Learning based Navigation Planning for Legged Robots in Challenging Terrain

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Introduction

Autonomous navigation of legged robots in unknown, challenging environments requires many conditions for a robot. One of the most important conditions is **traversability** which means the condition of being traversable, and a robot can traverse an unknown environment safely with traversability information of the map.

There has been several attempts to estimate the traversability of legged robot in unknown terrains.[2] 2.5D elevation map[3] is often utilized to describe the environment, but it has limitation on describing **multi-floor structure or over-hanging obstacles**. Therefore, we used **3D voxel-occupancy map** that can describe all features.

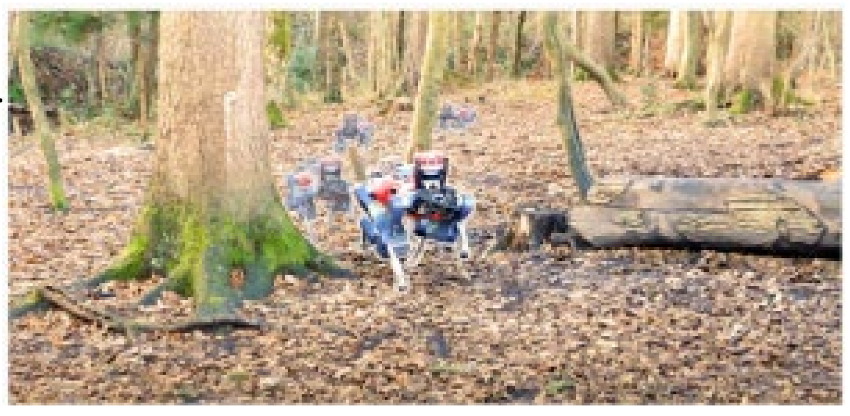

Fig 1. The legged robot ANYmal deployed in a forest[1]

For autonomous navigation we have to collect locomotion policy by simulating the traversal over generated maps using a physical simulator called **Issac Gym**[4]. To predict a traversability map of a real-world environment, a **sparse encoder-decoder network**[5] is trained from the generated maps in the form of a 3D voxel-occupancy map. Our navigation will depend on a traversability costmap predicted by the network.

Method

1) Terrain generation

- **Aim** : Generate large and diverse terrain with overhanging obstacles.
- **Ground structure** : Total 32m*32m. Random selection between plane ground / perlin noise based ground. Perlin noise ground is generated with random octaves, steps and frequency.
- **Obstacle structure** : Spawn 300~1000 random objects. Used object meshes from ShapeNet[6] database. 90% of objects are aligned to the surface and scaled as a factor of 0.5~1.5. 10% of objects are randomly oriented and float above the surface between 0~3m high.

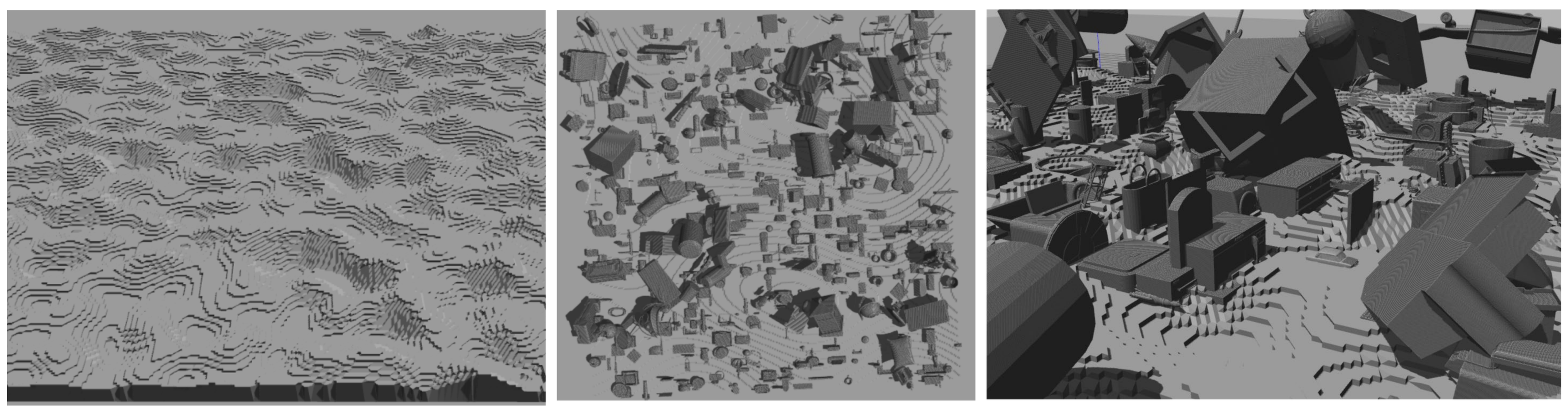

Fig 2. Terrain generation for traversability learning dataset(left to right) : Front view of ground terrain generated based on perlin noise; Bird-eye-view of randomly generated terrain; Zoomed-in view of randomly generated terrain.

