Neural Scene Representations for SLAM

Leonard Bruns

Overview

- Introduction: neural fields, NeRFs, and beyond
- Neural SLAM: SLAM with neural scene representations
- Neural graph mapping: efficient loop closure in neural SLAM
- Outlook: open research problems

Introduction

Neural Fields, NeRFs, and beyond

Shape and Scene Representations

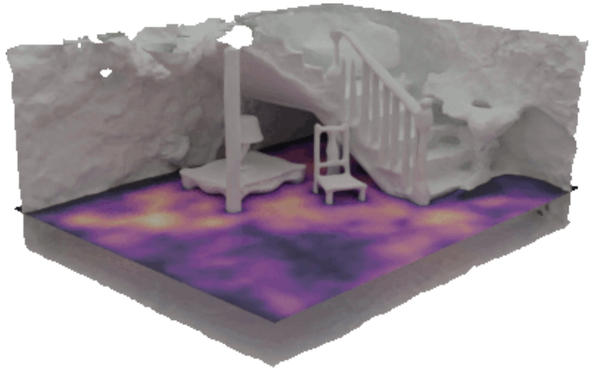
- Various shape / scene representations exist
- Surface representations
  - Store surface position and quantities on surface
  - Examples
    - Meshes
    - Point clouds
- Volumetric representations
  - Store quantities in volume
  - Examples
    - Voxel grid (dense, octrees, voxel hashing)
    - Neural fields
    - Set of Gaussians

Neural Fields

- Core idea: represent 3D shape by a simple neural network

$$f_\theta : \mathbb{R}^3 \to \mathbb{R}^3 \times \mathbb{R}$$
$$\boldsymbol{x} \mapsto (\boldsymbol{c}, \rho)$$

- Map 3D point $\boldsymbol{x}$ to color $\boldsymbol{c}$ and quantity ρ (e.g., SDF, occupancy, etc.)
- Properties
  - Continuous
  - Differentiable
  - Adaptive $\to$ potentially memory efficient

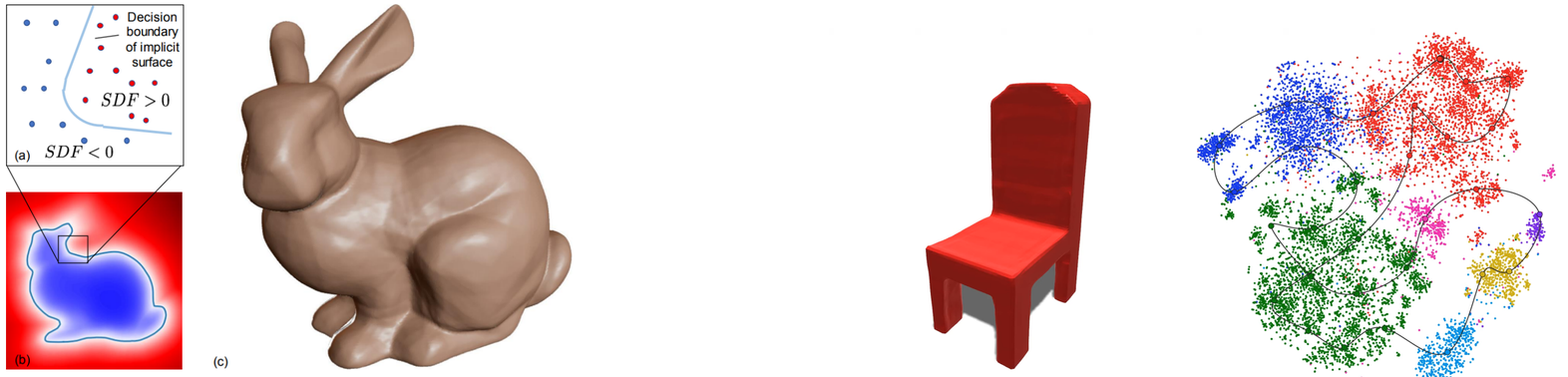


Neural Scene Representations

Early Works

- DeepSDF [1], occupancy network [2], ...
- Trained using direct 3D supervision (i.e., from mesh collections)
- Demonstrate shape interpolation by adding additional latent input

$$f_\theta : \mathbb{R}^3 \times \mathbb{R}^N \rightarrow \mathbb{R}$$
$$(\boldsymbol{x}, \boldsymbol{z}) \mapsto \rho$$



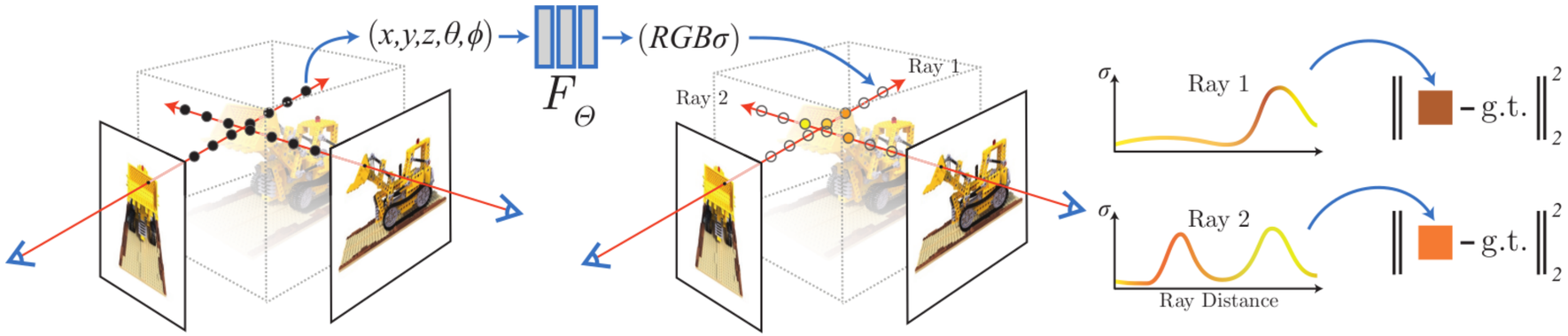
[1] DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation, Park et al., 2019
[2] Occupancy Networks: Learning 3D Reconstruction in Function Space, Mescheder et al., 2019
Video source: https://www.youtube.com/watch?v=C_XNdGGs6qM

