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SURVEY

A Survey on Localization for Autonomous Vehicles

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ABSTRACT Research on autonomous vehicles has made significant advances in recent years. To operate an autonomous vehicle safely and effectively, precise localization is essential. This study aims to present the state of the art in localization to scientists new to the area. It presents and summarizes works from the field of localization and suggests a classification for the works. Approaches to localization are mainly divided into three categories: conventional localization, machine-learning-based localization, and vehicle-to-everything (V2X) localization. Conventional localization primarily depends on high-definition (HD) maps or certain marks, such as landmarks and road marks. Machine-learning-based localization approaches include using neural networks, end-to-end approaches, as well as reinforcement learning for performing or improving localization. Moreover, V2X localization methods localize vehicles by communicating with other vehicles (V2V) or infrastructures (V2I). This study not only presents a bigger picture of the area of localization in autonomous driving but also presents the potentials and drawbacks of different localization methods. At the end of the review, some research areas open for future research are also highlighted.

INDEX TERMS Autonomous vehicle localization, map-based localization, mark-based localization, machine-learning-based localization, neural network, deep reinforcement learning, end-to-end localization, multi-vehicle localization.

I. INTRODUCTION

It is inevitable that autonomous vehicles will replace ordinary vehicles in the future to perform all kinds of transportation works [1]. Society of Automotive Engineers (SAE) has categorized vehicular autonomy into six levels (0 to 5), depending on the level of a human driver's involvement during vehicular operation [2]. Researchers from academia and industry alike are working hard toward the goal of full autonomy (level-5). The autonomy system of driverless vehicles typically depends on perception and decision-making, which are divided into various subsystems. Perception is mainly responsible for jobs such as obstacle detection (both static and dynamic), traffic signal detection, road marking detection, localization, and many more. On the other hand, decision-making includes tasks such as path planning, motion planning, behavior planning, control, etc., [3]. Reference [4] divided autonomous vehicle navigation into five main components: perception, localization and mapping, route planning, decision-making, and control. Localization can be defined as estimating the vehicle's pose (position, orientation) along with the associated uncertainty in a reference frame. Localization is essential for safe autonomous vehicle operation on the road, thus, is a prerequisite for autonomous driving. Often, during vehicular operation, an autonomous vehicle does not have prior knowledge about its environment, such as a new location, changes in a map, or the position of a dynamic obstacle. In that case, a vehicle must model its environment for carrying out basic tasks like path planning or obstacle avoidance. Thus, a correct estimation of vehicle location is very important for vehicular operation. Different approaches to the localization problem demand various sensing and processing resources, and they produce localization estimation with various properties. Some common methods are (i) localization using a prior map, (ii) simultaneous localization and mapping (SLAM), (iii) dead reckoning (DR) using IMU, (iv) vision-based localization, (v) beacon-based localization, etc., [5]. A few more methods are not

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mentioned in this work [5], such as localization using wireless communication or radio frequency identification (RFID), machine-learning-based localization, and many more. Generally (independent of solution methods), localization uses data from various sensors (global navigation satellite system (GNSS), light detection and ranging (LiDAR), radio detection and ranging (Radar), inertial measurement unit (IMU), camera, ultrasonic, etc.) and analyzing those data under the aegis of numerous methods [6]. For performing localization, the data from individual sensors must often be properly fused. This sensor data is then used to perform localization, i.e., a position and orientation estimation, which can be used for higher-level decision tasks.

Sensors are usually divided into two categories based on their use, i.e. (i) perceiving the environment (exteroceptive sensors) and (ii) measuring a robot's internal condition (proprioceptive sensors). Vehicle localization is often performed by fusing and processing data from exteroceptive sensors such as GNSS, LiDAR, Radar, and camera, and proprioceptive sensors like IMU, gyroscope, odometer, etc., [7]. Another way to categorize sensors is based on the source of measured energy. Passive sensors (camera, GNSS, inertial sensors) do not emit their own energy. In contrast, active sensors (LiDAR, Radar, etc.) emit energy, a part of which is then captured for the purpose of perceiving the environment [8]. Different sensors used for vehicle localization have their own unique drawbacks, such as LiDARs being costly, IMU and GNSS often being low precision, etc. Though the camera is a very intuitive sensor for observing the vehicle's environment, it also has drawbacks such as a narrow field of view [9]. LiDAR, despite being relatively costly, is useful for vehicle localization and tracking moving objects [10]. The principle of LiDAR operation is presented in Fig. 1. LiDAR operates on the principle of time of flight, where the time difference between emitting a laser beam and receiving back its reflection is used to estimate the distance of a physical object that caused the beam to be reflected [11].

GNSS is affordable and convenient for position estimation. However, it is unreliable due to satellite signals being blocked and reflected by tall buildings in urban settings [12], (shown in Fig. 2). Besides accuracy, availability and reliability are two significant issues for localization, and GNSS suffers in both cases. Different GNSS services can also be turned off or made unavailable to public users by the corresponding operators. So, GNSS is not optimal for reliable localization, especially for level-5 autonomy. Therefore, for true autonomy, a vehicle should be able to localize itself using its other exteroceptive sensors, such as cameras, LiDAR, etc. Robustness and accuracy are vital for localizing an autonomous vehicle to drive in an urban area, and robustness also includes localization in harsh weather conditions. Changing and adverse weather conditions are one of the most challenging problems in vehicle localization.

We know that the sensors are key for an autonomous robot to sense the environment and behave according to the situation. Vehicle localization can be performed using a single sensor such as LiDAR, camera, or Radar, or data from various sensors can be employed using sensor fusion to perform localization more robustly [13]. Using multiple sensors also provides redundancy in case one of the sensors fails [1]. Each sensor has its distinct characteristics. Combining and matching real-time data from multiple sensors and matching this information with a pre-built map could even provide a more accurate pose estimation [14]. From the above discussion, it is evident that sensors are fundamental for vehicle localization (especially cameras and LiDAR). Previously, some works have compared different sensors used for localization. For example, [15] presented a comparison of camera and LiDAR for autonomous vehicle localization.

In this survey, all the research works reviewed here were collected through "Google Scholar" using search keywords (such as vehicle localization, car localization, autonomous driving localization, map localization, neural network localization, CNN localization, visual localization, camera localization, LiDAR localization, Radar localization, end-to-end localization, reinforcement localization, V2I localization, V2V localization, weather localization, point cloud localization, and many more) related to autonomous ground vehicle localization. After collecting sufficient research papers, we screened them for works only on autonomous ground vehicles (and discarded the works on mobile robots, etc.). Similarly, we screened the papers for the localization of autonomous vehicles only, independent

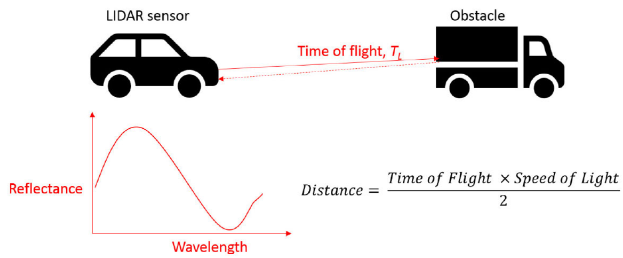

FIGURE 1. Principle of LiDAR operation, from [11].

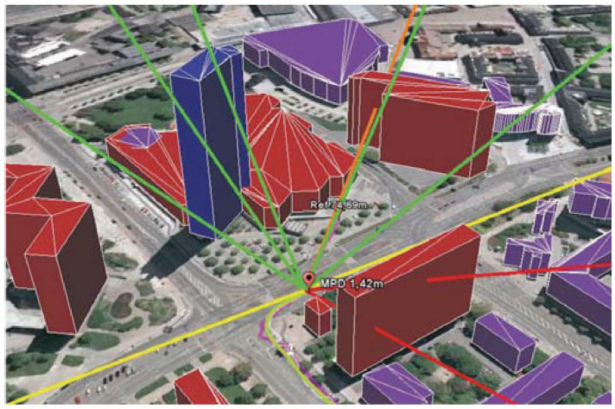

FIGURE 2. The connections between satellites and GNSS receivers can be blocked by tall buildings (represented by red lines) or might be directly observable (represented by green lines), from [12].