2) Starting pose evaluation

- **Aim** : Find valid starting points are needed for accurate traversability data before traversability simulation
- **Preprocessing** : Given generated map, voxelize terrain including obstacles(Figure 3.a), using binary voxelization (binvox[7]) method. Calculate robot spawn heights using generated voxel grid(Figure 3.b).
- **Robot Simulation:** In Isaac Gym, spawn quadruped robot(ANYmal C) for every point in a given map with pre-calculated heights.
- **Starting Point evaluation**: Check if the robot can sustain pose for episode duration(2 sec). Considered failure if force exerted on base and base velocity exceeds threshold. Test multiple times for each point and heading. (position resolution: 0.1m, heading resolution 10°).

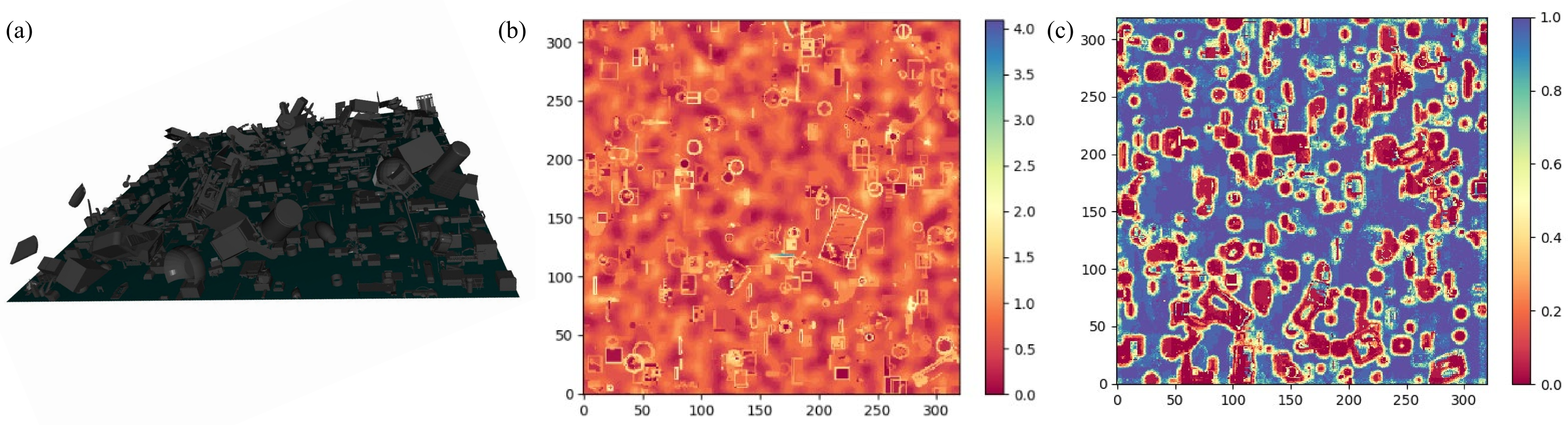

Fig 3. Starting point validation for traversability learning dataset(left to right) : Front view of ground terrain generated based on perlin noise; Bird-eye-view of randomly generated terrain. Colormap drawn based on the height(m); Zoomed-in view of randomly generated terrain. Colormap drawn based on standing successibility(0 to 1)

3) Traversability data collection

- **Aim** : Gain traversability data for each valid starting position by simulation.
- **Robot simulation**: For each starting point, 6 actions are simulated(Four translations in +x, -x, +y, -y direction. Two rotations in CW, CCW yaw direction.). For each action, 10 repetition is tried, with adding randomness on initial base velocity and orientation, for robust learning. Traversability is calculated by total number of succeeded attempt / total attempt(60) on each starting position. Attempt is regarded as success if 1) force exerted on base and base velocity didn't exceed threshold, 2) robot succeeded to reach the goal in episode duration(4 sec)
- **Process** : 5120 robots are simulated simultaneously in one terrain(32*32) in pararell. For one terrain, processing time 10hrs was required on average with headless run using RTX 2080 Ti as GPU.

