Experience-Based Prediction of Unknown Environments for Enhanced Belief Space Planning
Supplementary Material

Technical Report ANPL-2020-02

Omri Asraf and Vadim Indelman*

This document provides supplementary material to the paper [1]. Therefore, it should not be considered a self-contained document, but instead regarded as an appendix of [1].

Appendix A: Extended Map Distribution Prediction Results

The dataset that was used is KTH dataset [2] which includes 182 floor-plans and nearly 38,000 real-world rooms. The XML files of floor-plans were converted to 2D occupancy grid maps with fixed scale (four pixels for one meter). Next, each map was cut into sub-maps with fixed size (32/32 pixels). Finally, we created N tuples of sub-maps, action (direction and length of stride) and the ground truth map post action i.e (m, a, m') (see Fig. 1). In order to approximate the $\mathbb{P}(m'|m, a)$ we chose to use conditional VAE architecture as we describe in section III.c in [1]. The CVAE flow chart in the training and deployment stages is shown in Fig. 2.

In the training stage we used the KTH dataset (593,264 tuples of (m, a, m') in indoor enviourment) and separated this data to 80% train set and 20% test set. For each tuple in both sets we calculate the reconstruction error (RE) on the overlap area by novelty detection method that was presented in Section IV.A in [1], and additionally the prediction error (PE) on the unknown area against the ground truth. Figs. 3.a-b show the RE histogram of the train set and the test set: we can see very similar statistics in both of the sets, since both are of the same enviourment type (KTH dataset). Based on these results, we can define the novelty detection threshold to be 5 (See section III.E in [1]). In addition, in Fig. 4 we show the PE histogram of the train set and the test set. We can see most of the results are with prediction error less on 5 (see examples in section IV.A in [1]).

Appendix B: Extended BSP Simulation Results

In this paper, we extend the results of BSP in unknown environments simulation (see section IV.b in [1]). In the deployment we used Gazebo world different indoor enviourment of KTH dataset. Fifteen scenarios of planning sessions are tested. Each scenario includes a different environment and three actions that lead to an unknown area (see Fig. 5). In our work, the planning mission is to choose the best action that leads to the goal by the least uncertainty. Our approach suggests to leverage experience to predict the unknown area around the candidate actions given the partial map observed in the inference stage. The solution by a standard BSP method, denoted `baseline`, is to ignore the unknown future measurements (in our case point clouds) and take into consideration only the motion model. The non-realistic solution, denoted `GT-map`, is to use the ground truth maps to generate the expected future

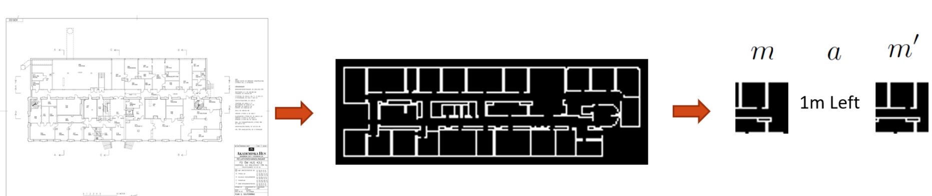

Figure 1: dataset processes.

*The authors are with the Department of Aerospace Engineering, Technion - Israel Institute of Technology, Haifa 32000, Israel, `asomri@campus.technion.ac.il, vadim.indelman@technion.ac.il`.

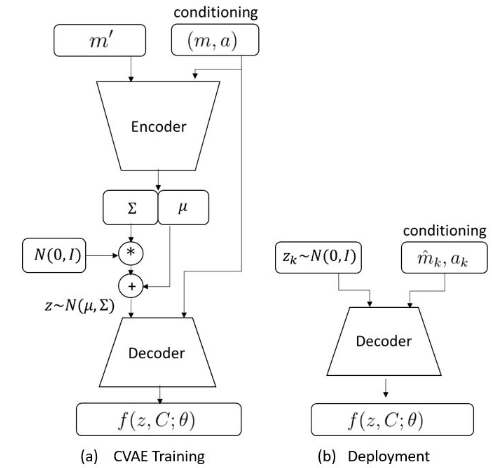

Figure 2: Training and Deployment.

