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Real-Time 2D Grid Map Generation for Terrain Traversability Using LiDAR Point Clouds

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***Abstract*—Autonomous navigation in unstructured environments requires efficient terrain mapping to enable safe and adaptive motion planning. This study presents a 2D grid map generation algorithm using geometric features from LiDAR point cloud data, inspired by the terrain Traversability mapping, Navigation and Excavation System (TNES). By computing slope and step height through principal component analysis (PCA) and applying threshold-based traversability scoring, the method eliminates reliance on semantic data. To evaluate the impact of a single sensor component, the generated traversability maps are converted into occupancy grid maps. Experimental validation using outdoor LiDAR data demonstrates 2D occupancy map generation time of 70 ms, which is faster than the sensor's 100 ms input frequency and confirming its suitability for real-time terrain analysis.**

***Keywords-component*—2D Grid Maps, LiDAR, Terrain Traversability, Point Cloud Processing, Occupancy Grid.**

I. INTRODUCTION

Autonomous navigation in unstructured environments presents significant challenges for robots and autonomous vehicles. These environments, often characterized by uneven terrain, obstacles, and unpredictable conditions, necessitate robust mapping and navigation systems. Two-dimensional (2D) grid maps provide a foundational representation for robots to perceive and navigate such environments. These maps are particularly useful for deep-learning-based navigation approaches because they discretize the world into a grid of cells, each representing a specific area in the environment, and assign attributes to these cells based on sensor data, such as occupancy, terrain type, or traversability [1]. This simplified representation allows robots to efficiently process and interpret complex environmental information.

Recent research has explored various approaches to 2D grid map generation, with a focus on improving accuracy, efficiency, and adaptability to dynamic environments. For example, Guan et al. [2]. presented a terrain Traversability mapping, Navigation and Excavation System (TNES) for autonomous excavators operating in complex worksites. Their system extracts terrain features from RGB images and 3D point clouds to create a traversability map, enabling the excavator to navigate challenging terrain features like deep pits and steep hills. This approach highlights the importance of integrating sensor data and real-time updates for accurate mapping in dynamic environments. 2D grid maps facilitate these real-time updates by allowing for efficient modification of cell attributes as the environment changes. For instance, if the excavator encounters a new obstacle, the corresponding cells in the 2D grid map can be quickly updated to reflect this change, enabling the robot to adjust its navigation strategy accordingly.

Flores-Aquino et al. [1] proposed an algorithm for generating 2D grid maps based on "dungeon environments." This algorithm creates maps with random rooms connected by pathways, providing a diverse dataset for training and testing machine-learning-based navigation approaches. The algorithm incorporates attributes such as path existence, optimal paths, and distances, which are crucial for evaluating the performance of navigation algorithms. This work demonstrates the importance of developing algorithms that generate maps with specific attributes tailored to the needs of different navigation tasks.

Other studies have investigated methods for incorporating uncertainty in traversability estimation [3], probing strategies for safe navigation on unknown rough terrain [4], and learning-based approaches for long-range traversability estimation [5]. For instance, Frey et al. [5] introduced the RoadRunner framework, which leverages geometry and semantics with heuristics to estimate terrain traversability for autonomous off-

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road driving. This framework incorporate learning-based methods to improve the accuracy and efficiency of traversability estimation.

Effective navigation in off-road environments also requires accurate trajectory tracking. Hoffmann et al. [6]. presented a nonlinear control law for autonomous automobile trajectory tracking in off-road environments. Their approach considers the orientation of the front wheels with respect to the desired trajectory, enabling more precise control. This research in trajectory tracking is closely related to 2D grid map generation because the accuracy of the map directly influences the robot's ability to follow a planned trajectory.

The generation of 2D grid maps is crucial for various applications, including autonomous driving, search and rescue, and planetary exploration. The introduction above highlights the ongoing development of sophisticated techniques for generating 2D grid maps that enable robots to effectively navigate challenging off-road environments. These techniques include incorporating real-time updates, handling uncertainty, utilizing learning-based approaches, and ensuring accurate trajectory tracking. As robots are increasingly deployed in complex and unstructured environments, the development of accurate and efficient 2D grid map generation techniques remains an active area of research.

