LiDAR-GNSS Fusion to Initiate Localization at Intermediate Points on a 3D Point Cloud Map

Abhishek Thakur*, C.A. Rakshith Ram*, Srivishnu Sathvik and P. Rajalakshmi
Department of Electrical Engineering, Indian Institute of Technology Hyderabad, India
* These authors contributed equally to this work.
email:{ee20resch11014, sm22mtech12003, ee24mtech02004}@iith.ac.in, raji@ee.iith.ac.in

2024 IEEE 100th Vehicular Technology Conference (VTC2024-Fall) | 979-8-3315-1778-6/24/$31.00 ©2024 IEEE | DOI: 10.1109/VTC2024-Fall63153.2024.10757568

Abstract*—LiDAR map-based localization and navigation play a crucial role in autonomous navigation, especially in GNSS-denied areas, by matching LiDAR data with a 3D point cloud map in real time. However, initiating localization from intermediate points on the map, distant from the origin, presents challenges. Typically, localization begins from the map's origin, where algorithms can easily match current points to those near the origin. Challenges arise when starting from intermediate points, where the algorithm tries to match the current points' features with those near the origin of the point cloud map. This mismatch can cause localization failure, leading to what is popularly known as the robot kidnapping problem. To tackle this challenge, we propose a solution involving the creation of unique nodes on the point cloud map by fusing LiDAR and GNSS data. Subsequently, live GNSS data is utilized to identify the nearest node, and the corresponding initial pose is published to initiate the localization problem at intermediate points on the map. Extensive real-time testing of this algorithm has been conducted at the IIT Hyderabad campus. The code for the same will be released at: *https://github.com/Rakshith-Ram/Localize_Anywhere

***Index Terms*—LiDAR, 3D Map, Localization, Autonomous Navigation, LiDAR-GNSS Fusion.**

I. Introduction

Autonomous vehicles rely heavily on precise localization and navigation systems to operate effectively in diverse environments. Among the various technologies utilized for this purpose, LiDAR map-based [1], [2] and GNSS-based positioning is widely used. However, achieving accurate localization using GNSS sensors requires an expensive RTK connection and is limited to a particular range. LiDAR map-based localization algorithms, providing centimetre-level accuracy, are widely employed for localization and navigation in GNSS-denied areas or where the GNSS signal is weak and imprecise. However, traditional LiDAR-based localization encounters significant challenges, especially when initiating localization from intermediate points on the LiDAR map rather than from the map's origin [3], [4], a scenario often referred to as the robot kidnapping problem. This issue arises when the localization algorithm inherently tries to align features of current LiDAR points with those of the map at the origin, resulting in localization failures. Due to this issue, LiDAR map-based localization and navigation are typically employed for fixed routes with predetermined start and goal positions. The sensor fusion approach can be applied to overcome the limitations of the localization algorithm by initiating localization from intermediate points on the 3D point cloud map. Our method combines LiDAR and low-cost GNSS data to generate 3D maps with unique nodes.

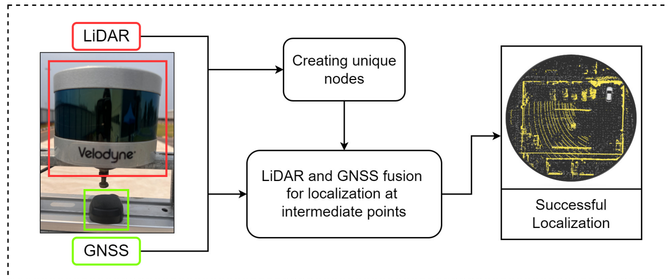

Fig. 1: System overview of the proposed algorithm.

This paper proposes a LiDAR-GNSS data fusion-based approach using a low-cost GNSS sensor to address the localization challenge at intermediate points distant from the origin. The structure and functionality of the proposed algorithm are shown in Fig. 1. This solution facilitates the initiation of navigation for autonomous vehicles from intermediate points on the map to the desired goal position. The major contributions of this paper are as follows:

- We propose a novel approach by creating unique node identities on the 3D point cloud map, leveraging LiDAR and GNSS data sensor fusion techniques to enhance localization and navigation.
- By integrating LiDAR and GNSS data, we identify the nearest node to the vehicle's current position and publish the corresponding initial pose. This approach enables the localization algorithm to initiate from intermediate points on the map in real-time.

