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Autonomous vehicle navigation using high-definition maps through CARLA-ROS simulator bridge

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Autonomous vehicle navigation using high-definition maps through CARLA-ROS simulator bridge

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Abstract. Autonomous vehicles (AV) have garnered significant interest in recent years due to its potential for controlling thousands of accidents that happen yearly due to human error. However, AV bring with it very complex and sophisticated requirements and challenges related to extensive testing of the algorithms and hardware in the physical world. The evolution of automotive simulation tools provides an opportunity to fully test and validate AV architectures without the risk of creating hazardous situations in real world. This research demonstrates the application of HD (High Definition) maps in autonomous vehicle navigation using ROS interface integrated with the CARLA (CAR Learning to Act) simulator. The sensor data includes Light Detection and Ranging (LiDAR), RGB-Depth (RGB-D), and vehicle odometry. HD maps play an important role in robustness of the autonomous systems where due to sensor obstruction or weather conditions the vehicle is unable to perceive the information ahead. It also aids the vehicle to sense its environment even outside from the sensor's field of view. The research is divided into the three fundamental concepts of Simultaneous Localization and Mapping (SLAM) approach that is, (i) mapping, (ii) localization, and (iii) navigation. Two ROS tools are used for mapping, (a) OctoMap mapping, and (ii) Real-Time Appearance-Based Mapping (RTAB-Map). We demonstrate the effectiveness of localization using RTAB-Map and compare actual path, position and orientation to their estimated equivalents. Our results show acceptable error in XY axes and exemplifies the error accumulated in Z axis.

Keywords. Autonomous localisation, mapping, ADAS, HD-maps, CARLA, ROS, OctoMap, RTAB-Map

1. Introduction
This paper focuses on the Autonomous Vehicle (AV) driving using the approach of HD maps to enhance their environmental perception. The issues related to traffic mismanagement, road accidents due to human error have led to the development of smarter technologies automatizing the driving experience through integration into smart cities. Intelligent Transport Systems (ITS) that leverage the field of big data and cloud services have played a vital role in developing such an ecosystem. Precisely, one of the most advanced technologies that take advantage of such services as part of the smart city

concept is an autonomous vehicle (driverless, self-driving, or automated car) that integrates within them, the field of advanced driver-assistance systems (ADAS). The two large categories for such autonomy are lateral (steering), and longitudinal (speed) controls [1, 2]. Moving towards the age of advanced autonomous vehicle technologies arises some major risks that cannot be predicted easily ahead of time or before experimentation. For this reason, the simulation environments came into existence to overcome the associated expense, time and risk with the real-world environment and testing. Original Equipment Manufacturer (OEM) use such tools to test their equipment in the simulated systems close to the real systems with their defined boundary limits before even building the first prototype [3]. Such simulators leverage from the ability to integrate various weather conditions, variations in driving behaviors, and various sensor configurations to make the controller robust and to have a real-world experience in the simulation [4]. Machine perception has evolved over the years. This evolution helps vehicle to perceive their environment better and to be able to make complex driving decision autonomously based on the information provided to it [5]. HD maps are one of such advancements in this sector. The AV industry has transformed from paper maps towards high quality, detailed digital maps of the world in the sensor environment to achieve maximum levels of autonomy.

In this research we have used the approach of mobile robotics for the AVs that uses the methodology of Simultaneous Localization and Mapping. SLAM distributes the problem of autonomous driving into three modules being, mapping, localization, and navigation [6]. To achieve this we have used the tools developed in the ROS environment for the ease of implementation and CARLA is used to leverage the advanced features of autonomous driving and sensor information that is provided by the platform [7, 8]. Mapping is carried out using OctoMap that generates a 3D point cloud based on LiDAR [9], and RTAB-Map that generates a 3D cloud with 6 Degrees of Freedom (DOF) map based on the fused information from RGBD camera, LiDAR, and odometry [10]. Localization is performed using RTAB-Map, which saves the images and features in its database while mapping. When the vehicle is spawned at any location, based on the local visual features observed through the camera and the scans produced thorough laser scans, it estimates the current location and orientation based on the feature matches throughout the database. For navigation, once the vehicle is localized, we pass the goal position to the vehicle that calculates the best path possible to that position using the A* (A-star) search algorithm [11] through the waypoint nodes created during mapping. Each section of the paper is divided into the similar modules. The objective of the paper is to explore real time map recreation and localization in a simulated environment and evaluate its merits. The rest of the manuscript presented as follows. The related works are discussed in Section 2, and the implementation and methodology is demonstrated in Section 3. In Section 4, the experimentation is discussed. Section 5 includes the experimentation results. Lastly, Section 6 concludes the paper.

