USC University of Southern California

Semantic Mapping of Object Affordance by Interactive Manipulation

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ROBOTIC EMBEDDED SYSTEMS LABORATORY

Motivation

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A robot enters a warehouse where it needs to rearrange disorganized boxes

- **Sokoban**
  - **Warehouse keeper**
  - **Arrange boxes in desired positions by pushing**
    - **Limited action**
    - **Sequence of action**
  - **NP-hard problem**
- **Problem for the robot**
  - **Understanding the environment**
  - **Understanding object affordances**

Paper overview

Assumption

Without any prior knowledge of map and objects

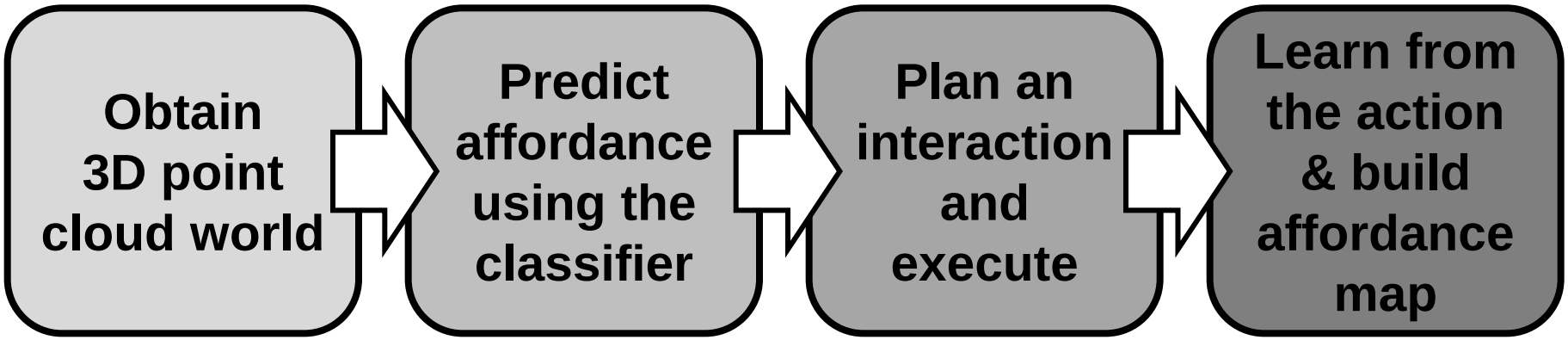
Goal

Build an affordance labeled world map

Purpose

A robot to figure out how to rearrange the world

Method



Data acquisition & mapping

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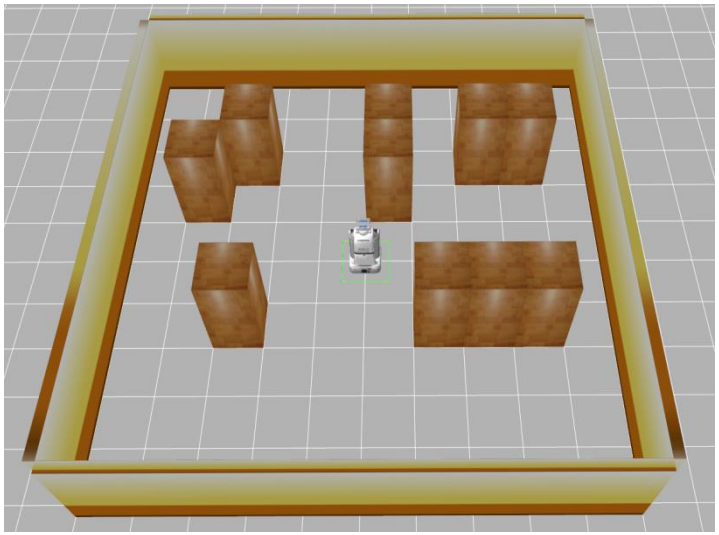
