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Review

High-Definition Map Representation Techniques for Automated Vehicles

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Abstract: Many studies in the field of robot navigation have focused on environment representation and localization. The goal of map representation is to summarize spatial information in topological and geometrical abstracts. By providing strong priors, maps improve the performance and reliability of automated robots. Due to the transition to fully automated driving in recent years, there has been a constant effort to design methods and technologies to improve the precision of road participants and the environment's information. Among these efforts is the High Definition (HD) Map concept. Making HD maps requires accuracy, completeness, verifiability, and extensibility. Because of the complexity of HD mapping, it is currently expensive and difficult to implement, particularly in an urban environment. In an urban traffic system, the road model is at least a map with sets of roads, lanes, and lane markers. While more research is being dedicated to mapping and localization, a comprehensive review of the various types of map representation is still required. This paper presents a brief overview of map representation, followed by a detailed literature review of HD Map for automated vehicles. The current state of AV mapping is encouraging, the field has matured to a point where detailed maps of complex environments are built in real-time and have been proved useful. Many existing techniques are robust to noise and can cope with a large range of environments. Nevertheless, there are still open problems for future research. AV mapping will continue to be a highly active research area essential to the goal of achieving full autonomy.

Keywords: Connected & Automated Vehicles, Navigation, High Definition (HD Map), Map Representation

1. Introduction

The problem of mobile robot navigation has traditionally been approached by breaking it down into three parts: environment mapping, localization, and trajectory planning. For Autonomous Vehicles (AVs), accurate and reliable self-localization is critical [1]. In order to operate safely, AVs must precisely predict the future actions and/or trajectories of other road participants [2–4]. For instance, the ability to accurately predict pedestrian behavior is crucial to ensure safe autonomous driving solutions. However, this task is challenging due to the fact that in general, pedestrian's trajectories can change rapidly and they lack temporal smoothness [5]. Accessing to the environment information in the form of a pre-built map can help with such challenging tasks. Furthermore, when combined with a pre-built map, a high-precision self-localization solution can transform the difficult problem of perception and scene interpretation into a less complex positioning problem [6,7]. The criteria for achieving accurate self-localization on the map have been discussed in [8].

The AVs intend to offer a safe and comfortable ride using the output of sensory units, a map, and a high-level route [9–11]. Meanwhile, in safety-critical applications such as self-driving cars, creating interpretable intermediate representations that explain why the car performed a given maneuver is critical for decision-making [12,13]. The autonomy problem can be partially handled in advance in an offline fashion, if the map is updated regularly and reliably [14]. Also, map data can be shared and updated by multiple AVs, allowing for real-time map updates and improving confidence in the accuracy of the map.

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The higher levels of autonomy requires the maps to be more refined in details with quality standards. In this context, the solution for high-precision localization is to provide a unified representation that combines the agent dynamics, collected by perception and tracking systems, with the scene context, commonly provided as prior knowledge in the form of High Definition (HD) maps [15–18].

Differently from the unified representation, other solutions uses an end-to-end approach that creates an internal learned map representation of the world [19–25]. End-to-end approaches that learn such internal mapping could be beneficial to scale self-driving solutions that can generalize and find optimal map representations for the driving task [26,27]. Towards this goal, the work in [28] is one of the earliest end-to-end systems and pioneered this field by using a neural network to directly control the AV. Current end-to-end solutions use simultaneous perception and prediction to provide outputs such as object tracking and predicted trajectories, or learning an intermediate semantic mapping that is used to control the AV, enabling end-to-end learning of the full autonomy system [23,26]. These approaches focus on imitating human drivers and learning a hidden representation, but are not interpretable.

End-to-end learnable neural network can perform joint perception, prediction, and motion planning for AVs while producing interpretable intermediate representations. The interpretable representations are used by the planner and help to explain the AV decisions [19,21]. In [19], authors present an end-to-end approach for predicting intermediate representations in the form of an online map as well as agents' dynamics and their current and future states. The solution produces probabilistic intermediate representations that are interpretable and ready to use for the motion planner. Although directly outputting driving commands is a general solution, it may have stability and robustness issues, and a combination of HD map and internal latent representations (features map) can be advantageous [20] and can be also learned end-to-end from human demonstrations [21]. This is accomplished through the use of a novel differentiable semantic occupancy representation, which is explicitly used as a cost in the motion planning process.