The paper is structured as follows: Section II reviews the literature related to this work. Section III describes the methodology to fuse LiDAR and GNSS data for initiating localization at intermediate points on a 3D point cloud map. Section IV presents the results and analysis. Section V concludes the study.

II. Literature Survey

The 3D map created by LiDAR has each space point in 3D coordinates (x, y, z) with respect to the map's origin [12]. The LiDAR-based localization algorithm aligns the current point cloud data from the LiDAR sensor with a point cloud map to determine the position and orientation of robots [6]. In [7],

979-8-3315-1778-6/24/$31.00 ©2024 IEEE

the author initiates localization and navigation from the map's origin. However, the algorithm in [7] fails to localize when the vehicle starts from any intermediate position away from the origin. In [8], the author discusses the robot kidnapped problem in a 2D occupancy grid map created by a robot equipped with a 2D-LIDAR sensor and cliff sensor tested in a small indoor environment. However, there is a lack of discussion on localization, which is far from the origin. In [9], the author introduces a series of visual keyframes using 2D LiDAR and camera sensors to the environment map with LiDAR in the SLAM process to address the robot kidnapped problem. However, this method doesn't address situations where similar image features are not found when the robot starts far from the origin points. In [10], a method is presented to efficiently tackle the kidnapped robot problem in small indoor rooms using Monte Carlo localization (MCL) by dynamically adjusting particle generation and distribution based on time variation, it effectively narrows down potential robot locations. In [11], the author provides a survey on global LiDAR localization for mobile robots, discussing open challenges and promising directions. Localization of autonomous vehicles using LiDAR sensors at intermediate points far from the origin of a 3D point cloud map is still a challenge, which is addressed in this paper.

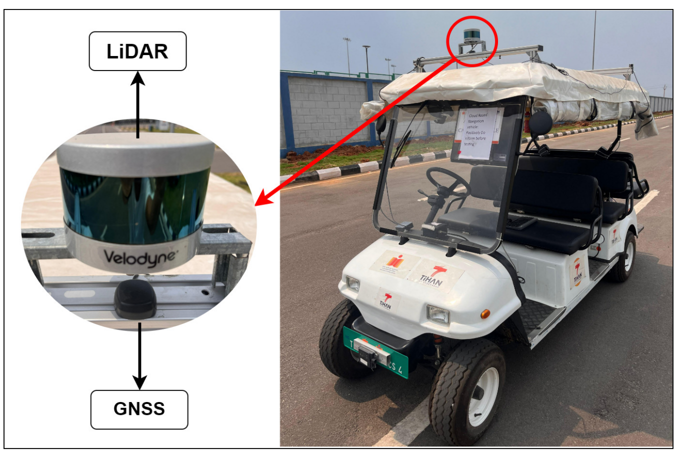

Fig. 2: The vehicle equipped with LiDAR and GNSS sensors, on which our algorithm was tested.

III. Methodology

The sensor fusion approach effectively integrates data from LiDAR and low-cost GNSS to create 3D maps. By combining the precise spatial data from LiDAR with the positional information from GNSS, the system compensates for the limitations of the localization algorithm, allowing it to initiate localization from intermediate points on the 3D point cloud map. A golf cart mounted with LiDAR and GNSS sensors is used in this experiment for mapping and testing the localization algorithm, as shown in Fig. 2. The methodology is described in detail in this section.

