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Visual and light detection and ranging-based simultaneous localization and mapping for self-driving cars

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ABSTRACT

In recent years, there has been a strong demand for self-driving cars. For safe navigation, self-driving cars need both precise localization and robust mapping. While global navigation satellite system (GNSS) can be used to locate vehicles, it has some limitations, such as satellite signal absence (tunnels and caves), which restrict its use in urban scenarios. Simultaneous localization and mapping (SLAM) are an excellent solution for identifying a vehicle's position while at the same time constructing a representation of the environment. SLAM-based visual and light detection and ranging (LIDAR) refer to using cameras and LIDAR as source of external information. This paper presents an implementation of SLAM algorithm for building a map of environment and obtaining car's trajectory using LIDAR scans. A detailed overview of current visual and LIDAR SLAM approaches has also been provided and discussed. Simulation results referred to LIDAR scans indicate that SLAM is convenient and helpful in localization and mapping.

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1. INTRODUCTION

Self-driving cars are regarded as the next big thing, benefiting from intelligent transportation systems, smart cities, internet of things (IoT), and new technologies such as machine learning. At present, automotive industry has contributed towards innovation and economic growth. Navigation for autonomous driving vehicles is a very active research area [1], [2]. In order to ensure efficiency and safety of traffic systems that rely on driving strategies [3], researchers around the world are concentrating their efforts on advancement of this subject [4]. In this context, defense advanced research projects agency (DARPA) has been regularly organizing a grand challenge of autonomous [5].

One of the most important criteria for autonomous navigation is an accurate localization of the car itself. Global navigation satellite system (GNSS) is the most used localization system, providing absolute positioning with high accuracy [6]. However, in special conditions such as multi-path effect and latency, restrict its use [7].

Only by representing environment using different kinds of sensors would robots be able to navigate in these conditions. The process of representing environment or constructing a map and estimating position of a car simultaneously called simultaneous localization and mapping (SLAM) [8]. SLAM is a solution for several applications, including self-driving cars [9], mobile robots [10], unmanned aerial vehicles (UAV)

[11], and autonomous underwater vehicles [12]. Many SLAM techniques for self-driving cars are discussed in literature [13]. Liu and Miura [14] presented an ORB-SLAM-based visual dynamic SLAM algorithm for real-time tracking and mapping. In dynamic indoor environments, results show that the algorithm is efficient and accurate. Wang *et al.* [15] proposed a robust multi-lidar for self-localization and mapping problems. According to the authors, the suggested solution produced better results than single lidar approaches. In this paper, after surveying and discussing the approaches of SLAM-based cameras and light detection and ranging (LIDAR), we focused on SLAM using LIDAR sensors in order to create a map of an environment and locate the pose of a self-driving car.

The remainder of this paper is structured: section 2 discusses sensors for perception and localization. Techniques based on LIDAR and cameras for localization are also presented. Section 3 shows results obtained by implementation of SLAM algorithm. Finally, section 4 concludes by discussing future orientations and remaining challenges.

2. METHOD

2.1. Sensors based localization

Localization and mapping are the most important requirements for self-driving cars. Car needs to know where it is as well as its environment at all times and in any conditions. Car must be able to localize itself and generate a map of its surroundings called a “local map”. Map obtained by global positioning system (GPS) is insufficient because the environment is extremely dynamic. As a result, creating a local map and integrating it with the global map is required for more accurate navigation. Several sensors used for localization are presented below, as well as a synthesis of techniques based on cameras and Lidar.

2.1.1. Sensors of perception

In self-driving cars, perception frameworks can detect and interpret surrounding environment dependent on different sorts of sensors. Sensors are extensively ordered into two sorts, depending on what property they record. They are exteroceptive if they record an environmental property. Then again, if sensors record a property of ego vehicle, they are proprioceptive. Classification and characteristics of sensors used in perception are shown in Table 1.

