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On the Ecosystem of High-Definition (HD) Maps

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***Abstract*—High-definition (HD) maps have recently gained critical importance in automated driving applications due to their ability to contain a high density of information, far exceeding traditional maps. They offer precise instructions for automated driving software agents. However, the construction and maintenance of HD maps present several challenges. Moreover, the unprecedented detail and precision of geo-referenced information extraction have sparked new potential applications. This paper provides a comprehensive review of the extensive body of literature on HD maps. We categorize the principal tasks discussed in the literature into eight main sub-areas. These sub-areas encompass the research work focused on the creation, maintenance, and various applications of HD maps. We underscore key directions in each sub-area and delve into the associated challenges. Further, we spotlight potential future directions to broaden the scope of HD maps usage in an array of applications.**

***Index Terms*—Spatial databases, Knowledge and data engineering tools and techniques, Navigation**

I. Introduction

Digital maps, e.g., Google Maps, Bing Maps, and Apple Maps, are being extensively used in various applications by hundreds of millions of users every day. All traditional digital maps are designed and developed for human-to-machine interactions. So, there is an implicit assumption that a human user is consuming the mapping information, such as using maps in driving or searching for points of interest (POIs). Recently, major applications, such as autonomous driving, have invalidated this fundamental assumption and introduced the need for digital maps that are designed and developed for machine-to-machine interaction [1]–[3]. In autonomous driving, maps are used for the perception of distances that are beyond the sensors' ranges. In this case, the consumer is not a cognitive human, but an automated software driver. Other applications that use automated map consumers include motion planning [4], [5] and 3D object detection [6]–[8].

Driven by the rise of automated map users like self-driving cars, High-Definition (HD) maps emerge. Compared to traditional maps with meter-level accuracy, HD maps offer high-resolution details, accurate to centimeters [2], [9]. These details cater to "machine" consumers, enabling them to "recognize" lane boundaries, signs, road obstacles and other information typically understood by humans. This is achieved by vectorizing the surrounding environment and on-map computation of precise displacements and angles, going beyond conventional map-making methods.

The applications of high-resolution maps are popular in indoor environments, where robots use detailed maps in combination with sensors to navigate smart spaces like factories and workshops, health facilities and homes, etc [10], [11]. However, the shift from small and controlled indoor settings to the vast and dynamic outdoor environments for self-driving vehicles necessitates new approaches to address fundamental challenges in map creation and usage [12]–[15]. This has spurred significant research efforts in this area.

Building and maintaining HD maps globally, depending only on specialized equipment, is a cost-prohibitive task. Currently, comprehensive coverage doesn't exist. This open research area faces challenges in partially automating the integration of available big spatial data into HD maps. Several works have addressed these challenges, aiming for large-scale, detailed map development and maintenance.

In this paper, we provide a lengthy glimpse of the literature on building, maintaining, and using HD maps. It is extremely challenging to cover the whole literature of such a rich topic. Nevertheless, due to the importance and richness of the topic, there is a need for research efforts to summarize the current status and discuss research opportunities. Our objective in the paper is to take a middle position, we outline the main sub-areas of research in this literature, pointing out some of the existing challenges and future directions. Yet, we encourage readers to refer to the whole literature for a deep coverage for all existing research in one of these sub-areas as it is beyond of our scope to cover an extensive list of references in such a rich topic. We particularly refer to [16] for map generation techniques in particular.