2. Literature review

Ilci et. al. [12] have discussed the evolution of creating high definition 3D map using Global Navigation Satellite Systems (GNSS), Inertial Measurement Unit (IMU), and Light Detection and Ranging (LiDAR) to aid autonomous vehicle navigation. They emphasized the importance of accurate vehicle positioning and environment perception to address the criticality of high risk situations in the field of AVs. It is proposed that a robust sensor configuration can mitigate the errors and limitations of various sensors operating under different environmental conditions having separate source of perception, However, their main objective was to obtain cm-level accuracy based just on the Velodyne LiDAR sensor and using no other additional sensors to create a detailed HD map with the help of MATLAB. Choi et. al [4] proposes the simulation based autonomous driving tests using HD maps. The research conducts 3D map generation using LiDAR data provided by the CarMaker simulator integrated with ROS. Liu et. al. [13] discusses the enormous contribution of research towards HD maps. Their paper provides a detailed review on the frameworks used for such applications along with providing the history of navigation map for autonomous driving. They have directed their research towards discussing the structures, features and functionalities, their standardization and required accuracy. Further, advancing towards vehicle localization based on HD maps and its numerical analysis encouraging the application of HD maps in autonomous vehicles. Bauer et. al. [14] researches on the localization for AVs using GNSS and quantifies their accuracy and integration. They discuss the unpredictability of environmental factors that decreases localization accuracy based on GNSS fused with introceptive sensors. The research focuses on the advantages provided by HD maps that are fused to the sensor data to increase localization estimation accuracy and their benefits in the real-world applications. Ravi et. al. [15] discusses the reliability of LiDAR for 3D map generation. They have discussed about the high computation requirement in LiDAR while processing millions of points per second and their add up computations in clustering, tracking, classifying and detection, which makes it impractical for the real-time execution. In their research, they have proposed a real-time dynamic object detection algorithm that leverages the offline map produced by LiDAR to mitigate the processing time required. Their approach uses offline maps integrated with online mapping to increase its ability to detect dynamic variations in the environment. The proposed architecture was evaluated using the CARLA simulator. Seif et.al. [16] articulates detailed introduction towards the important technological advancements in autonomous driving for smart cities. They have discussed various technologies ranging from data analysis and road infrastructure to onboard and cloud computing. Specifically the challenges faced during the application of HD maps as the base technology for AVs is shared through their article.

3. Methodology

In this section, the proposed methodology is discussed for autonomous navigation. The first phase starts with creating a detailed HD map of the environment using RGB-D sensor and LiDAR. We then move towards the second phase of localization that uses the previously stored visual data in the database while mapping. This database includes waypoints from the mapping phase which are used to navigate the vehicle autonomously. Figure 1 shows a transform graph of the simulation at the runtime where ego vehicle is connected to the map frame in the synchronous mode and through it all the other sensors are attached and have a frame transformation. Additional visual transformations were applied to all the camera sensors to shift the coordinate system aligned to the vehicle's frame of reference (90 degrees offset).

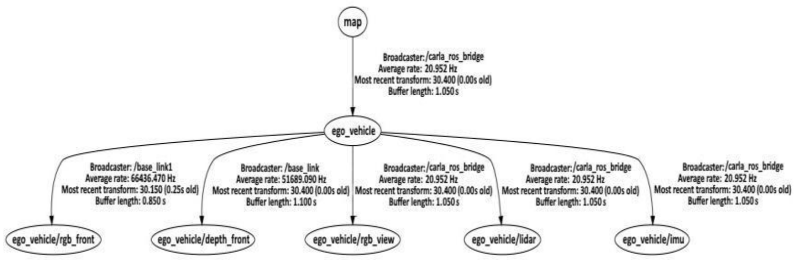


Figure 1. Associated transform frames linked to the simulator world.

3.1. Mapping

To generate high definition 3D maps of the dynamic environments in the simulator, we touched upon two state of the art methods for map generation. OctoMap constructs a 3D map of the environment using LiDAR point cloud data. This generates a high definition 2D and 3D map by driving through the environment. The map features are not required to be known in advance. Rather, the map is generated dynamically overtime. RTAB-Map has multiple configurations and uses RGB-D or a stereo camera setup. For this paper, we focused on it's RGB-D application. A map is generated using RGBD data and is fused with laser scans to generate more accurate projections. Vehicle odometry is recorded to estimate the position of the vehicle in the 3D map generated. RTAB-Map compares two images to determine how likely a new image came from an already explored environment or an unexplored one. If a loop closure hypothesis is accepted the current image gets stitched to an already existing instance of the map.