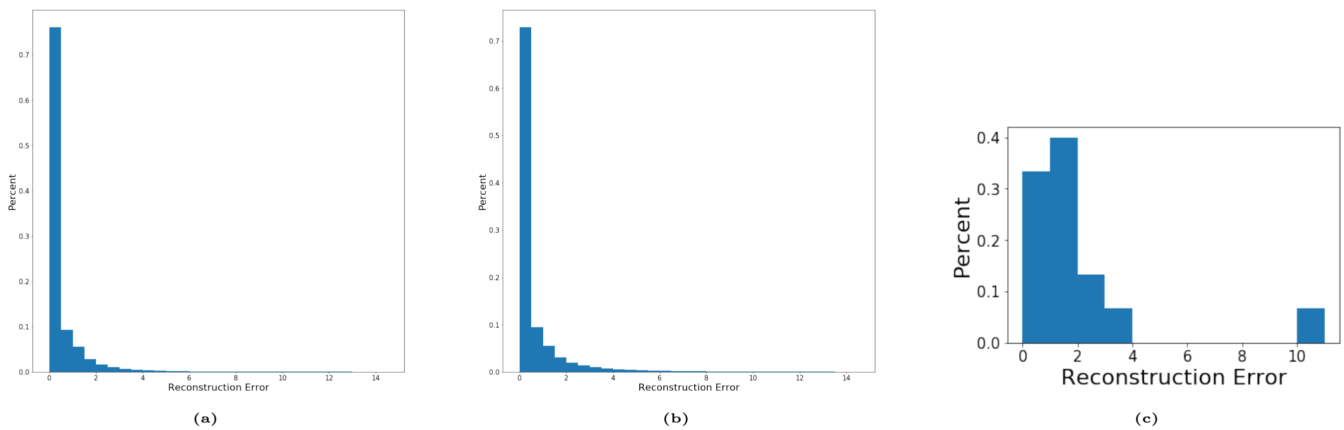

Figure 3: Reconstruction error histogram. (a) trainset; (b) testset; (c) deployment scenarios;.

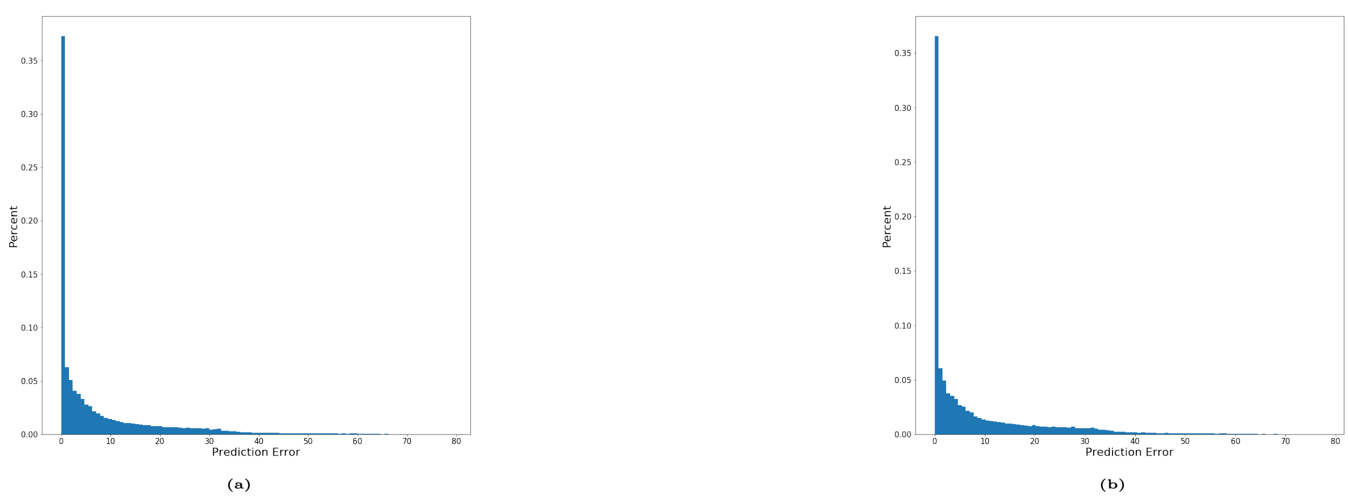

Figure 4: Prediction error histogram. (a) trainset; (b) testset;

measurements and take them into consideration in the objective function calculation. Fig. 6 showed the objective function calculation by these three BSP approaches. We can see that with our approach, actions ordering is closer to the `GT-map` BSP method compared to `baseline`. Fig. 3.c shows the reconstruction error from the Gazebo scenarios and shows one example (scenario 15) to how we could recognize unfamiliar environments and avoid using wrong predictions.