We classify the literature into two main categories that are outlined in Table I: (1) *HD maps design and construction* (Section II). This category corresponds to the first three rows in Table I and highlights techniques that model, design, and build HD maps' content. It is further categorized into: (1.1) *Modeling and design* (Section II-A) that highlights data models and design schemes that are used to represent HD mapping data. (1.2) *Map creation* that highlights major directions to build HD maps' content. (1.3) *HD map maintenance and update* that highlights major directions to keep HD maps up to date despite having a significantly higher change rate compared to traditional maps. (2) *HD maps applications* (Section III). This second category has discussed five sub-areas that are branched from autonomous navigation in both outdoor and indoor environments. The five applications' sub-areas

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TABLE I
TAXONOMY OF THE PRESENTED TECHNIQUES

Design and Construction	Map Modeling and Design	[3], [17]–[25]
	Map Creation	[26]–[40]
	Map Maintenance and Update	[10], [11], [41]–[47]
Applications	Localization	[22], [48]–[57]
	Pose Estimation	[22], [23], [58]
	Path Planning	[2], [44], [52], [59]–[62]
	Perception	[6], [54], [63]
	ATVs	[11], [64]

correspond to the last five rows in Table I, and summarized as follows: (2.1) *Localization* applications that use HD maps to position objects with high accuracy in real time. (2.2) *Pose estimation* that uses HD maps to understand a detailed view of the surrounding environment. (2.3) *Path planning* techniques that generate end-to-end high-precision routes to be consumed by machines for routing. (2.4) *Perception* that uses HD maps to improve real-time accuracy of information perceived about the surrounding elements. (2.5) *Automated transfer vehicles (ATVs)* that use HD maps in indoor environments, e.g., smart factories. The rest of this paper discusses each category and its sub-areas.

II. HD MAPS DESIGN AND CONSTRUCTION

HD maps introduce fundamental changes to existing mapping frameworks. So, a significant portion of the current efforts is being made in designing new data models for HD maps and new frameworks to automate collecting high-resolution mapping data from various data sources. This section presents three sub-categories: *HD maps modeling and design* (Section II-A), *HD map creation* and *HD map maintenance and update* (Section II-B).

A. HD Maps Modeling and Design

Lack of standardization in HD maps poses a major challenge [65]. While NDS (Navigation Data Standard) is a prominent format [18], its complexity discourages adoption, leading to vendor-specific layers and hindering reusability [65], [66]. Recent research combats this by proposing unified models through various approaches: extending existing models [21], leveraging existing maps and images [17], [23], and designing new techniques [19], [20]; to enable richer mapping details.

HiDAM [21] is a research-friendly HD map data model extending the node-edge structure to incorporate richer information like lane systems and diverse landmarks (on-road and off-road). Unlike traditional models, each road segment becomes a multi-directional lane bundle representing parallel lanes. HiDAM addresses compatibility with existing applications through its node-edge foundation and explores future applications beyond self-driving cars.

The work of [19] proposes a hardware-efficient Weighted Mode Filter (WMoF) for Full-HD depth maps using VLSI architecture. WMoF leverages different external memory levels to construct the Full-HD Depth Map to include the benefits of each circuit or major leak. This approach enables Full-HD depth map creation at 43 fps with only 5.4 KB of memory.

Inspired by robotics, [17] proposes "semantics maps" for outdoor tasks, incorporating commonsense knowledge with object classification. This HD map variant defines the world as a tuple of entities, poses, and attributes. Each entity will be associated with one pose and can be associated with a subset of attributes [22]. The vectorized elements in the map definition are the same as the vectorized road defined in HD maps. Harsha Vardhan in [3] discusses a globally accepted definition of HD maps in what, how, and why terms. The map in this definition contains only vectorized elements and can achieve high precision (error less than 1 meter). However, satisfying the basic needs cannot ensure the quality of HD maps since more processing techniques, e.g., the accuracy of localization, are considered in the process of evaluation.

HDMI-Loc [23] tackles memory inefficiency in aerial image-based localization. It represents the vector map as a top view 8-bit image, with each bit representing a label for an element class. Localization involves matching this image with an online 8-bit image database using a bitwise particle filter, significantly reducing storage and update costs. This approach can perform localization with a median error of only 0.3m over an 11km drive.

Lanelet2 [20] offers an open source, layered mapping framework designed for diverse applications like localization, motion planning, and highly automated driving. Its three layers are: (1) Physical: stores the usual real observable elements. (2) Relational: connects physical elements to lanes, areas, and traffic rules. (3) Topological: implicitly inferred from spatial relationships in the relational layer.