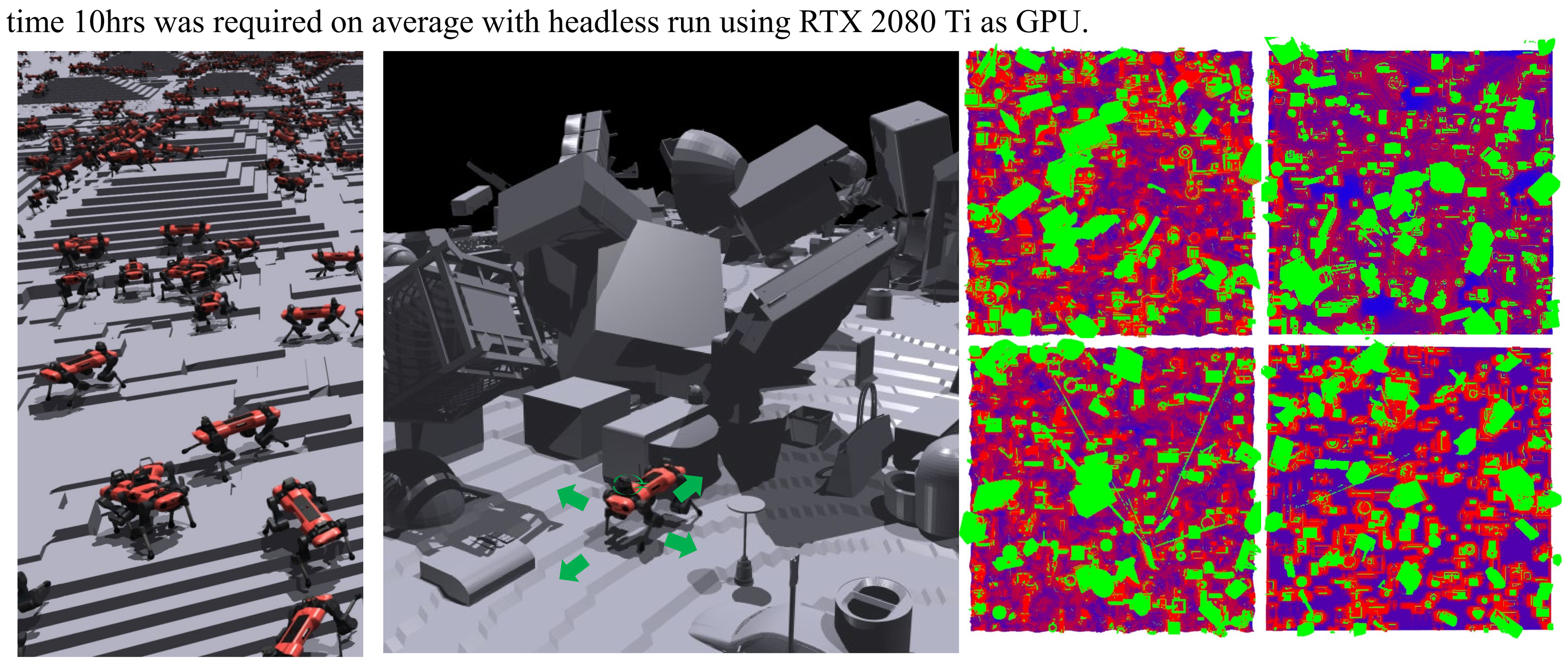

Fig 4. Traversability data collection example(left to right): Traversability data collection simulation on Isaac Gym in pararell[4]. (Due to hardware limits, there visualizing actual simulation was limited); Traversability simulation example for single robot on randomly generated terrain with 6 actions(green arrows); Example of two generated traversability maps of randomly generated terrains. Green structures are obstacles that are not regarded as possible spawn position. Red and blue colormaps are drawn based on traversability(0: red, 1: blue)

4) Traversability Prediction Network(TPN)

- **Aim:** In order to produce a traversability map using given voxel map data, Traversability Prediction Network(TPN) using generative sparse detection network is developed. [8]
- **Input** : 3D voxel-occupancy map(8m x 8m), 160 maps(Data augmented from ten 32m*32m maps by rotation.)
- **Output**: Traversability map(same scale with an input).
- **Structure** : U-net based semantic segmentation network with 2 skip connections, and consists of encoder-decoder structure. Especially, its decoder block has generative convolution transpose layer to upsample given feature. It uses MinkowskiEngine as a running engine for sparse tensor deep learning.[5]
- Parameters : Optimizer - ADAM with weight decay. Batch size – 8, Number of epoch : 20, Loss: MSE to ground truth data + reconstruction loss. Accuracy at validation set: MSE.