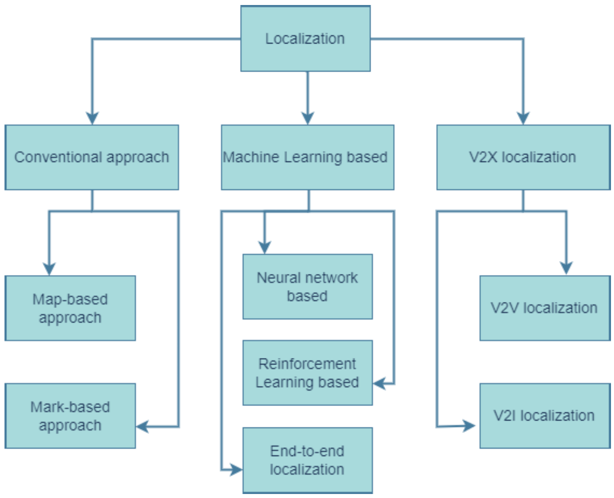

FIGURE 3. Categories of localization techniques presented in this work.

TABLE 1. Comparison between vehicle localization topics covered by previous survey papers and our survey.

Works	Conventional localization	Machine-learning-based localization	V2X localization
[1]	✓	✓	✗
[4]	✓	✗	✗
[10]	✓	✓	✗
[11]	✓	✗	✓
[16]	✓	✗	✗
[17]	✓	✗	✗
[18]	✓	✗	✓
[19]	✓	✓	✗
[20]	✓	✗	✓
Ours	✓	✓	✓

of the localization approaches. After that, we categorize localization into three main categories (shown in Fig. 3). First, we review conventional localization approaches (shown in section II). Such approaches usually use exteroceptive sensor data and employ Bayes-filter-based methods to perform localization within a prior map. This category also includes localization using road marks and landmarks. Then, we review modern approaches that employ machine learning in one form or another to perform or improve the localization (section III). Lastly, we review localization works based on communication between a vehicle and other vehicles or infrastructures (section IV). A few survey works on localization have been conducted by researchers ([1], [4], [10], [11], [16], [17], [18], [19], [20]) previously, but none of them address conventional localization, machine-learning-based (ML-based) localization, and V2X localization methods together (Table 1). We point out the strengths and weaknesses of different methods as well as their suitability in different contexts and point out open areas of research in the field of localization. At the end of the paper, we present a summary table (Table 2) that lists works that fall under different categories and includes details such as sensors used, methods employed, and the accuracy achieved by corresponding works.

II. CONVENTIONAL LOCALIZATION

The camera is a vital exteroceptive low-cost sensor that can be used for visual perception and scene detection in various weather conditions [21]. LiDAR is also commonly used for object detection and scene perception besides the camera. The conventional localization approaches mainly depend on the perception from onboard sensors like cameras, LiDAR, Radar, etc. Perception information from sensors such as cameras and LiDAR is often first used to build a map of the environment in which a vehicle is meant to operate. Sometimes, existing maps such as OpenSteetMap[1] can provide a foundation for such maps. During autonomous operation, perception information from the sensors is matched with the prior map for localization. In some cases, landmarks, road marks, etc., are also used in the matching process. Sometimes, sensors such as IMU, GNSS, gyroscope, odometer, etc., are also employed in addition to the above-mentioned primary sensors, i.e., camera and LiDAR, to achieve robustness in localization.

Most conventional localization approaches can be divided into map-based approaches and mark-based approaches [22]. For map-based approaches, a detailed map with suitable features is required to match with extracted sensors' data for localization. On the other hand, mark-based approaches do not require a detailed map; the positions of the markings are enough for localization [22]. Nevertheless, few works, such as [23], exploited marking concepts such as landmarks during map creation and localization. The work proposed vision-only localization by a monocular camera that used landmarks to create a visual map by taking images through the mapping trajectory. They then achieved a centimeter-level localization accuracy through map matching in the GNSS-denied region. In the conventional localization section, we have discussed both approaches (map-based and mark-based) according to the main focuses of the corresponding works.

So, in summary, map-based approaches mainly deal with map generation and localization inside the prior map. And the marking-based methods consider elements such as road markings, lane markings, and landmarks as detectable objects to perform vehicle localization. The concept of SLAM is worth mentioning here [24], [25]. In SLAM, a robot or vehicle builds a map of a priori unknown environment while also localizing in it simultaneously [26]. The topic of SLAM is out of the scope of this review.

[1] www.openstreetmap.org

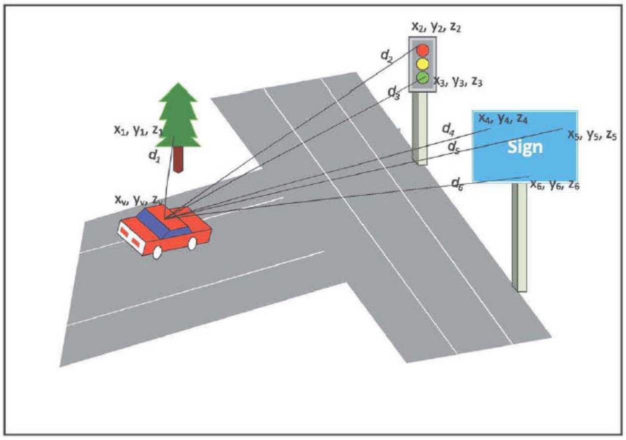

FIGURE 4. HD map-based vehicle localization, from [28].

A. MAP-BASED APPROACH

The SLAM method is very well used in localization for robots and autonomous vehicles. However, the traditional SLAM method suffers from the error growth problems [27]. SLAM requires enormous storage space, high computing power, and quick data transmission ability [28]. Therefore, the necessity of a prior map-based localization, which is more accurate and requires less computational effort, is well understood. Fig. 4 shows an HD map-based vehicle localization framework. HD map contains various types of environmental information, which requires high data volume, and high computational effort is needed (like in SLAM) to analyze and fuse the map data and the sensor information. It is also difficult to evaluate the performance of map matching in complex urban areas [29]. Despite that, localization based on HD map generation and matching is a popular technique due to their (i.e. HD maps') suitability and availability, along with the continuously reducing cost of LiDAR sensors. Nevertheless, some conditions should be met to acquire reliable localization, such as feature adequacy, local similarity, layout, and representation quality of the map [30]. Reference [30] proposed a mapping capability evaluation technique by performing localization with the help of a normal distribution transformation (NDT) scan-matching framework.

LiDAR is a very useful sensor in creating an HD map, such as in [31], LiDAR point cloud data and post-processed localization measurements accumulated, then assembled the measurements to create a full HD map. The work proposed a map-making method suitable for localization through map-matching, but no localization was performed there. Reference [32] accumulated several Velodyne LiDARs (seven) to fuse and generate point clouds for producing a high-definition 3D map with georeferencing coordinate information through the GNSS/IMU. The map is meant to help perform a LiDAR-based localization through map matching, but the work does not cover the localization process. Reference [33] used 3D LiDAR-generated range images to create a mesh-based map by Poisson surface reconstruction, then localize an ego vehicle inside the map with the help of the Monte Carlo localization (MCL) framework. Reference [34] used the SeqPolar localization technique featured in two steps: first, creating a polarized LiDAR map, and then, a second-order HMM-based (hidden Markov model) localization through map matching. A renowned approach of map-based localization through a probabilistic map is proposed in [35]. The process incorporates Global Positioning System (GPS), LiDAR, and IMU sensor data to build a probabilistic grid map and use that map for localization through a 2D histogram filter.