HDMapGen [24] employs a two-level hierarchical graph for HD map generation. A global graph, where nodes represent lane endpoints or intersections and edges signify lane connections, captures overall map structure. Each lane's curvature details are then modeled by a local graph.

B. HD Maps Construction

This section highlights methods to construct HD maps. HD maps creation and update are among the most challenging tasks in the literature of HD maps. As previously introduced, HD maps provide significant additional content compared to traditional maps to enable machine-to-machine information consumption. Collecting and organizing such new content to create and update HD maps is very costly on a large scale for two reasons. First, creating and updating HD maps requires human input, which is prone to errors and inefficient in terms of time [67]. Second, HD maps are constantly changing at a rapid pace [1]. This introduces the need for automated techniques for HD maps' creation and update. Thus, several research efforts are being made, by both academic and industrial researchers, to enable building HD maps worldwide. Several data sources and different computational techniques are being used to automate or semi-automate this process. We highlight below methods for *map creation* and *map maintenance and update*.

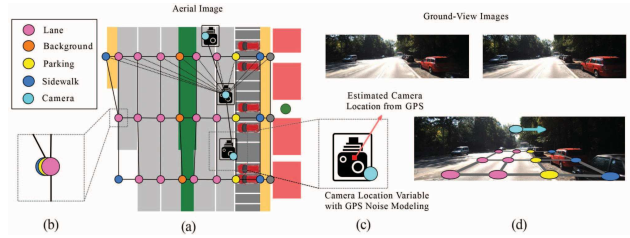

Fig. 1. Image-based lane extraction [27]

(1) Map Creation

Dabeer et al. [29] propose a cost-effective HD map creation pipeline using crowdsourcing with cost-effective sensors. Leveraging the "crowd capacity", their approach collects diverse mapping information. Sensor data help triangulate road signs and lane markings. This information is continuously refined through corrective feedback mechanisms, achieving mean absolute accuracy below 20 cm. This method tackles the high-cost barrier associated with traditional HD map creation.

Kim et al. [31] leverage crowdsourcing to add new feature layers to existing HD maps, addressing latency and cost concerns. Their method enriches the existing map with crowdsourced information without extra cost, resources, or latency, achieving centimeter-level accuracy unlike the few meters' accuracy in traditional maps. Additionally, decoupling the layers allows enriching map content through separate crowdsourcing applications and isolates human error within layers, enabling targeted improvement in later stages.

Chen et al. [26] leverage ground-level LiDAR for large-scale HD map creation in mobile mapping systems. Compared to video-based methods, LiDAR offers: (1) Direct acquisition of 3D coordinates: minimizing errors and improving localization accuracy. (2) Reduced processing: Enabling large-scale support. (3) Lighting and shadow invariance: unlike cameras. (4) Robustness for irregular shapes: handling occlusions and sharp curves. (5) Distance-agnostic object distinction: accurately separating foreground and background. This approach processes large datasets efficiently, as demonstrated by their 3.1-minute processing time.

LiDAR is one of the most popular technologies that are used solely to collect 3D mapping data as part of mobile mapping systems. It is utilized by [32] for automated HD map creation and update, eliminating manual effort. Their approach leverages LiDAR data in a five-step process: (1) Generate a 3D point cloud of the scene. (2) Convert it to a 2D projection. (3) Eliminate ground data from the projection. (4) Extract road boundaries. (5) Apply a probabilistic fusion model to refine map boundaries. This method achieves an average absolute pose error of 1.83m for road scenes ranging from hundreds of meters to 10 kilometers.

Since LiDAR is not a cheap technology, [35] explore using existing LiDAR sensors in vehicles for on-the-go HD map creation, achieving centimeter-level accuracy (around 2 cm). While not a traditional mobile mapping system, it leverages readily available sensors for cost-effective 3D mapping. This approach benefits autonomous vehicles by providing a detailed representation of their surroundings, overcoming limitations in real-time object detection and simplifying perception tasks.