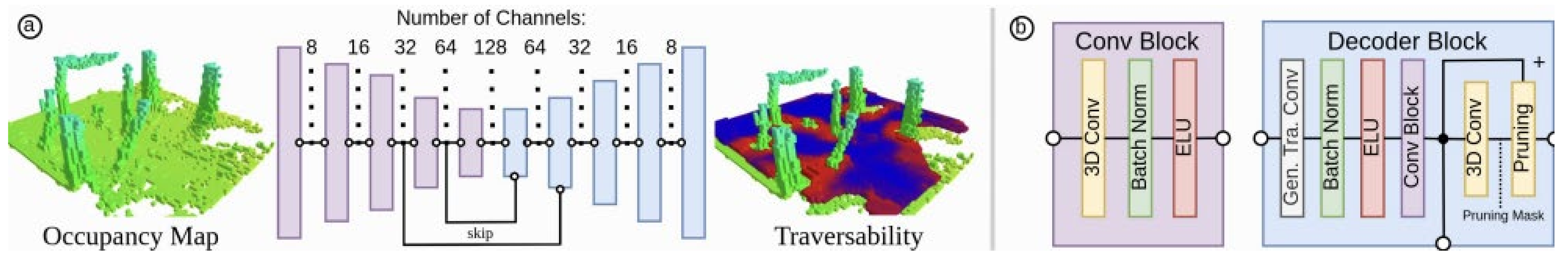

Fig 5. (a) Simplified TPN Architecture, (b) Block Structure of convolution block and decoder block.

5) Path planning from traversability map

- **Aim :** Conduct global planning based on ROS navigation stack. Structure is introduced at [Figure 6.a]
- **Global planner** : 2D grid search (A* search)
- **Local planner**: Dynamic Window Approach (DWA) algorithm based on, Sample robot state (Vx, Vy, Vtheta) / Simulate for short range and evaluate with costs / Select highest score trajectory.
- **Traversability costmap**: To evaluate Generated local trajectories, used estimated traversability cost as 2d costmap.
- **Simulation validation**: Using Gazebo Ros simulation tools. Simulation environments contains multiple objects from ShapeNet[6] models.([Figure 6.b])

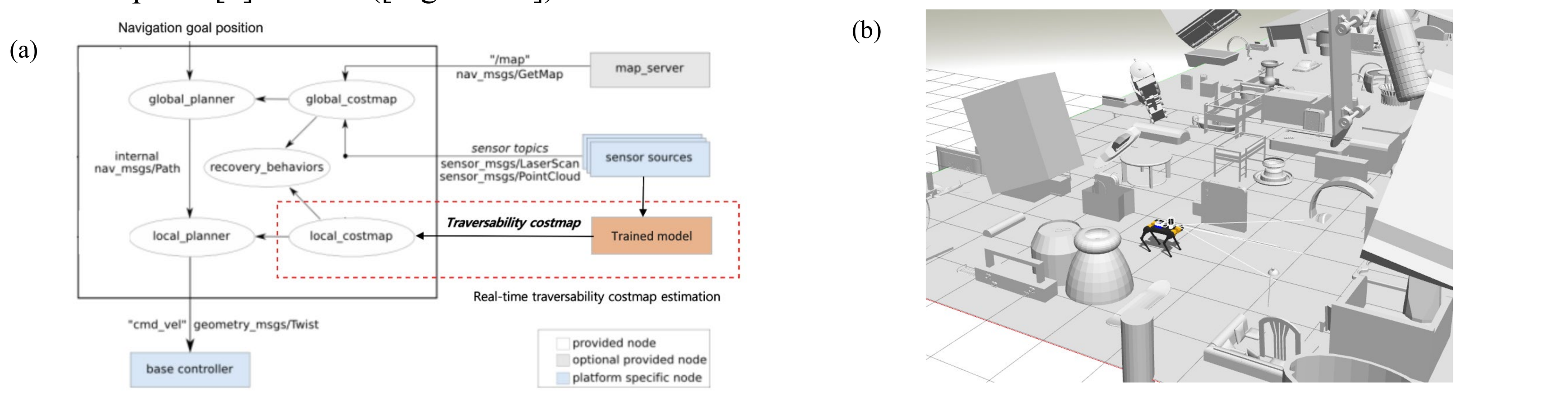

Fig 6. (a) Global planning structure using traversability map based on ROS navaigation stack, (b) Path planning simulation from Gazebo on randomly generated terrain

6) Traversability estimation in real world.

