High Definition Maps in Urban Context

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Abstract

Part of the challenges in the quest for smart cities is to enable effective navigation for different types of mobile users: from pedestrians, through drivers, to autonomous vehicles. While the data sources to facilitate such tasks abound, one of the pressing problems is how to enable efficient management and download of the data needed to populate the screens of devices with the appropriate visualization.

In this paper, we present an overview of the different issues and the main features of the existing technologies that, in one way or another, could be used as foundations for effective solution for generating quality maps. We also discuss the possible approaches for addressing such issues in the context of accurate self-localization of vehicles.

1 Introduction and Motivation

Highly accurate, precise, and detailed lane-level maps – also known as High Definition (HD) Maps, as described in Open Lane Model by the Navigation Data Standard (NDS) [1] – are critical for enabling safe automated driving. Lane-level maps augment vehicle sensor information for contextual analysis of the environment, assist the vehicle in executing controlled maneuvers beyond its sensing range, and provide precise vehicle positioning and orientation in map coordinates [2]. These maps often include localization objects such as signs, barriers, poles, and surface markings to provide the vehicle with a more comprehensive and accurate knowledge of the environment. Given that there are millions of kilometers of roads in the world, it is cost-prohibitive and time-consuming to manually create and maintain such lane information at a centimeter-level precision. Currently, and for the foreseeable future, most automobile manufacturers are focused on autonomous driving on large, controlled interstate highways.

The road networks pertaining to urban settings are often represented by nodes and links (equivalently, vertices and edges) and are mainly classified in two categories, which can further be refined to sub-categories: *interstates* (highway grade and above, which have most length of links) and *local roads* (urban region and sub-urban region, which contains most number of nodes). Compared to local roads, interstates typically have higher quality (and standardized) construction, clearer traffic patterns, and fewer possible hazards (pedestrians, etc.). Moreover, these roads support the majority of the transportation industry and as such, autonomous trucks are among the first vehicles to actually apply autonomous driving techniques [3]. The lengths of the three largest highway networks in the world, U.S., China, and India, are 103, 446, and 79 thousand kilometers [4] respectively. Considering currently reported HD Maps manual modeling efficiency, it could take years to map the entire high level road networks even with thousands of workers. Hence, many HD map automated/semi-automated modeling algorithms are proposed to tackle this problem in highway scenario. At the same time, in urban (city) scenario, road construction is less standardized, has weaker featured objects – e.g., bad lane marking paint, flatten curb, tree occlusion, etc. – and has more uncertainties of non-road objects such as construction zones, nearby vehicles, trees, etc. These factors make HD map modeling an extremely hard problem to be fully (or even semi) automated at present. The amount of human labor required to model a city, by far exceeds the amount required for modeling hundreds of miles of highway network(s).

Many works in spatial and spatio-temporal databases, as well as Geospatial Information Systems (GIS), have generated mature algorithms that were designed to build complete/refined map-based applications. Whether it is the mature GIS systems or research prototypes, there are two basic facets of the problem: how to generate the data, and how to store/retrieve it.

In the rest of this paper, we overview the popular (Tile-based) data structure for representing maps in Section 2. Section 3 follows with a discussion of popular techniques for modeling HD maps/data. Section 4 presents a more focused discussion on autonomous driving and HD maps and gives concluding remarks.