References

[1] O. Asraf and V. Indelman. Experience-based prediction of unknown environments for enhanced belief space planning. *IEEE Robotics and Automation Letters (RA-L)*, 2020. Submitted.

[2] Alper Aydemir, Patric Jensfelt, and John Folkesson. What can we learn from 38,000 rooms? reasoning about unexplored space in indoor environments. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 4675–4682. IEEE, 2012.

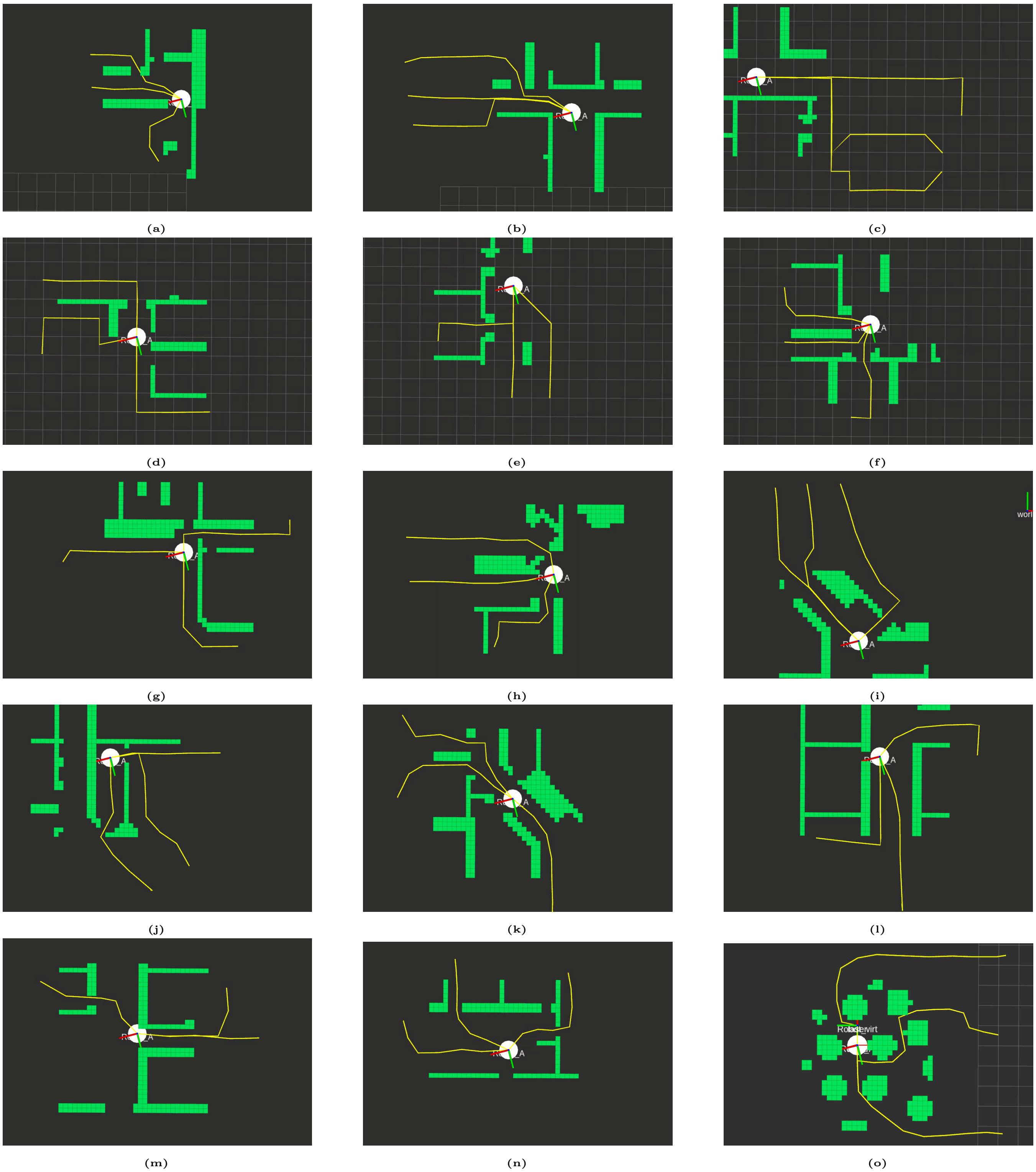

Figure 5: Light green - coditional map, yellow - three candidate actions. Figures (a)-(o) according to planning scenarios 1-15 from Table 1 in [1].