Table 1. Sensors of perception

Sensors	Camera	LIDAR	Radar	Ultrasonic	GNSS/IMU	Odometry
Role	Essential for correctly perceiving environment	Detailed 3D scene geometry	Object detection and relative speed estimation	Short-range all-weather distance measurement. Unaffected by lighting.	Measure of ego vehicle states	Tracks wheel and calculate overall speed and orientation
Characteristics	Resolution Field of view Dynamic range	Number of beams Points per second Rotation rate Field of view	Range field of view accuracy	Range Field of view Cost		
Type	Exteroceptive	Exteroceptive	Exteroceptive	Exteroceptive	Proprioceptive	Proprioceptive

2.1.2. Camera-based localization

There are several localization techniques presented in literature that use only cameras [16], [17] or integration of camera [18] to improve performance of these techniques. Suhr *et al.* [19] proposed, in urban environments, using GPS/IMU for global positioning and camera for recognition of road markers as well as lane markers to find both lateral and longitudinal positioning. Authors noted that this technique gives, in one of 5 experiments, lateral errors of 0.49 m, longitudinal errors of 0.95 m and 1.18 m Euclidean error on average. Li *et al.* [20] suggested, in urban environments also, a vision-based localization approach using only cameras. Hybrid method combines a topological map to estimate a global position with a metric map to find a fine localization. Authors noted that this low-cost approach gives mean positioning errors of 0.75 m.

2.1.3. LIDAR-based localization

LIDAR is another important sensor which is able to improve localization performance for self-driving cars. It scans the surrounding environment and generates multiple points to build a 3D map using light detection and ranging. LIDAR is known to offer precise and robust measurements of the environment. Because it is expensive compared to other sensors, LIDAR is employed only to build map, and camera is utilized to localize vehicle.

Wolcott and Eustice [21] suggested a generic probabilistic localization method based on a 3D LIDAR scanner. This technique models world as a fast and exact multiresolution map of a mixture of Gaussians. Gaussian mixture maps for localization were evaluated on two autonomous vehicles, in adverse weather conditions, and resulted in longitudinal and lateral RMS errors below 0.1 m and 0.13 m, respectively. Hata and Wolf [22] proposed, in the urban environment, a method based on multilayer LIDAR to estimate the vehicle localization using map of environment created by LIDAR sensor. Authors noted that this proposed approach gives longitudinal, lateral and angular errors of 0.1395 m, 0.204 m and 0.019 rad, respectively.

2.1.4. Summary

Camera-based localization solutions provide excellent performance. Error is caused by a low-textured environment or sensitivity to light changes, which is the biggest drawback of this solution. Finally, image processing necessitates a high level of computational complexity. LIDAR, on the other hand, is known for its ease of use and accuracy. To take advantage of benefits of each sensor, several techniques use sensor fusion as we will see in the next chapter. Table 2 summarizes camera and LIDAR based localization.

Table 2. Summary of camera and LIDAR based localization

	Study	Accuracy
Camera-based localization	[19]	Longitudinal error 0.95 m Lateral error 0.49 m Euclidean error 1.18 m
	[20]	Positioning error of 0.75 m
Lidar-based localization	[21]	Longitudinal error 0.1 m Lateral error 0.13 m
	[22]	Longitudinal error 0.1395 m Lateral error 0.204 m Angular error 0.019 rad

2.2. Vision and LIDAR based SLAM

2.2.1. Principle of SLAM

SLAM is a technique for simultaneously creating an online map and locating a car on it. It is a common practice in self-driving cars that works effectively in both indoor and outdoor environments and performs well [23]. But it remains less efficient than prebuilt map localization due to high environmental challenges, such as high speed and a large number of dynamic vehicles [24].

2.2.2. Probabilistic modeling of the SLAM problem

In order to model the SLAM problem, we consider a vehicle moving through an unknown environment, as given in Figure 1. The idea is to use a graph to model the SLAM problem, which includes the position x_t of the robot as well as map landmarks m_i. Lines connecting positions represent the trajectory of the robot, and arrows represent the distance to landmarks. The position data is obtained by proprioceptive sensors mounted on the robot. Furthermore, landmarks are extracted from the environment using proprioceptive sensors such as LIDAR.