While existing research has made significant progress, there is a growing need for methods that can robustly estimate terrain traversability across varying environmental conditions and with minimal computational burden. Relying solely on geometric features from point clouds offers a promising avenue to achieve this. By focusing on geometric features, the effects of different environments and weather conditions on the point cloud data can be systematically studied, leading to a deeper understanding of thier influence on traversability estimations. This knowledge can then be used to develop more robust and adaptable algorithms that capable of generalizing well across different scenarios. Moreover, this approach can potentially reduce computational complexity compared to methods that rely on both geometric and semantic information, making it more suitable for real-time applications on resource-constrained platforms.

This study addresses the aforementioned gap by developing a 2D grid map generation method that leverages the geometric features of point clouds, based on the TNES approach, to efficiently and accurately estimate terrain traversability. The research objective is to create a 2D mapping algorithm that can operate in real-time with minimal computational resources while maintaining high accuracy and robustness in harsh excavation environments.

The remainder of this paper is organized as follows: Section II introduces Terrain Traversability Mapping using the TNES System. Section III describes Geometric Features of Point Clouds, including slope and step height estimation. Section IV explains the conversion of Traversability Maps to Occupancy Maps. Section V presents Results and Discussion, highlighting experimental validation. Finally, Section VI concludes the study with key findings and future directions.

II. TERRAIN TRAVERSABILITY MAPPING USING THE TNES SYSTEM

A. *Overview of Terrain Traversability Mapping*

Terrain traversability mapping involves generating a map that evaluates the ease of navigating various terrains. The terrain Traversability mapping, Navigation and Excavation System (TNES), introduced in [2], utilizes geometric features extracted from point cloud data obtained from LiDAR sensors, along with RGB cameras for visual context. Point clouds provide a detailed 3D representation of the environment, capturing the shape and geometry of the terrain. By analyzing the geometric features of the point cloud, the TNES method can accurately assess the traversability of the terrain, even in challenging environments.

B. *Advantages of TNES*

TNES has several key advantages. It enables efficient geometric traversability mapping by computing terrain features such as slope and step height from point cloud data in real-time, eliminating the need for semantic information while maintaining low computational load for deployment on resource-constrained platforms. It ensures a robust traversability assessment by accurately estimating terrain navigability using geometric thresholds tailored to excavator specifications such as size, weight, etc. Additionally, Its dynamic adaptability allows for adjustable thresholds and parameters (grid map cell size, number of nearest neighbors, slope condition, etc.) to accommodate various excavator configurations and terrain types.

III. GEOMETRIC FEATURES OF POINT CLOUDS FOR TRAVERSABILITY MAP

The terrain is represented as an elevation grid map and is updated in real-time based on incoming point clouds. Each grid cell in the map stores the average height value of the latest p points within this cell, as well as overall information about those points like update time, slope, step height. A geometric traversability score is calculated for each grid cell [2]. The TNES method extracts several geometric features from the point cloud data to generate the traversability map. These features includes:

A. *Slope Estimation*

Each grid cell g is abstracted to a single point $p = \{x, y, z\}$, where x, y is the center of the cell in the global coordinate frame and z is the height value of the grid [2]. The slope s in an arbitrary grid cell g is computed by the angle between the surface normal and the z-axis of the global coordinate frame:

$$s = \arccos(n_z), \quad n_z \in [0, 1] \tag{1}$$

where n_z is the component of the normal $\tilde{n}$ on the z-axis. Similar to [2] [7], Principal Component Analysis (PCA) is used to calculate the normal direction of a grid cell. The covariance matrix C_{cov} of the nearest neighbors of the query grid cell is calculated as follows:

