HERE Technologies Research Proposal

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1 Introduction

Autonomous vehicles have the potential to revolutionize the transportation industry by drastically improving safety and efficiency of transportation. In order to navigate through complex environments the vehicles rely on wide array of sensors like Light Detection And Ranging (LiDAR), Camera, Inertial Measurement Unit (IMU), Global Navigation Satellite System (GNSS). The level of autonomy in Autonomous Driving Systems is determined by its ability to perceive and navigate in complex environments. Simultaneous Localization And Mapping (SLAM) has been an active area of research in Robotics [1] [2]. To accomplish this task the system needs to sense and generate an accurate map of the environment using different SLAM techniques, find its location in the map using Monte Carlo Localization [3] or Kalman filter based localizations and navigate to the destination. Several approaches have been proposed [1] [4], however the most successful one [5] was developed by Stanford Artificial Intelligence Lab.

Most of the related work conducted has been focused on very specific and constrained environments, however to achieve a fully autonomous system, the challenge of mapping large-scale environments needs to be tackled. The objective of this project is to develop a system that can not only generate a three dimensional large-scale map but also add more detailed information to the map data.

2 Related Work

Different Mapping Techniques that have been deployed for generating map data can be broadly classified into LiDAR Mapping [6], Visual Mapping [7] and Sensor Fusion based Mapping [8]. LiDAR based mapping is usually preferred as it generates accurate point clouds data which provide a depth perception of the image. This depth information is extremely useful in navigation. Visual mapping is primarily based on camera data. Unlike LiDARs, Cameras require ambient lighting and cannot provide depth information by default. However, cameras provide better scene segmentation and understanding [9]. We can also use multi camera system [10] to gain depth perception along with different wide field of view lenses or fisheye lenses [11] to gain more information. The sensor fusion based approach tries to combine the data from all the sensors and generates a map that has a depth perception of LiDAR as well as better scene segmentation of Camera. Other sensors commonly used are RADAR for navigation and obstacle detection, IMU and GNSS for better localization. Figure 1 lists all the advantages and drawbacks of different sensors and provides a graphical explanation of how sensor fusion helps in overcoming individual sensor shortcomings.

Figure 1: Sensor Comparison [12]

The data collected from all these sensors is then processed and map is generated. Different map generation methods for unknown map environments are based on probabilistic frameworks. In the case of autonomous vehicles the real-time map generation is very computationally intensive, needs very heavy optimization. The online probabilistic algorithms are based on Markov assumption to estimate the current pose and generate map agnostic of the previous data collected about the same environment. Markov assumption states that past information is irrelevant if pose and map is known. This assumption helps in reducing the computational complexity and is very useful in small-scale environments [13]. The most commonly used online algorithms are Unscented Kalman Filter [14], FastSLAM [15] and FastSLAM 2.0 [16]. The offline set of probabilistic algorithms integrate previous and present data to estimate previous set of poses visited by the vehicle and generate the map based on it. GraphSLAm is one of the most successful implementations of offline Full-SLAM (offline algorithms that estimate the entirety of previous poses) [4].

3 Proposed Mapping Technique

We propose a system which builds on previously mentioned work and improves on it by focusing on two major aspects:

- Reusing Prior Maps
- Adding more information to Existing Map Data

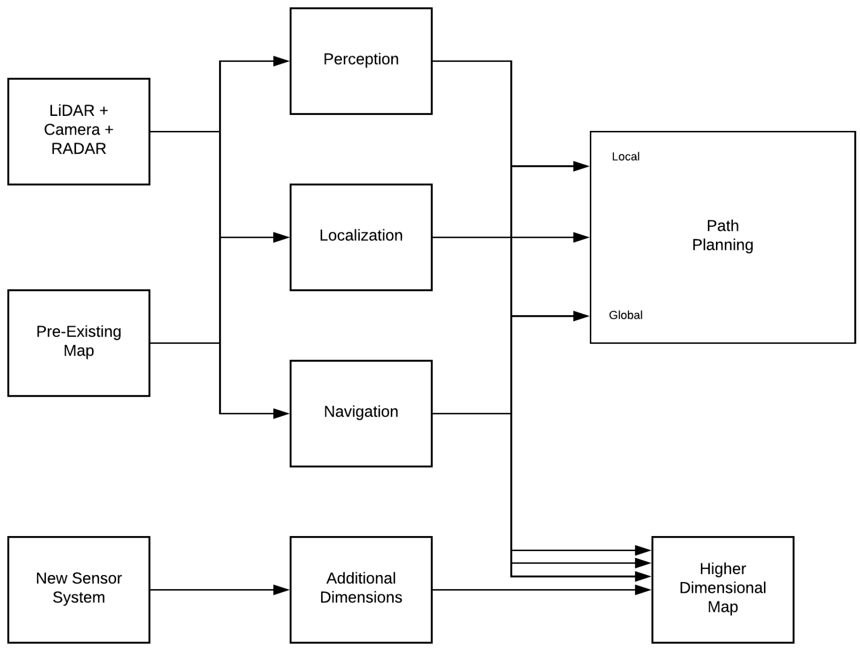

Figure 2: Proposed System

Cite 9 remaining papers

4 Conclusion

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