3.2. Localization and navigation
With a high definition 3D map previously generated by RTABMap saved in the database, the loop closure detector will start to accept the loop closure hypothesis as we drive the vehicle through the map and the RGB-D input matches the data in the database. After matching the features of both the input and data from the map saved in the database, it estimates a localized position of the vehicle with a co-variance ball. a loop closure hypothesis gets accepted with an instance of the map saved in the database. While map generation, RTAB-Map saves waypoints after a set interval of time and lists it as an index number. We then set a destination for the vehicle and these waypoints are used to determine the best route to reach that destination while localizing.

4. Experimentation and results
This section demonstrate the experiments carried out using the tools and methodology discussed in the previous section. Digital maps were created using a pure LiDAR based approach as well as fusion between the RGB-D and LiDAR data approach, Localization was performed based on the visual feature mapping and matching technique for loop closure detection and pose estimation. Navigated path is then easily calculated through the waypoints saved during mapping mode. This section also evaluates the qualitative and quantitative results for all the three basic components discussed for navigation using the HD maps and the waypoint approach.

4.1. Mapping
Two approaches of HD map creation are discussed in this section. The complete digital maps are also visualized in this section. Later, the generated maps were exported to multiple formats into a single file easy to be deployed and for future use. Using LiDAR to scan the environment, we get a 3D map of the world. The map is able to model the environments arbitrarily without any dependency from the past. OctoMap saves the map efficiently both on disk and in memory. The last Point Cloud Data (PCD) file generated contains all the scans from the previous instances and the files are not required to combine to get the reconstruction of the entire map resulting in a compact final file. This helps in bandwidth restricted scenarios where entire map data needs to be transferred to and from a vehicle. Figure 2(a) shows the reconstructed map of the town in CARLA simulator using OctoMap mapping.The depth-map from CARLA simulator is perpendicular to the view of the camera and requires a transform to map over the same plane that the camera captures. Some parameters need to be fixed for RTAB-Map to work in an open world environment like CARLA simulator and not accept improper loop closures. Figure 2(c) represents the the data RTAB-Map uses to reconstruct the environment. The plotted cyan dots represent the surfaces where laser scans bounce from. Figure 2(d) visualizes SLAM (simultaneous localization and mapping) based approach using RTAB-Map and the vehicle odometry going through the recreated environment. RTAB-Map uses sensor fusion to generate an accurate representation of the environment. We can fuse RGB-D data with 3D LiDAR for 6DoF mapping or with laser scans for 3DoF. Figure 2(b) shows fused depth cloud and LiDAR data to reconstruct the map digitally. Figure 2(e) is the visual representation of the digital map exported from MeshLab having the fused meshes of LiDAR as well as the depth cloud.

4.2. Localization
RTAB-Map takes RGB-D images as input and compares them to the previously generated instances of the map in the database, if enough features match, it accepts a loop closure hypothesis and estimates the pose. The said pose has vehicle position and orientation of the vehicle with respect to the environment. Localized pose accumulates some error, we compare the localized pose to the actual pose of the vehicle extracted from CARLA simulator to visually see the error. Figure 2(f) shows highlighted green outline of the vehicle pose (location and orientation) extracted from CARLA and the localized pose with co-variance to compare the estimation error visually.

(a) OctoMap mapping. (b) RGB-D and LiDAR. (c) Laser and RGB-D.

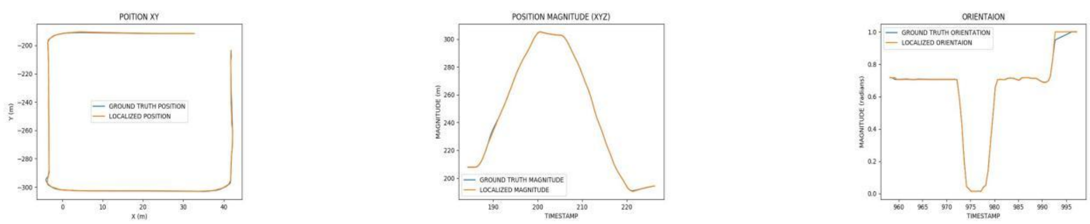
(d) SLAM using RGB-D. (e) Fused sensor data. (f) Localization comparison.

Figure 2. Reconstructed map of the town in CARLA simulator.

4.2.1. Error analysis for pose. To test the validity of localization through RTAB-Map in CARLA simulator we completed a benchmark run and drove the vehicle in a loop for 300 meters. To quantify the results, the Root Mean Square Error (RMSE) were calculated for pose, which contains error analysis for position and orientation.