$$
\begin{aligned}
C_{\text{cov}} &= \frac{1}{k}\sum_{i=1}^{k}\left(p_i-\bar{p}\right)\left(p_i-\bar{p}\right)^T, \\
C_{\text{cov}}\,\tilde{v}_j &= \lambda_j\,\tilde{v}_j, \quad j\in\{0,1,2\}, \quad \lambda_i<\lambda_j \text{ if } i<j,
\end{aligned} \tag{2}
$$

where k is the number of neighbors considered in the neighborhood of g, $p_i = \{x, y, z\}$ is the position of the neighbor grid in the global coordinate frame, $\bar{p}$ is the 3D centroid of the neighbors, λ_j is the j-th eigenvalue of the covariance matrix, and $\tilde{v}_j$ is the j-th eigenvector. The surface normal $\tilde{n}$ of grid g is the eigenvector $\tilde{v}_0$ corresponding to the smallest eigenvalue λ_0.

The purpose of the slope estimation is to obtain the shape of the terrain and avoid navigating on a steep surface.

B. Step Height Estimation

The step height h is computed as the largest height difference between the center point p of the grid and its k_0 nearest neighbors [2]:

$$
h = \max\left|p_z - p_{z_i}\right|, i\in\{1,\ldots,k_0\} \tag{3}
$$

where p_z is the height of the grid center, and p_{z_i} are the heights of its k_0 nearest neighbors.

C. Geometric Traversability Estimation

Based on information about the slope and step height of the terrain, a geometric traversability score T_{geo} can be calculated [2]. According to the physical constraints of the mobile platform (excavator in this study), some critical values, s_{cri}, s_{safe}, h_{cri}, and h_{safe}, were established as thresholds for safety and danger detection. The critical slope s_{cri} represents the maximum allowable incline beyond which the excavator's stability, traction, and overall maneuverability are compromised, while the safe slope s_{safe} defines a conservative threshold below which the terrain is deemed reliably navigable. Similarly, the critical step height h_{cri} specifies the maximum vertical displacement that the excavator can safely overcome without risking damage or instability, and the safe step height h_{safe} provides a lower bound that ensures a high level of safety during operation. These thresholds, which are often determined through a combination of experimental testing and simulation studies, serve not only to prevent navigation in hazardous conditions when the surface exceeds the excavator's operational limits but also to reduce unnecessary computational load by quickly identifying areas where the terrain is sufficiently flat. The formula for the geometric traversability T_{geo} for each grid is given by [2]:

$$
T_{geo} = \begin{cases} 0, & \text{if } s>s_{cri} \text{ or } h>h_{cri}, \\ 1, & \text{if } s<s_{safe} \text{ or } h<h_{safe}, \\ \max\Big(1-\Big(\alpha_1\dfrac{s}{s_{cri}}+\alpha_2\dfrac{h}{h_{cri}}\Big),0\Big), & \text{otherwise.} \end{cases} \tag{4}
$$

Here, the weights α_1 and α_2 satisfy $\alpha_1 + \alpha_2 = 1$.

In this formula, α_1 and α_2 are weighting parameters that determine the relative importance of slope (s) and step height (h) in the traversability assessment. These parameters can be adjusted to fine-tune the traversability score based on the specific characteristics of the terrain and the robot's capabilities. For example, in scenarios where slope is a more critical factor than step height, α_1 can be set to a higher value than α_2. Conversely, if step height is more crucial, α_2 can be given a higher weight.

IV. CONVERTING TRAVERSABILITY MAP TO OCCUPANCY MAP

To facilitate the excavator's navigation and path planning, the generated traversability map needs to be converted into an occupancy grid map. This conversion is critical because occupancy grid maps provide a simplified, discrete representation of the environment that is both computationally efficient and compatible with standard navigation and path planning algorithms. This conversion process involves representing the terrain as a grid, assigning traversability scores to each cell, and then applying a threshold to binarize the map into traversable and non-traversable areas. Finally, post-processing techniques are employed to refine the occupancy map. Each detail is provided as follows.