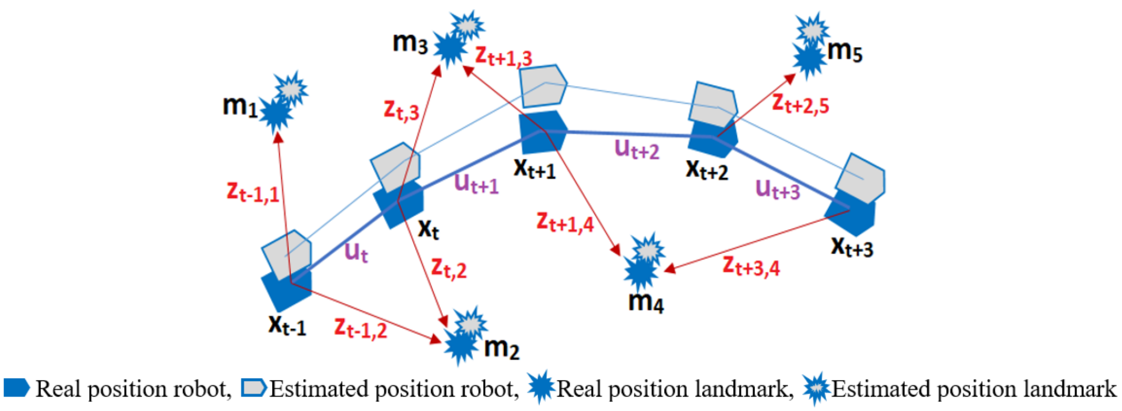

Figure 1. Basic idea of SLAM

At time t we define the following quantities: x_t is state vector that represents a vehicle; $\mathrm{u_t}$ is control vector applied at $t-1$ to drive vehicle to $\mathrm{x_t}$; $\mathrm{m_i}$ is vector representing i^{th} landmark; $z_{t,i}$ is observation of i^{th} landmark. Assuming that duration between two successive positions is constant and equal to T, the instant t becomes kT. To simplify calculations, we will use index $kT = k$. Then, from time 0 to kT, the following sets are defined:

- $\mathrm{X_{0:k}} = \{\mathrm{x_0, x_1, \dots, x_k}\}$: set of vehicle locations;
- $\mathrm{U_{0:k}} = \{\mathrm{u_0, u_1, \dots, u_k}\}$: set of control inputs;
- $\mathrm{Z_{0:k}} = \{\mathrm{z_0, z_1, \dots, z_k}\}$: set of observations;
- $\mathrm{M} = \{\mathrm{m_1, m_2, \dots, m_k}\}$: set of landmarks or maps.

a) Modeling of localization

Problem of localization consists of calculating a vehicle's position in a given environment using environmental data such as observation and command history [25]. This problem is represented by estimation of probability distribution.

$$\mathrm{P(x_k|Z_{0:k}, U_{0:k}, M)}$$

This formulation, which represents global localization, uses all of data from history of observations and commands. This gives an accurate estimation of position, but it substantially complicates the calculations. To simplify computational complexity, we estimate position at time kT using only data from time $(\mathrm{k}-1)\mathrm{T}$. This is local localization represented by:

$$\mathrm{P(x_k|z_{k-1}, u_{k-1}, x_{k-1}, M)}$$

Implementing this model will greatly reduce algorithm's complexity, but accuracy will degrade as a result.

b) Modeling of mapping

Process of building an environment map using sensor data and history of real robot placements is known as mapping. Mathematically, mapping problem can be modeled.

$$\mathrm{P(m_k|Z_{0:k}, X_{0:k})}$$

To create a good mapping, robot's position must be exact and accurate.

c) Modeling of SLAM

SLAM's probabilistic modeling necessitates determination of the probability quantity at each time step.

$$\mathrm{P(x_k, M|Z_{0:k}, U_{0:k}, x_0)}$$

This calculation is divided into two parts by (1) and (2), describing the position update and the observation update, respectively.

$$P(x_k, M|Z_{0:k-1}, U_{0:k}, x_0) = \int [\,P(x_k|x_{k-1}, u_k) * P(x_{k-1}, M|Z_{0:k-1}, U_{0:k-1}, x_0)]dx_{k-1} \tag{1}$$

$$P(x_k, M|Z_{0:k}, U_{0:k}, x_0) = \frac{P(z_k|x_k, M) * P(x_k, M|Z_{0:k-1}, U_{0:k}, x_0)}{P(z_k|Z_{0:k-1}, U_{0:k})} \tag{2}$$