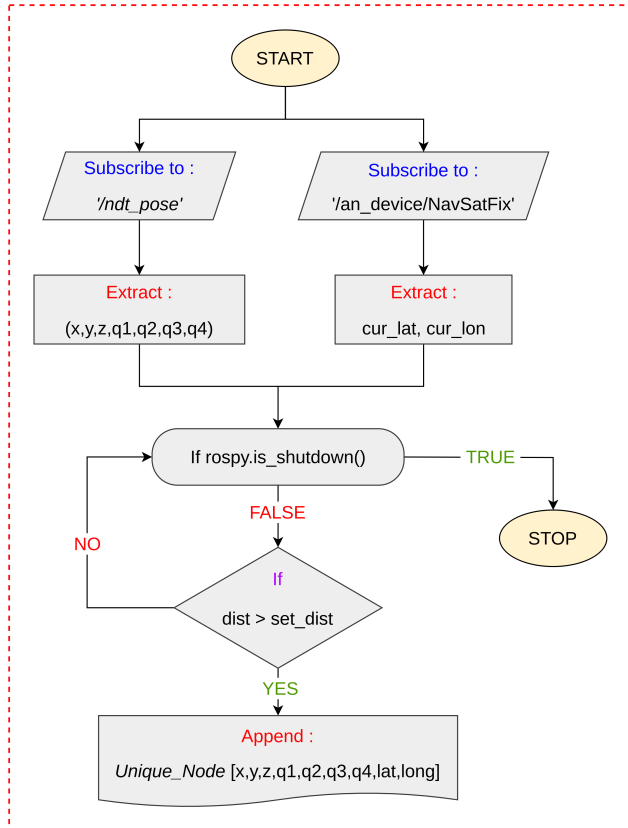

Fig. 3: Flowchart for Unique Node creation using LiDAR pose and GNSS global position on 3D point cloud map.

A. *LiDAR and GNSS Fusion Approach*

The LiDAR and GNSS fusion approach integrates data from LiDAR and GNSS sensors to enable vehicle localization at any intermediate point within the vast point cloud map. Existing LiDAR-based localization algorithms fail to initiate localization at intermediate points because they typically initiate localization from the map's origin. In our algorithm, a unique node is created on the 3D point cloud map, containing GNSS data: latitude and longitude, as well as the corresponding position and orientation of the vehicle on the point cloud map.

B. *Creation of Unique Nodes on point cloud map*

A 3D point cloud map is generated using LiDAR odometry and mapping algorithms by stitching continuous frame LiDAR data [12]. Unique nodes are then created on the 3D point cloud map, each consisting of latitude and longitude coordinates from the GNSS sensor, along with their corresponding pose and orientation of the vehicle on the map. A ROS topic, "/ndt_pose", is published by the Simultaneous Localization and Mapping (SLAM) algorithm to provide the vehicle's current position and orientation, while GNSS data is published in the ROS topic "/an_device/NavSatFix", as depicted in Fig. 3. Nodes are created at fixed threshold intervals. When the