(a) Position: Figure 3(a) shows the path covered by the vehicle with the red curve showing the actual position of the vehicle extracted from the topic of carla/markers and the blue curve depicting the estimated path of the vehicle. Figure 3(b) demonstrates the error comparison between the magnitude of position of the vehicle with the estimated localization. We add the magnitudes of the position from X, Y and Z axis from both actual position and estimated position and plot them against time to compare the error. Figure 3(c) demonstrates the error comparison between the actual vehicle path with the localized path coming from RTAB-Map in 3D. This shows us that most of the error is accumulated in Z-axis, which is not explicitly required to navigate the car, where the path is required in a bird's eye view form (top-down 2D view) and such error can be eliminated using IMU or GPS fusion. This error lead us to calculate RMSE of XY magnitude.

(b) Orientation: Figure 5(a) shows the orientation magnitude (ω) curve for the ground truth and the estimated data. We log the angular velocity data of the vehicle along with the estimated values and plot them over time with the movement of the vehicle to compare the results. The RMSE was calculated based on the estimated data (when localized) and its respective actual data, which are shown in Table 1.



(a) actual vs estimated path. (b) actual vs estimated position. (c) actual vs estimated orientation.

Figure 3. Comparison in terms of path, position, and orientation.

Table 1. Root Mean Square Error (RMSE) for pose.

Position (XYZ) m	Position (XY) m	Orientation (ω) rad
0.7435	0.3088	0.00644

4.3. Navigation

The odometry generated during the mapping phase is saved as an array of waypoints through the environment. These waypoints are generated after a set interval of time and can be updated by changing the RTAB-Map update rate. If we provide an end goal or destination while localizing, a navigation path is calculated from the previously generated waypoints. Figure 4 shows a the global path being generated with a list of waypoints leading to the destination and RTAB-Map publishing the next most goal for the car to drive through and also shows three final outputs leading towards the autonomous navigation. (i) (top left) calculated global path (a list of waypoints leading to the destination) published and visible on the terminal along with the local path publishing the next goal at every instance and changes to the next one once the previous one is reached, (ii) (bottom left) control commands calculated through the PID controller and published on a topic to be subscribed by the vehicle to autonomously navigate through the generated points, and (iii) (right) the visual illustration for all containing the local path (next goal) shown as green curve, the waypoint nodes created during mapping, and the localized pose of the vehicle with covariance.

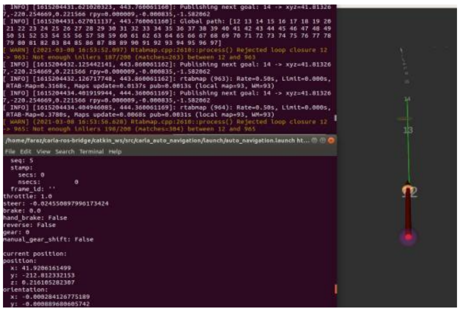
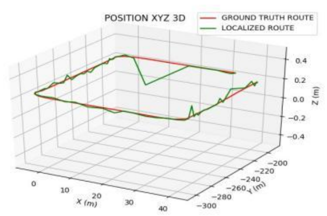
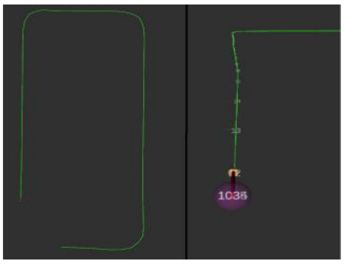


Figure 4. depicts navigation path based on the waypoints and shows localized car and the waypoints.

We use the localized pose and environment waypoints from RTAB-Map to calculate and create a route to the destination. Figure 5(b) shows the global path calculated to reach the destination starting from the current location along with the localized position and orientation of the vehicle on the calculated path.



(a)



(b)

Figure 5. (a) vehicle's actual vs estimated path (b) global path.

5. Conclusion and future work

This research demonstrated the application of HD maps generated through RTAB-Map in autonomous vehicle navigation using ROS interface integrated with the CARLA simulator. The experimentation shows that the mapping and localization method can be a viable option for estimating the position of the vehicle. It is observed that the major part of the error is accumulated in the Z axis which has negligible impact on the estimation of the position of the vehicle. It is further noticed that the error in vehicle orientation and XY position can be minimized using IMU and GNSS sensors respectively. For future work we plan on comparing loop closure matches at different times of day, traffic and weather conditions examining the performance of HD remapping and localization.

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