$\mathrm{P(x_k|x_{k-1}, u_k)}$: represent vehicle's motion model (transition model). $\mathrm{P(z_k|x_k, M)}$: describes observation model. $\eta = \frac{1}{\mathrm{P(z_k|Z_{0:k-1}, U_{0:k})}}$: a normalization constant that depends on transition and observation models. Finally, we can model SLAM problem by (3).

$$P(x_k, M|Z_{0:k}, U_{0:k}, x_0) = \eta * P(z_k|x_k, M) * \int [\,P(x_k|x_{k-1}, u_k) * P(x_{k-1}, M|Z_{0:k-1}, U_{0:k-1}, x_0)]dx_{k-1} \tag{3}$$

2.2.3. Resolution of the SLAM problem

SLAM problem is regarded as a critical factor of self-driving cars. Many problems, however, continue to prevent use of SLAM algorithms in vehicles that should be able to travel hundreds of kilometers in a variety of conditions [26]. The main methods for solving this problem are based on the process shown in Figure 2.

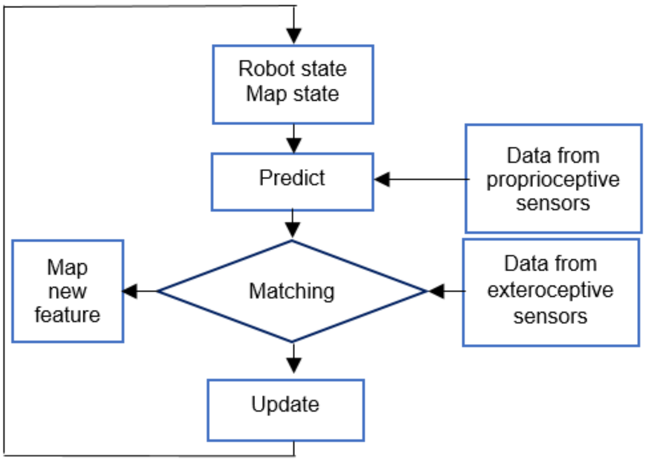

Figure 2. Block diagram of SLAM process

2.2.4. Visual SLAM

Visual simultaneous localization and mapping (V-SLAM) is the problem of establishing location of a vehicle in an area while also building a representation of explored region using images as only source of external knowledge. V-SLAM extracts features from observed images for localization in dynamic and complex environments. Due to techniques-based computer vision employed, visual SLAM is an active area of research. Visual SLAM (or vision-based SLAM) refers to use of cameras as only exteroceptive sensor. When visual SLAM systems are complemented with data from proprioceptive sensors, it is called visual-inertial SLAM. Localization process consists of two stages: global localization using topological map and local localization using metric map. Li *et al.* presented in [20] an approach for vision-based localization, using hybrid environment model, which combines topological map with metric map to represent environment. Nodes of topological map are described by a holistic image descriptor, while interest point descriptors define nature landmarks on metric map. This technique, tested in urban environment, contributes to the development of a precise (errors mean of 74.54 cm and errors deviation of 91.43 cm) and effective localization method.

2.2.5. Introspective vision for SLAM (IV-SLAM)

V-SLAM algorithms consider that feature extraction errors are independent and identically distributed, which is not always true. This hypothesis makes the tracking quality of the V-SLAM algorithms low, especially when the detected images include difficult conditions. To address such challenges, the authors in [27] presented an introspective vision for SLAM (IV-SLAM). In this approach, the noise process of errors from visual features is specifically modelled as context dependent in IV-SLAM. In comparison to V-SLAM, results show that IV-SLAM is able to accurately predict sources of error in input images and decreases tracking error.

2.2.6. LIDAR based SLAM

Because of its simplicity and precision, 3D mapping with LIDAR is commonly used to solve SLAM problem [28]. LIDAR can, in fact, achieve a low drift motion estimation while maintaining a manageable computational complexity [29]. Study in [30] claims that distortions in collected data are caused by moving at high speeds, an impact that most studies overlook, including all of details about vehicles' displacement. Idea is to use velocimetry and then look at measurement's distortion.

