Tracking Large Scale Articulated Models with Belief Propagation for Task Informed Grasping & Manipulation

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Maintaining belief over possible hypotheses will enable robots to perform tasks under partial observations.

Objectives

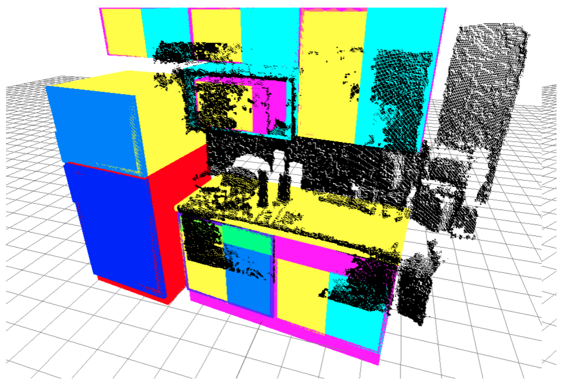
1. Estimate and track the pose of large scale articulated models such as kitchen.
2. Maintain and propagate belief over the possible poses of the articulated models.

Robot is required to perform tasks in kitchen

Challenges

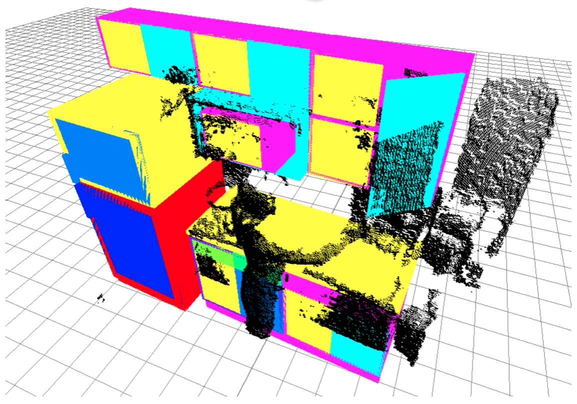
- **External objects are part of the observation.**
- **Limited view of the onboard sensor.**
- **Noisy sensor observations for large scale environment.**

frame = 1



- **External agent's interaction causing occlusions and change of pose.**

frame = N

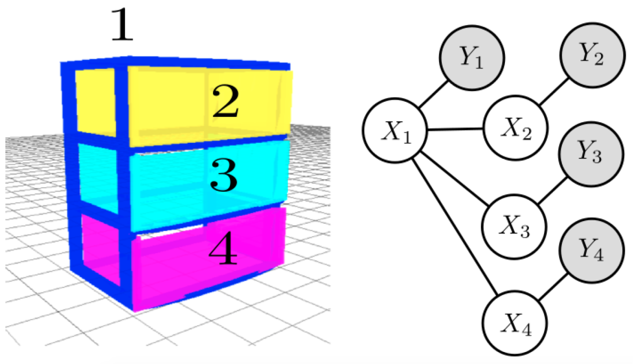


Original Scene RGB frames

True pose of the kitchen model ovelayed on point cloud observations

Approach and Related Work

The problem can be formulated as a pairwise Markov Random Field (MRF), where each hidden node (continuous pose variable) is an observed object-part's pose and the edges denote the articulation constraints between the parts. Efficient Belief Propagation (PMPNBP) [1] will be extended to perform pose estimation and tracking of large scale articulated models.



Joint Probability Distribution: $p(X,Y) = \frac{1}{Z} \prod_{(s,t)\in E} \underbrace{\boxed{\psi_{s,t}(X_s,X_t)}}_{\text{Pairwise term}} \prod_{s\in V} \underbrace{\boxed{\phi_s(X_s,Y_s)}}_{\text{Unary term}}$

Message Passing in Continuous domain:

$$m^n_{t\to s}(X_s) \leftarrow \int_{X_t\in \mathbb{H}_D} \Big(\psi_{st}(X_s,X_t)\phi_t(X_t,Y_t) \prod_{u\in\rho(t)\setminus s} m^{n-1}_{u\to t}(X_t) \Big) dX_t$$

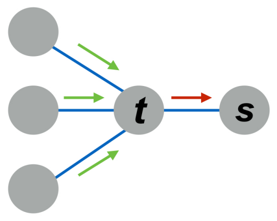
Messages approximated as a mixture of Gaussians and sampling techniques used to compute the update

$$m_{t\to s}(X_s) = \sum_{i=1}^{M} w^{(i)}_{ts} \mathcal{N}(X_s; \mu^{(i)}_{ts}, \Lambda^{(i)}_{ts})$$

Marginal Belief of each node:

$$bel^n_s(X_s) \propto \phi_s(X_s,Y_s) \prod_{t\in\rho(s)} m^n_{t\to s}(X_s)$$

$$bel^n_s = \{(w^{(i)}_s, \mu^{(i)}_s, \Lambda^{(i)}_s) : 1 \le i \le T\}$$



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