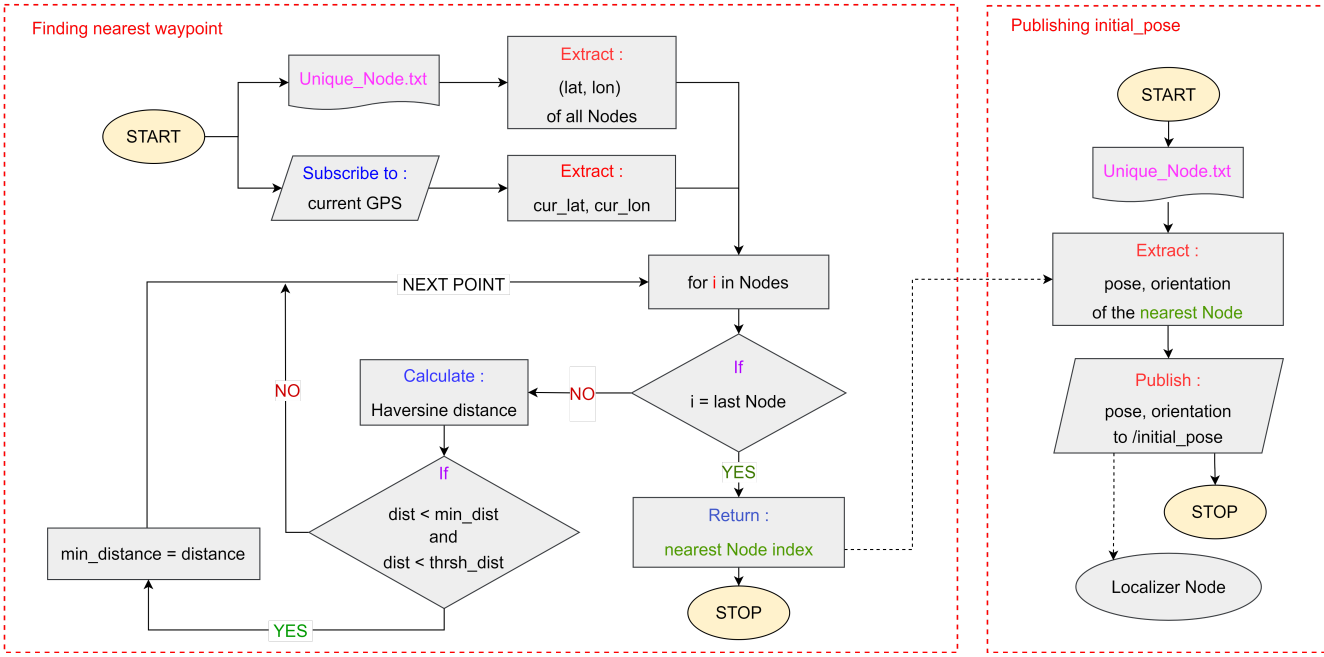

Fig. 4: Flowchart for finding the nearest unique node using LiDAR-GNSS fusion and publishing the initial pose data.

vehicle travels a distance greater than a certain fixed threshold (1.5m) compared to its previous position on the map, data, i.e., local position and orientation from the localization rostopic and global position from the GNSS sensor via ROS topics, are appended. Subsequently, a unique node is created on the map and stored in a file. The $i-th$ index of a unique node is stored and represented as:

$$UN_i = [x_i, y_i, z_i, q_{x,i}, q_{y,i}, q_{z,i}, q_{w,i}, lat_i, lon_i] \quad (1)$$

Here, i varies from 1 to n, $[x_i, y_i, z_i], [q_{x,i}, q_{y,i}, q_{z,i}, q_{w,i}]$ represent the local position and orientation with respect to the map frame, and $[lat_i, lon_i]$ denote the corresponding latitude and longitude.

C. Finding Nearest Node

Once the map with unique nodes containing GNSS data is created, the vehicle has to be localized on the map in real time to initiate navigation. Let the vehicle be at any unknown intermediate points on the path. From the GNSS sensor, the current latitude and longitude of the vehicle is taken. Then, after converting the current latitude and longitude from degrees to radians, the difference in latitude and longitude between the current GNSS coordinate is calculated with each unique node as:

$$\Delta lat = lat_{i+1} - lat_i \quad (2)$$

$$\Delta lon = lon_{i+1} - lon_i \quad (3)$$

The chord length relative to the radius of the earth sphere is calculated as:

$$a = \sin^2\left(\frac{\Delta lat}{2}\right) + \cos(lat_i)\cos(lat_{i+1})\sin^2\left(\frac{\Delta lon}{2}\right) \quad (4)$$

The angular distance in radians along the surface of the earth is calculated as:

$$c = 2\arctan\left(\frac{\sqrt{a}}{\sqrt{1-a}}\right) \quad (5)$$

The distances between the GNSS coordinates are calculated using the Haversine formula.

$$d = R \times c \quad (6)$$

Here, R represents the radius of the Earth. The distance between the current GNSS position and each node, starting from the first node, is calculated. The minimum distance, initialized with (∞), is updated in a loop when the distance is less than the previous minimum distance. Once the distance is less than the minimum distance and the distance threshold, the nearest node on the map, closest to the vehicle, is determined as shown in the flowchart diagram in Fig. 4.

D. Publishing Initial Pose

The unique node is determined, where each node contains a local position and orientation concerning the LiDAR map frame. Using this information, an initial pose topic of the message type "geometry_msgs/PoseWithCovarianceStamped" is created. The initial pose topic contains a header, pose, and orientation. This topic is then subscribed to by the localizer node to initiate the point cloud matching process on the map for localizing the vehicle, as shown in Fig. 4. The matching score of the current point cloud with the map cloud is calculated from the initial pose published by normal distribution transform using this equation [3]:

$$S = \sum_{i}^{N} \exp \frac{-({x'}_i - \mu_i)^\top \mathbf{\Sigma}_i^{-1} (x'_i - \mu_\mathbf{i})}{2} \quad (7)$$

