LiDAR-based Localization for Autonomous Vehicles – Survey and Recent Trends

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***Abstract*—Autonomous driving technology has gained significant interest recently due to its potential for efficiency, convenience, and safety. Within this context, localization, which aims to determine the precise location of the vehicle, is a crucial technique for the operation of autonomous vehicles. Among various localization techniques that have been proposed, LiDAR has gained significant attention for its ability to provide high-quality 3D data and its resistance to light variations. Consequently, LiDAR sensor-based localization has emerged as a fundamental approach in autonomous navigation systems. This paper reviews research efforts related to LiDAR-based localization. We categorize these efforts based on two main criteria: *(1) Sensor Data Usage Method*, *(2) Map Utilization Method*. We aim to analyze the potential and limitations of each approach, understand current research trends, and suggest future directions for research in this field.**

***Index Terms*—LiDAR, Localization, Mapping, Autonomous vehicles, SLAM**

I. Introduction

Autonomous vehicle technology is rapidly gaining attention due to its potential to revolutionize various aspects of transportation. Companies such as Google's Waymo, Intel's Mobileye and Hyundai's Motional are developing this technology. There are several reasons for the growing need for autonomous vehicles. First, autonomous driving can significantly improve traffic management and convenience. This convenience extends to individuals who are unable to drive, allowing them to travel independently. Additionally, human errors cause a significant number of accidents. According to the NHTSA, urban traffic fatalities increased by approximately 60 % over the past 10 years, with 32 % of these fatalities involving alcohol-impaired driving [1].

To achieve high performance in autonomous driving, localization plays a significant role in autonomous driving. It is a crucial technology that enables autonomous vehicles to accurately determine their position, allowing them to drive safely on the road. Fig. 1 illustrates the pipeline of how autonomous driving is processed. Without accurate localization, an autonomous system cannot properly do next steps such as

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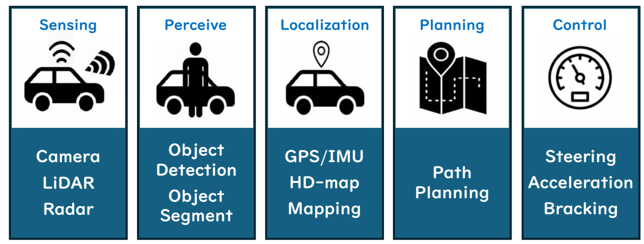


Fig. 1: Autonomous Vehicle's Pipeline

path planning, speed control, and braking. This can lead to significant problems to an autonomous system. For instance, localization error can cause a vehicle to misunderstand its position, leading to potential collisions or traffic disturbances. For an autonomous vehicle system to be reliable under any environmental conditions, it has to achieve accuracy of around 10 cm. This high level of precision is essential for the vehicle to navigate safely and efficiently, avoiding obstacles and staying within its designated path.

Achieving such accuracy involves sophisticated technologies and algorithms that process sensor data, such as *LiDAR, radar, GPS, and cameras*, to continuously update the vehicle's position in real time. Among various localization techniques, LiDAR has gained significant attention due to its exceptional capabilities in providing high-resolution 3D data. LiDAR operates by emitting laser pulses and measuring the time it takes for the reflections to return, creating detailed 3D data, *Point Cloud*. This technology is highly valued for its robustness under various lighting conditions [2], making it a fundamental sensor for localization in autonomous vehicles. The goal of this survey is to review research efforts related to LiDAR-based localization.

We categorize these efforts based on two main criteria:

1) *Sensor Data Usage Method*
   - LiDAR-only vs. Sensor fusion
2) *Map Utilization Method*
   - Global Map vs. Local Map

Table I shows a summary of the categorization. Then, we analyze the potential and limitations of each approach. Finally, we discuss recent changes and provide future directions.

II. Background

In this section, we will explore techniques for LiDAR-based localization. We will start by explaining the concepts of mapping and localization, followed by a discussion of point cloud registration, a technique used in LiDAR-based mapping and localization.

A. Mapping & Localization

Mapping is an essential component for enabling autonomous vehicles to navigate safely and effectively in unknown environments. Just like humans find their way using maps, autonomous vehicles also rely on maps for navigation. However, without a pre-existing map, the navigation process can be significantly downgraded.

Mapping is the process of generating an accurate map of the surroundings by using various sensors, especially when a prior map is unavailable. This map plays a crucial role in helping the vehicle determine its own location, recognize important landmarks, and ensure safe navigation. Based on the map created during the mapping process, the autonomous vehicle can identify landmarks and calculate and estimate its path. The map also aids in identifying potential obstacles, enabling the vehicle to adjust its path accordingly and avoid collisions. In short, mapping forms the foundation upon which safe and reliable autonomous driving is built, guiding the vehicle through both familiar and unfamiliar environments with precision and confidence.