It is also common to rasterize HD maps into a top-down view or Bird's-Eye-View (BEV) map, which can be referred to as a 3D top-view map that respects the nature of the data, making the learning process easier as it can leverage priors about objects' geometry [21,22,29–33]. Because height localization information is less valuable for AVs, the relevant information that an AV requires for decision-making could be suitably encoded using a BEV map representation. Using BEW as an output of the perception module will result in interpretable and easy-to-use representation for prediction and motion planning modules [22,30,33].

Despite significant progress in this area, it still presents significant challenges due to the nature of sensor noise and practical constraints during map creation. Existing mapping algorithms are commonly surprisingly complex, both from a mathematical and from an implementation point of view. As a result, novel map representations are required for the full adoption of AV. This review provides a general review of the most common map representation approaches, with a focus on AV mapping. It describes and compares various approaches and their applications, in contrast to the current literature that frequently focuses on HD maps.

2. Real-Time (Online) Mapping

Robotics applications frequently necessitate real-time processing. This means that the input data must be processed at a rate that is faster than or equal to the input data's rate. Real-Time mappings allow the robot to map out unknown environments and perform localization in that map at the same time. However, as the action of driving gradually transfers from humans to machines, the role and scope of maps extends beyond navigation. As a result, offline map-based approaches have received more attention in most AV applications during the last decade. The computational problem of constructing or updating a map of

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an unknown environment while simultaneously tracking an agent's location within it is known as simultaneous localization and mapping (SLAM).

2.1. Simultaneous Localization And Mapping (SLAM)

In many applications, such as indoor robot navigation, offline maps are not available [34,35]. The agent can utilize SLAM to construct a map on the fly from raw sensory data (Mapping) while also using that constructed map to maintain track of its location (localization) [36–42]. SLAM techniques perform well over short distances, but they suffer from accumulative inaccuracy over longer distances due to their dependent nature, meanwhile, loop closure modules in SLAM systems (and pose graph optimization) will compensate for the errors and correct the accumulated drift. The map representations employed in SLAM techniques can vary widely, but the most major distinction is whether they are 2D or 3D orientated, or a combination of both. It's reasonable to suppose that when the SLAM is paired with a combination of sensors (GPS, IMU, LIDAR, and radar), it will perform better. Figure 1 shows a result of SLAM using Cartographer package [43]. ORB-SLAM is among the most

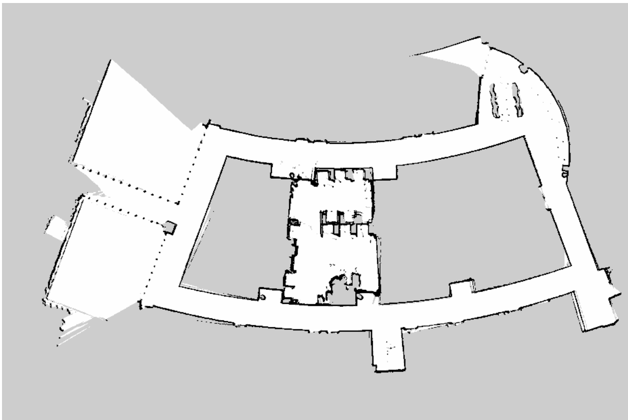

Figure 1. Map of ECE department at University of Central Florida using Cartographer package [43] and hokuyo 2D LiDAR.

well-known mapping and localization system that it operates in real-time while keeping localization and tracking accuracy at a desirable level [44–47]. In [48], authors showed that a multilayer perceptron (MLP) can be used as the only scene representation in a real-time SLAM system using a hand-held RGB-D camera. For SLAM algorithms implemantation refer to [49].

3. Highly/Moderately Simplified Map Representations

This category of maps is mainly utilized in the robotics domain and can be classified into three sub-categories: topological maps, metric maps, and Geometric Maps.

3.1. Topological Maps

The topological maps are mainly graph-based representations, exclusively deal with places and their interactions [50–52], describes the environment as a collection of nodes (locations) connected by edges [53]. An edge between two nodes is labeled with a probability distribution over the relative locations of the two poses, conditioned to their mutual measurements [54]. A world representation based on this simplification makes map extension easier and provide the required information for path planning and motion prediction [55–59]. Despite the world model's reduction, topological representations lose the sense of proximity, lack explicit information regarding the space's occupancy. Many authors have approached this problem by storing additional data or combining it with metric maps [53,60].