Using specialized equipment is not always affordable or needed, so combining cheaper methods for map creation has got considerable attention in the literature. Hirabayashi et al. [33] propose an accurate method for traffic light extraction from images using camera and 3D information fusion. Their approach achieves 97% average precision through a three-part implementation: (1) Autoware integration, which Implements the traffic light recognition module within the Autoware framework, (2) SSD implementation, for training and recognizing color states, and (3) the Inter-frame filter.

Another method that combines cheap data sources to improve the accuracy and scalability of map creation is [27]. It combines aerial and ground-level images for high-resolution road extraction (0.57m error), showcasing improvement over GPS+IMU (1.67m error on average). Their four-phase technique, depicted in Figure 1, decodes aerial images and leverages ground images to cooperatively create a gridded HD map. This approach shows a great improvement in road center alignment and ground feature localization, with an inference time of 6 seconds per kilometer.

In [30], HD maps are directly used on a pilot emulator project. The pilot model is based on the conventional training experience in the previous work, but in the model the use of HD maps is crucial in providing a more accurate relationship between the pilot and the actual environment. The model achieves an accuracy of 2 cm.

Machine-crowd crowdsourcing is also proposed to create HD maps through crowdsourced probe data from connected vehicles [28], capitalizing on the projected millions of terabytes of vehicle probe data by 2019 [36]. Their scalable infrastructure ingests, manages, and analyzes this data to build layered HD maps. They propose two approaches: one assuming limited probe data (GPS only) and achieving a 2.4m accuracy, and another approach requiring additional sensor data that can be retrieved from a series of vehicle sensors yielding a 1.9m accuracy.

Maeda et al. [37] also propose a cost-effective method for HD map generation using readily available camera data and a lane detection algorithm to localize the driving car on the road. Detected lane information is then integrated with the lines' information on the HD map without requiring expensive sensors. By piggybacking lane extraction overhead on the localization process, they achieve map updates with minimal overhead compared to dedicated HD map construction methods.

Smartphone-based HD map creation is explored in [34]. They leverage a Kalman filter to refine sensor data and employ a deep neural network combined with color and gradient information for lane detection. The approach achieves better than a 3 meter accuracy.

Companies in the industry field create their own HD maps for autonomous driving. Waymo [68] let their team members manually drive a car equipped with LiDAR sensors in a new location to capture the necessary data. TomTom [69] employs AI and machine learning techniques to create and update their HD maps. HERE Technologies also uses AI to create maps from the data collected via DGPS, IMU, and LiDAR.

Zhou et al. [38] proposes an automatic technique to construct lane-level HD maps for urban scenes. The map is first represented as a directed cyclic graph from OpenStreetMap, which is an online mapping database. Semantic segmentation is then performed on 2D images from ego vehicles to explore the lane semantics on a birds-eye-view domain.

HDMapNet [25] offers an on-the-fly HD map construction framework using onboard sensors. Processing camera and LiDAR point clouds, it effectively predicts map elements. HDMapNet is bench-marked on the nuScenes dataset and improves semantic segmentation significantly.

Wei et al. [39] present a framework for HD map creation combining aerial imagery, vehicle telemetry, and navigation maps. They leverage pre-processed aerial images, informed by aggregated vehicle telemetry, to classify roads and predict lane configurations using a convolutional neural network (CNN). This approach integrates diverse data sources for efficient HD map generation.

(2) Map Maintenance and Update

HD maps demand much more updates due to their vast amount of information compared to traditional maps. This poses a challenge: balancing update frequency to maintain accuracy with cost-effectiveness. Some methods that are proposed in the literature to handle map updates are actually used in building maps in the first place before putting the update mode into action. This can be accomplished by combining the update methods with traditional maps as a preliminary map version, or a lower-cost HD map that did not capture all the details. Regardless of the method, update methods are vital for both building and maintaining accurate HD maps.