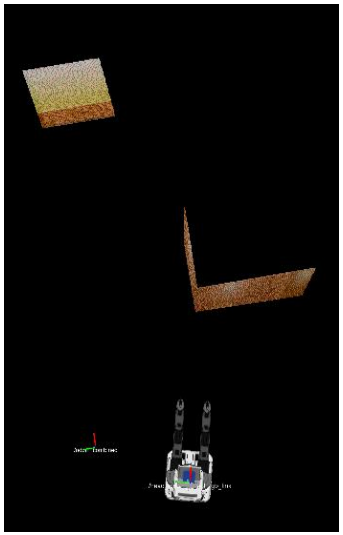
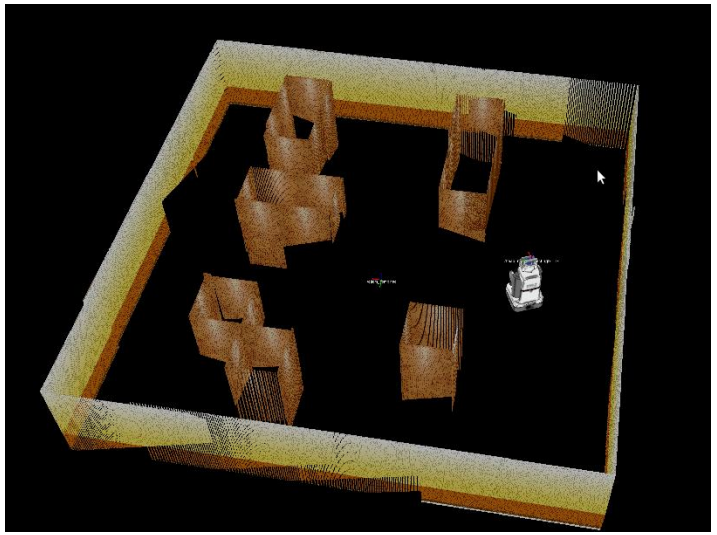
- **3D Point Cloud acquisition**
  - **Microsoft Kinect mounted on the head of PR2**
- **Grid world mapping**
  - **2D occupancy grid map**
  - **Frontier-based exploration algorithm**
  - **Odometry based EKF SLAM**

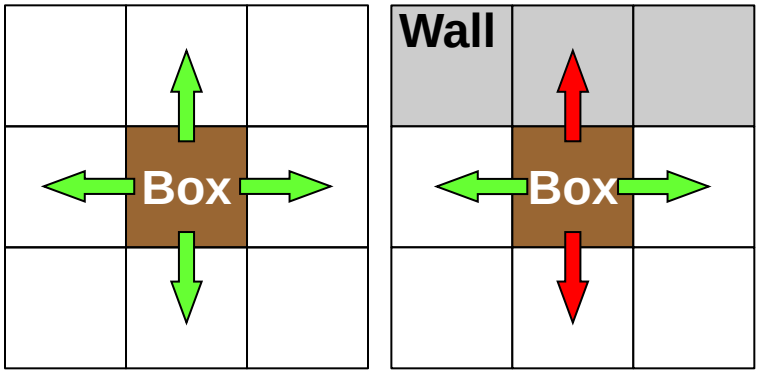






Prediction of affordance label

- **Affordance labels**
  - Pushability in 4 directions
  - Unit - one cell
  - Affected by relative positions



- **Prediction** [Kim *et al*. 2014]
  - Use geometric features
    - Unary features – shape, normal, centroid, span
    - Pairwise features – relative positions of neighboring cells
  - Learn parameters from examples scenes with randomly placed objects
  - Logistic regression
    - Predict each affordance labels

label

$$f^{l}(x) = \underbrace{\beta_0^l}_{\text{parameters}} + \sum_{i=1}^{n} \underbrace{\beta_i^l x_i}_{\text{features}}, \qquad p^l(x) = \frac{e^{f^{l}(x)}}{1 + e^{f^{l}(x)}}$$