3.2. Metric Maps

Contrary to topological maps, in metric maps, the objects are represented with precise coordinates. Such maps contain all the required information for a mapping or navigation algorithm to function [61]. In these methods, the map size is directly proportionate to the region of interest's area. Therefore, mapping of vast areas, especially in 3D representation, is computationally expensive. *Landmark-based maps*, *occupancy grid maps*, and *geometric maps* are the most popular metric mapping methods.

3.2.1. Landmark-based Maps

Landmark-based representations, also known as feature-based representations, are used to identify and maintain the postures of specific distinguishing Landmarks [62]. The landmarks must be unique and identifiable by the robot perception system, which is a prerequisite in these representations. Landmarks can be defined as sophisticated descriptors, rather than raw sensor data. Points, lines, and corners can be used to create a minimalist description of the landscape.

3.2.2. Occupancy Grid Maps

Occupancy grid maps [63] divide the environment into so-called grid cells. Each cell contains data about the area it covers [64]. Figure 2 shows an example of a simple grid map. It's typical to save a single value in each cell that represents the likelihood of being an obstacle there. Traditional probability-based techniques, such as particle or Kalman filters, are most typically used to combine input from several sensors and localizing to a known prior map [65–68].

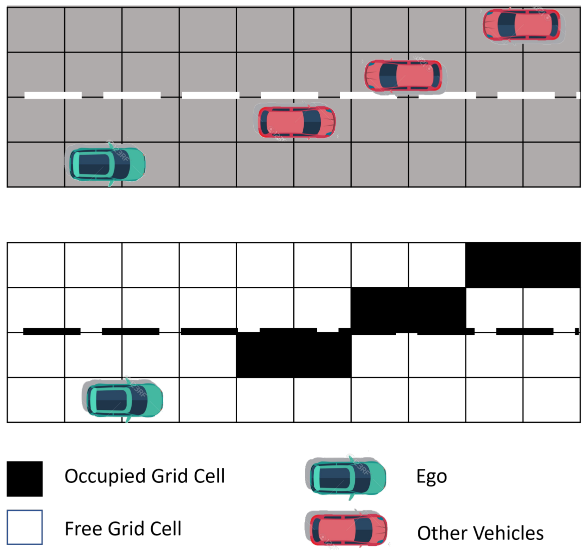

Figure 2. Top: Real-world objects in the map. Down: Grid Map representation with grid cells occupied by the real-world objects.

Occupancy grid maps can be either 2D or 3D [69]. A version known as 2.5D contains height information in an extended 2D grid cell map rather than being a pure 3D grid map [70]. Regular grids or sparse grids can be used to create grid maps. Regular grids discretize continuous space into cells with the same dimensions for the entire region, whereas sparse grids extend the concept of the regular grid by grouping regions with the same values in a tree-like fashion. This map can be used to predict multi-pedestrian movements [71] as well as obstacle crossing. In general, the occupancy grid maps can be categorized as follows:

- **Octree**: The Octree Encoding [72] is a 3D hierarchical octal tree structure capable of representing objects with any morphology at any resolution. Because the memory required for representation and manipulation is on the order of the area of the object,

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it is commonly employed in systems that require 3D data storage due to its great efficiency [73–81].

- **Costmap**: The costmap represents the difficulty of traversing different areas of the map. The cost is calculated by integrating the static map, local obstacle information, and the inflation layer, and it takes the shape of an occupancy grid with abstract values that do not represent any measurement of the environment. It's mostly utilized in path planning [82,83].

3.3. Geometric Maps

The geometric maps attempt to represent the sensory data with discrete simplified geometric shapes such as circles or polygons [84]. The geometric maps represent the surroundings efficiently without sacrificing too much information, however, it impedes trajectory calculation and data management in general. As a result, this method is rarely used in practice, and the occupancy grid map alternative is preferred [85,86].

4. High Accuracy Map Representations

Currently, academics and manufacturers are working to develop Advanced Driver Assistance Systems (ADAS) to attain high level autonomy in vehicles. Maps can be used for a variety of purposes, including lowering computation cost by providing the offline maps as a prior, implementing safety measures, avoiding sensor range constraints, and sharing maps data among different AVs, all of which can improve ADAS accuracy and reliability. According to [87,88], High Accuracy map representations can be loosely categorized based on their level of information into one of three categories: *Digital Maps*, *Enhanced Digital Maps*, and *HD Maps*. Traditional street maps, such as Google Map, are digital maps. Road geometry, signage, lane design, and speed limits are all included in enhanced digital maps. Finally, HD maps incorporate all of the features found in the preceding categories, as well as a semantically segmented 3D representation of the agent's surrounding.