A. Occupancy Grid Representation

The terrain is divided into a grid, where each cell initially stores a continuous traversability score (T_{geo}) derived from slope and step height measurements. Converting this continuous map into a binary occupancy grid simplifies the data by clearly designating each cell as either traversable (free) or non-traversable (occupied). This clear delineation reduces the computational burden during path planning and ensures that the mapping aligns with the specific requirements of our application.

In our work, the occupancy grid representation enables real-time updates, with an average computation time of 70 ms per update. This rapid update capability is critical for surface leveling tasks in dynamic excavation environments where terrain conditions can change quickly. The binary nature of the occupancy grid minimizes the complexities associated with processing continuous data, thereby allowing the path planning algorithm to operate on a stable and easily interpretable map.

Moreover, the simplified free/occupied classification directly supports the use of grid-based planning algorithms, which are well-suited for our surface leveling application. By reducing noise and focusing on a clear thresholding of traversability scores, the occupancy grid format enhances both the efficiency and reliability of autonomous navigation in our real-time system.

B. Threshold-Based Binarization

A threshold ($T_{threshold}$) is applied to the traversability scores:

$$
O(x,y) = \begin{cases} 1, & \text{if } T_{\text{geo}} < T_{\text{threshold}} \quad \text{(non-traversable)}, \\ 0, & \text{if } T_{\text{geo}} > T_{\text{threshold}} \quad \text{(traversable)}. \end{cases} \tag{5}
$$

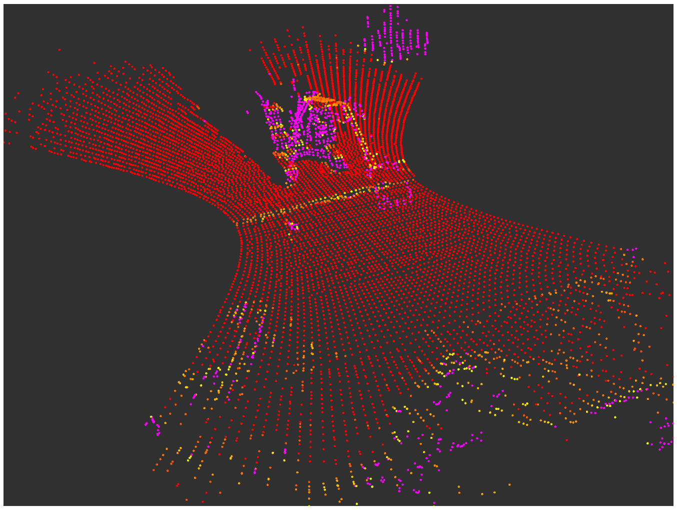

Figure. 1. Single frame from the point cloud dataset.

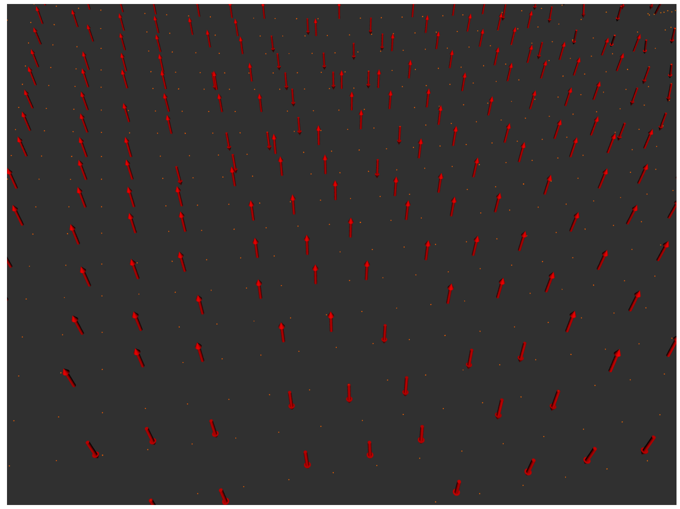

Figure. 2. Surface normals computed from the voxelized point cloud data.

C. Post-Processing

Smoothing techniques, such as morphological operations, are applied to reduce noise in the occupancy map. Small isolated traversable or non-traversable regions can be merged with neighboring regions based on predefined criteria.