The characteristics of an urban area are complex due to the presence of semi-static and dynamic objects. To achieve a robust localization, it is crucial to check consistency to manage the discrepancy between map and sensor data. Reference [36] proposed Fourier-Mellin transformation (FMT) for map matching to estimate the vehicle's global pose and incorporated a cumulative sum test for checking the consistency of the map. The localization measurement used the Kalman filter (KF) framework to combine LiDAR odometry, wheel odometry, map matching result, and GPS. Reference [37] presented a sensor fusion of 3D LiDAR, GNSS, wheel odometry, and inertial data to match and verify better localization accuracy in a prior map. More conveniently, the map could also be used where some data is invalid or corrupted in a part of the map. Although an updated map helps more precise vehicle localization, [38] performed a reliable vehicle localization (even in the nighttime, in shadow, and with dynamic obstacles) using a three-years-old 3D map. The work used a 3D point cloud map (PCL) generated by a 3D LiDAR but localized with a stereo camera through map matching by transforming the real-world coordinate system to the camera coordinate and synthesizing the virtual depth and intensity of the 3D PCL map.

To perform localization robustly, the map should be updated concerning the real world regarding feature information. In [39], a SLAMCU (Simultaneous Localization And Map Change Update) algorithm detects and updates the HD map. The Dempster-Shafer evidence theory is applied to detect the change in the map. Then Rao-Blackwellized particle filter (RBPF) is used to estimate and update the vehicle state inside the map. A point cloud-based robust localization through the particle filter (PF) method using data fusion between vertical and road intensity information from a prior map has been proposed in [40]. In this work, the iterative closest point (ICP) algorithm is used for map matching, and the PF-based localization method is used to estimate the vehicle pose through the vehicle's sensor system such as 3D LiDAR, IMU, RTK-GPS (real-time kinematics global positioning system), wheel odometry, and map matching information. Reference [41] tried to achieve robust localization based on the extended Kalman filter (EKF) using the map-matching result along with the sensor fusion information through IMU, cellular signal, and GNSS signal. The work presented a comparison between the experimental error of with-GNSS and without-GNSS features. The GNSS failure case is very commonly observed in a highway tunnel area. Reference [42] used a 3D LiDAR to extract predefined tunnel facility points, and an EKF helps pose estimation by matching those features. Reference [43] used a prior map for matching to help vehicle localization through visual odometry and road markings. Reference [44] showed another example of a map matching-based vehicle localization technique by matching between offline prior maps and online 3D point clouds, which also corrected the gathered drift by LiDAR-only odometry during localization.

Conventional map-based localization often suffers from changes in maps during nighttime or harsh weather. Often, features inside the prior map look different at various times of the day and night or in different seasons [45]. For example, lane marking on a road could be partially invisible or fully covered by snow in snowy weather. In that situation, it is important to use sensors that are less error-prone to harsh weather, or a technique is required to reconstruct the map during driving for real-time localization. Reference [46] improved localization accuracy in harsh weather conditions by using principal component analysis (PCA) to reconstruct LiDAR images to enhance the quality of the map images. After edge-profile matching with preexisting map information and successfully detecting the snow lines inside the lanes, the ego vehicle performed lateral localization with lane-level accuracy. An experiment took place in JAPAN to verify the robustness of localization, and achieved a lateral error within 20 cm at 60 km/h vehicle speed. Another approach of localization in snowy winter conditions is performed through 76GHz millimeter-wave Radar-based (MWR) map generation in [47]. The localization is performed by error propagation uncertainty modeling and verifies a comparison between two states: with and without snow, using Radar data and previous LiDAR data as a baseline. The experimental verification shows a 25 cm root mean square error (RMSE) independent of snowfall conditions. Reference [48] investigated the possibility of replacing LiDAR with Radar for mapping and localization in all weather conditions. In this paper, the author presents a comparison between LiDAR-only, Radar-only, and cross-modal Radar-to-LiDAR-based work. They assert that the conventional ideas about LIDAR's sensitivity in weather conditions are exaggerated, and LiDAR-only based localization performs better than the other two approaches. Reference [49] localized vehicles in severe weather conditions (fog, snow) just using standard equipment like GPS, a camera, and a 3D map. In this work, GPS estimates the vehicle's pose and yaw angle. The work then corrects the vehicle's state, pitch, and roll angle by road marking information collected through the camera and 3D road map (from projected map in the image).

Visual map creation and localization of a vehicle inside the visual map is a state-of-the-art technique of modern research. The process behind the visual map creation is very straightforward. The map is created by a sequence of images taken from a constant distance called nodes inside an ordinary map or road trajectory. The image-represented nodes are linked with positioning information (e.g., through GNSS) and used later during image matching to extract the position information. Reference [50] utilized a visual map to determine the current vehicle position by using a monocular camera and a GPS receiver. In this work, first, GPS data is linked to multiple feature types such as the image's holistic and local features. Then, the k-nearest neighborhood (KNN) in these feature spaces is used to find the vehicle pose in a visual map. A piece of advanced knowledge about routine traffic images (e.g., edges of the car and their relation to a vehicle pose) could help to develop a model for pose estimation [51]. The localization method needs to access the local image gradient data from the input video stream of the vehicle motion. The process could eliminate the hassle of traditional feature extraction and matching, and efficiently identify a 3D object from a 2D image to help the localization process based on previous knowledge of analyzed traffic images mentioned before [51].

Due to the availability and continuous reduction of the cost of LiDARs, they are now commonly used for creating a LiDAR-based PCL. LiDAR-generated maps are often used in the localization process as a prior map for map matching and estimating the pose and location of an ego vehicle. Reference [52] proposed a LiDAR-based localization by creating a 3D PCL through mobile laser scanning and used that map for localization through key features extraction and matching. Reference [53] used a 3D LiDAR to detect a larger extent of dense curb points and a robust regression method called least trimmed squares (LTS) to handle blocking scenes. The MCL algorithm estimates the pose of a vehicle from the support of curb maps for path planning and safe navigation. A similar work is proposed in [54] using GPOM (Gaussian Process Occupancy Maps), where an OGM (Occupancy grid maps) was built with road marking data and GPOM constructed with curb data to help the MCL algorithm. Reference [55] used 3D LiDAR data for localization by the MCL method with the help of a Neural Network to find the overlap between 3D laser scans and a pre-built map. The matching technique between 3D LiDAR data and a high-precision prior map for localization is also shown in both [56] and [57]. The ICP algorithm helps to estimate the matching, and KF is used to locate the pose and orientation of those vehicles. Other steps, such as curb detection and contour extraction from the curb, also helped the localization process by providing useful information about the curbs. Reference [58] used 3D NDT-based scan-matching in a prior 3D PCL developed through multilayer LiDAR. An EKF-based localization is established using the information collected from the NDT-based scan-matching and DR. Hessian matrix-based pose uncertainty measurement played an important role in optimizing the scan-matching. The average absolute error achieved in a rural mountainous environment is 8 cm and 38 cm in lateral and longitudinal directions, respectively. In [59], a prior

PCL is generated by using graph SLAM techniques, with synthetic LIDAR as input. Then, the synthetic 2D LiDAR and odometry information are used with the MCL method for precise vehicle localization in 3D urban areas. Reference [60] proposed low-cost KF-based vehicle localization in a PCL using precise and robust segmentation-based LiDAR and MEMS IMU (micro-electro-mechanical system inertial measurement unit), which achieved centimeter-level accuracy (3 to 5 cm). Reference [61] used a multilayer LiDAR to build a PCL where the upper layer is built of the 2D point cloud from vertical features, and the lower layer is made of a combination of ground and curb features. The MCL algorithm is used in this environment to estimate the optimal position. Referenced [62] also used multiple LiDARs and NDT for mapping and matching to perform vehicle localization.