If the map is kept accurate and used intelligently, with an understanding of its own limitations, a HD map can be thought of as an extra sensor that is unaffected by environmental occlusions with a nearly perfect detection system.

4.1. Digital Maps

A conventional digital map is a traditional electronic street map and is given by a variety of map providers, such as Google Map. These are topometric (topological and metric) maps that encode street layout, names, and distances. It's worth noting that an automated car can still benefit from these prior maps, but they're unlikely to be a crucial facilitator of fully autonomous operation on their own (as opposed to HD maps). Even with an up-to-date digital map, the lack of positionally accurate and identifiable environment data (such as the location of a stop sign) limits the extent to which it can assist an automated vehicle. However, such level of information is still sufficient for high-level navigation tasks, such as finding the shortest path from point A to point B.

4.2. Enhanced Digital Maps

An enhanced digital map is a conventional digital map that has had certain augmented data, making it useful for both ADAS and AVs. Road speed restrictions, road curvature, lane structure, and road signage have all been added to a basic digital map. The list below goes through each of these additions based on TomTom's ADAS map [89].

- Road Curvature
- Gradient (slope) of the roads
- Curvature (sharpness) at junctions
- Lane markings at junctions
- Traffic signs
- Speed restrictions (necessary for adaptive cruise control)

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Due to the lack of a clear distinction between an enhanced digital map and a HD map, researchers classify any map that stores a 3D world representation as an HD map, while the rest are classified as enhanced digital maps.

4.3. High Definition (HD) Maps

A High Definition (HD) map is a 3D representation of the world that supplements an enhanced digital map [90,91]. A combination of sensors, including LiDAR, radar, and cameras, can be used to create this representation. High positional accuracy, on the order of $10cm$, is a common feature of all HD maps [92]. Although technology constraints limit the highest possible accuracy of map features, higher precision is always desirable.

A HD map can be as simple as a collection of accurate positioning of road signs, lane markings, and guardrails in the surroundings, or be as complex as a dense semantically segmented LiDAR point clouds that stores the distance to every obstacle around the agent as shown in Figure 3. For more information refer to [93].

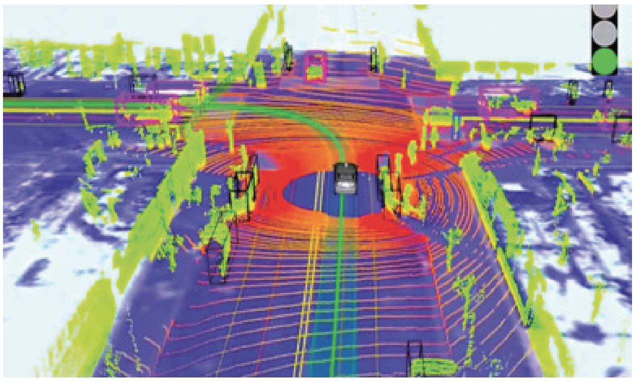
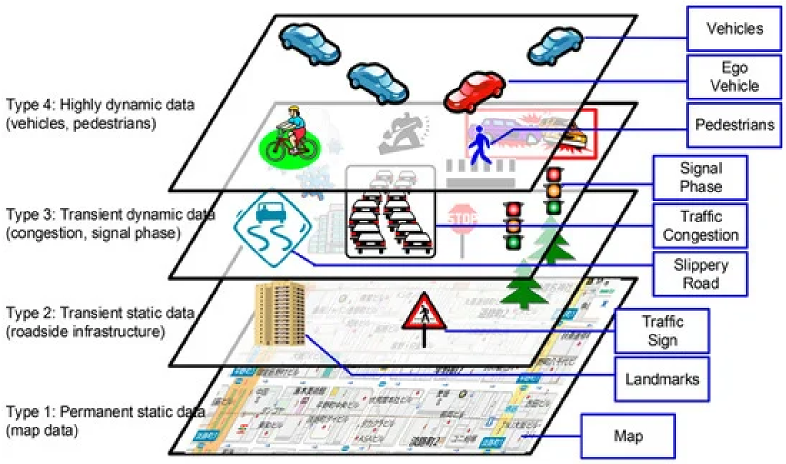


Figure 3. The complexity of data collected by a Velodyne LiDAR is demonstrated by a point cloud image of a vehicle approaching an intersection [94].