SLAMCU leverages a dynamic Bayesian network (DBN) to detect and update HD map changes efficiently. DBN acts as an inference graph with known nodes as inputs (actions/physical changes), estimated nodes, and unknown nodes. Known inputs come from a measurement model solving a localization problem. The DBN transfers nodes from unknown to estimated through inference with edge constraints, utilizing known inputs. Detected and updated map changes are reported to the HD map database for sharing with other vehicles/systems. Evaluation on real-world HD map data of traffic signs (20km highway) showed an average position error of 0.8m with 0.9m standard deviation and 96.12% accuracy for estimated map changes, Figure 2 shows a histogram of position error to estimate the rough distribution, approximated by the red curve.

Pannen et al. [42], [44] propose a dynamic HD map update system utilizing data from a "machine-crowd" of connected autonomous vehicles. The proposed technique makes reliable prior information on lane markings and road edges available to automated driving functions. It operates in real-time, estimating the probability of change based on floating cards

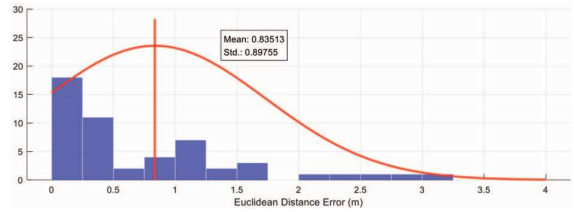

Fig. 2. SLAMCU mapping error for the position estimation of new map features [41]

data (FCD) and updating the map when required. It functions through three key pipelines: change detection, job creation, and map updating. Scalability is achieved by partitioning the workload and aggregating results from smaller areas. A novel map learning component leverages both FCD data and real-time trajectory statistics to learn new map updates incrementally. Robust localization is ensured through two-particle filters, followed by metric calculations and classifier application with boosted performance. Evaluated on 300 traversals across seven construction sites, the system showcases its effectiveness. Notably, multi-traversal classification achieves significantly higher performance (98.7% sensitivity, 81.2% specificity) compared to single-traversal methods.

Tas et al. [10], [11] propose an HD-map update methodology for Autonomous Transfer Vehicles (ATVs) in smart factories. The methodology uses visual simultaneous localization and mapping (SLAM) with object detection and localization. Their key contribution is detecting new or missing safety signs by comparing the valid HD-map data with a virtual HD map constructed from visual sensors. An improved grid map incorporating visual SLAM and object detection is used to position detected objects which are then batched as map updates.

Liu et al. [43] propose an incremental HD map update technique that combines historical data with updated sensor measurements using a Kalman filter-based fusion algorithm. This improves map element position and semantic confidence. It also quickly adapts to slight environmental changes by including a time decay term. Unmatched elements are fed back with historical information for future matching attempts.

Kim et al. [45] offer a low-cost HD map update method using crowdsourced data from inexpensive sensors. To address the data's inherent uncertainty and low accuracy, they propose a lane learner algorithm leveraging the geometric features of all crowdsourced lane information.

Diff-Net [46] is an end-to-end deep learning approach that leverages a neural network (DNN) to detect HD map changes in a single step. Projecting map elements into rasterized images allows the DNN to compare features extracted from camera data and the images, revealing map changes directly.

Qi et al. [47] propose a distributed crowd-sensing approach for HD map updates. Leveraging sensors in autonomous vehicles and roadside units (RSUs), MEC servers within each RSU pre-process data by matching it against the onboard HD map and extract changes. This data is then transmitted and aggregated in a central node.

Wang et al. [40] propose a tightly-coupled framework using multiple non-repetitive LiDARs for HD map construction. Their synchronization strategy merges extracted features from diverse LiDAR sensors, including Livox, mechanical, and MEMS LiDARs.