Test point	Unique Node Id number	Distance from map's origin (meter)	Traditional NDT [6]		LiDAR+GNSS (Ours)		
			Matching time (ms)	Localized	Code execution time (ms)	Matching time (ms)	Localized
1	1	0.20	35.64	✓	4.3992	23.50	✓
2	2	5.07	46.92	✓	4.4403	33.51	✓
3	3	9.45	–	×	4.4906	48.75	✓
4	6	16.37	–	×	4.4922	54.36	✓
5	38	60.72	–	×	4.5404	55.26	✓
6	60	99.80	–	×	4.5925	53.62	✓
7	155	251.24	–	×	4.6815	52.05	✓
8	400	497.54	–	×	4.8598	55.65	✓
9	495	537.15	–	×	4.9318	55.70	✓
10	738	734.39	–	×	4.9905	55.78	✓

TABLE I: Comparison of localization performance between Traditional NDT and Our Algorithm across 10 test points.

Through iterative scan matching and optimization techniques,

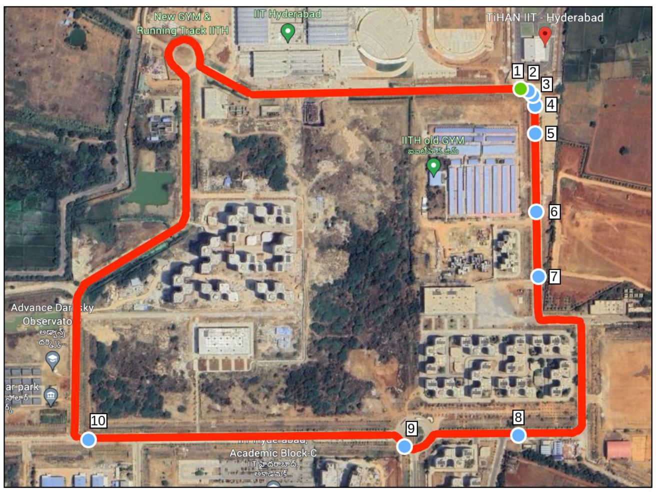

Fig. 5: Satellite map with path traversed by the vehicle and 10 testing locations marked in blue.

the algorithm aligns the sensor data with the map to estimate the robot's position and orientation accurately. The score is optimized to determine the accurate position and orientation of the vehicle by iterating using Newton's non-linear optimization:

$$x'_{i+1} = x'_i - \frac{f'(x'_i)}{f''(x_i)} \tag{8}$$

IV. Results and Analysis

The sensors employed in the vehicle for testing include a 16-channel Velodyne VLP-16 LiDAR and an Advanced Navigation (Spatial) GNSS sensor. Computation is facilitated by the Robot Operating System (ROS) framework, running on an HP i7-1165G7 system equipped with 16GB of RAM. A 3D point cloud map of a 2.25 km route is created inside the IIT Hyderabad campus near TiHAN testbed [13]–[15] using a Velodyne 16-channel LiDAR, as illustrated in Fig. 6. The map consists of 1495 unique nodes spaced equidistantly at intervals of 1.5 meters. Each node stores global position data along with its corresponding local position and orientation as depicted in Fig. 6, Fig. 7.

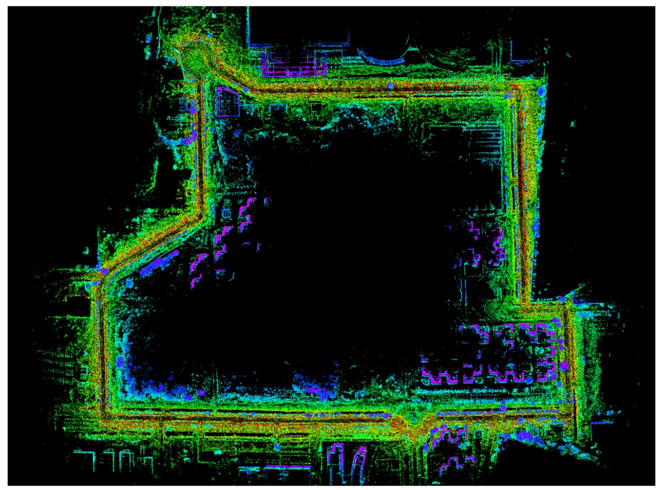

Fig. 6: 3D point cloud map with unique nodes along the path, constructed using LiDAR and GNSS data.