- **Aim :** Using quadruped robot RBQ-3, LiDAR Ouster 1-32, Computer Jetson AGX Orin, process real-world traversability data from trained model.
- **Procedure :** 1) Pointcloud data from LiDAR is processed by fast_lio SLAM algorithm [9]. 2) 3D occupancy voxel map is generated from point cloud map by Octomap server as 0.1m resolution[10]. 3) Local voxel map of 8m * 8m * 5m around the robot is passed to trained model, returns traversability labeled voxel map. 4) Traversability map is processed as traversability costmap, and provides path generated from path planning algorithm of (5)

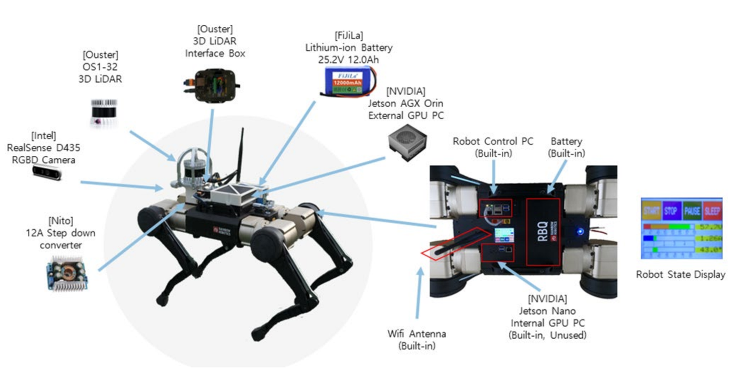

Fig 7. Sensor system of quadruped robot RBQ-3

Evaluation

1) TPN Evaluation

- **Loss :** Refering [Figure 99]. At each epoch, MSE to the validation data set remained under 0.02 and kept reducing.
- **Visualization** : Visualization example of estimated traversability map for the validation map is given at [Figure 99]. We found that performance of TPN was below the expectation.

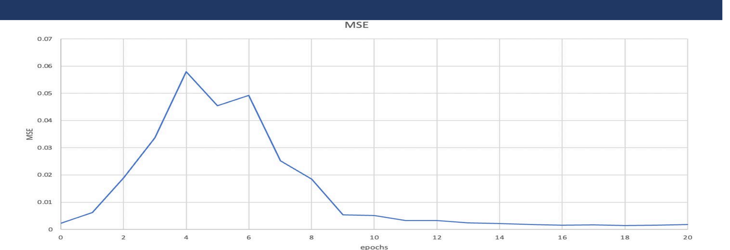

Fig 8. Loss graph of TPN. x-axis indicate epochs, and y-axis indicates MSE loss calculated from

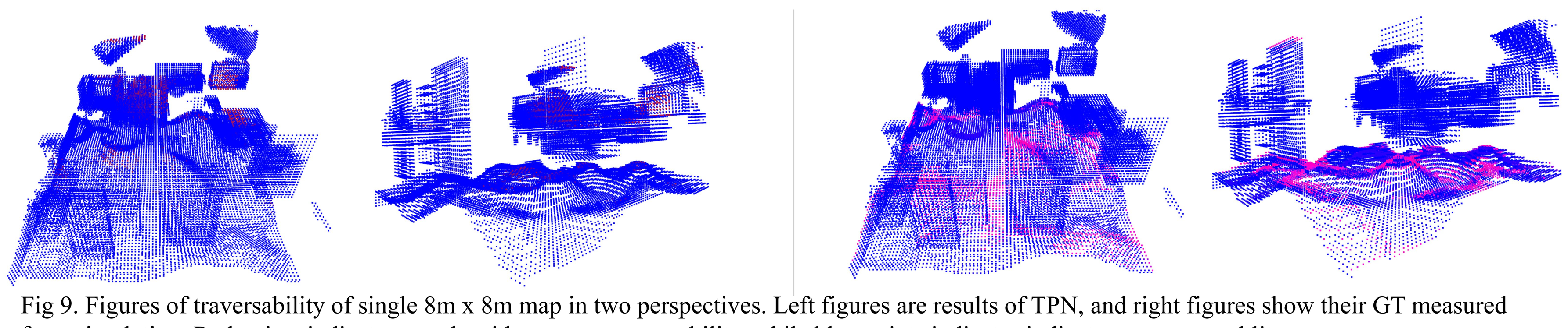

Fig 9. Figures of traversability of single 8m x 8m map in two perspectives. Left figures are results of TPN, and right figures show their GT measured from simulation. Red points indicates voxels with nonzero traversability, while blue points indicate zero traversablity.