III. HD Maps Applications

While high-resolution maps have found success in controlled indoor environments e.g., for robots in smart factories and workshops [10], [11], their application to outdoor autonomous navigation for self-driving vehicles [12], [13], [70], [71] presents fundamentally different challenges. The larger scale and less controlled nature of outdoor settings challenge key assumptions made about indoor environments, leading to new and exciting research avenues. Despite the potential of several HD map techniques to be used in a wider variety of applications (as discussed in Section IV), the existing literature primarily focuses on outdoor autonomous navigation. This complex task encompasses several sub-applications, each requiring specialized approaches. This section highlights research methods proposed for four key categories: *localization, pose estimation, path planning,* and *perception*, in addition to methods specific to *automated transfer vehicles (ATVs)*. The rest of this section highlights each of these categories.

(1) Localization. Localization is the most popular application that uses HD-maps in autonomous driving. Localization is used to position vehicles as well as road objects (e.g., signs, obstacles). A road segment in an HD map is detailed into multiple components including lane marking, centerline, pedestrian crossing, signs, and obstacles. Thus, accurately localizing objects within these close components (centimeter-level) is a challenging task that is fundamental to facilitate real-time autonomous driving decision making.

For lane-level localization in autonomous vehicles, Ghallabi et al. [50] propose a method utilizing a multi-layer LiDAR sensor. Their approach relies on road lane markings and an HD map. It achieves lane-level accuracy by segmenting road points from the LiDAR point cloud, extracting markings using the intensity of LiDAR data, and finally, matching them against the map for localization. The segmentation process leverages ring geometry analysis to eliminate non-road elements that are not smooth and discontinuous like vegetation and gravel. This is followed by a Hough line transform using an apriori information on the environment to detect lane markings. Finally, a map-matching algorithm has been implemented to validate the detection phase. While promising results have been achieved on highway-like test tracks, the absence of reliable landmarks in highways raises concerns about the method ability to maintain acceptable accuracy in actual highways.

Juang [72] leverages pre-mapped on-road landmarks for localization using triangulation with known landmark locations. It proposes a landmark detection method using LiDAR scans for detection based on size, shape, reflectivity, and height. Building on this, [53] incorporates High Reflective Landmarks (HRLs) as 3D map elements and proposes an HRL detection and map-matching approach using LiDAR data and a particle filter for localization based on the unique reflectivity of HRLs.

Geometry influence of sign detection on localization is discussed in [49]. It proposes a high-precision localization system using HD maps. Geometric strength is assessed under various scenarios considering feature distribution, quantity, and vehicle-feature distance. Results show primary influence from feature number and distance; random distribution, abundant features, and close proximity yield better estimation for the vehicle position.

Lane-based localization using a particle filter and road surface is explored by Bauer et al. [48]. They divide the road into 3D surfaces based on lane markings and evaluate each particle state against the HD map, localizing it on a specific surface. When a particle leaves a surface area, it is re-localized on a new surface (lane) on the other side of the targeted accessor for speedup, and to ensure it remains on lane surfaces throughout the process.

Han et al. [51] present a map matching technology for robust vehicle localization. They propose a novel line segmentation matching model and geometric correction for extracted road markings from inverse perspective mapping (IPM). Tested on real autonomous vehicles, the technique successfully acquired the autonomous driving license of the Republic of Korea.

HD map-based localization using low-cost advanced driver assistance system (ADAS) sensors for automated vehicles is proposed in [54]. This approach leverages LiDAR, RADAR, vision, and GPS alongside existing vehicle sensors that provide information on speed, acceleration, steering angle, etc. The algorithm incorporates environmental feature representation with low-cost sensor data, digital map analysis, location correction based on map-matching , verification gates, and extended Kalman filter positioning and fusion for robust localization.

MLVHM [22] proposes segmenting HD maps properties into small monocular segments for low-cost vehicle localization using camera images. It utilizes an image processing module to extract visual and geometric features, and a map module to leverage key points features, enabling initial pose prediction. The initial pose associates frame motion information with objects to output object locations. Pose estimation techniques are highlighted later in the section.

