Embodied Depth Prediction Supplemental Material

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In this supplemental document, we provide experimental details of our method (Section A) and additional visualization results (Section B). Please refer to the supplemental webpage for video results.

A. Experimental Details

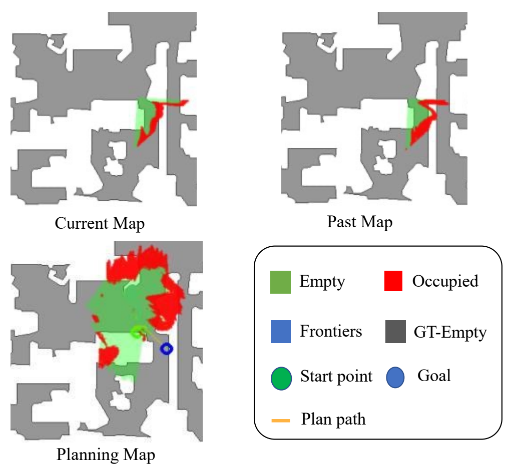
Network Architecture. Our Embodied Depth Network (EDN) takes as input multiple RGB images and their corresponding camera poses and outputs an inverse depth map. To ensure a fair comparison with related networks, we used two past frames to predict the depth. The coarse depth map is obtained as explained in Section 3.5, using a pretrained RAFT [8] model on KITTI [6] dataset. The refinement network architecture is based on a UNet [7], which comprises a ResNet18 [4] encoder to extract features from both the coarse depth map and the current RGB image. These features are then fused using point-wise addition and fed into the decoder, which is a DispNet similar to [10]. The output of the decoder has sigmoid activation layers, while ELU nonlinearities [2] are used elsewhere. We convert the sigmoid output x to depth D using $D = 1/(ax + b)$, where a and b are chosen to ensure that D falls between 0.1 and 20 meters.

Training Details. To train our model, we employ a photometric loss computed from the 4th frame to the current frame for simulations and the 15th frame for real-world data. We set the weight of the smoothness term to 10^{-3}. We use the ADAM optimizer [5] with a learning rate of 10^{-4} and a batch size of 12 on a single Nvidia GTX Titan X. We initialize the model with 6,000 frames of data for warm-up and then train the model every 3,000 frames of data. Once we reach a maximum dataset size of 30,000 frames, we perform an additional 3-epoch training.

B. Additional Results

Active Data Collection. We provide further visualization details on our active data collection strategy, which enables our method to effectively explore and select informative views to improve depth estimation accuracy. The frontier

(a) Illustration of Frontier Exploration. The agent sets the goal to the center of one randomly-picked frontier group which is based on the occupancy map.



(b) Illustration of Depth-Inconsistency Exploration. The agent checks the inconsistent areas between current and past occupancy maps and sets the goal to the center of the depth-inconsistency areas.

Figure 1: **Active Exploration Demo.** We show the top-down maps displaying traversable areas (grey) and untraversable areas (white) to illustrate our method.

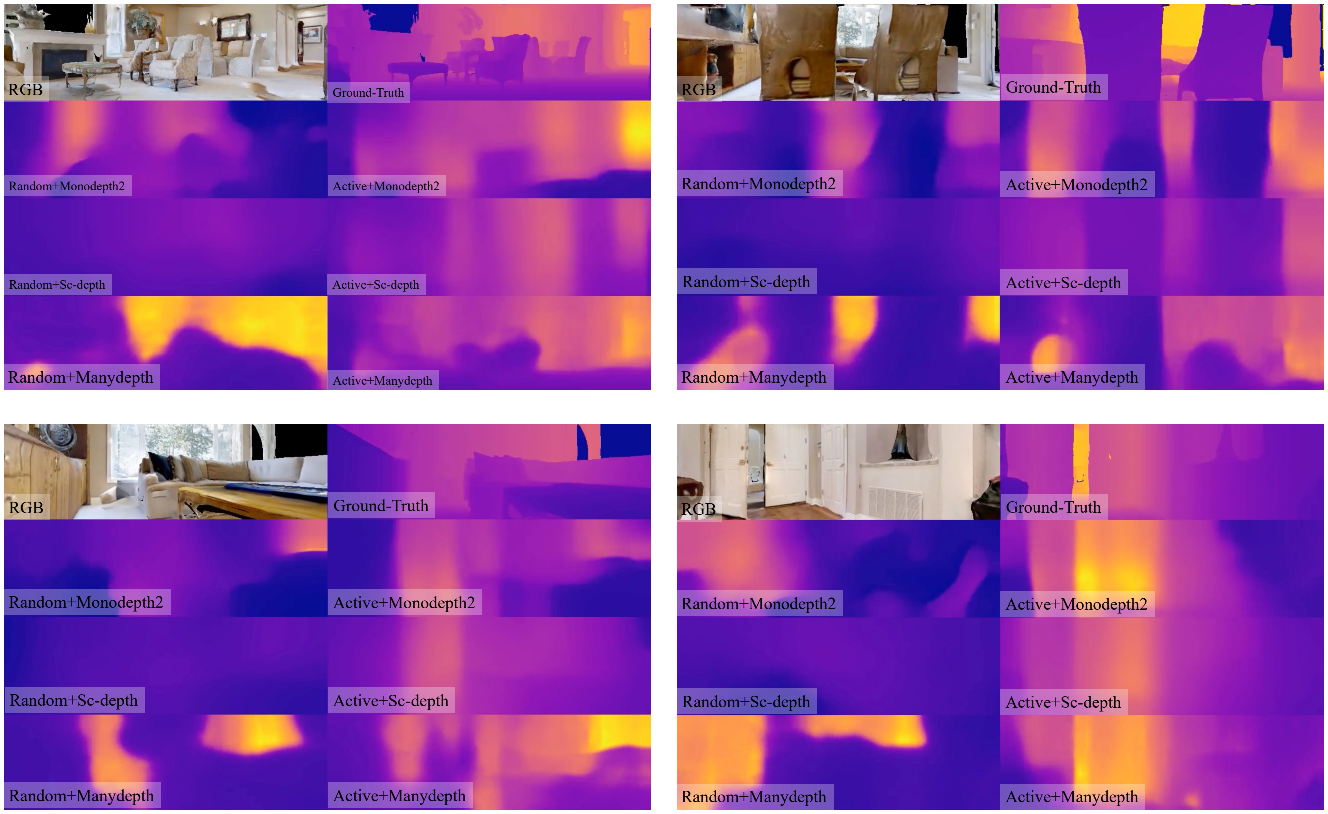


Figure 2: **Depth Predictions in Different Models.** Our active policy improves the performance of all of the baseline models.

exploration expands the distribution of data by selecting views that are close to the current field of view but have not yet been observed. This strategy ensures that the network has access to a diverse set of viewpoints, which can help it learn to generalize better across different scenes. On the other hand, the depth-inconsistency exploration strategy aims to identify areas in the scene where the network is uncertain about its depth predictions. Our active strategy can guide the new data collection even in cases in which the network outputs an ambiguous prediction.

Depth Predictions in Different Models. We compare the performance of different depth estimation models under random and active data collection policies in Fig. 2. Specifically, we visualize the depth predictions of three different models: Monodepth2[3], Sc-Depth[1], and ManyDepth[9]. We find that our active policy consistently improves the performance of all of the baseline models, producing depth predictions that are more accurate than those obtained with random data collection. Our results demonstrate the effectiveness of our proposed active data collection strategy in improving depth estimation accuracy across a range of different models.

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