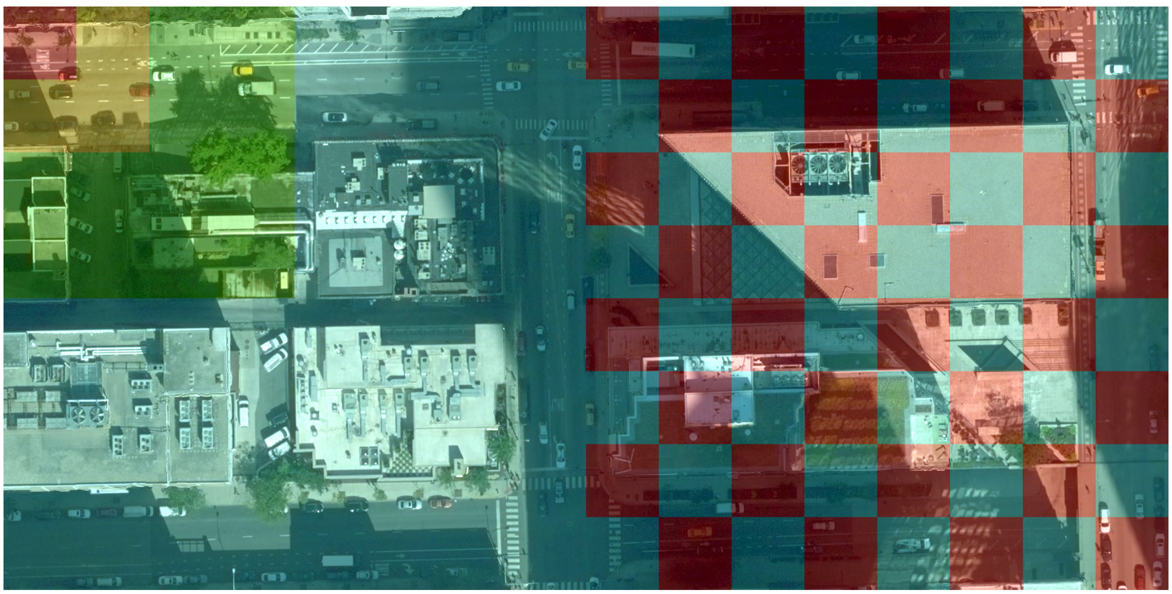


Figure 1: Overlay of hierarchical tile sizes in real world at level 18 (cyan), 19 (green), 20 (yellow) and 21 (red) on satellite image in downtown Chicago, near $41.890853, -87.628045$. Tile size at level 21 (red) is 14.21 meters (tile size is not fixed and subject to latitude and longitude).

2 Tile Based Map Data Structure

Tile-based data structure is being widely used in GIS [5] largely due to its inherent advantages such as: (1) ease of maintenance (the data warehouse, in other words, is easy to read, edit, and not too complicated for updates and insertion of new data); (2) enabling discrete addressing scheme (also amenable for parallelization of the computations); and (3) flexibility in terms of multi-resolution information representation, when one needs to sacrifice space to improve efficiency. Typically, they are hierarchically structured over some base-level, which offers compatibility with most of the GIS data warehouses and applications such as HD maps[1], web-based GISs (e.g. map viewers, satellite image viewers, etc.), as well as Location-Based Services and Digital Terrain Model (for geology and meteorology).

[1]We note that the Navigation Data Standard (NDS) relies on a tile-based database, and is being widely used among auto makers for navigation purpose, see https://www.nds-association.org/#thestandard

Hierarchical tiled-based systems recursively partition the map data into four quadrants (similar to Quadtres), and save the subdivided data of each level – essentially, pre-storing it at different resolutions. The advantage is that one can now have an added flexibility to query different level detail of data (resolution) on demand – thus accommodating to diverse requests' configurations and requirements.

Figure 1 illustrates the tile-based system in real world, from level 18 to level 21.

3 HD Maps Modeling

Highly accurate, precise, and detailed lane-level maps, also known as High Definition (HD) Maps, are critical to enable safe automated driving [6]. Lane-level maps augment vehicle's sensors information for contextual analysis of the environment. This, in turn, assists the vehicles in executing controlled maneuvers beyond its sensing range, and provides more precise vehicle positioning and orientation in map coordinates. HD maps often include localization objects such as signs, barriers, poles, and surface markings to provide the vehicle a more comprehensive and accurate knowledge of the environment. The three most frequently used types of such objects are: lane boundary, occupancy grid and text information (cf. [2]). An illustration is shown in Figure 2.