Hery et al. [55] propose a decentralized cooperative localization method using local dynamic maps (LDMs) exchanged between vehicles. Their framework addresses the unknown degree of LDM error correlations using 2D LiDAR for pose estimation. To reduce errors, they introduce a bias estimator that leverages geo-referenced features from HD maps when a Global Navigation Satellite System (GNSS) is used.

The work of [56] achieves localization by combining HD maps with image semantics in two stages: initialization and tracking. In the first stage, a car equipped with a GPS is used to provide coarse initialization combined with fine pose searching. The second stage refines the vehicle's pose by aligning the semantic segmentation result between the image and landmarks in HD maps.

Usorac et al. [57] create an object localization HD map layer by fusing traffic data from cameras, GPS, and a central Automotive Video Logger system. Objects are detected using YOLOv4 object detection algorithm.

(2) Pose estimation. While pose estimation is primarily employed for localization assistance as in MLVHM [22], some research explores pose estimation as a distinct task. Unlike localization's focus on precise object positioning, pose estimation offers broader scene understanding, spanning beyond the immediate vicinity (typically a few meters). For instance, HDMI-Loc [23] achieves a full six degrees of freedom (6-DoF) global pose estimation leveraging semantic road data from HD maps and query stereo images. A particle filter initially estimates the vehicle's 4-DoF partial pose (translation and heading) through patch image matching. Subsequently, roll and pitch are calculated, yielding a complete 6-DoF pose relative to the HD map.

Stannartz et al. [58] leverage semantic information to resolve data association ambiguities between measurements and HD map landmarks. Their method, tested in controlled CARLA simulations, demonstrates accurate pose estimation.

(3) Path planning. Beyond localization and pose estimation, path planning applications generate complete navigation paths using HD maps. These applications provide detailed routing instructions for machines like self-driving cars, analogous to navigation apps like Google Maps and Apple Maps. Li et al. [60] propose a low-cost vector map-based approach for navigation. Recording the vector map offline enables optimal route planning for any starting and ending point. However, conventional HD maps face storage challenges. For instance, Pannen et al. [44] require 200 GB for 20,000 miles of roads (10 MB/mile). To address this, Li et al. use high-precision DGPS to extract latitude and longitude, mark key data (lanes, links, speed limits, signs) and remove large-scale laser point cloud data. This reduces storage size to 300 KB for 3 miles (100 KB/mile), a two-order-of-magnitude improvement while maintaining navigation accuracy.

Jian et al. [52] propose a two-step path planning approach utilizing semantic road information from HD maps. The first step, path set generation, reflects vehicle kinematics onto the lane coordinate system and leverages this, along with HD map lane details, to generate optimized path sets. The subsequent path selection step employs their inertia-like path selection algorithm to identify a stable path for obstacle avoidance.

Chu et al. [61] propose a Predictive Cruise Control (PCC) system using HD maps for fuel-efficient driving. They formulate the PCC problem as a nonlinear model predictive control (MPC) and propose a fast solver. They construct a novel shift-map to define different working regions from the application's perspective, and integrate real-time HD map information into the system. This approach achieved an 8.73% fuel saving compared to a factory-installed adaptive cruise control system over a 370 km route.

A bidirectional hybrid path search (BHPS) technique is proposed in [62]. Leveraging lane-level HD maps to extract global driving environment info, BHPS runs a bidirectional hybrid path search combining forward BFS search-reverse Dijkstra search and forward Dijkstra search-reverse BFS search.