B. Point cloud registration

Point cloud registration is the process of calculating the transformation matrix for the same model, captured from different perspectives. Once the transformation matrix is determined, the point clouds are aligned into a common coordinate system and stitched together [3]. This process is crucial for tasks such as 3D reconstruction, object recognition, robot positioning and navigation, and automatic map building. The Iterative Closest Point (ICP) [4] and Normal Distribution Transform (NDT) [5] algorithms are fundamental methods used for point cloud registration.

One of the key factors in achieving better registration is determining an accurate initial guess for the transformation matrix, as poor initial guesses can lead to the problem of local minima. To address this, coarse registration is typically used to estimate the initial guess, followed by fine registration to refine the alignment [3]. In cases where HD maps or GPS signals are available, precise position information can be obtained, allowing for a good initial guess. This helps to avoid the issue of local minima, leading to more accurate and reliable registration.

III. LiDAR-Based Localization: A Review

In this section, we will provide an overview of various methodologies related to LiDAR-based localization. Given the extensive research in this area, we will categorize LiDAR-based localization methods into two key aspects:

1) *Sensor Data Usage Method*: This includes approaches that rely on LiDAR data, which can be independent of other sensors *(LiDAR-only localization)* and those that combine LiDAR with other sensors *(Sensor fusion localization)*.
2) *Map Utilization Method*: This encompasses techniques based on Global Map, leveraging *prior High-Definition (HD) maps* as well as those that use *Local Map* using collected sensor data.

This categorization clarifies the unique characteristics of each approach, helping identify the most suitable technology for specific applications

A. Sensor Data Usage - LiDAR-only

LiDAR-only localization can operate independently without relying on other sensors when they (e.g., cameras, GPS, or radar) are unavailable. This method is computationally efficient compared to multiple sensor methods as it focuses on processing data from a single source. It can reduce complexity and computational load, allowing for faster processing. This independence from other sensors simplifies the system and reduces its susceptibility to other sensors' failure or inaccuracy [14].

For example, the purpose of the KISS-ICP [6] is to provide a simple yet effective localization system. The system focuses on reducing complexity by using minimal parameters, eliminating the need for additional sensors like Inertial Measurement Unit (IMU). CT-ICP [7] introduces a technique that allows for continuous-time odometry and robust registration, even during high-frequency motions. This method compensates for distortions in scan data due to rapid movement, enhancing localization accuracy without the need for additional sensors [8], [9], [14].

However, there are some problems with LiDAR-only method. Firstly, LiDAR is sensitive to adverse weather conditions such as fog, rain, and snow [20]. In such conditions, the laser signals can be distorted or scattered, leading to degraded quality of the collected data. This can reduce the accuracy of the generated 3D point clouds, which can cause errors in localization and potentially affect the safety of autonomous systems. Additionally, LiDAR has a limited sensing range, particularly when detecting objects at long distances [21]. As a result, LiDAR-only systems may struggle to accurately identify and track distant objects, reducing overall effectiveness in some applications.

B. Sensor Data Usage - Sensor fusion

While LiDAR-based localization is advantageous due to its high-resolution 3D point cloud generation, it has some limitations. It requires support from additional sensors. LiDAR-based localization with additional sensors can be divided into two categories: sensor fusion and LiDAR-Inertial methods. Sensor fusion is the process of integrating data from multiple sensors to produce more accurate, reliable, and comprehensive information [22]. LiDAR Inertial method integrates LiDAR with IMU sensors. Kim et al. [10] and Wu et al. [11] conducted localization using LiDAR-Inertial Odometry (LIO), which is

