software security. In addition, real-time system backup method can be used to ensure the integrity of data when the software is unavailability. For account management, the system can employ a privacy database to protect the security of user accounts and passwords. Users should be vigilant about personal privacy, frequently changing account passwords, avoiding virus intrusion, and at the same time taking advantage of device lock and other device management software to manage the device to prevent malicious users from destroying the system.

VII. CONCLUSION AND FUTURE WORK

This paper briefly analyzes and summarizes the state-of-the-art vehicle localization methods, and presents their comprehensive performance analysis and challenges. To sum up, the LiDAR-based method has excellent data collection performance because it collects data with high accuracy and less time delay. So, LiDAR is more suitable for applications with high accuracy requirements. However, since it is difficult to popularize due to its expensive cost, one feasible method is to share LiDAR between multiple vehicles by using communication techniques. Through data sharing, the number of LiDAR deployed in the system can be reduced, thereby reducing economic expenditure. Although methods based on the IMU, GPS, radar, and ultrasonic sensors cannot meet the high accuracy requirements, they have excellent performance in terms of availability and scalability as auxiliary sensors. By using data fusion based methods, excellent comprehensive performance can be achieved. However, challenges still remain in terms of fault tolerance and data fusion process. Since the AI technique can effectively improve the performance of vision-based and LiDAR-based localization methods, the high time and computational overhead problems caused by image processing should be effectively solved. In addition, considering the many types of sensors and data in the future ITS, the redundancy of collected data needs to be considered. Moreover, for cooperative localization algorithms, data sharing can effectively enhance the cooperation among various objects in the system. However, when the number of vehicles or the amount of data collected by sensors is large, the network performance requirements are high. The current 5G communication technique can greatly enhance network performance and the efficiency of data transmission, providing reliable communication for the vehicle localization system. Meanwhile, when there are a large number of sensors in the system, fault detection and security still face big challenges. Therefore, it is necessary to design an efficient fault detection and network protection mechanism.

Furthermore, challenges for data collection and data processing are highlighted. As previously discussed, since the multi-sensor cooperative vehicle localization methods have excellent comprehensive performance, they have great potential for the establishment of future large-scale ITS. For data collection, the first step is to select effective sensors based on different environments (such as road conditions and weather). For example, the GPS is not effective in forests or tunnels, and the vision-based sensors are not suitable in day-night changed scenarios. In addition, the cost of the sensors selected and deployed in the system can not be ignored. For data processing, the data fusion method is an indispensable technique for realizing multi-sensor cooperative vehicle localization. Designing an effective data fusion method needs to consider the correlation between resource data, in order to reduce the impact of data incest problems on positioning accuracy. In MSMV system, data redundancy cannot be ignored since it has bad influence on localization efficiency. For example, the redundant data can cause unnecessary overhead in computing resources. For data fusion structure, decentralized and distributed manner have more potential than centralized manner, because they don't need a central data fusion center. Another issue to consider is data transmission and sharing, as V2X communication technique relies on vehicle networks and infrastructure. Therefore, when implementing cooperative vehicle localization system, the availability of the vehicle network must first be considered. Additionally, security issues cannot be ignored, including data storage security, data sharing security, etc.

In future work, the performance of localization algorithms in centralized, decentralized, and distributed structures will be researched and conducted. Additionally, the vehicle localization algorithm for applications with weak GPS signals, such as urban canyons, will be investigated, focusing on the deployment of sensors in this scenario and the influence of the surrounding environment characteristics on the performance of vehicle localization. Moreover, the security of vehicle communication networks has always been a serious topic. In the future, the impact of network attack methods, such as replay attacks, on the localization performance of vehicles in the localization system will be investigated. Finally, specific research on the impact of time delay and energy consumption on localization performance during data transmission and processing in the future ITS will be proposed.

APPENDIX A
METHOD OF SELECTING THE COMPETITIVE REFERENCES

In our work, the 'Google scholar' is used to search related literature. We first use the keyword 'Vehicle localization' and select the publication year from 2017 to 2023. We obtained about 16900 results. Then, other keywords are added to find more precise methods, which is shown in the table 6.

Moreover, based on the searching result provided by 'Google scholar', we read the reference title, year of publication, publisher, and number of citations, and selected the most relevant literature for reading.

TABLE 6. Number of publications with different keywords.