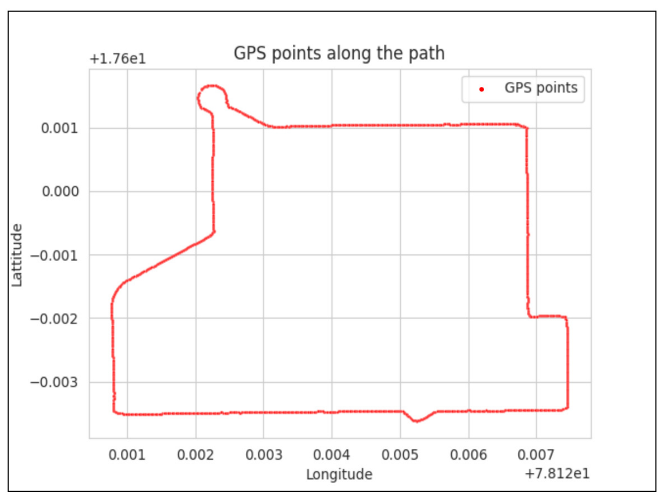

Fig. 7: Plot of GNSS data from Unique Nodes along the path.

To evaluate localization performance, traditional NDT localization [4] and our approach are tested at ten designated test points, as indicated in Fig. 5. At test points 1 and 2 near the origin, the traditional NDT localization algorithm successfully

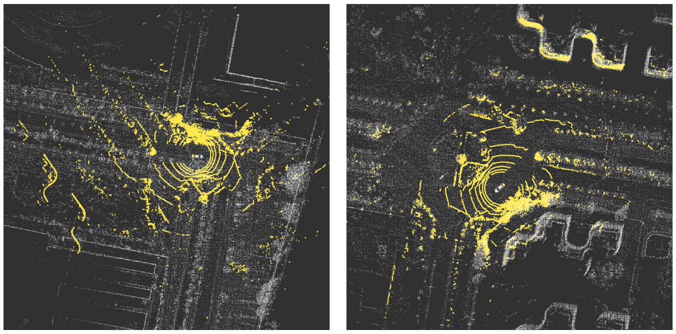

Fig. 8: Traditional localization algorithm failed to localize (left), whereas our algorithm successfully localized (right) at Test Point 9.

localizes the vehicle. However, as a turning occurs at the 3rd test point, and it's farther from the origin, the traditional NDT method fails to localize the vehicle at subsequent test points, as indicated in Table I. In contrast, our approach utilizes LiDAR and GNSS data to identify the nearest node and provide the corresponding pose as the initial pose to the localizer node. By optimizing using Newton optimization, our algorithm successfully localizes the vehicle at all test points, as shown in Table I. The column code execution time in Table I indicates the time to determine the nearest node and publish the initial pose topic. The matching time represents the localization algorithm's time to optimize the NDT score for accurate vehicle localization. Fig. 8 shows a test point 9, where the traditional localization algorithm failed to localize when initiated from the origin. In contrast, our algorithm succeeded in the localizing task using the initial pose determined by the sensor fusion approach. Our approach demonstrates superior performance in localizing the vehicle across various test points compared to traditional NDT.

V. Conclusion

This paper proposes a novel technique based on LiDAR-GNSS sensor fusion to overcome the initialization challenges in localization at any intermediate points on a 3D point cloud map. Unique nodes are created on a 3D LiDAR map, each containing GNSS coordinates and its corresponding 3D local position on the point cloud map. Real-time GNSS data is utilized to identify the nearest node on the point cloud map, and the corresponding pose is then published as the initial pose to the localizer node to initiate the localization process. The algorithm has been tested in real-time on a 3D map covering a 2.25km stretch at the IIT Hyderabad campus. Our algorithm successfully localized even at a distance of 700m from the origin in real-time. While traditional localization algorithms typically work near the origin only, our algorithm demonstrates effectiveness even far from the origin at any intermediate point on the map.

Acknowledgment

This work is supported by the Prime Minister Research Fellowship (PMRF) and DST National Mission Interdisciplinary Cyber-Physical Systems (NM-ICPS), Technology Innovation Hub on Autonomous Navigation and Data Acquisition Systems: TiHAN Foundation at Indian Institute of Technology (IIT) Hyderabad.

References

[1] J. Zhang, S. Singh, "LOAM: Lidar odometry and mapping in real-time," InRobotics: Science and Systems Vol. 2, No. 9, pp. 1-9, 2014.