The camera is an attractive sensing modality to be used in conjunction with LiDAR to make the localization process strong and cheap simultaneously [63]. In the typical LiDAR-camera-based localization, LiDAR is employed for creating the map, and the camera is used to estimate the position according to the map [16]. The strategy mentioned above is tested in [63], where the authors first created a 3D ground map with the help of a 3D LiDAR scanner by measuring surface reflectivity, then exploit a single monocular camera to match the mutual information with the map for localization. In the next paper [64], the authors extended their previous work [63] to make it exploitable in harsh weather conditions by adding a novel scan-matching algorithm that uses Gaussian mixture maps. The Gaussian mixture maps use a set of Gaussian mixtures over the z-height distribution instead of ground reflectivity. Again, in their next work [65], the authors implemented robust localization in severe weather conditions and improved the accuracy further by strengthening the previous Gaussian mixture maps with a mixture of reflectivity distribution of the environment, characterizing the z-height, and several Gaussian mixtures. Then, the localization process used an EKF and the previously mentioned map for localization through map matching by a camera. On the other hand, another work [66] extended the previously discussed ground reflectivity grid-based map-making ideas with a more feasible and faster alternative called an alternative edge reflectivity grid representation. This process uses data from multiple LiDARs, which are invariants of robot motion, angle, range, and laser source. Then, an EKF-based localization was performed through map matching by a camera.

For commercializing autonomous vehicles, it is essential to design these vehicles with affordable sensors. A low-cost sensor set (MEMs-based gyroscope, ordinary GNSS, USB camera) and localization using the KF within a prior map is presented in [67]. A low-cost vehicle localization based on DR and lane marking detection information is shown in [68], where the GNSS is also used to correct the measurement bias near traffic crossings. This work achieves 5 cm lateral and 112 cm longitudinal accuracy by exploiting lane and traffic signs in a sparse semantic map with low-cost sensor fusion (camera, GPS, IMU, and wheel encoders) by a Bayesian filtering framework and just using 0.3% of storage data of LiDAR-based approaches. Another example of using low data storage through a compressed road scene map has been presented in [69]. Usually, HD maps take many minor details that do not contribute to localization and sometimes lead to drift problems or negatively contribute to map-matching performance. The mentioned work contains three steps: mapping, map matching, and sensor fusion for localization. First, a 3D point cloud-based grid map is compressed into a 2D grid map. The well-known MCL framework is used for map matching and localization through sensor fusion by IMU, wheel-encoder-produced vehicle motion data, and map matching results. Localization could be possible using just a Radar, which is very cost-efficient and does not demand large data storage. Reference [70] utilized automotive grade Radars and the ICP algorithm to match the Radar data with a prior map created from the sensors' (GNSS, IMU, Radar) data. The EKF localization method is also implemented (in the same work) with ICP for precise vehicle localization.

Real-life robustness can be achieved by ground-penetrating Radar (GPR), independent of chaotic environments and adverse weather conditions [71]. GPR uses features that lie inside the ground, and due to its low-frequency RF (radio frequency) energy, it is less vulnerable to failure in harsh weather situations during localization. Reference [72] also utilized GPR to achieve robust vehicle localization, perform over 17 KM of driving in various challenging weather conditions, and perform precise localization without using LiDAR or cameras. In both cases of GPR mentioned above, mapping uses underground infrastructure information, i.e., features beneath the ground, and localizes within that prior map. Different types of maps have been studied for vehicle localization by the research community. An efficient localization technique proposed by [73] is based on a pre-built numerical map in which vehicle localization depends only on a vision sensor. This is done in a two-steps process. The first step is road marking feature extraction and ego-motion estimation. The next step is the computation of vehicle pose by matching the map feature information through the EKF and PF methods. Besides the numerical map, the OpenStreetMap is another type of common map used as a prior map instead of building an own map. Reference [74] used a 3D range scanner to achieve a road network from OpenStreetMap data, then utilized the MCL technique to classify the road from non-road areas and successfully localize a mobile robot inside the map. Reference [75] also utilized the OpenStreetMap with visual odometry and the MCL framework for localization. Moreover, this method helped overcome the drift problem in visual odometry during the localization process.

B. MARK-BASED APPROACH

The presence of dynamic objects like vehicles and pedestrians in an urban area can make using generic features challenging for localization. Landmarks or road marks, on the other hand, could act as robust features, and can thus be utilized

FIGURE 5. Schematic illustration of pole-like landmarks in red on a street, from [77].

for performing localization. The main difference here, i.e., in landmark or road-mark-based localization methods, is that these methods do not require a detailed or high-definition map of the environment. These methods usually use sparse maps of environments that contain landmark or road mark positions.

In literature, landmarks such as trees, traffic light poles, street light poles, traffic signs, tall buildings, etc., have been used for vehicle localization (an example of pole-like landmarks is shown in Fig. 5). Strong localization accuracy is achievable using landmarks, especially in GNSS-challenged small urban areas where GNSS does not work properly [76]. Reference [77] presented the use of pole-like landmarks for performing localization. The drawback of this method is the non-ubiquity of such landmarks in every region. The experimental results, which used LiDAR and stereo cameras as sensors and the MCL technique, provide errors less than 30 cm for LiDAR, below 50 cm for the stereo camera, and less than a 1-degree heading error. Reference [78] also used pole-based landmarks for localization with the help of a voxel grid-based detection method and the PF for pose estimation. On the other hand, [79] used 3D-LiDAR data extracted pole landmarks for performing localization. Reference [80] utilized traffic light information as position markers and fused IMU data with this information through the EKF for localization. Reference [81] used pre-existing roadside snow poles, onboard sensors, and a four-layer laser scanner to perform robust localization on snow-covered roads through landmark-based map matching. Reference [82] used road marking poles covered with reflective tape for localization in an outdoor parking area. The work uses odometry and 3D Lidar information fused inside an EKF for performing localization. Reference [83] utilized GNSS, 3D LiDAR, Radar, pole-like landmarks, and IMU sensor data for real-time vehicle localization. To successfully fuse those sensors' data for localization, they proposed real-time MCL methods such as the PF and unscented Kalman filter (UKF), and the ICP algorithm for map matching. As mentioned earlier, one challenge in performing localization using pole-like landmarks is their availability in an environment. Reference [84] solved this challenge with an innovative idea that tall buildings are often available in urban areas to be used as landmarks. This proposed method uses the vertical corner features of buildings through 3D LiDAR, the ICP algorithm to perform matching, and an EKF for localization.

Lane markings are often used in the context of vehicle localization to achieve precise lateral localization on roads. Reference [85], for instance, utilized an HD map and a monocular vision camera to detect the lateral distance between the vehicle and lane markings, and then fused GPS coordinates with this information using the KF method for precise localization. One of the pioneering works on vehicle localization [86] uses information such as lane markings embedded in prior maps, L1-GPS, video camera features, and vehicle data for performing localization. This paper presents a lane-marking-based map-building process in the first stage and a map-matching-based localization process by the dynamic KF in the second stage. Reference [87] utilized a front-looking camera to detect lane markings, and used this information to update the particle weights for the PF algorithm, and integrated an HD map to find the vehicle position within the map. Vehicle odometry measurements and GNSS information are also incorporated to perform this vehicle localization. Commonly, localization is based on some information given by road features such as lane markings, so incorporating other elements like guardrails could help minimize the absence of such information to prevent localization failure. Reference [88] presented EKF-based localization using HD map and advanced driving assistant system (ADAS) environment sensors. A monocular camera and a Radar are used to detect the lane information and guardrails, respectively. Then, the EKF used these sensors' information and ICP algorithm-based map-matching results for vehicle localization.