A high-definition map is usually divided into numerous layers, each of which contains different sorts of data. Figure 4 illustrates a HD map along with its layer, originally published in [95]. Also, Figure 5 illustrates the layers of HD map defined by HERE [96].



Dynamic Map.png

Figure 4. The features and layers of HD map [95]

In Lyft's HD map, the five core layers are described as follows[97,98]:

- **Base map layer**: The entire HD map is layered on-top of a standard street map.
- **Geometric map layer**: The geometric layer in Lyft's maps contains a 3D representation of the surrounding road network. This 3D representation is provided by a voxel map with voxels of $5cm \times 5cm \times 5cm$ and was built using sensory data of LiDAR and cameras. Voxels are a cheaper alternative to point clouds in terms of required storage.

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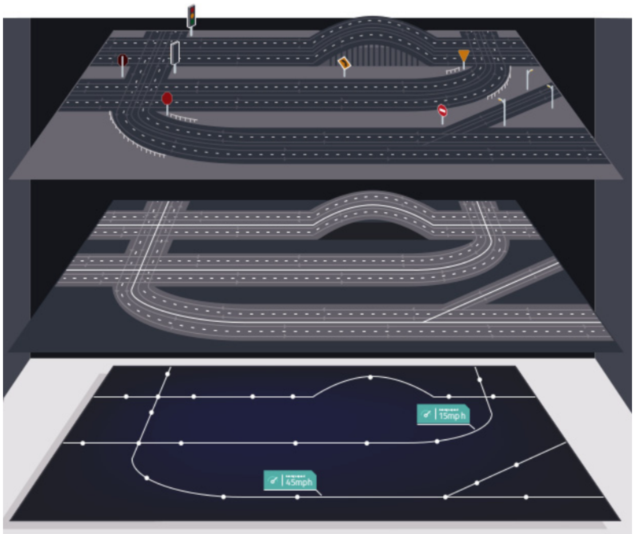

Figure 5. HD map structure defined by HERE: **HD road (Down)** consists of topology, the direction of travel, intersections, slope, ramps, rules, boundaries, and tunnels. **HD lanes (Middle)** consist of lane level features, such as boundaries, types, lines, and widths. **HD localization (Top)** consists of road furniture, such as traffic lights and traffic signs [96].

- **Semantic map layer**: The semantic map layer contains all semantic data, such as lane marker placements, travel directions, and traffic sign locations [21,99,100]. Within the semantic layer, there are three major sub-layers:
  - Road graph layer
  - Lane geometry layer
  - Semantic features include all objects relevant to the driving task, such as traffic lights, pedestrian crossings, and road signs.
- **Map priors layer**: This layer adds to the semantic layer by integrating data that has been learned via experience (crowd sourced data). For example, the average time it takes for a traffic light to turn green or the likelihood of coming across parked vehicles on the side of a narrow route, allows the AV to raise its "caution" while driving.
- **Real-time knowledge layer**: *Which is the only layer designed to be updated in real-time*, to reflect changing conditions like traffic congestion, accidents and road work.

Based on a combination of the open-source Apollo software [101] and DeepMap's U.S. patent [102], another core layers description of the HD map is offered below.

- **Lane positions and widths**: Position of lane markings in 2D along with the type of lane (solid line, dashed line, etc). Lane markings may also indicate intersections, road edges, and off-ramps.
- **Road Sign Positions**: 3D position of road signage includes stop signs, traffic lights, give way signs, one-way road signs, traffic signs. This task is especially challenging when signage conventions and road rules varies by country.
- **Special road features**: Such as pedestrian crossings, school zones, speed bumps,bicycle lanes and bus lanes.
- **Occupancy map**: A spatial 3D representation of the road and all physical objects around the road. This representation can be stored as mesh geometry, point cloud or voxels. The 3D model is essential to centimeter-level accuracy in the AV's location on the map.

5. Localization in HD Maps

Road DNA, proposed by TomTom [103], is one of possible solutions for localization problem in HD maps. In this method, the detailed 3D representation of the road environment with all features and depth information is compressed into a collection of 2D raster images, where

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the image intensity corresponds to the depth of certain area of the environment. A 2D depth image was also created utilizing the agent's sensor data. The Road DNA solution allows for precise localization with substantially fewer data storage requirements, compared to using dense LiDAR point clouds. For accurate localization, pattern matching algorithms were applied. Since significant structural changes occur less frequently in a road environment than appearance changes, depth photos can be more resistant to environmental changes than raw camera images.

