Learning-based 3D Occupancy Prediction for Autonomous Navigation in Occluded Environments

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Abstract—In autonomous navigation of mobile robots, sensors suffer from massive occlusion in cluttered environments, leaving significant amount of space unknown during planning. In practice, treating the unknown space in optimistic or pessimistic ways both set limitations on planning performance, thus aggressiveness and safety cannot be satisfied at the same time. However, humans can infer the exact shape of the obstacles from only partial observation and generate non-conservative trajectories that avoid possible collisions in occluded space. Mimicking human behavior, in this paper, we propose a method based on deep neural network to predict occupancy distribution of unknown space reliably. Specifically, the proposed method utilizes contextual information of environments and learns from prior knowledge to predict obstacle distributions in occluded space. We use unlabeled and no-ground-truth data to train our network and successfully apply it to real-time navigation in unseen environments without any refinement. Results show that our method leverages the performance of a kinodynamic planner by improving security with no reduction of speed in clustered environments.

I. INTRODUCTION

Although many works have been proposed towards autonomous navigation tasks in unknown cluttered environments in recent years, a safe and fast scheme for light-weight platforms like UAVs and UGVs is still yet to be attained. For most navigation systems, the effect of navigation tasks is mainly conditioned by two aspects: the way to sense and represent the environments and the manner to maneuver in the partially observed world. In such systems, the mapping module plays a vital role in fusing noisy sensor inputs into free and occupied space for the planner module to address and perform collision checking.

Most depth sensors, like LiDAR and depth cameras, provide only surface information of objects. Therefore, only limited surfaces of objects can be perceived as occupied while the space shaded by these surfaces remains unknown, as shown in Fig. 1. The unknown space, however, can be rather large in indoor environments like offices where massive occlusions are prone to happen. It puts the planner manner into a dilemma since the way to reason about unknown space can significantly affect navigation tasks’ execution. To this end, two strategies are commonly used, but both with their own pros and cons. One conservative manner is to treat the unknown regions as occupied and only plan trajectories in free space. It guarantees safety but limits moving speed since a stopping condition has to be met in short-range free space. The other manner acts optimistically and treats the unknown as free, generating aggressive trajectories into the unknown, but it often becomes overconfident and results in collisions. Therefore, designing a framework that fuses the advantages of both these two strategies yet avoids their limitations has been an attractive topic in robotic navigation.

In this paper, we address the above issues from a mapping perspective. Inspired by the fact that humans always make implicit predictions for obscured obstacles based on prior knowledge and generate safe but non-conservative decisions to avoid obstacles, we opt to extend the mapping module in current navigation systems to facilitate existing planners. In other words, we seek to infer the occupancy information from partial observations of the world and generate a more complete predicted map with occupancy prediction in the unknown space. The predicted map is then used for generating trajectories to avoid possible collisions in advance.

Using limited observation to predict the unknown can be considered a variant of scene completion. However, current scene completion models can hardly run in real-time, and none of them are used in a dynamic process like navigation.
In this paper, we propose Occupancy Prediction Network (OPNet), a lightweight 3D fully-convolutional network with an affordable computation burden. It takes a simple grid map with unknown space as input, and outputs occupancy classification of every single grid. Furthermore, we provide OPNet as a general mapping plug-in to leverage the performance of autonomous navigation in cluttered environments.

The main contributions of this paper are:

1) A lightweight yet effective network model OPNet to predict 3D occupancy information of occluded space. It takes in incomplete map produced by limited perception, and infers occupancy information of the unknown space in real-time. The training data of our method can be generated from real-world data without ground-truth or labels.

2) A general method to plan with map prediction. We integrate OPNet as a mapping plug-in and testing it in simulation and real-world navigation experiments, outperforming both optimistic and conservative planning.

II. RELATED WORK

A. Planning with Map Uncertainty

To simultaneously guarantee both safe and fast maneuvers in a partially observed environment, some works are recently proposed from the planning perspective. Tordesillas et al. [1] propose to generate both pessimistic and optimistic trajectories at the same time, with a conservative one only in the safe region as a backup. However, this method consumes unnecessary computation since most backup trajectories would never be executed. Some works [2, 3] plan an informative trajectory considering the vehicle’s field of view (FOV), which improves the predictability and safety. However, these works require an additional mechanism to conduct visibility planning and are indeed conservative planning ways, thus they are still constrained by the sensing range of the vehicles. In [4], a learning-based method is proposed to predict the risk in the next planning horizon by detecting the novelty of surrounding environments. Then this estimated risk is used to guide the driving speed of a ground vehicle. This method is limited to 2D environments and can only provide limited information, such as the risk or cost, to help the planner make high-level decisions on speed.

