NRI: Collaborative: Sketching Geometry and Physics Informed Inference for Mobile Robot Manipulation in Cluttered Scenes

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4 PROGRESS
perception robotics grounded reasoning systems
Laboratory for Progress at the University of Michigan

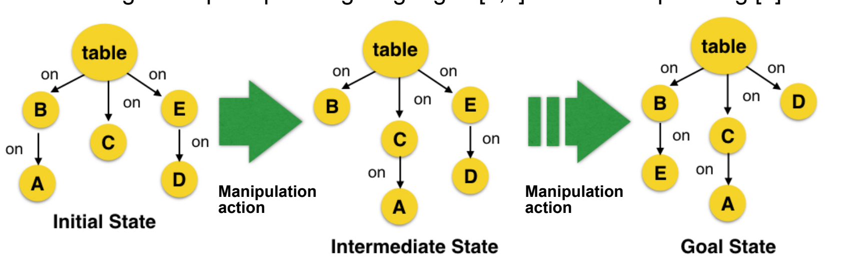
INTRODUCTION

This project aims to enable autonomous **goal-directed robot manipulation** of cluttered scenes. Manipulation of objects in a complex cluttered scene demands accurate scene estimation [1, 3], particularly for object poses and geometries. Towards this end, we explore pose estimation and geometry data collection as the two principal activities of our project to develop: (1) physics-informed pose estimation methods (initially described [2]) and (2) object geometry extraction using sketch-based interfaces [5]. Our current results have been used to demonstrate manipulation in cluttered scenes with the Willow Garage PR2 and Fetch mobile manipulation platforms. We now factor this problem as a Markov Random Field due to the complexity and dimensionality of scenes. Our larger goal is to enable **Semantic Robot Programming** [9], where users demonstrate goals to autonomous robots as desired scene states in 3D semantic maps.

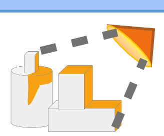
MOTIVATION

Goal-directed task planning

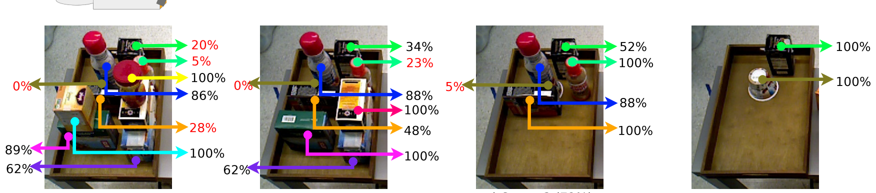
A scene graph representation is amenable to autonomous task execution by robots using descriptive planning languages [6,7] and motion planning [8]



Measure of Clutterness



We propose a measure to analyze the clutter ness of a scene using the proportion of scene object visibilitv.



a) Scene 1 (51%)   b) Scene 2 (53%)   c) Scene 3 (72%)   d) Scene 3 (88%)

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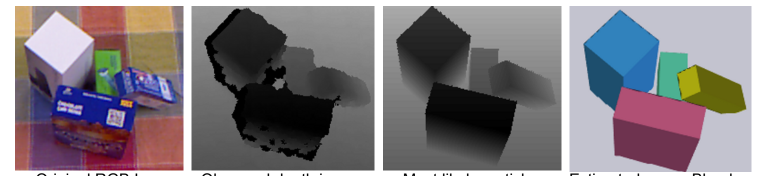
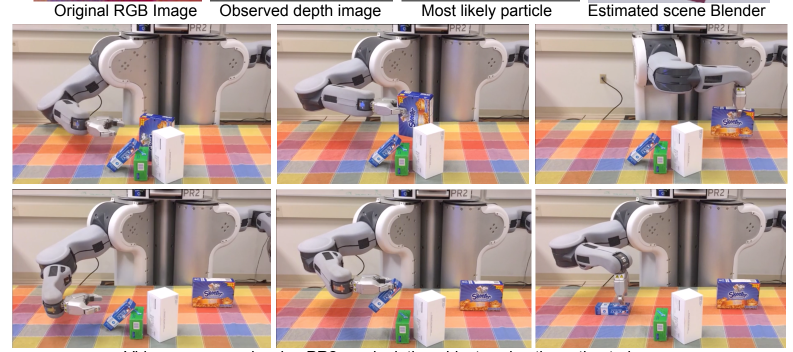
PHYSICS INFORMED SCENE ESTIMATION [2] FOLLOWED BY MANIPULATION