2.2.7. Visual-LIDAR fusion-based SLAM

To further improve the robustness of SLAM, such as respect for aggressive movements and absence of visual features, researchers are focusing on vision-LIDAR approaches. Techniques which combine LIDAR and stereo cameras. Approach proposed by Seo and Chou in [31] allows us to create a LIDAR map and a visual map with map points in different modalities, then use them together to optimize odometry residuals such that LIDAR map and operating environment have global coherence. Work proposed in [32] gave a combination of low-cost LIDAR sensor and vision sensor. A specific cost function that considers both scan and feature constraints is proposed to perform graph optimization. In order to speed up loop detection, a specific model with visual features is used to create a 2.5D map.

3. RESULTS AND DISCUSSION

3.1. Configuration

This section shows some results produced by implementation of SLAM algorithm in order to build a map of environment and a robot trajectory using LIDAR scans. MATLAB software was used to generate these simulation results. A data set of laser scans acquired from a real mobile robot is available in MATLAB.

3.2. Results

Algorithm begins to aggregate and connect LIDAR scans as robot moves from a start point to an arrival location. Figure 3 shows a pose graph for first 15 scans that is linked between them. Figure 4 shows final built map (magenta color) and trajectory of robot (green color).

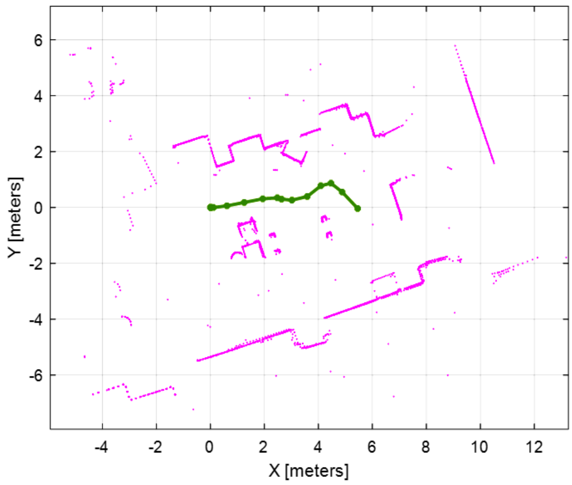

Figure 3. Pose graph for initial 15 scans

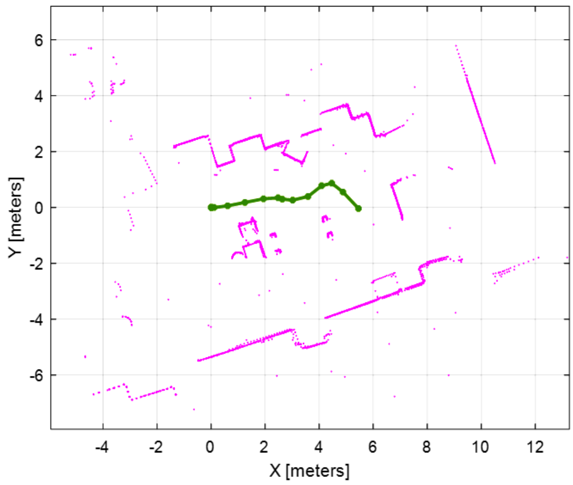

Figure 4. Final built map and robot's trajectory

By comparing collected scans, the robot identifies recently visited positions and may create loop closures along its itinerary. The loop closure data is used to update the map of environment and correct the trajectory of robot. Identification of the first loop closure can be observed in Figure 5 (red color). Figure 6. shows two loop closures that were detected automatically during robot displacement. After constructing and optimizing the pose graph, the algorithm operates on this data to produce an occupancy map that describes the area. Results obtained are presented in Figures 7 and 8.