B. Navigation in Predicted Maps

Map prediction shows great potential in the field of exploration. Rakesh et al. [5] use a predicted map to compute flood-fill information gain to guide exploration. Manish et al. [6] use a CNN model to predict topological features in subterranean tunnel networks. Kapil [7] predict the occupancy map beyond the sensor’s FOV. Nevertheless, all these works operated only in 2D simulators. Hepp et al. [8] do not directly predict the map but use a deep neural network to estimate the utility of viewpoints.

For planning, Amine et al. [9] use a Conditional Neural Process based network to predict potential upcoming turns in maps. By map prediction, their planner can generate smoother and more efficient trajectories in their test environment: single-path 2D mazes with frequent corners and U-turns. However, this work does not consider any obstacle other than 2D walls, and its training environment and evaluation environment are almost the same. In contrast, our proposed method can work in random 3D cluttered environments and real-world experiments.

C. Shape and Scene Completion

Completing 3D shapes has been well-studied in geometry processing. Many surface reconstruction methods like Poisson Surface Reconstruction [10, 11] aim to fit a surface and treat point cloud observations as data points in the optimization process. These methods are capable of filling small holes. One of the first data-driven structured prediction methods is Voxlets [12], which uses a random decision forest to predict unknown voxel in a depth image. Recently, various deep learning-based approaches have been developed for scene completion. Song et al. constructed SUNCG [13], a large-scale dataset of synthetic 3D scenes with dense volumetric annotations. They also present SSCNet, an end-to-end 3D convolutional network that takes a single depth image as input and simultaneously outputs occupancy and semantic labels for all voxels in the camera view frustum. Lately, ScanComplete [14] and SG-NN [15] show great capacity for completion of larger missing regions in large-scale scans. The computational cost of these models is far too high for real-time usage, and there are no experiments for on-line successive completion. As their main purpose is to reconstruct high-resolution mesh, we can trim the model and reduce the resolution to meet navigation needs.

III. METHODOLOGY

A. Overview

Our work consists of two parts: an occupancy predictor and a general mapping method to combine map prediction with dense grid map for collision checking in navigation.

The predictor model takes as input a dense grid map with known region and outputs a “completed” map with occupancy classification for every grid. Although the probability of being occupied of the grids in the input map is continuous, for stability the grids are categorized by user-defined thresholds into three kinds: free, occupied, and unknown. We train our predictor in a self-supervised manner that enables us to use unlabeled no-ground-truth dataset. By learning the difference between the input built by limited scans with massive occlusions and the more completed target with much less known space, the network learns to complete the occluded space in the input.

Our collision checking method is based on a double layer grid map. One layer stores the original map, which is managed independently, and the other layer stores the predicted map. The original layer, a fused occupancy map containing more information than a single sensor frame, provides the predictor’s input. The predictor’s output is used to update the prediction layer, by fusion or replacement. Collision
B. Training Data Generation

For data generation, we use the Matterport3D dataset [16], an RGB-D dataset containing depth images of building-scale scenes and the corresponding 6-DoF camera poses. We design the following data generation process to simulate occlusion in a navigation process. Follow the work in SG-NN [15], we first build room-level maps as $M_{\text{target}}$ with 5cm resolution, and then sample $4m \times 4m \times 2m$ blocks in each room as basic units of our training data. Input data of a block $S_{\text{input}}$ is initialized as fully unknown while target data $S_{\text{target}}$ is cropped from $M_{\text{target}}$. After getting a block’s target data, we attempt to sample a virtual collision-free paths in it and uniformly set a group of way points on each path. Then we simulate scans on these way points considering $S_{\text{target}}$ as ground-truth occupancy map and fuse these scans in $S_{\text{input}}$. In this way, some space in $S_{\text{target}}$ become occluded in $S_{\text{input}}$. Defining $\text{known_ratio}$ as the number of known grids in $S_{\text{input}}$ divided by number of known grids in $S_{\text{target}}$, we reject blocks with $\text{known_ratio}$ less than 25%.

We generate about 15,000 blocks using data of 80 buildings in Matterport3D, 65 buildings for the training set and 15 buildings for the validation set. Note that fully convolution networks can take in input of varying sizes at inference time, enabling a trade-off between computational cost and prediction range.