Keywords	Number of publications
Vehicle localization	16900
GPS-based vehicle localization	5340
IMU-based vehicle localization	2870
LiDAR-based vehicle localization	11700
Cooperative vehicle localization	16400
Data-fusion based vehicle localization	9820
Map-based vehicle localization	10100
Camera-based vehicle localization	10700

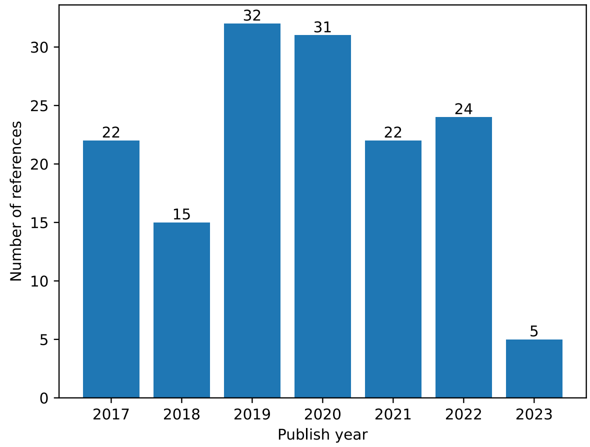

FIGURE 7. The number of our cited references in different year.

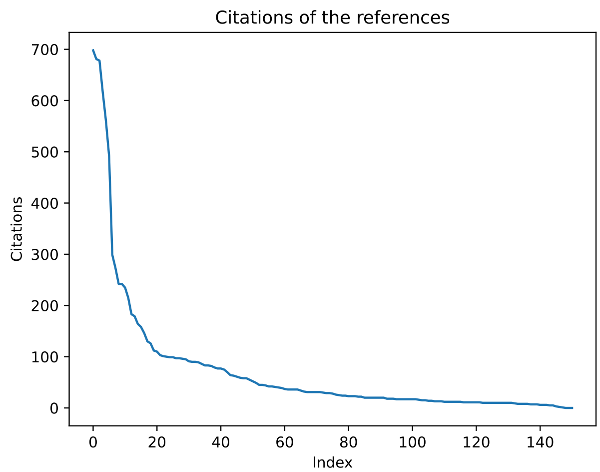

FIGURE 8. The number of citations of the cited references.

We have selected references published in the most recent year possible, and publications from excellent publishers, such as IEEE Transaction on intelligent transportation systems, IEEE Transaction on vehicular technology, IEEE Access, and so on. Please note that the journal papers are preferred over conference papers.

In addition, the publication year of references that we cite in our paper is shown in the figure 7.

Furthermore, the citations of the references we used is shown in the figure 8. We sorted the citations of all references in descending order, and then we plotted this figure. Please note that about 60 percent of the references are cited over 20 times. However, some of them not have reached 20 citations yet, because they were published in the last two years.

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XIAOYU SHAN received the bachelor's degree in computer science from the Nanjing University of Posts and Telecommunications (NJUPT), Nanjing, China, in 2015, and the master's degree from ESIGELEC, Normandy University, Rouen, France, in 2020, where he is currently pursuing the Ph.D. degree. His major research interest includes wireless sensor networks.

ADNANE CABANI received the M.S. degree from INSA Rouen Normandie, France, the Ph.D. degree in computer science from the IT Laboratory, Information Processing and Systems (LITIS), INSA Rouen Normandie, in 2008, and the HDR degree, French Accreditation to Direct Research, from Normandy University, in March 2021.

He has been a Professor in computer science with ESIGELEC/IRSEEM, Normandy University, since 2008. He is currently an Academic Coordinator of master's information systems and a member of the steering committee of federative structure in logistics SFLog FED 4230. He has coauthored 70 research papers in the areas of intelligent transport systems and logistics.

HOUCINE CHAFOUK (Member, IEEE) received the M.S. and Ph.D. degrees in automatic control from the University of Nancy, Nancy, France, in 1986 and 1990, respectively. Then, he joined the Graduate School of Electrical Engineering, ESIGELEC, Rouen, France. From 2000 to 2008, he was the Leader of the Automatics Control and Systems Research Team and the Research Head of ESIGELEC. He is currently with IRSEEM/ESIGELEC, Normandy University, Rouen. From 2000 to 2018, he was the coauthor of 115 research papers in the areas of advanced control systems, fault tolerant control and fault diagnosis applied to renewal energy, and automotive and aerospace fields.