V. RESULTS AND DISCUSSION

Lidar's datasets (point clouds) for the surface leveling task were collected to test geometric feature extraction and traversability map generation at the outdoor test site at Korea Construction Equipment Technology Institute in South Korea. An Ouster Lidar OS-0 was selected as the Lidar sensor, and the point clouds were obtained at a frequency of 100 ms. A single frame from the point cloud datasets is shown in Fig. 1.

As the first step of the developed mapping algorithm, voxel grids were applied to each point cloud to downsample, making the data more manageable. The second step involved filtering out the point cloud representing the excavator body from the dataset. Since the excavator's dimensions and posture/position at each timeframe (using body roll, body pitch, body yaw, and boom angle) were identified, filtering out the points belonging to the excavator was straightforward.

Next, the geometric features of the voxelized data were calculated. By computing the covariance matrix for a point and its eight nearest neighbors, the surface normals were determined, as described in Section III, Part A. The results of this process are illustrated in Fig. 2.

After calculating the surface normals, the slope was derived using (1). For step height estimation, the number of neighboring points was set to eight, and (3) was used to compute the step height for each grid cell. The generated traversability map covered an area of 10m × 10m, with a grid resolution of 0.5m × 0.5m per cell. This resolution was chosen based on the bucket size of the excavator, ensuring that each cell represents a manageable working area where non-occupied cells can be easily identified and modified for excavation tasks. This balance between computational efficiency and terrain detail allows for accurate traversability analysis.

TABLE. I
PARAMETERS FOR SURFACE LEVELING APPLICATION

Parameter	Value
Critical slope (s_{cri})	30°
Safe slope (s_{safe})	5°
Critical step height (h_{cri})	0.25 m
Safe step height (h_{safe})	0.1 m

Finally, the traversability score was computed using the given formula (4). For the surface leveling application considered in this project, the parameters used are shown in Table I.

Since both slope and step height contribute equally to the traversability score, each weighting factor (α_1 and α_2) was set to 0.5. The resulting local grid map generated from this process is presented in Fig. 3.

Using this traversability map, a 2D grid map was generated

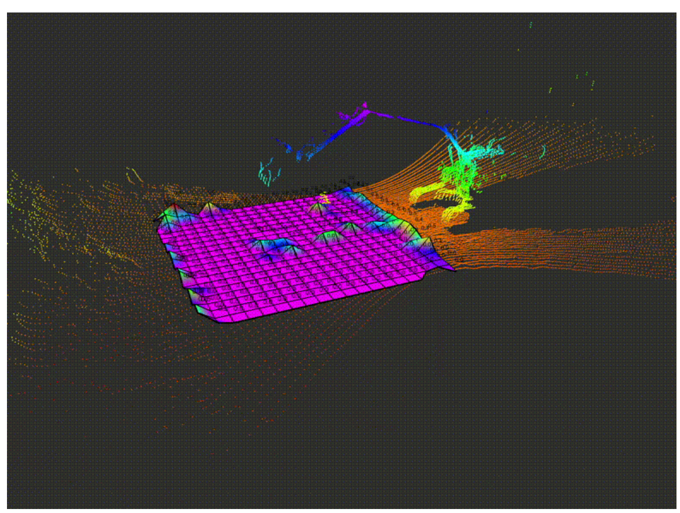

Figure. 3. Local grid map generated from the traversability mapping process.

for surface leveling applications.

VI. Conclusion

In this study, a 2D grid map was successfully generated using geometric features extracted from Lidar's point clouds under the excavator's surface leveling task.The generation of a 2D occupancy map takes an average of 70 ms, which is faster than the point cloud data input frequency of 100 ms, demonstrating its suitability for real-time applications.

Since this study specifically focused on surface leveling, the geometric features used were sufficient for generating a 2D occupancy map. However, for other applications such as slope excavation and trenching, mapping accuracy and robustness can be improved by adding features such as curvature, elevation, and roughness, and incorporating more sensors for data fusion.

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