

Multi-Resolution 3D Scene Graph Construction and Optimization

Improving 3D Object Representations in the REACT Framework

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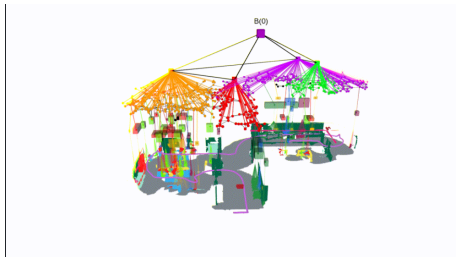
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The Goal: From Monolithic Maps to Per Object Resolution

For a robot to be truly useful in our world, it needs more than just a map. It needs to "understand" the scene.

Project Context:

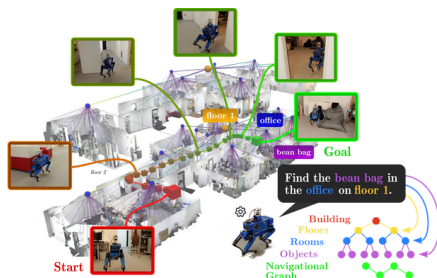
- **Hydra (MIT):** A powerful framework for large-scale 3D reconstruction. Its primary output is a 3D scene graph with a single, detailed 3D mesh of the environment.
- **REACT (Aalto):** Builds on Hydra to add an efficient clustering of object nodes.



The Scene Graph: A Robot's Brain Map

A scene graph organizes a 3D scene into a meaningful hierarchy.

- It's not just geometry; it's a network of **nodes** (things) and **edges** (relationships).
- **Nodes**: Rooms, objects (a chair), the robot itself.
- **Edges**: Relationships like "is inside," "is on top of."



How Hydra Currently Builds the Scene

The current pipeline relies on a monolithic (single-piece) representation.

The Process:

- 1 Fuse sensor data into a **Truncated Signed Distance Function (TSDF)**. Each voxel's distance value $D(x)$ is updated via a running weighted average:

$$D_{new}(x) = \frac{W_{old}(x)D_{old}(x) + w_{new}d_{new}(x)}{W_{old}(x) + w_{new}}$$

- 2 Extract a single, unified **3D mesh** from this volume.
- 3 Identify objects by segmenting or "cutting out" pieces of this global mesh.

Disadvantages of the Monolithic Approach

This "one-size-fits-all" model creates significant limitations for robotic interaction.

- **Problem 1: Fixed Resolution**

- A large wall and a small, intricate coffee mug are represented with the same level of detail.
- This is inefficient and lacks the fidelity needed for tasks like grasping.

- **Problem 2: Geometric Entanglement**

- Objects are fundamentally "stitched into" the fabric of the world mesh.
- Treating an object as an independent entity for analysis or manipulation is computationally expensive and clumsy.

The Core Idea: Independent Object Representations

My work decouples the object's representation from the global map.

The Goal: Instead of a coarse mesh cutout, each object node in the scene graph will now store its own **dedicated, high-fidelity point cloud**. This allows us to maintain a lightweight global map for navigation while having rich, detailed models of objects for interaction.



The Theoretical Workflow

I've integrated a new pipeline for creating and refining these object-centric models.

- 1 **Instance Segmentation:** Identify object instances in the 2D camera image.
- 2 **High-Res Cloud Generation:** Project the 2D mask into 3D using depth data.
- 3 **Data Association (ICP):** Precisely align the new cloud with the existing model using the Iterative Closest Point algorithm. The objective is to find the rotation \mathbf{R} and translation \mathbf{t} that minimize the error:

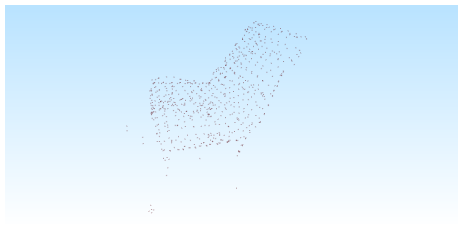
$$\min_{\mathbf{R}, \mathbf{t}} \sum_{i=1}^N \|(\mathbf{R}\mathbf{p}_i + \mathbf{t}) - \mathbf{q}_i\|^2$$

- 4 **Model Fusion & Refinement:** Merge the aligned cloud and apply voxel grid downsampling to maintain a consistent density.
- 5 **Attribute Update:** Recalculate a tighter bounding box and update the object's position.

Example: The Impact of High-Fidelity Models

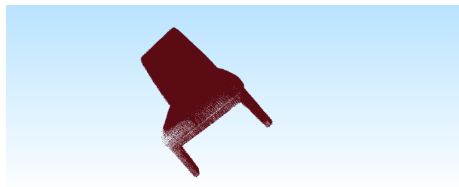
Before: Coarse Mesh Segment

- Low detail, noisy.
- Derived from global TSDF.
- Difficult for grasp planning.



After: Fused Point Cloud

- High detail, clean.
- Fused from multiple sensor views.
- Ideal for manipulation and analysis.



Next Steps: Next Week

What could be improved?

- The ICP and downsampling parameters are currently fixed. They could be adapted based on object category (e.g., a 'sofa' needs different settings than a 'cup').

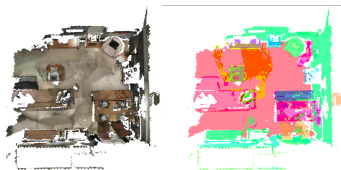
Immediate Implementation Goals:

- Implement per-label parameters for ICP and downsampling to improve registration quality.
- Benchmark the performance gain in terms of memory usage and object localization accuracy.
- Implement a publisher node to visualize the incremental fusion of objects point clouds.

The Next Frontier: Per-Object TSDF Fusion

Per object point cloud implementation is a great achievement but for a truly solid, watertight 3D model, the next step is to give each object its own miniature **TSDF volume**.

- This allows for robust fusion of observations over time, filling in holes and removing noise.
- We can then extract a high-quality, continuous mesh for each object on demand.
- This approach is inspired by seminal works like **Panoptic Mapping (ETH Zurich)**, which demonstrates the power of this hybrid mapping strategy.



Results obtained

This shift from a monolithic to a hybrid, object-centric model is critical for the project.

- **Computational Efficiency:** Use lightweight models for navigation and high-detail models only when needed for interaction.
- **Enhanced Capability:** Enables advanced manipulation. A robot can't plan a precise grasp on a blurry model; it needs the high fidelity this method provides.
- **Scalability & Robustness:** The system can map larger, more complex environments without getting bogged down by unnecessary detail, and object models become more robust over time.

Key Inspirations and Frameworks:

- Rosinol, A., et al. (2022). *Hydra: A Real-time Spatial Perception System for 3D Scene Graph Construction and Optimization*. IEEE Robotics and Automation Letters. (MIT-SPARK)
- Aalto Intelligent Robotics. *REACT Project*.
github.com/aalto-intelligent-robotics/REACT
- Schmid, L., et al. (2022). *Panoptic Multi-TSDFs: a Flexible Representation for Online Multi-resolution Volumetric Mapping...* In 2022 IEEE ICRA.