C. Occupancy Prediction Network

Our predictor network generates occupancy classification for each grid within the input block. Its input can be occupancy grids or TSDF, and so is the output. For simplicity, in this paper, we only introduce occupancy grids, where a value is stored representing the grid’s states. All grids in our grid map are initialized as unknown with value -1. Every time a new scan comes in, observed grids are updated to a value between 0 and 1: values greater than a threshold means occupied and free otherwise, as general occupancy grid mapping does. The actual input value is discretized into trinary values -1, 0 and 1, representing unknown, free, and occupied.

We use a U-Net [17] style architecture, an encoder, and a decoder with skip connections between them. Fig. 3 shows the general architecture of our model. We use Atrous Spatial Pyramid Pooling (ASPP) [18] to expand the network’s receptive field and contact contextual information of different scales. We implement our network in Pytorch and train it on our dataset, using the Adam optimizer and stepped learning rate from $1e^{-4}$ to $1e^{-3}$. Training for 15 epochs takes around 6 hours on a TITAN X Pascal with a batch size of 20 requiring 7.5 GB of GPU memory.

We use binary cross-entropy loss for occupancy grids output, while TSDF output with smoothed $l1$ gets equivalent performance. To focus on completion, we give “missing” grids that are observed in $S_{\text{target}}$ but unobserved in $S_{\text{input}}$ extra loss weight. We also give grids that are occupied in $S_{\text{target}}$ extra weight to balance data distribution. Grids that are unobserved in $S_{\text{target}}$ do not account for the loss.

D. Map Generation and Collision Checking

As stated before, the map we use for navigation is represented as a double layer dense occupancy grid map. The first layer is the original occupancy map fused by raw sensor inputs, and the second layer is the predicted occupancy map generated from the predictor network which is used for local collision checking during planning.

All grids in the original layer and the prediction layer are initialized with value -1, meaning unobserved and unpredicted. When updating the predicted map, a block of voxels consists of trinary values (free, occupied, and unknown) is taken from the original map and fed into the predictor, which generates the probability of being occupied for all grids inside this block. The output of the network is used to update the block grids of the same position in the prediction map.

When performing collision checking in path-finding, both map layers are utilized to embrace richer information of the unknown space and stability of the known space, as shown in Fig. 4. Some rules are designed for collision checking, for instance, if a grid is recorded in both layers, a weighted sum of values of both layers is considered: values greater than a threshold means occupied and free otherwise. The weights can be tuned according to the characteristic of particular sensor. For example, if a LiDAR is used as we do in the real-world experiment, a higher weight for the original occupancy

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**Fig. 3: OPNet: Obstacle prediction network.** Take a grid map as input and generate a predicted map of the same size. Activation layers and Batch normalization layers are not shown in this figure. The convolution parameters are shown as the number of filters, kernel size, stride, and dilation.
map is set to favor the belief of the observation source. Grids neither observed nor predicted (out of prediction range) are considered free in preferring operating in an optimistic manner.

It is worth mentioning that, as these two layers are updated asynchronously, delay in prediction will not affect the original map, thus in the worst case, this double layer map is as complete as a conventional occupancy map without extra latency. Above updating and collision checking rules can stabilize the frequently changed prediction, meanwhile providing flexibility.

IV. BENCHMARK AND EXPERIMENT

In this section, we evaluate our prediction model with state-of-the-art prediction networks for classification accuracy and inference speed. Furthermore, we use the predicted map for UAV and UGV navigation in both simulation and real-world experiments with different collision checking schemes, showing the improvement of robustness with our predicted map as a plug-in.

A. Prediction of The Unknown

We choose two representative scene completion models, SSCNet [13] and SG-NN [15] for comparison. SSCNet is originally trained by complete ground truth and semantic labels on synthetic dataset SUNCG, and SG-NN can be trained on real-world TSDF. For SSCNet, as semantic segmentation is no longer required, we cut the number of channels of its most convolution layers by half. We use SG-NN’s 2-receptive field rather than multiple 3D convolution layers or large kernels that are computationally expensive. For real-time usage, our model can run at 20 Hz on an NVIDIA Xavier platform with 80×80×40 input and 10 Hz with 120×120×40 input. To be aware, the scale of the dataset that we use for training is relatively small because SUNCG is no longer available anymore. However, our approach is self-supervised, which enables us to use our own sensor scans or synthetics environment to provide extra data.