Interactive manipulation

- **Goal**
  - Reduce overall belief entropy of the affordance map
- **Solution**
  - Interact with the object to discover its affordance
  - Learn from the experience and update affordance classifier
- **Approach**
  - Exhaustive manipulation – try to investigate every occupied cell
  - Expectation maximization – choose an action that reveals maximum information
- **Probability distribution of Markov random field**

$$P(x_1, x_2, \ldots, x_N) = \frac{1}{Z} \prod_{i=1}^{N} g_i(x_i) \prod_{<i,j>} f_{ij}(x_i, x_j)$$

Unary Potentials Pairwise Potentials

  - Compute estimated entropy loss of each possible interaction

Example of interactive manipulation

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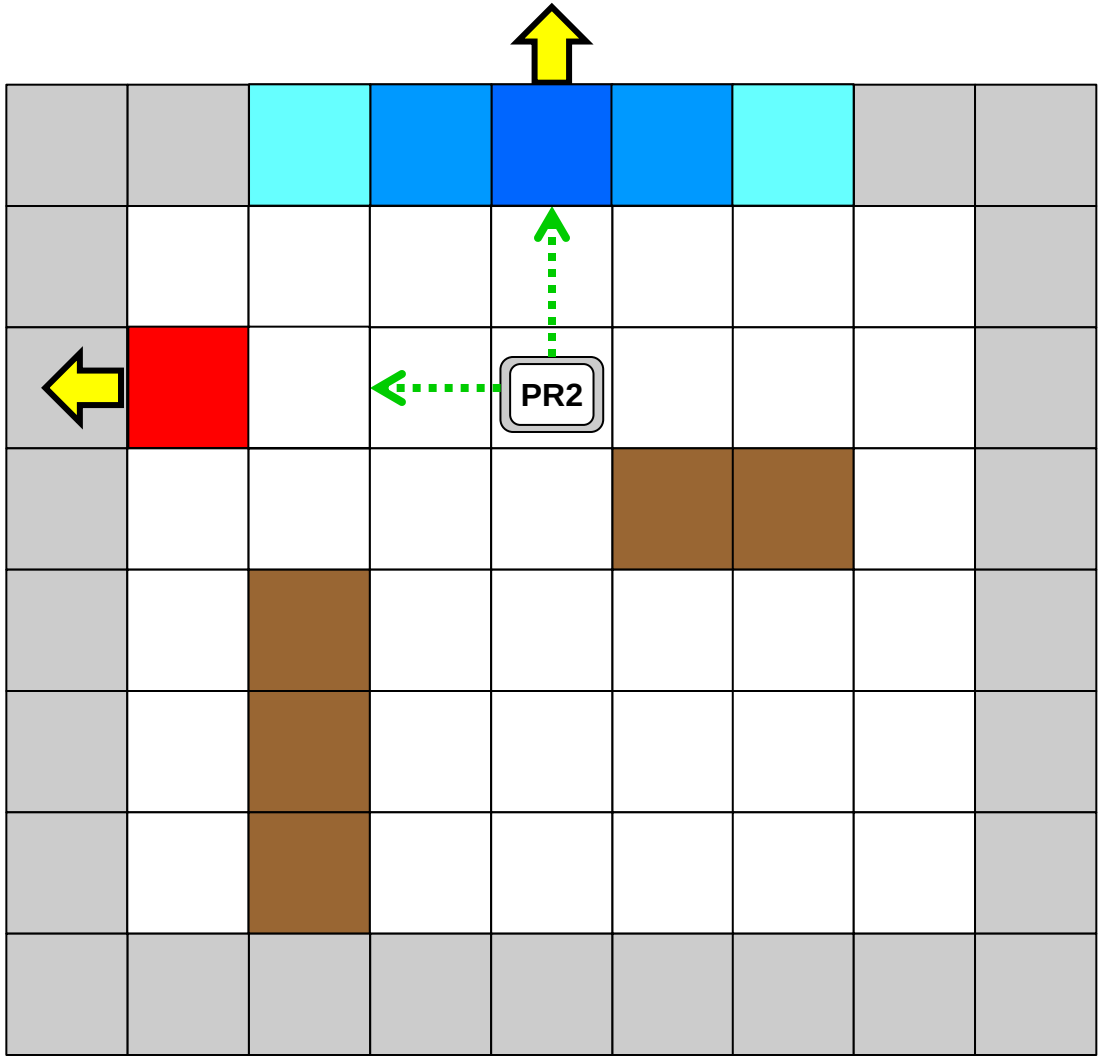