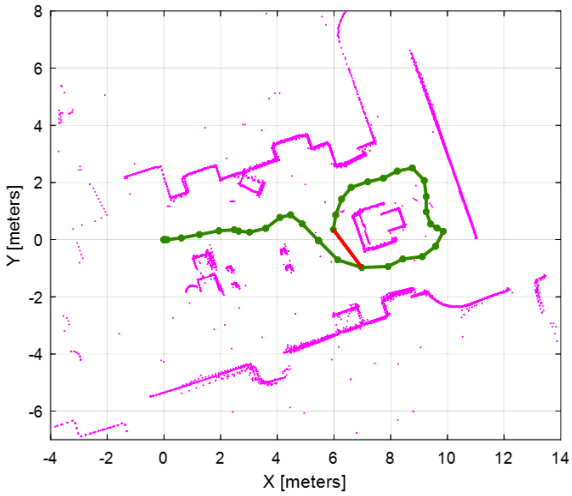

Figure 5. Detection of first loop closure

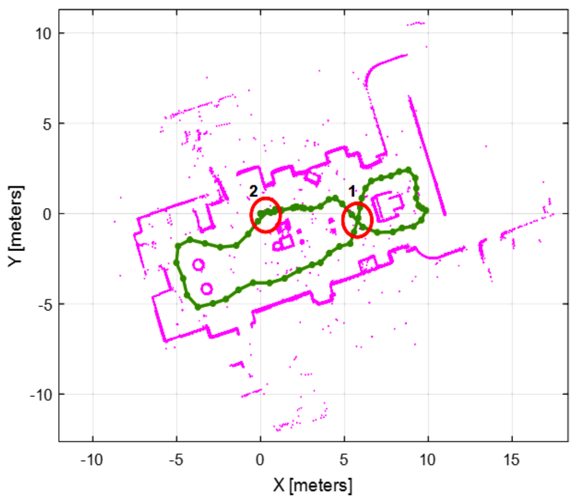

Figure 6. Two loop closures in final build map

3.3. Summary

In this section we presented the results of a MATLAB simulation using SLAM algorithm. We started with pose graph for first 15 scans, and then we showed first loop closure. All of scans are combined to create final map and robot trajectory shown in Figure 6. Using optimized scans and poses, we also built an occupancy map.

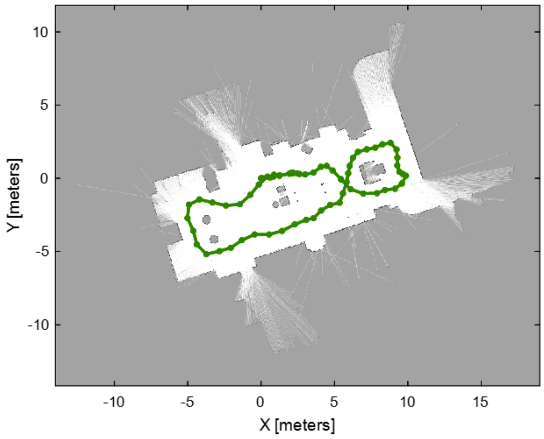

Figure 7. Occupancy map

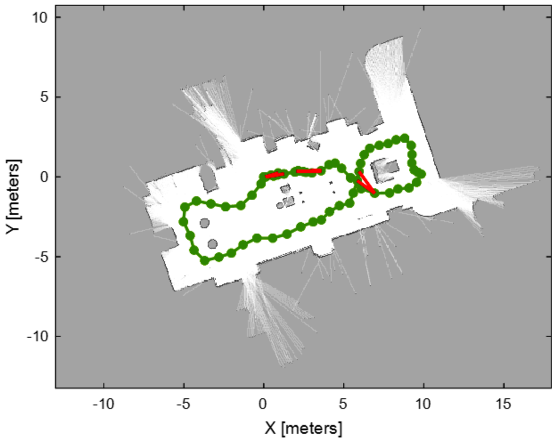

Figure 8. Loop closure in occupancy map

4. CONCLUSION

In this paper, we introduced the concept of localization, which is an essential component of self-driving cars. We illustrated state-of-the-art techniques for locating vehicles using a camera and LIDAR. We were concerned about its accuracy. Then we discussed SLAM method, that can give position of a car while simultaneously building a map of environment. Some of these approaches, such as Visual SLAM, IV-SLAM, LIDAR SLAM and visual-LIDAR fusion SLAM are discussed. We illustrated accuracy and robustness of SLAM solutions in last section by implementing LIDAR SLAM algorithm in MATLAB and showing the results. In the future, we will try a hybridized implementation of SLAM algorithm using camera and LIDAR fusion. We will also study several approaches to improving algorithm's performance.

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