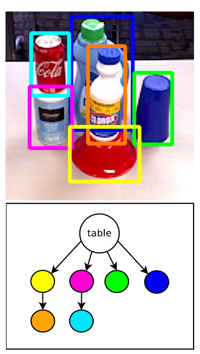


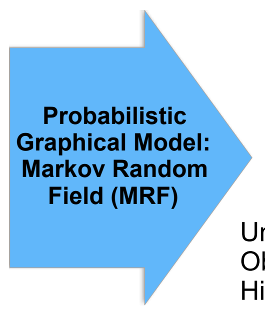
Original RGB Image   Observed depth image   Most likely particle   Estimated scene Blender

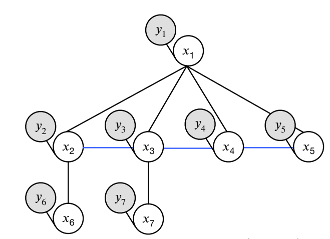


Video sequence showing PR2 manipulating objects using the estimated poses

NONPARAMETRIC SCENE ESTIMATION







Undirected Graph $G = (V, E)$
Observed Variables $Y = \{y_s \mid y_s \in V\}$
Hidden Variables $X = \{x_s \mid x_s \in V\}$

Joint Probability Distribution:

$$p(x, y) = \frac{1}{Z} \prod_{(s,t) \in E} \psi_{s,t}(x_s, x_t) \prod_{s \in V} \phi_s(x_s, y_s)$$

Pairwise term   Unary term

Message Passing in Continuous domain:

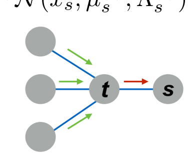
$$m_{ts}(x_s) \leftarrow \int_{x_t \in \mathbb{R}^d} \left(\phi_t(x_t, y_t) \psi_{s,t}(x_s, x_t) \prod_{u \in \rho(t) \setminus s} m_{ut}(x_t) dx_t \right)$$

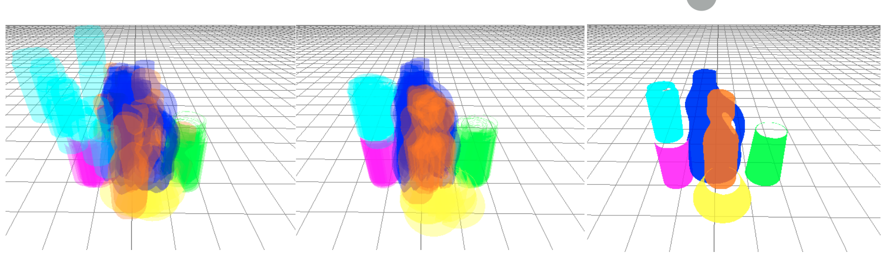
Messages approximated as mixture of Gaussians and sampling techniques used to compute the update [10]

$$m_{ts}(x_s) = \sum_{i=1}^{M} w_s^{(i)} \mathcal{N}(x_s; \mu_s^{(i)}, \Lambda_s^{(i)})$$

Marginal Belief of each node:

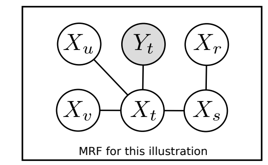
$$b_s(x_s) \propto \phi_s(x_s) \prod_{t \in \rho(s)} m_{ts}(x_s)$$