HD path planning dives deep into the intricacies of navigation, offering lane-level directions, and not only a bird's-eye or road segment view of the route. This requires combining road-segment-level routing with lane-level techniques like lane-level localization and map matching. One promising approach is *Simultaneous Localization and Mapping* (SLAM) used in [2]. By reconciling real-time sensor data with cloud-based HD maps, SLAM creates a virtual picture of the car's surroundings, enabling precise localization and relation to other road users. Alternatively, lane-level map matching with a particle filter, as in [59], offers an efficient method. This involves pre-loading the entire map (feasible due to its limited size), populating the initial filter sample set and matching it to the road network, and then running a real-time execution loop.

(4) Perception. Beyond their crucial role in prediction (e.g., localization) and planning (e.g., path generation), HD maps are increasingly explored for enhancing perception in autonomous driving. Perception is responsible for understanding the surroundings, while the rest of the autonomous driving pipeline (i.e., prediction, planning and control) use this understanding to produce driving decisions in real time. For instance, HDNET [6] uses HD map information to improve perception by improving 3D object detection on roads. It integrates geometric and semantic map priors into LiDAR representations. When no HD map is available, a map prediction module that estimates two map priors online using one LiDAR scan is used. HDNET consistently outperformed competitors, confirming the significant value for HD maps in perception [6], [54].

Masi et al. [63] presents a cooperative perception system for autonomous vehicles navigating in a complex scenario. The proposed system is an HD map-aided system that merges information from roadside cameras with a LiDAR-sensor equipped vehicle. Two experimental vehicles are used along a roadside camera and the experimental results show an improvement in the estimation accuracy of perceived objects' state.

(5) Automated transfer vehicles (ATVs). ATVs are a modern application for HD maps in indoor settings like smart factories. Tas et al. [11] propose an ATV-based method for updating indoor factory HD maps using visual SLAM with object detection and positioning (highlighted in Section II-B). This method effectively identifies new or missing safety and direction signs by leveraging existing HD map information and sensor data. In erroneous scenarios, accurate and robust ATVs are crucial for real-time corrective decisions [64], which highly depends on the accuracy of indoor HD maps. However, due to the unique challenges of indoor navigation and its extensive coverage in robotics literature, as highlighted at the beginning of this section, a detailed discussion of indoor HD maps is beyond the scope of this paper.

IV. Conclusion and Discussion

This paper has presented a bird's eye view on modern high-definition (HD) map literature, motivated by the shift of autonomous driving to machine-based map consumers in outdoor environments. This fundamentally differs from indoor HD maps studied in robotics applications like smart factories and healthcare facilities. These differences drive extensive research on outdoor HD map construction and usage in outdoor environments. Due to the vast literature, this paper provides only a lengthy glimpse into key research categories, offering valuable pointers for deeper exploration of specific sub-areas by interested readers.

The paper categorized the HD map literature into two main areas: (1) HD map design and construction and (2) applications. The first includes: (1.1) HD map modeling and design, (1.2) map creation techniques, and (1.3) maintenance/update methods, addressing the higher change rate of HD maps compared to traditional ones. The second covers five sub-areas related to autonomous navigation in both outdoor and indoor environments: (2.1) *Localization*: High-accuracy object positioning using HD maps in real time. (2.2) *Pose estimation*: Detailed understanding of the environment through HD maps. (2.3) *Path planning*: Generating precise machine-usable routes. (2.4) *Perception*: Enhancing real-time perception accuracy of the surroundings. (2.5) *Automated Transfer Vehicles (ATVs)*: HD map usage in indoor environments e.g., smart factories.

While primarily aimed at self-driving cars, HD maps offer potential for diverse applications beyond the automotive domain. Their granular detail opens doors for breakthroughs in different fields as shown by on-going research projects using Google geo images for tree disease detection, building tree atlas in certain areas, and studying urban development and human migrations through analyzing data from different time snapshots. Through the on-going efforts on HD map techniques, researchers will gain access to a relatively cheap and high-resolution data source. However, due to the challenge of the enormous map data size, improvements are needed for efficient data management [73] and format compactness and efficiency [18]. In addition, HD mapping gaps pose challenges for the growing machine learning literature in computer vision, spatial data analysis, and GeoAI.

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