Many works in the literature do not just rely on lane markings but also take into account other markings on roads, such as crosswalks, stop lines, etc., for performing localization. References [89] and [90], for instance, used crosswalks, and continuous and dashed road markings for performing vehicle localization. They used the Otsu thresholding method for detecting road markings from LiDAR point clouds. Here, the MCL algorithm incorporates a feature detection method based on the LiDAR reflective intensity information in [89] or LTS and ring compression analysis in [90] for localization. Reference [91] presented a free-resolution probability distribution map (FRPDM) which is based on road marking data perceived by LiDAR. Using such a map, the work achieves position errors (RMSE) of 5.7 cm and 17.8 cm in lateral and longitudinal directions, respectively, with the root mean square (RMS) heading error being 0.281 degrees. This result outperformed the same author's previous work [92], where the RMSE were 13.6 cm and 22.3 cm in lateral and longitudinal directions, respectively. In that previous work, i.e., [92], a binary occupancy grid map was used as an extended line map (ELM) using a 3D LiDAR with the help of the Hough transformation. Fast Fourier transform (FFT) correlation matching was used to perform the ELM-based localization. Another example of Hough transformation to detect road lane marking is presented in [93]. In this work, map-based localization using the accumulation of multilayer LiDAR data and the PF algorithm is implemented to acquire lane-level accuracy through road lane marking detection. An extension of this work is proposed for localization by LiDAR-based road sign detection inside an HD map in [94]. Reference [95] used road link information from a single camera to perform localization. The vehicle's position is estimated by matching the GPS information and HD map via the ICP algorithm. One of the pioneering works on road marking detection (not localization) through video input from a vehicle's camera is shown in [96]. An extension of this work for localization by corner feature detection from the image of road markings is presented in [97], which is applicable for different road markings and in various light conditions.

III. MACHINE-LEARNING-BASED LOCALIZATION

Machine learning is an emerging topic that is being applied to solve real-life problems in many domains. The various tasks of autonomous driving, for example, pedestrian detection, road marking detection, traffic light detection, vehicle localization, pose estimation, motion planning, cyber security of vehicles, automotive parking, etc., could be solved by machine learning, especially deep learning algorithms [98]. Sometimes, ML-based methods provide superior results compared to conventional methods for solving the above-mentioned autonomous driving sub-tasks. Moreover, machine learning methods are sometimes used to enhance the conventional methods. For example, [99] used the SVM (Support Vector Machines) method to improve EKF-based vehicle localization during GPS outage. Not only that, the ML technique is also used in improving FM-based (frequency modulation) vehicle localization named RadioLoc in [100]. Below, we discuss ML-based techniques that are used for performing or improving localization in autonomous driving. We divide the works into three sections. First, we present works that employ neural networks, mainly convolutional neural networks (CNN) or recurrent neural networks (RNN), for performing or enhancing vehicle localization. Then, we present works that employ reinforcement learning for this purpose. Finally, we discuss methods that take an end-to-end approach to localization in autonomous driving.

A. NEURAL NETWORK

Often, map generation is a vital step for the navigation of an autonomous vehicle. One challenge for map generation is the presence of dynamic objects and temporary obstacles, which require continuous updating of the map. Reference [101] used a deep learning architecture to construct a durable map from 3D LiDAR data by filtering removable objects based on the convolutional dual-view architecture, which helps the ego vehicle for LiDAR-based re-localization and trajectory estimation. Another example of object detection and removable object substitution by the CNN is shown in [102]. In this work, the deep-learning-based CNN method replaces part of the traditional visual SLAM for localization. Reference [103] proposed a dynamic-SLAM framework based on the SSD (single-shot detector) by a CNN for mapping and monocular visual localization. So, neural networks are a handy tool for improving conventional localization techniques. Reference [104] utilized a CNN to match LiDAR data and satellite images of the same areas, thus providing probabilities for the correspondences. Once the probabilities of matches between satellite and LiDAR data have been established, the localization is performed within a PF framework. Neural networks are also employed in different works to perform sensor fusion, and the fused data is then used for performing localization. Reference [105] used satellite and ground images to extract robust features for the CNN-based pose estimation and optimize through a neural network. Based on a relative camera pose, a geometry projection module that bridges the vast cross-view domain gap, projects features from the satellite map to the ground view. A differentiable Levenberg-Marquardt (LM) module helps minimize the differences between the projected and observed features, and the whole procedure trains in an end-to-end manner. Like satellite images, high-resolution aerial images have also been used for vehicle localization using CNN [106]. Another study on CNN-based vehicle localization is presented in [107], which uses a bird's-eye view elevation map and the deep representation of object features. Reference [108] employed the CNN for camera-Radar sensor fusion as well as for vehicle's corner detection. This information is then used in a PF framework for vehicle localization. Reference [109] proposed a localization technique using a multimodal sensor fusion framework that used depth information from a 3D LiDAR and semantic segmentation information from RGB images through a CNN architecture called ERFnet. It is clear from the above discussion that CNN is a useful tool for vehicle localization, and usually assists in sensor fusion.

Several deep learning techniques are also used along with the Bayes filter or other conventional methods for improving localization accuracy. A vehicle localization method based on an EKF and deep learning is proposed in [110]. In this work, the authors tried to eliminate the sensor noise influence in a microelectromechanical-system-based inertial navigation system (INS) by introducing an improved extended Kalman filter (IEKF). Then, the position estimation is measured by multiple long short-term memory (multi-LSTM) based on the Gaussian mixture model and Kullback-Leibler (KL) distance. The study focused on and successfully improved localization accuracy by combining the IEKF and multi-LSTM in the presence of GPS outages, but found that the longer the GPS outage, the higher the localization error. Another example of using neural networks for lateral localization in harsh weather is shown in [111]. The work employs a neural network to match edge profiles on the road in

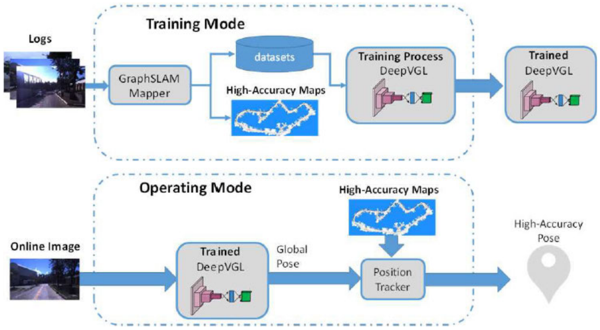

FIGURE 6. **Deep Global Visual Localization (DeepVGL), example of a visual localization, from [114].**

differing weather conditions, thus assisting in precise lateral localization. Reference [112] proposed a novel L3-Net (Learning based LiDAR Localization) system that works by mathcing pre-built map and online LiDAR point clouds based on several deep learning procedures (both the CNN and RNN). Reference [113] established LocNet by incorporating artificial statistics and a Siamese neural network for LiDAR data to convert a place recognition problem to a similarity model problem for feature learning. A dimension reduction of sensor data is performed to create a low-storage prior map. A PF algorithm is utilized in this map for localization tasks such as pose estimation after place recognition.

However, in recent years, the deep learning algorithm, i.e., the neural network methods, has mostly been used for the visual localization task among all other localization techniques. Reference [114] proposed a deep visual global localization (DeepVGL) through the deep neural network using image data to estimate the vehicle's global pose and extend its localization capacity in different weather conditions (shown in Fig. 6). The DeepVGL located a self-driving car within 0.2 meters in 75 percent of its test cases. Reference [115] improved the mentioned DeepVGL method for more robust localization using some data augmentation techniques. Reference [116] built a local semantic map using wheel-inertial ego-motion and image sequences. A supervised neural network helps visual localization through matching between the map and online map database, and an invariant KF is used to fuse the other onboard sensors with the visual localization. Another example of visual localization is also shown in [117], where images are kept in a database with GPS coordinate information and retrieved for position estimation through a CNN-based localization model. Reference [118] arranged images as input and corresponding relative pose vector as output for the CNN-based visual localization. The authors trained a hybrid weightless neural network system for visual localization in this work. Over the last year, many researchers have used visual localization in everyday autonomous vehicle research to execute the localization task. Reference [119] proposed a localization technique called ImPosing (Implicit Pose Encoding), which uses a 3D scene representation or a set of geo-referenced images for performing localization. Moreover, [120] proposed a CNN-based visual localization method to perform localization in various weather conditions, where the k-Means technique is used to obtain precise coordinates, and depth images are combined with RGB images using the IHS (Intensity Hue Saturation) method to check the positional accuracy of the CNN.