TABLE I: Categorized LiDAR-based Localization method

Mapping	Sensor Usage	Pros	Cons	Reference
Local Map	LiDAR-only	- Achieves independence from other sensors - Reduces complexity and computational load	- Sensitive to adverse weather conditions - Struggles with long-range object detection	[6], [7], [8], [9]
	LiDAR Inertial	- Improves pose estimation and alignment - Handles dynamic environments and fast motion - Compensates for sensor drift	- Increases complexity due to added IMU - Requires calibration between LiDAR and IMU	[10], [11]
	Sensor Fusion	- Combines strengths of multiple sensors - More robust in complex or dynamic scenarios - Provides better accuracy and redundancy	- Increased complexity and computational demands - Requires synchronization and calibration - Each sensor contributes its own noise	[12], [13]
Global Map	LiDAR-only	- Provides centimeter-level accuracy - No need for external sensors - Efficient for known/static environments	- Requires regular updates to HD maps - Struggles in changing environments without updates - Dependent on pre-existing maps	[14], [15], [16]
	LiDAR Inertial	- Supports robust initial pose estimation - Provides resilience in sensor-limited conditions	- Higher system complexity with IMU integration - Dependent on reliable IMU and sensor fusion algorithms - Not as useful in open areas with strong GPS signals	[17],
	Sensor Fusion	- Provides superior accuracy in complex environments - Overcomes limitations of individual sensors	- Adds significant computational and system complexity - Requires extensive sensor calibration and fusion algorithms - Potentially higher cost and power consumption	[18], [19]

part of the LiDAR inertial method. The difference between sensor fusion and LiDAR Inertial is that LiDAR Inertial only depends on IMU, while sensor fusion can integrate many other sensors, such as radar and cameras.

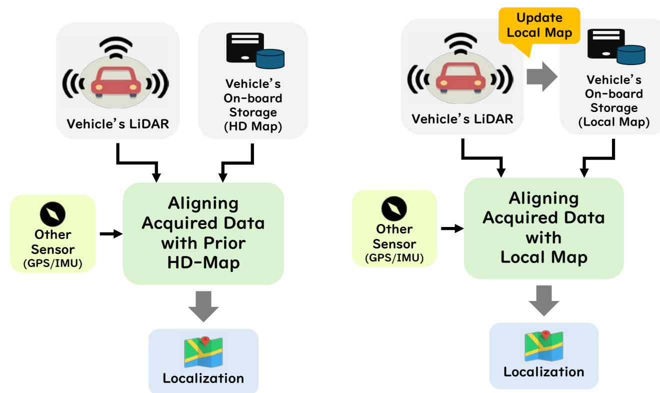
By combining each sensor's strengths, sensor fusion compensates for the limitations of individual sensors. For example, Lin et al. [12] demonstrate that LIO subsystem constructs the geometric structure of the map, while the Visual-Inertial Odometry (VIO) subsystem renders the texture of the map. The main advantage of this sensor fusion approach is its ability to overcome the limitations of individual sensors. It not only provides enriched data but also helps overcome the limitations of each sensor. Another example is Boche et al. [13], which combines LIO and VIO. It proposes a new LiDAR-based residual formulation that generates consistent maps without requiring time-consuming data association processes like ICP. Some method combines LiDAR with radar sensors, using the radar's long range sensing capability [19].

However, using and integrating many sensors simultaneously increases the complexity of systems. The process of fusing data from various sensors can lead to increased hardware and software demands, requiring more resources and effort in design and implementation. Additionally, noise and errors produced by each sensor during the fusion process can significantly impact the final results.

C. Map-based - Global Map Localization

Global Map Localization is a technique that relies on prebuilt HD maps to estimate the position of a vehicle. Fig. 2a illustrates the process of localization using a global map. It compares sensor data with the HD map to evaluate the vehicle's current location [23]. An HD map includes detailed data such as the layout of roads and buildings as well as finer details like lane markings, traffic signs, and even curbs [24]. Using the prior map method plays a critical role in autonomous driving by providing a highly detailed, static representation of the environment.

These rich environmental details allow for precise localization, often achieving centimeter-level accuracy, which is essential for ensuring the safety and reliability of autonomous vehicles. Additionally, since the map is static, transforming each data point's coordinate system to the map's reference frame is straightforward, allowing for faster calculations [16]. Moreover, a prior HD map helps with localization when other sensors are unavailable. For instance, Tao et al. [18] demonstrate that when a vehicle is inside the tunnel and GPS is unavailable, the HD map can still support localization. Efraim et al. [15] use LiDAR and camera to achieve drift-free localization and precise point cloud registration. Another case is Song et al. [17], which uses LiDAR inertial localization with a prior map. These methods help improve initial pose estimation and enhance localization accuracy.



(a) Global Map's Pipeline

(b) Local Map's Pipeline

Fig. 2: Comparison of (a) Global Map's Pipeline and (b) Local Map's Pipeline.

However, using HD maps comes with its own set of challenges. To maintain their accuracy and relevance, HD maps must be regularly updated to reflect environmental changes, such as new road layouts, construction, or modified traffic signals. This updating process can be both costly and time-consuming, as it often requires new data to be collected, processed, and integrated into the existing map.