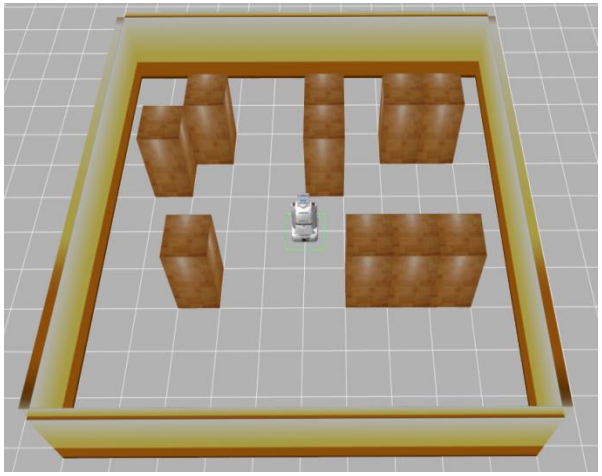
Entropy
ex) 0.34 → 0

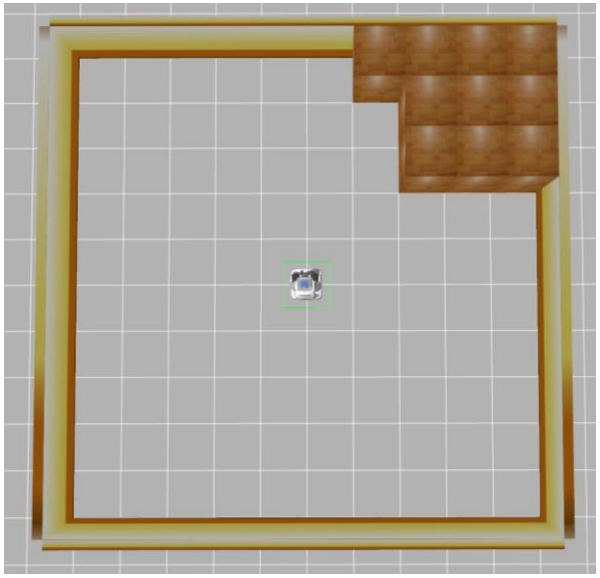
Entropy
ex) 0.85 → 0
0.51 → 0.43
0.48 → 0.31
0.59 → 0.48
0.45 → 0.29

Estimated label
0
1
NOT pushable
Pushable

Experimental Setup

- **Settings**
  - **Simulated warehouse by Gazebo**
  - **PR2**
  - **Microsoft Kinect**
- **Training examples**
  - **Randomly configured examples with ground truth**
  - **Learn parameters for both classifier and MRF potentials**
- **Goal**
  - **Build a 2D grid map of the world**
  - **Build an affordance map**
  - **Compare result with different approach for interactive manipulation (*e.g.* exhaustive vs. expectation maximization)**
  - **Plan and execute a rearrangement using existing sokoban algorithm**





Conclusion & future work

- **Semantic mapping of object affordance for interactive manipulation**
  - **Map the world with 2D occupancy grid**
  - **Predict affordances using geometric features**
  - **Estimate information gain of possible interaction**
  - **Train and learn for better prediction and optimal manipulation**

- **Future work**
  - **Various objects (e.g. household objects) for more generalized planning**
  - **Complex manipulation of affordances (e.g. pulling, lifting, etc.)**
  - **Adaptable classifier for different robot configurations**

Thank you !!!