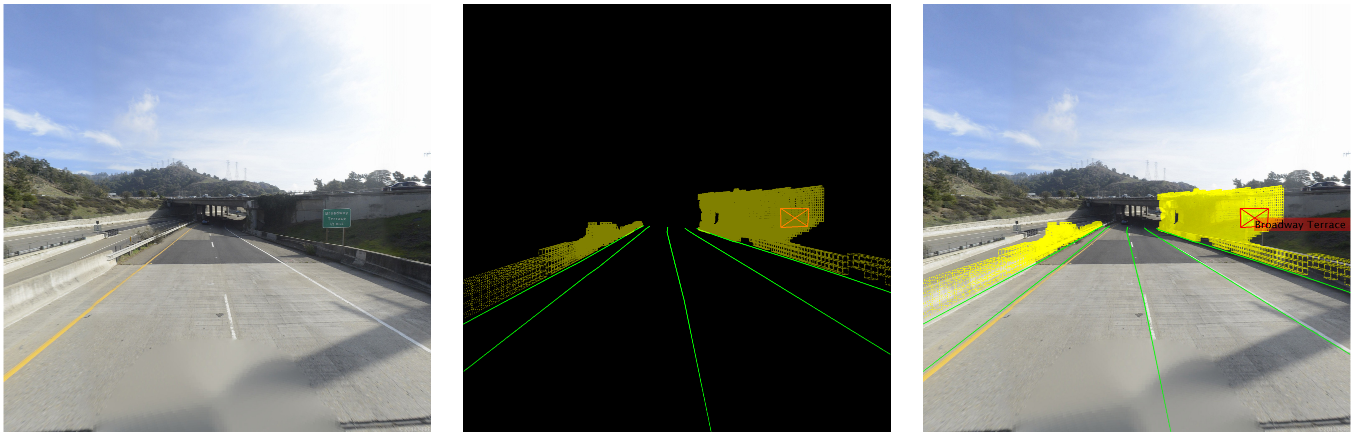
3.1 Lane Boundary Geometry

Ground based data, mainly from imagery and LiDAR, is the primary data source used to automatically extract lane information [7] in academia and industry. It has distinct advantages such as high precision, rich information (e.g. color and geometry), and is usually not affected by to top-down occlusion (e.g. trees, buildings, overpasses and tunnels). Some reseachers [8, 9, 10] have proposed to detect road surfaces and lane markings from LiDAR using the highly accurate and precise 3D measurements in a LiDAR point cloud. Moreover, a point cloud aligned with perspective imagery can be used to generate training data [11] to assist lane-marking detection in perspective imagery. On the other hand, ground based data sources have many limitations such as object occlusion, infrequent updates, prohibitive cost (i.e., data storage, computation and acquisition) and limited coverage.

State of the art HD maps modeling techniques extract lane marking from different kinds of sources. One such kind is ground based data mainly from imagery and LiDAR [7, 9, 10, 11]. Another kind of source is the 3D aerial based data, for example, from satellite or drones [12, 13, 14, 15].

3.2 Occupancy Grid and Terrain Model

In many applications, the occupancy grids are extracted mainly from ground based LiDAR point cloud [16, 17]. We note that the terrain models (more specifically, Digital Terrain Models) also originate from ground based LiDAR [18]. These can be "perceived" as the occupancy grids underneath the vehicle, and be categorized as a type of occupancy grid. Thinking about the size of each type of HD map components, the number of occupancy grids is significantly larger than the number of control points from line boundary geometry [2]. This, in turn, often results in ignoring the data size of lane boundaries – especially in urban areas, where buildings, poles, trees and other stationary objects all over the place.



(a) (b) (c)

Figure 2: Illustration of HD map components: (a) one sample segment of road from perspective view; (b) three key components of a HD map: lane boundary geometry (green lines), occupancy grid (yellow voxels) in 25-cm resolution and road sign (red bounding box) within 36 meters from view point; and (c) overlay of HD map and street view image.

4 HD Map Application: Accurate Vehicle Self-Localization

Vehicle self-localization (ego-localization) is a key component of autonomous driving and often depends on a combination of sensor-based and HD-Map-based location data. It demands high precision, real-time, and robust data management and algorithmic techniques that can handle very harsh conditions such as GPS denial/imprecision, traffic occlusion, and low lighting.

The standards of definition precision in the context of vehicle self-localization are mainly based on, and used in approaches relying upon, Global Navigation Satellite System (GNSS) [19, 20]). With the trends of miniaturization and commercialization of LiDAR devices, many Simultaneous Localization And Mapping (SLAM) systems have been proposed. LiDAR techniques are known for their high precision as 3D information is captured directly, compared to reconstructing 3D information from a 2D stereo camera. These two approaches are typically used to solve point cloud based localization. SLAM can be performed in a known environment (i.e. occupancy grid map) [21, 22, 23].

Alternatively, lane-level objects such as lane markings [24], pole-like objects [25], curbs [26], and even occupancy grids [27] can be detected and used for self-localization. Using additional information such as HD Maps, features can be used to estimate vehicle/camera position using triangulation. While LiDAR-based solutions are superior in terms of effectiveness, their shortcomings are: (1) the actual cost ; and (2) weather dependency [28]. These limitations have a significant impact on limit the use of LiDAR-based solutions for performing point-cloud based self-localization.

No matter which approach or combination of approaches are used to localize the vehicle, an HD map with real-time object detection and recognition algorithms are one of the key components towards enabling the use of self-driving vehicles in urban settings.

State of the art HD map modeling techniques are fairly well adopted for use in highway scenarios - which directly benefits autonomous driving for interstate logistic. This enables significant savings in labor cost and efficiency, with the expectation to even further decrease such costs in the near future. However, solving this problem in urban scenarios – which is more related to citizens daily commute – has still a lot of challenges. Existing techniques for objects detection and recognition, based on the traditional Machine Learning (ML) approaches are not effective enough. This, in turn, also spurs the need for different ML methodologies – namely, the training data of urban HD map (especially lane markings and boundaries) is costly, and even inaccurate since it involves worker's personal perspective.

Complementary to this – even if one assumes that the data warehouse (tile-based structure) and data (HD maps) are readily available, enhancing systems performance is another challenging topic, and of course, more challenges are raising. The size of HD map is too big to be expected to be stored in vehicles on-board devices. Thus, novel efficient map data retrieval algorithms and transmission paradigms are needed for improving the adoption of autonomous vehicles in urban settings.

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