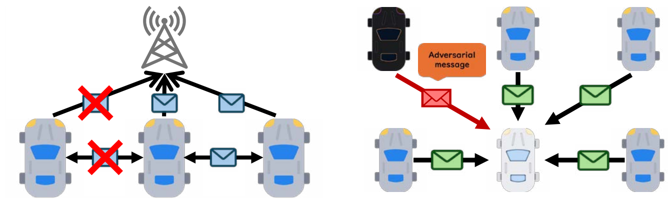
D. Map-based - Local Map Localization

Local Map Localization involves using sensor data to create a local map through mapping and then using a local map for localization. Fig. 2b shows how localization is performed using a local map. SLAM is one of the methods that use the local map for localization. It is a technique that enables a vehicle to create a map of an unknown environment and simultaneously determine the location of the vehicle within the map [25]. Unlike Global Map Localization, SLAM dynamically constructs the map in real-time using sensor data. Recently, LiDAR has become the primary sensor for SLAM due to its wide field of view and high precision in distance measurements [26]. SLAM provides significant flexibility and autonomy, enabling vehicles to navigate in unknown or changing environments. It allows vehicles to be highly adaptable to dynamic situations. For example, Isaacson et al. [8] show autonomy without relying on pre-existing maps. It steps further by leveraging neural implicit representations, which enable it to handle complex environments more efficiently.

However, performing pose estimation, there is no accurate global map at the start. Therefore, in situations where the GPS signal is weak, localization must rely solely on internal sensors. In another case, the errors that occur from each sensor accumulate over time, which is known as drift. This drift can degrade the accuracy of pose estimation. If the pose estimation is inaccurate, it can negatively impact the accuracy of both the mapping and localization in the SLAM system. Additionally, LiDAR-SLAM requires significant computational resources due to the large volume of 3D point clouds. Real-time processing and updating require considerable computational resources due to their inherent complexity. Thus, the LiDAR Odometry and Mapping (LOAM) [9] method was introduced to improve the real-time performance of SLAM. It can enhance real-time capabilities by aligning only feature points during point cloud registration.

IV. Recent Works

A single-source system uses LiDAR information collected from a single vehicle. In this approach, the vehicle independently collects LiDAR data to perceive its surroundings or estimate its position. A multi-source system refers to one that integrates LiDAR information collected from multiple vehicles. Most localization systems aim to localize independently and accurately. However, single-source sensors have several limitations. For instance, LiDAR range limitations, object occlusion, and blind spots can make a single-source system unreliable. In this case, it causes misperception or detection failures leading to an unreliable system [27]. Lastly, HD maps are often criticized for their high costs and maintenance difficulties, making them impractical. To address these issues, multi-source perception has emerged as an alternative, and many recent studies have focused on this area [28]–[33]. In multi-source perception, many vehicles communicate with each other and share data, allowing them to gain a broader and more accurate view of their surroundings. However, a significant issue in studies on multi-source perception is that the following aspects are often overlooked.



(a) Network Error **(b)** Adversarial

Fig. 3: The case of multi-source perception problems

A. *Lack of Validation under Unstable Network Conditions*

Most multi-source systems lack validation under unstable network conditions. While some papers consider network environments in multi-source systems [34], most do not account for network conditions. Fig. 3a illustrates the scenario when the network is not functioning properly. When vehicles share captured data, network conditions must be considered, as real-world networks are highly complex and unpredictable. Otherwise, the accuracy and real-time performance may not be guaranteed in cases of poor network conditions. Incorporating additional evaluation criteria related to network conditions is necessary. For example, experiments under congestion, high packet loss, or limited bandwidth would help build a more robust system.

B. *Insufficient Protection Against Malicious Attack*

There is insufficient protection against malicious or faulty data exchanges. In autonomous driving, the accuracy of localization and perception is important as it is directly related to safety. Multi-source perception significantly improves accuracy. However, the problem arises when the information from each source is inaccurate or subjected to malicious attacks. Fig. 3b illustrates the scenario of an attack from a malicious vehicle. Most research on multi-source perception does not consider these issues. Adversarial attacks, such as adding spoofed obstacles or walls, can cause incorrect driving decisions and lead to collisions [35]. However, these factors are often overlooked. Although recent papers have addressed these adversarial attacks [36], much more research is still necessary.

V. Conclusion

In this paper, we surveyed various LiDAR-based localization techniques. While each approach has its strengths, they also have significant challenges. Recent advancements in multi-source systems show potential to address some of these challenges but still face issues like network reliability and data security. Most research focused on improving the performance of localization and perception. However, a large amount of research does not consider diverse problem scenarios, which remains a significant issue. To resolve these challenges, future research should focus on improving the reliability and robustness of LiDAR-based localization in autonomous systems.

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