Semantic Mapping of Object Affordance by Interactive Manipulation

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***Abstract*—Given an organizing task in an unknown environment, a robot needs to understand the affordances of objects. In this paper, we propose a technique to build the affordance map efficiently by planning an interactive manipulation based on prediction. A Markov Random Field is constructed based on the 2D occupancy grid map and the prior affordances are predicted with the classifier using geometric features. The affordance map is refined by manipulating objects which have the highest reduction of uncertainty according to the MRF model.**

I. Introduction

Imagine a robot is deployed to a warehouse to rearrange disorganized boxes. Without any prior knowledge of the environment, the robot must explore the world and identify target objects which need to be moved. Understanding object affordances [1], relative functionalities between the robot and objects, is the key factor to solve such problem. First, the robot can utilize its sensors to recognize objects and estimate corresponding affordances. Meanwhile, the relative positions of objects should be considered as they would affect affordances as well: a box may not be pushable if other boxes lie behind it. Also, interactions with objects are important as some affordances cannot be described by visual cues only: an empty box would be light enough to be pushed while a stuffed box would not be. To thoroughly understand the affordances of objects, visual perception, configuration interpretation, and interactive manipulation are necessary.

In this paper, we propose an algorithm to semantically map the object affordances as follows: 1) Build a map of the environment, 2) Predict affordances of the map based on observations, 3) Plan an interactive manipulation to confirm the affordances of objects and reduce the uncertainty of affordance map. The resulting affordance map can further be utilized to execute the rearrangement.

II. Affordance prediction and manipulation planning

A. Building a grid map and collecting visual data

We will use existing frontier-based exploration and SLAM techniques to build a map of an unknown environment. The occupancy of the objects will be discretized into a 2D grid and sensor data will be stored as 3D point clouds using a RGB-D camera during the exploration.

B. Affordance prediction based on geometric features

Previously, we studied the semantic labeling of 3D point cloud with object affordance [2]. By using unary and pairwise geometric features, we could successfully train the classifier to predict affordance labels. Here, we apply the classifier to predict 4 affordance labels of an occupied cell in the 2D grid map: pushable up, down, left, and right. To define an affordance, a parameter is required to describe the measure of such affordance like how far an object can be pushed forward. To generalize this property, we set all affordance parameters to be a unit cell.

C. Manipulation scheme for mapping affordance

Based upon the affordance prediction, we need a plan to verify the affordance of each cell by manipulation. Here, we apply a Markov Random Field by setting each grid cell to be a node and connecting the edges between neighboring cells. Relative positions of objects and affordances, such as neighboring wall segments sharing similar affordances, are encoded in the edge potentials. The unary and pairwise potential functions can be obtained from training examples and we can estimate the effect of manipulation by predicting the change of probability. Thus, we can compute reward function for each possible manipulation by calculating a cost and an expected information gain. The cost can be counted by assuming moving one cell to be equally costly as pushing one cell. The reward of manipulation would be the predicted uncertainty reduction.

III. Experiments and expected results

The experiment will be conducted in the simulated gazebo warehouse with a PR2 robot. To train the potentials, we will build maps with different configurations whose ground truths are manually labeled. The quality of the resulting affordance map can be compared with the ground truth. The performance of planning algorithm should be compared to that of exhaustive manipulation or greedy based manipulation scheme. The initial classifier can further be improved with manipulation-observations results by adding additional training examples.

IV. Conclusion

We have propose a novel approach to map the unknown environment with semantic object affordance labels.

References

[1] J.J. Gibson. The concept of affordances. *Perceiving, acting, and knowing*, pages 67–82, 1977.

[2] D. Kim and G. Sukhatme. Semantic labeling of object affordance for robot manipulation. In *IEEE/RSJ International Conference on Robotics and Automation*, 2014.