The CNN-based localization is also useful for uncertainty measurement and improves the accuracy via uncertainty-aware perception. Reference [121] proposed a CNN-based algorithm called CoordiNet to predict the camera pose from a single image; it also provides the uncertainty estimation of the pose. A single loss function managed the learning of the pose and uncertainty, and an EKF also helped its test time fusion. Reference [122] used a multi-task uncertainty-aware perception model for robust localization by a monocular vision camera and vehicle odometry. This work used traffic lights and only lane borders to create an image-based sparse map, then localize the ego vehicle using pose graph localization inside the map. Deep learning has also been employed for curb detection. Reference [123] proposed a precise and low-cost lateral localization method that uses a mono-vision fish eye camera and a deep curb detection network.

B. REINFORCEMENT LEARNING

Reinforcement learning (RL) is one of the powerful Artificial Intelligent (AI) models that can be applied to automotive applications to teach machines through their environment and mistakes. The RL method was improved by deep learning (and thus Deep Reinforcement Learning, or DRL) and became popular day by day after a successful introduction by Google DeepMind. DRL can be applied to various autonomous vehicle tasks through multiple techniques and algorithms. Reference [124] proposed a short overview of the use case of the DRL framework for autonomous driving, which suggested that CNN and RNN are suitable for perception and localization tasks, respectively, and that DRL is more convenient for planning and control. Among a few localization tasks studied through RL, [125] used RL to improve the localization results, where RL helped the usual KF method to adjust its noise covariance matrix and positioning accuracy. The setup is called the adaptive Kalman filter navigation algorithm based on reinforcement learning (RL-AKF), where the united navigation system is considered as the environment, and correcting current positioning errors is considered as a reward, to optimize the positioning noise. However, the experimental results show that the proposed method depends on GNSS/INS, which are prone to errors such as GNSS outages. Reference [126] used RL-based Deep Q-Learning Localizer (DQLL) to improve lane level localization after CNN-based lane detection through bounding boxes. Reference [127] utilized a reinforcement-learning-based learning-to-optimize (RL-L2O) method to improve LiDAR-based 3D object detection and localization by training in an end-to-end manner. The using of the RL method to improve localization is also shown in [128], but the work used unmanned aerial vehicles (UAVs) to perform localization for a connected and autonomous vehicle (CAV).

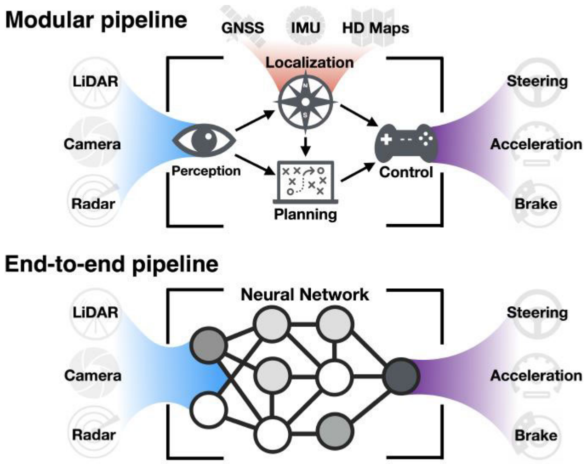

FIGURE 7. Comparison between a generic modular system and an end-to-end framework, from [129].

The DRL approach is mainly used for planning and controlling tasks [124]. And to a limited extent for perception and vehicle localization, as discussed above, mostly for optimizing the localization results. As RL does not require data labeling as in the case of supervised learning, localization using reinforcement learning has potential for future research. However, the RL method is in the beginning stage for the localization task, so the researchers could start their research with how to complete a whole localization process with the RL or DRL method instead of only improving results with the RL method after completing a localization task with other methods. Even while completing a planning or control task for vehicular operation, how DRL could produce localization information besides planning or control tasks needs further investigation.

C. END-TO-END LOCALIZATION

The end-to-end driving method (also known as behavior reflex) is a compelling approach to optimizing the driving process, as in these methods, a single end-to-end network is used to solve different driving sub-tasks. End-to-end networks consider all or most sub-tasks together as a single machine learning task (using supervised imitation learning or reinforcement learning) to map input sensor data to wheel and steering commands. On the other hand, a modular pipeline is maintained by the composition of interconnected modules such as perception, localization, planning, and control. A comparison between a generic modular system and an end-to-end framework is shown in Fig. 7, [129].

A deep recurrent convolutional neural network to improve the geometric information of visual odometry is used in [130] in an end-to-end and sequence-to-sequence probabilistic manner. The end-to-end technique mentioned here differs from usual end-to-end driving and is utilized for pose estimation as output to perform localization through visual odometry. Another example of pose estimation is mentioned in [131], where the authors proposed end-to-end learning for pose estimation as output and applied CNN to train a prior data source from Google Street view panoramas. This work actually improved the PoseNet architecture by an end-to-end localization without having a map by synthesizing new images. Reference [132] proposed a deep attention mechanism to find some stable, distinctive, and salient features to match for visual localization through an end-to-end neural network. Reference [133] presented three types of localization in an end-to-end manner, starting with road-level localization (RLL) using OpenStreetMap data and GPS. Then, they present ego-lane level localization (ELL) using prior lane markings, and finally, lane-level localization (LLL) using the YOLO detector [134], composed of a Bayesian network and HMM in a probabilistic framework.

One way to divide end-to-end approaches is to divide them into two categories: one that maps sensor data to control and one that maps sensor data to localization. In the context of the second category, pose estimation-based visual localization has been studied in the literature. Another avenue that demands further investigation is end-to-end networks that map sensor data to both localization and control commands. Reference [135] proposed this through a variational neural network to map between raw camera data and probabilistic localization information along with a deterministic control command. Among all other machine learning approaches, the end-to-end method is the most prominent for future research due to its simplicity in application. However, there are still many questions to be answered. For example, what should be the proper inputs to increase the accuracy of the localization? In an end-to-end method, there is some lack of interpretability; how can we improve those areas through proper investigation? How do we localize using an end-to-end approach without depending on an HD map and in a weather-invariant manner?

IV. V2X LOCALIZATION

Vehicle-to-everything (V2X) is a cooperative operation between vehicles and objects, which is a part of the intelligent transport system (ITS) studies and is based on the internet and different types of wireless communication. Vehicle-to-everything refers to communication between vehicles and others, such as; vehicle-to-vehicle (V2V), vehicle-to-pedestrian (V2P), vehicle-to-infrastructure (V2I), vehicle-to-network (V2N), etc., [136].

A. V2V LOCALIZATION

In the V2V localization system, the ego vehicle communicates with neighboring vehicles to share information about their positions, directions, trajectories, distances, etc. (Fig. 8) [11]. Using the shared information, the vehicle estimates its position without having high-precision sensors [137]. In [137], the authors used a doubled-layer consistency check for robust localization. At first, GNSS pseudo-range measurements are used to reduce multi-path biases for both the ego vehicle and neighboring vehicles. Then, GNSS double-difference-based relative positioning is used to exclude the

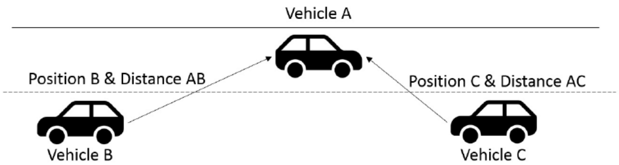

FIGURE 8. Calculating distance from the nearer vehicle, a multi-vehicle localization framework [11].