B. Simulated UAV Navigation

We conduct simulated 3D UAV navigations in two kinds of scenes: a 30m×30m narrow corridor and a 20m×20m large square room, filling with different sized obstacles, causing massive occlusions. The UAV needs to fly from one waypoint to another in the previously unknown environment. Mapping and trajectory planning are conducted on the fly based on instantaneous scans from a simulated laser sensor. Re-plan is conducted at a regular frequency as well as when the currently tracking trajectory is blocked by newly observed obstacles.

For collision checking, we compare our method with two other schemes: the Aggressive way that checking only in the original occupancy map with the unknown as free,
Fig. 5: Prediction results in the validation set. (a) A living room. (b) A desk in front of a window. Objects in the upright corner of this image are not successfully predicted because it is totally unobserved. (c) A bathroom. The predicted obstacle is thicker than it should be, and some holes are filled by mistake, which might be glasses of a window.

and the Conservative way that checking in the predicted occupancy map with the unknown as occupied. As for the planning module, we adopt a kinodynamic planner [19] that finds asymptotically optimal trajectories as planning time increases. Maximum speed is set as 5m/s. 100 trials with different obstacle placements are conducted in both scenes for each collision checking scheme, and we record average travel time, travel length, emergency stop times, and success rate for comparison.

The results listed in Table II show that when we plan and perform collision checking in the proposed way, most statistics are improved. Owing to the accurate prediction of the unknown and being able to avoid unrevealed obstacles in advance, our method results in fewer emergency stops and a higher success rate compared with the aggressive way while still achieving comparable travel time and overall travel length. Moreover, all aspects outperform the conservative way. The low success rate and high emergency stop times of the conservative planning is mainly caused by the severe occlusions, leaving strictly limited known space for planning.

An instance of the traveled trajectory is shown in Fig. 6. Plan with our proposed prediction mapping and collision checking results in overall smooth paths, while the aggressive way usually leads to emergency stops and results in winding paths. The conservative way, which only plans in known free space, however, influenced by the limited perception view caused by severe occlusions, needs to seek goals backward sometimes and leaves the paths winding as well.

C. Real-world UGV Navigation

UGV real-time navigation tasks in unknown environments are conducted to show the capability of our predicted map being used for navigation in real-world online. The UGV platform we use is a DJI Robomaster AI robot1 equipped with a LiDAR2, an IMU and a Jetson AGX Xavier3 for all the onboard computing, including localization (done with LIO-SAM [20]), mapping, network inferring, planning and control of the UGV.

Firstly, we provide some instances that the predicted map improves the results of the planner greatly. In a scene shown in Fig. 7, the UGV needs to navigate to a place behind the wall, but the perception is occluded by a front obstacle at the beginning, thus building an incomplete original occupancy map (Fig. 7a) of the wall behind with a “door” in the

1https://www.robomaster.com/zh-CN/products/components/detail/2499
2https://www.robosense.ai/rsliadar/rs-lidar-16
3https://www.nvidia.com/en-us/autonomous-machines/embedded-systems/jetson-agx-xavier/
Fig. 6: The path traveled in the corridor simulation. The proposed method (Red) generates overall smooth paths while both paths generated in the conservative way (Green) and in the aggressive way (Yellow) are rather winding.

(a) Navigate in an aggressive manner in the original occupancy map. Unknown space is treated as free. The left image shows the winding traveled path. The right image shows the trajectory planned at the beginning through the occluded space. Red and yellow grids represent the original occupancy grids.

(b) Navigate with the proposed prediction mapping and collision checking. The left image shows the smooth traveled path. The right image shows the trajectory planned at the beginning bypassing the predicted wall. Blue and purple grids represent the predicted occupancy grids.

Fig. 7: Composite image of navigating to a position behind a wall.

In this paper, we propose a lightweight yet effective 3D convolutional network that learns to complete the occupancy information in occluded space. Benchmark results show higher accuracy and less inference time in the occupancy prediction task. We also propose a general method to combine map prediction with the mapping module to leverage planning performance. The effectiveness of the predicted map to facilitate planning is validated in real-time navigation tasks with both simulation and real-world experiments.

The main limitation of our network model, however, is the lack of diversity in training data as many deep learning methods do. As a result, generalization to unseen environments might be hard. Nevertheless, our method shows capability in improving the planner’s performance in our random simulation environments and helps to solve difficult tasks in real-world experiments. For future work, we aim to take the camera’s FOV into account, which is more limited, and implement our method on a lighter platform with only depth cameras.
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