In [104], a robust ego-motion estimation technique using sensors and a map matching technique with HD maps was presented. The authors proposed a new line segmentation matching model and a geometric correction approach of road making obtained by inverse perspective mapping (IPM) methodology for the map matching technique with HD map. Combining these two technologies increases robustness and accuracy, according to the author's experiments.

Authors in [18] compare sensory scans to an HD map using a particle filter. Their study integrates data from an IMU and a GPS receiver to determine location. The Root Mean Squared Error (RMSE) of localization accuracy was 2.8m without an HD map prior, 1.5m with an HD map and odometry (IMU), and 1.2m with an HD map, odometry, and GPS. While the obtained accuracy is not as good as commercial methods, the results confirm the significant effect of having prior HD maps on AV's localization.

For LiDAR-enabled self-driving cars, the Iterative Closest Point (ICP) algorithm is commonly used to match a 3D LiDAR point cloud to a previously collected set of points in the map. The ICP algorithm is a least-squares optimizer that tries to determine the best rotation, scale, and translation to transform a set of incoming LiDAR points into a database set of points iteratively [105]. The strategies for aligning LiDAR points using ICP are discussed in [106]. They also utilize a Kalman Filter to fuse sensor data.

Finally, RTK (Real-Time Kinematic) GPS can be used to obtain highly accurate localization. However, because RTK GPS relies on a network of ground stations to function properly, extra infrastructure will be required to have AVs locate themselves accurately using this technique. In densely built urban environments, GPS is also vulnerable to dropouts, interference, and multipath reflection, which, although acceptable for long-range navigation planning, is insufficient for second by second local positioning-based control of AVs.

6. Limitations and Challenges

The broad range of traffic laws between countries, such as restrictions for turning left and right, is one of the challenges in generating HD maps [107,108]. The required data storage for HD maps caused another challenge. Google's Waymo AV, for example, collects about 1GB of data every 20 seconds [109]. Since each AV has limited storage space, the vehicle must perform a dynamic map download and cache refresh routine as it travels across the surroundings. DeepMaps' map tiling technique [102] separates the whole HD map into map tiles and downloads the necessary map tiles based on the vehicle position to decrease the memory requirement. The third issue is exact vehicle localization inside the HD map, which is accomplished by comparing incoming sensor data with the current map and updating the map. Processing of incoming sensory data required onboard high performing processing resources and real-time execution of the commands need latency time of less than 10 ms [110].

The HD map update and maintenance is also a major challenge [107,111]. There are millions of kilometers of roads in the world, and many HD map modeling algorithms are proposed for highway scenarios and neglect input anomaly (such as bad lane marking paint, flatten curb, tree occlusion), and uncertainties of non-road objects (such as construction zones, nearby vehicles, trees). However, in reality, such uncertainties and anomalies are present in many urban and rural roads. Therefore, more efforts are needed to mitigate the effect of these problems.

7. Conclusion and Future Work

Both specialist mapping businesses, as well as automated vehicle companies, have started to generate HD maps for AVs. There exists a wide range of HD map solutions available or in development, ranging from lightweight HD map solutions that primarily store lane markings and lane logic (Atlatec, Apollo), to maps that include full 3D point cloud representations (Waymo). While the most comprehensive maps with full 3D representations provide the best assurance of safety, they are costly to generate and maintain and necessitate massive amounts of data. A layered strategy, in which precise 3D data is updated less frequently and a lower-memory 2D representation of the road network is updated considerably more frequently, could be the optimal answer.

In order to implement real-time safety-critical HD maps for AVs, some fundamental challenges must be overcome. This include providing a consistent communication system between agents and HD map providers to transfer agent's location and corresponding semantic information in real-time, a mechanism for informing HD map provider about changes to static road features (such as road signs) or anomalies and consequently rectifying such anomalies, and finally policy considerations on whether HD maps should be privately or publicly owned and operated.

In this paper we reviewed the major map representations and important open problems in the field of AV mapping. The current state of AV mapping is encouraging, the field has matured to a point where detailed maps of complex environments are built in real-time and have been proved useful. Many existing techniques are robust to noise and can cope with a large range of environments. Nevertheless, there are still open problems for future research. It is heartwarming to see new applications and innovations in map representation that can generalize to previously unseen scenarios, are scalable for real-time applications, and are applicable to unstructured, disaster, and extreme weather environments where many of the techniques described are ineffective. AV mapping will remain a highly active research area critical to achieving full autonomy.

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