multi-path and non-line-of-sight effects. Reference [138] presented a V2V communication-based positioning system with the help of a GPS receiver and a ranging sensor, which improved a standalone GPS-based work by up to 85 percent on average in the experimental results. In contrast, [139] used an RFID system to achieve localization accuracy where the localization system uses both V2V and reader-to-tag (RFID tag that contains road-related information) communication to recognize and correct the localization error. The technique achieves submeter-level localization error with a meager maintenance cost (one dollar per kilometer) on GPS-free roads. Despite the cost efficiency, RFID-based localization is only suitable for short and fixed routes such as sightseeing buses [18]. Reference [140] discussed the effect of road configuration on V2V-based localization; they mentioned that the uniform distribution of connected vehicles could reduce the cooperative map-matching error. Therefore, the non-uniform distribution of surrounding vehicles could be a problem for vehicle-to-vehicle localization. A multi-vehicle system with a hierarchical control architecture is proposed to explore an unknown environment collaboratively by [141]. Deep reinforcement learning is used to avoid collisions between those collaborative multi-vehicles, and a novel dynamic Voronoi partition is applied to avoid exploring duplication by the working vehicles. Reference [142] proposed split co-variance intersection filter method for cooperative localization through data fusion. In the method, each vehicle maintains the estimation of decomposed group state, shares the estimation with another vehicle, and updates the estimation with the ego vehicle's sensor data and estimation sent from the other vehicles. Reference [143] proposed indirect V2V relative pose estimation (InDV2VRPE), which replaces direct V2V relative pose estimation for multi-vehicle cooperative localization and improves localization accuracy.

B. V2I LOCALIZATION

The vehicle-to-infrastructure (V2I) system uses infrastructure such as cellular base stations or roadside units (RSUs) instead of surrounding vehicles for communication. The RSU helps ego vehicles estimate their position more accurately, and there are some advantages of using V2I localization over the V2V system. Reference [11] discussed those advantages as: (a) estimating location more accurately due to the fixed position of the RSUs; (b) being more reliable due to a fixed number of RSUs within the transmission range; (c) sharing some critical information like weather conditions, traffic flow, accident events, etc.; and (d) enhancing traffic management systems and vehicle control. Reference [144] used impulse Radio-ultra wide band (IR-UWB) for V2I localization using RSUs. Three different localization techniques, i.e., direction of arrival (DOA), time of arrival (TOA), and time difference of arrival (TDOA), and their combinations are tested for better accuracy. The evaluation through the MATLAB simulator shows that the combination of DOA and TDOA works better for the localization task. Another benefit achieved by this work employing IR-UWB is its high precision and low maintenance cost. Reference [145] used V2I communication-based vehicle location information for vehicle localization in a tunnel environment. A comparison between the KF on both the Doppler shift and TOA measurements and the EKF on only Doppler shift measurements is presented, where the EKF-based work outperforms the KF-based work. Reference [146] used beacon packets of RSUs and angle of arrival (AOA) estimation for performing a GNSS-free V2I localization. A weighted least squares algorithm helps vehicle localization through information such as the AOA of the beacon packet and the position of the RSUs. Another work on GNSS-free high-accuracy V2I localization is discussed in [147]. The authors used a KF to fuse kinematics information from an inertial navigation system (INS) and an INS-Assisted Single RSU (only on one side of the road), which provides a localization accuracy of 1.8 m, which they claim is significantly better than their GPS-based technique. The performance is cost-efficient and noteworthy, as it outstrips the existing RSU-based approach by up to 73.3 percent.

V. CONCLUSION

This work presented a concise overview of research on the localization of autonomous vehicles. To understand the recent progress, localization is divided into three categories. First, conventional localization is presented and split into two subcategories. In the first category, localization focused on map-based approaches, which discussed localization in a prior HD map, generation of an HD map, consistency checking and updating of a prior map, localization inside a map during harsh weather, visual maps, LiDAR-based PCL, and a few other types of maps. The second category discussed marking-based localization, such as lane marking, road marking, and landmarking. In recent years, ML-based localization has caught the boundless interest of autonomous vehicle researchers. Machine learning contains various methods and algorithms to precisely analyze the sensor's data for localization or improve localization accuracy. The ML-based method is discussed in the neural network, reinforcement learning, and end-to-end localization categories. Finally, collaborative vehicle localization discussed two main localization techniques: vehicle-to-vehicle and vehicle-to-infrastructure-based localization.

This survey provided outlines of previous works on localization from various points of view and compared their results (sensors, methods, accuracy) in Table 2, which will be a guideline for the new researchers of autonomous vehicle localization to choose the best way to work on localization.

TABLE 2. Summary table.

Sensors	Localization methods	Accuracies	Works
Conventional localization			
LiDAR, IMU, GNSS	Error state KF-based localization through sensor fusion in various challenging locations	5-10 cm (RMSE)	[14]
Cameras, GNSS, IMU	Map-based visual localization	7.06cm (mean error)	[21]
Camera	Vision-based vehicle localization in corridors	2.25cm (mean error)	[22]
Camera	Vision-based localization using a visual map	<10cm	[23]
LiDAR, GNSS	Map-based localization using abstract maps	20cm (multilayer 2D vector map), and 43cm (planar surface map) (mean)	[27]
Camera, IMU, wheel speed sensor, GNSS	Vision-based localization by road markings detection	49cm lateral and 95cm longitudinal (mean)	[29]
Camera, LiDAR, GNSS, IMU, odometer	Localization based on the NDT scan-matching	7cm (best case)	[30]
LiDAR, GNSS	Range image-based LiDAR localization using the MCL framework	46cm lateral and 70cm longitudinal (RMSE)	[33]
LiDAR, GNSS, IMU	Map (polarized LiDAR map) matching using the second-order HMM for localization	30cm (mean)	[34]
GNSS, IMU, LiDAR	Histogram filter-based localization using a probabilistic map	<10cm (RMS accuracy)	[35]
LiDAR, wheel odometry, GNSS	KF-based localization using FMT-based map matching	12cm (median Euclidean error)	[36]
Camera	PF-based localization using a stereo camera-based 3D PCL	<10cm (RMSE)	[38]
Camera, GNSS	Detect the map changes by the Dempster-Shafer evidence theory and localization by the RBPF	83.5cm (mean), 89.75cm (standard deviation)	[39]
GNSS, IMU, wheel odometry, LiDAR	Entropy-weighted PF-based localization through sensor fusion and ICP-based map matching	<10cm (both mean and standard deviation)	[40]
GNSS, IMU, cellular signals of opportunity (SOPs)	EKF-based localization through sensor fusion and map matching information	280cm (with GNSS), 312cm (without GNSS) (RMSE)	[41]
LiDAR, IMU, GNSS	EKF-based localization using LiDAR-based tunnel facility point detection and matching	<20cm (RMSE)	[42]
Camera, LiDAR, Radar, GNSS	Localization inside a prior map using visual odometry and road markings	<10cm	[43]
LiDAR, camera, GNSS, IMU	PCA to reconstruct LiDAR images, and edge profile matching for localization	35cm lateral	[46]
LiDAR, Radar, IMU, camera, wheel encoder	Map-based localization using a 76GHz omnidirectional millimeter-wave Radar-based map	25cm lateral (RMSE)	[47]