[2] H. Wang, C. Wang, C. -L. Chen and L. Xie, "F-LOAM : Fast LiDAR Odometry and Mapping," 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Prague, Czech Republic, 2021, pp. 4390-4396, doi: 10.1109/IROS51168.2021.9636655.

[3] A. Carballo et al., "Characterization of Multiple 3D LiDARs for Localization and Mapping Performance using the NDT Algorithm," 2021 IEEE Intelligent Vehicles Symposium Workshops (IV Workshops), Nagoya, Japan, 2021, pp. 327-334, doi: 10.1109/IVWorkshops54471.2021.9669244.

[4] Z. Zhou et al., "NDT-Transformer: Large-Scale 3D Point Cloud Localisation using the Normal Distribution Transform Representation," 2021 IEEE International Conference on Robotics and Automation (ICRA), Xi'an, China, 2021, pp. 5654-5660, doi: 10.1109/ICRA48506.2021.9560932.

[5] A. Thakur and P. Rajalakshmi, "Real-time 3D Map Generation and Analysis Using Multi-channel LiDAR Sensor," 2024 IEEE 9th International Conference for Convergence in Technology (I2CT), Pune, India, 2024, pp. 1-5, doi: 10.1109/I2CT61223.2024.10544111.

[6] Yin-Chiu Kan, Li-Ta Hsu and E. Chung, "Performance Evaluation on Map-Based NDT Scan Matching Localization Using Simulated Occlusion Datasets," in IEEE Sensors Letters, vol. 5, no. 3, pp. 1-4, March 2021, Art no. 5500204, doi: 10.1109/LSENS.2021.3060097.

[7] A. Thakur and P. Rajalakshmi, "LiDAR-Based Optimized Normal Distribution Transform Localization on 3-D Map for Autonomous Navigation," in IEEE Open Journal of Instrumentation and Measurement, vol. 3, pp. 1-11, 2024, Art no. 8500211, doi: 10.1109/OJIM.2024.3412219.

[8] Z. Su, X. Zhou, T. Cheng, H. Zhang, B. Xu and W. Chen, "Global localization of a mobile robot using lidar and visual features," 2017 IEEE International Conference on Robotics and Biomimetics (ROBIO), Macau, Macao, 2017, pp. 2377-2383, doi: 10.1109/ROBIO.2017.8324775.

[9] L. Feng et al., "A Global Localization System for Mobile Robot Using LIDAR Sensor," 2017 IEEE 7th Annual International Conference on CYBER Technology in Automation, Control, and Intelligent Systems (CYBER), Honolulu, HI, USA, 2017, pp. 478-483, doi: 10.1109/CYBER.2017.8446067.

[10] J. Meng et al., "An Efficient and Robust Approach to Solve the Kidnapped Robot Problem Considering Time Variation," 2020 IEEE REGION 10 CONFERENCE (TENCON), Osaka, Japan, 2020, pp. 379-384, doi: 10.1109/TENCON50793.2020.9293778.

[11] Yin H, Xu X, Lu S, Chen X, Xiong R, Shen S, Stachniss C, Wang Y. A survey on global lidar localization: Challenges, advances and open problems. International Journal of Computer Vision. 2024 Mar 6:1-33.

[12] A. Thakur, B. Anand, H. Verma and P. Rajalakshmi, "Real Time Lidar Odometry and Mapping and Creation of Vector Map," 2022 8th International Conference on Automation, Robotics and Applications (ICARA), Prague, Czech Republic, 2022, pp. 181-185, doi: 10.1109/ICARA55094.2022.9738576.

[13] TIAND: TiHAN IITH Autonomous Navigation Dataset [Online]. Available: https://tihan.iith.ac.in/tiand/

[14] N. Kumar, S. Abhilash, A. Thakur et al., "TIAND: A Multimodal Dataset for Autonomy on Indian Roads," 2024 IEEE Intelligent Vehicles Symposium (IV), Jeju Island, Korea, Republic of, 2024, pp. 688-694, doi: 10.1109/IV55156.2024.10588583

[15] TiHAN: TiHAN IITH Autonomous Navigation Testbed [Online]. Available: https://tihan.iith.ac.in/tihan-iith-testbed/