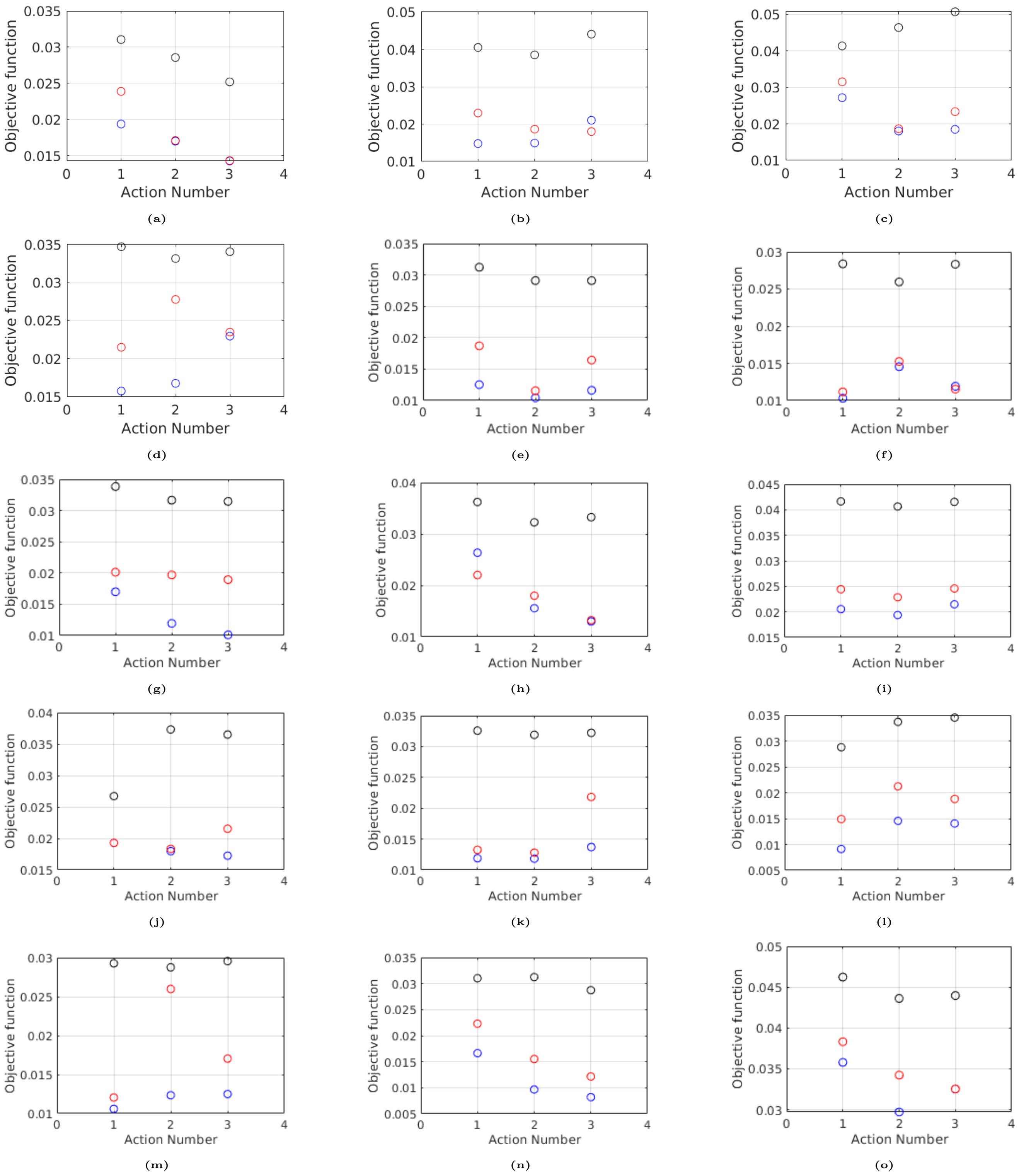

Figure 6: Objective function values for the three BSP methods. `baseline` in black, `our approach` in red, `GT-map` in blue. Figures (a)-(o) according to planning scenarios 1-15 from Table 1 in [1].