- **Failure discussion :** During reconstruction with generative convolution transpose, some regional data is removed since coordinates get lost. Since we had to make all the dataset, number of total dataset was below 1000, even if data augmentation had been applied.

2) Path planning

- Path planning was successfully done on gazebo simulation and showed that robot **can traverse below over-hanging obstacles**(Figure 10.a,b).10Hz real-time update was available using costmap, therefore it is expected that this planning algorithm will successfully work in real world too.

3) Traversability estimation in real world.

- **Local 3d voxel-occupancy map** that can be inserted into the TPN model was successfully attained in real time.(Figure 10.c,d)
- If the model was successfully trained, we expect this can provide real-world path planning.

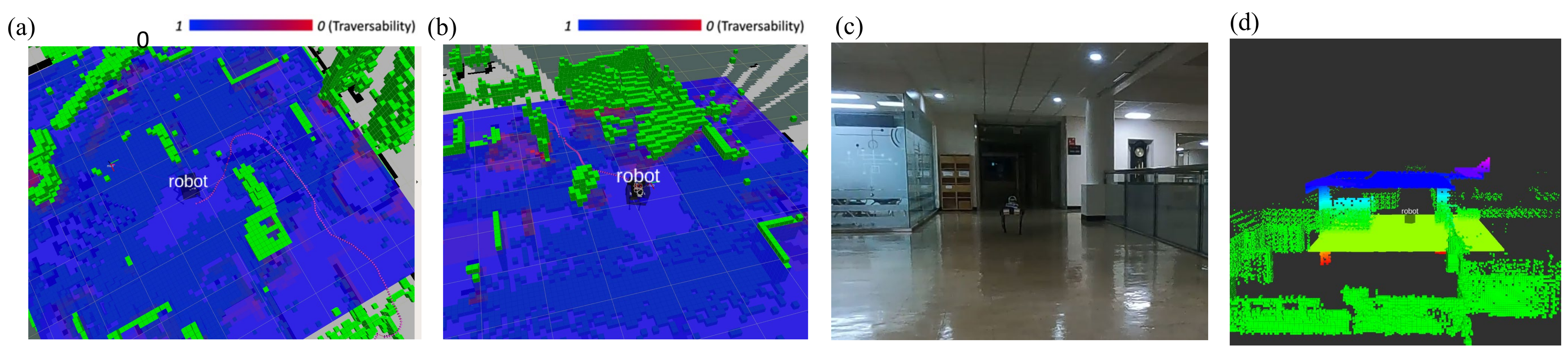

Fig 10. a, b) Traversability costmap projected to 2D map and path planning(purple line) from robot. Green voxels represents object obstacles from lidar. Blue and red colormap shows the traversability. c,d) Traversability estimation in real-word. c: RBQ-3 in building. d: rviz visualization of situation of c).green voxels indicate the map generated from fast_lio[8] algorithm, and rainbow pointclouds indicate the local 3d voxel-occupancy map that can be go through TPN. Colormaps indicate the height from the ground.

Conclusion

- We **successfully generated traversability dataset** by simulation on Isaac Gym, and since the simulation was parerell and time accelerable, it took only 10% of time than real-world data collection(assuming single robot working for episode duration at each position), and it is much more safe and economical.
- Our TPN model **didn't show good performance in real world dataset**. With larger dataset and more epochs, finetuning can be done much better by fusing some layers or masking into the network, coordinates can be preserved and more regional features will be passed to the following layer during training.
- Even though we failed to train the model successfully, we **developed a system** that can calculate the traversability for the **real-world in real-time** by RBQ-3 robot if we have a proper model.
- But calculating traversability in real-world had some limitations. Since the LiDAR couldn't fully detect the floor surfaces, we had to fill the floor as the ground base. This makes the robot that **cannot detect the features such as hole** or stairs that is below from the starting position.

Reference

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