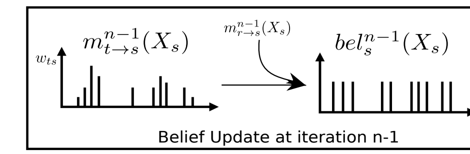


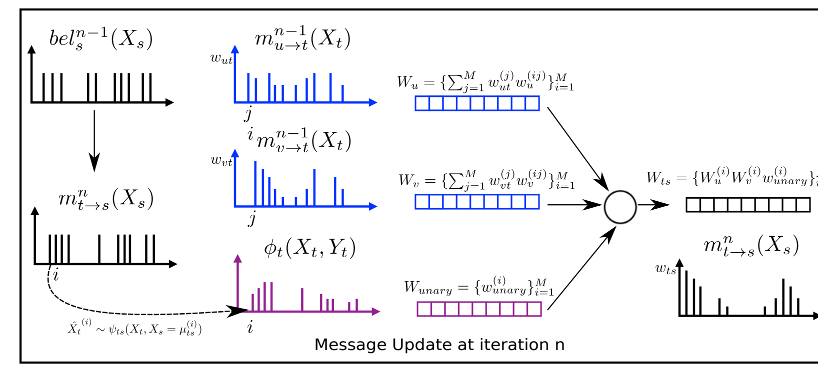


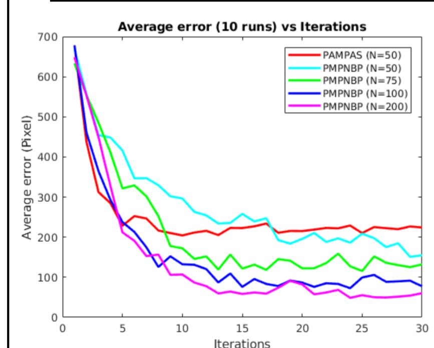
Initial Belief Samples   Final Belief Samples   Final Pose Estimates

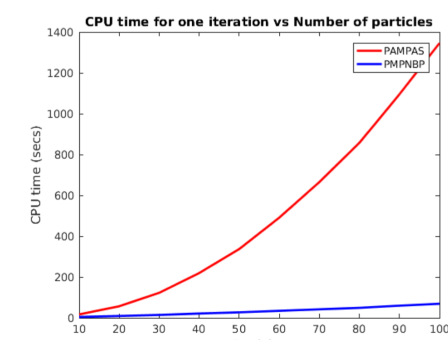
PULL MESSAGE PASSING FOR NONPARAMETRIC BELIEF PROPAGATION (PMPNBP) [11]



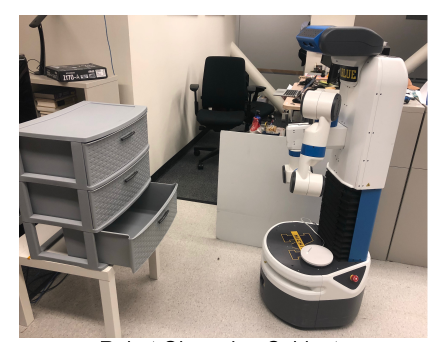




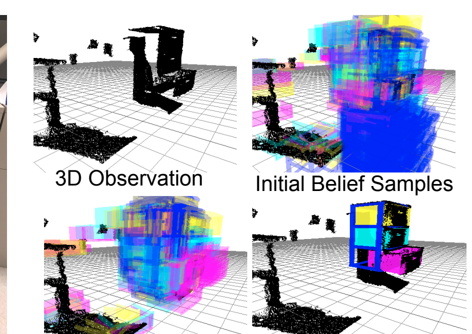




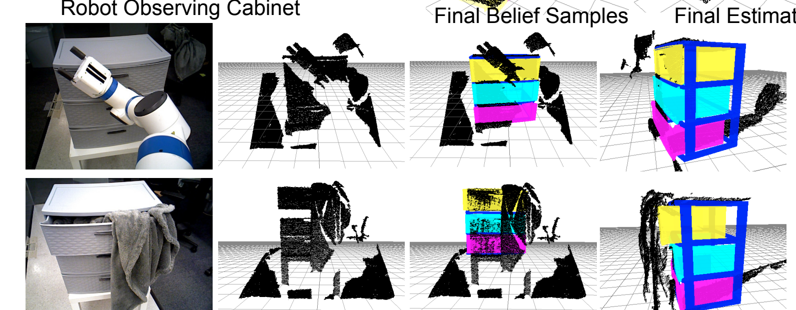
POSE ESTIMATION OF ARTICULATED OBJECTS WITH PMPNBP



Robot Observing Cabinet



3D Observation   Initial Belief Samples   Final Belief Samples   Final Estimate



Original Scene   Point Cloud Observation   Final Pose Estimates in different views