TABLE 2. *(Continued.)* **Summary table.**

LiDAR, Radar, camera, GNSS, IMU, wheel encoder	LiDAR-only, Radar-only, and LiDAR-Radar localization	5.2cm lateral and 4.9cm longitudinal (best mean error) for LiDAR-only localization	[48]
Camera, GNSS	Visual localization using the KNN and a visual map	<35cm (mean)	[50]
LiDAR, GNSS	LiDAR-based localization using a 3D PCL	The mean error is between 15cm to 50cm	[52]
LiDAR, GNSS	MCL using 3D LiDAR data and Neural-network-based map matching	<100cm (RMSE)	[55]
LiDAR, GNSS, INS	KF-based localization using ICP-based map matching and 3D LiDAR-based curb detection	19.1cm lateral and 162.3cm longitudinal (mean error)	[56]
LiDAR, GNSS	KF-based localization using ICP-based map matching and 3D LiDAR-based curb detection	19cm lateral and 46cm longitudinal (mean error)	[57]
LiDAR, DR, GNSS, camera	LiDAR-based localization using the EKF through 3D NDT scan-matching in a 3D PCL	38cm longitudinal and 8cm lateral (mean)	[58]
LiDAR, IMU, GNSS	KF-based LiDAR localization in a PCL	3-5 cm (RMSE)	[60]
LiDAR, GNSS	MCL using a double-layer features map	20cm lateral and 30cm longitudinal	[61]
LiDAR, camera, IMU, wheel encoder, GNSS	Visual localization within reflectivity-based LiDAR maps	19.1cm longitudinal and 14.3cm lateral (RMSE)	[63]
LiDAR, GNSS, INS	Fast LiDAR localization using multiresolution Gaussian mixture maps	15.5cm longitudinal and 10.3cm lateral for the downtown area, 18cm longitudinal and 9.4cm lateral for the snowy downtown area (mean)	[64]
GNSS, IMU, wheel odometry, LiDAR	LIDAR localization using multiresolution Gaussian mixture maps	<13cm (RMSE)	[65]
LiDAR, GNSS, IMU	Ground-edge-based LiDAR localization	<5cm (RMSE)	[66]
LiDAR, camera, GNSS, IMU, wheel encoder	Bayesian filtering localization using a sparse semantic HD map	5cm lateral and 112cm longitudinal (mean)	[68]
LiDAR, IMU, GNSS, wheel encoder	MCL through a compressed road scene map	<10cm (mean absolute error (MAE))	[69]
Radar, GNSS, IMU	EKF-based Radar-localization using ICP-based scan-matching against a recorded map	7cm lateral and 38cm longitudinal (RMSE)	[70]
Radar, GNSS, IMU	GPR-based localization through a map that uses features beneath the ground	4cm (RMS)	[71]
Camera, LiDAR, Radar, GNSS, INS	EKF- and PF-based localization using a numerical map	<20cm (distance root mean squared (DRMS))	[73]
LiDAR, camera, GNSS	Adaptive MCL using semantic and pole-like landmarks (trees, traffic signs, street lamps)	<30cm for LiDARs, <50cm for stereo cameras (RMSE)	[77]

TABLE 2. *(Continued.)* Summary table.

Camera, GNSS, INS, wheel speed encoder	EKF-based localization using traffic lights as landmarks in a traffic light map	0cm to 50cm	[80]
LiDAR, GNSS, IMU	EKF-based localization using landmarks	<30cm in the x-direction and <50cm in the y-direction (RMSE)	[82]
LiDAR, Radar, GNSS, IMU	MCL (PF and UKF) using pole-like landmarks	11cm (mean error)	[83]
LiDAR, GNSS, INS	Vertical corner feature-based (buildings as landmarks) vehicle localization using a 3D LiDAR and ICP-based scan-matching	13.8cm (2D RMS horizontal error)	[84]
Camera, GNSS, IMU	Lane marking aided vehicle localization using the KF	<125cm (95th percentile horizontal, lateral, and longitudinal positioning errors)	[86]
Camera, GNSS, IMU, vehicle odometry	PF-based localization using a prior HD map	RMSE 120cm (best case)	[87]
LiDAR, GNSS	Road markings detection using the LiDAR reflective intensity data for the MCL	119.82cm longitudinal and 31.19cm lateral	[89]
LiDAR, GNSS, INS	MCL using multilayer LiDAR-based road markings detection	<30cm	[90]
3D LiDAR, GPS/DR	Free-resolution probability distributions map-based localization using the EKF	5.7cm lateral and 17.8cm longitudinal (RMSE)	[91]
LiDAR, camera, GNSS, INS	LiDAR localization using the ELM and FFT-based map matching	13.6cm lateral and 22.3cm longitudinal (RMS position error)	[92]
LiDAR, GNSS, IMU	PF-based LIDAR-localization through lane markings detection	22cm (cross-track accuracy)	[93]
LiDAR, GNSS, IMU	Extension of [93] for a third-party map	31cm (best)	[94]
Camera, GNSS, INS	Localization using the ICP-based map-matching	89.2cm (mean), 78.1cm (standard deviation)	[95]
Camera, GNSS	Visual localization using traffic signs painted on the road	<100cm (MAE)	[97]
Machine-learning-based localization			
FM	FM-based vehicle localization using ML-based FM signal processing (RadioLoc)	An average error of <20cm in an open road, <70cm in a tunnel	[100]
Camera, Radar	PF-based localization by CNN-based camera and Radar fusion and corner detection	66cm maximum, and total RMSE is 18.31cm	[108]
MEMS-INS, GNSS, wheel speed sensor, steering angle sensor, cameras	EKF-based localization and RNN-based optimization	The RMSEs during GPS outages with 30, 60, and 120 seconds durations are 234, 269, and 308 cm, respectively	[110]

TABLE 2. *(Continued.)* Summary table.

LiDAR, camera	Lateral road marks reconstruction and edge profile matching through a neural network	2.8cm (best case), 9.4cm (best mean)	[111]
LiDAR, GNSS, IMU	Deep-learning-based (RNN and CNN) LiDAR localization in a PCL	The final estimated offsets (53.8cm, 99.3cm, 1.001°) and their ground truths (52.4cm, 99.4cm, 1.044°)	[112]
Camera, IMU, GNSS, LiDAR	Visual global localization based on deep neural networks	20cm (75% of the time)	[114]
Camera, IMU, GNSS, wheel speed sensors	Visual localization by a neural network and KF	16.7cm longitudinal and 3.9cm lateral (MAE)	[116]
Camera, GNSS	Visual localization by a neural network	120cm (mean error)	[118]
Camera	CNN-based visual localization and uncertainty estimation, and the EKF helped in its test time fusion	29cm (median error)	[121]
Camera	Uncertainty aware perception and visual localization	19cm lateral and 45cm longitudinal (MAE)	[122]
Camera, GNSS	Mono-vision-based lateral localization using deep-learning-based curb detection	<3.5cm lateral (mean)	[123]
GNSS, IMU	RL-AKF	Mean error 65.17cm (10s GNSS outage), around 1500cm (300s GNSS outage)	[125]
Camera, GNSS, IMU	End-to-end localization by expanding the PoseNet architecture by synthesizing new images	Less accurate compared to the original method (around 750 to 800 cm against 250 to 300 cm), but faster in computation and independent of camera position	[131]
V2X localization			
GNSS, wave communication (WC)	GNSS-based V2V localization	<1000cm	[137]
GNSS, ranging sensor, WC	Sensors-based V2V localization	60cm (mean)	[138]
RFID, INS	RFID-based V2V localization	<100cm (mean)	[139]
IR-UWB	IR-UWB-based V2I localization	0 to 2000cm	[144]
WC	RSU-based localization using the beacon packets from RSU	Maximum RMSE up to 1000cm (approx.)	[146]
WC, INS	Localization using INS-assisted single RSU and the KF	180cm (RMSE)	[147]

By summarizing all the recent works depending on their approaches, sensor setup, methods, and algorithms, this study found some research areas appealing to achieving better localization accuracy but still need further investigation. For example, use cases of deep reinforcement learning and end-to-end methods for precise localization, localization in harsh weather and through the various seasons, localization in rural areas and highways, etc., which are still disregarded by the autonomous vehicle research community.

Based on the research works presented here, this study also found that autonomous vehicle localization will progressively be based on ML methods. This trend has already begun and will increase in the future. ML-based localization will be used either to improve the results of conventional localization, which are based on HD map or Bayes filter-like algorithms, or as standalone ML-based localization. ML-based standalone localization methods include visual localization, training a neural network in an end-to-end manner to perform localization, and optimization of localization by the RL method. Improvements in technology, such as internet availability and speed, wireless communication using 5G and radio frequency technologies, etc., will catalyze the research towards smart cities and ITS. Thus, V2X localization will also be a topic of significant research in the future.

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