Neural Scene Representations

Neural Radiance Field (NeRF)

- Train neural field using indirect 2D supervision
- Camera poses fixed (e.g., from structure-from-motion)
- Add 2D view direction as additional input

$$f_\theta : \mathbb{R}^3 \times \mathbb{R}^2 \rightarrow \mathbb{R}^3 \times \mathbb{R}$$
$$(\boldsymbol{x}, \boldsymbol{d}) \mapsto (\boldsymbol{c}, \sigma)$$

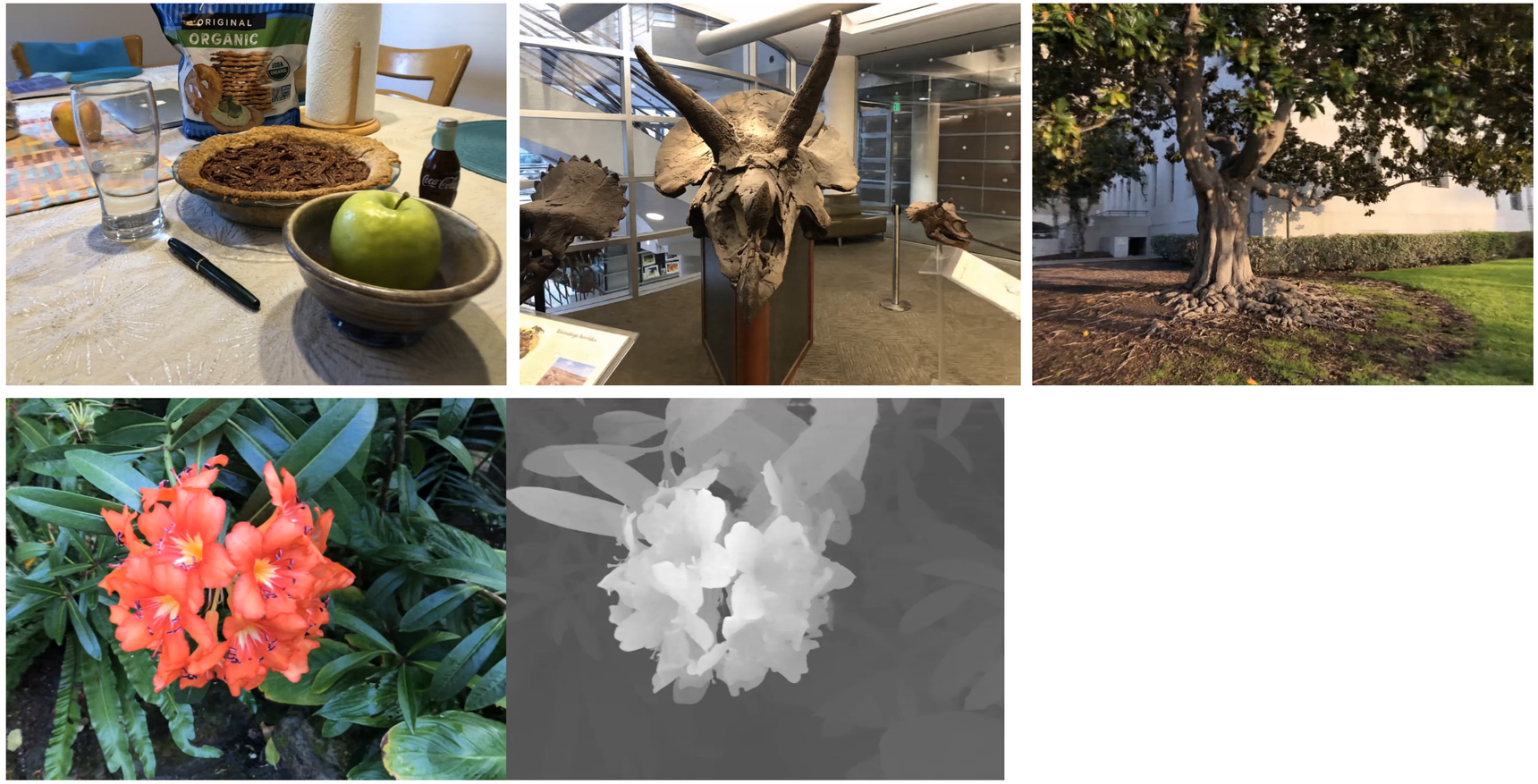


NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis, Mildenhall et al., 2020

Neural Scene Representations

Neural Radiance Field (NeRF)

- NeRF Examples



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Neural Scene Representations

Neural Radiance Field (NeRF)

- NeRF Examples

- Limitations
  - Mainly limited to small forward-facing scenes
  - Isolevel for surfaces not well-defined
  - Optimization time (~hours)
  - Rendering time (~seconds for single 1080p frame)

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Neural Scene Representations

Follow-up Works

- Surfaces: NeuS [1]

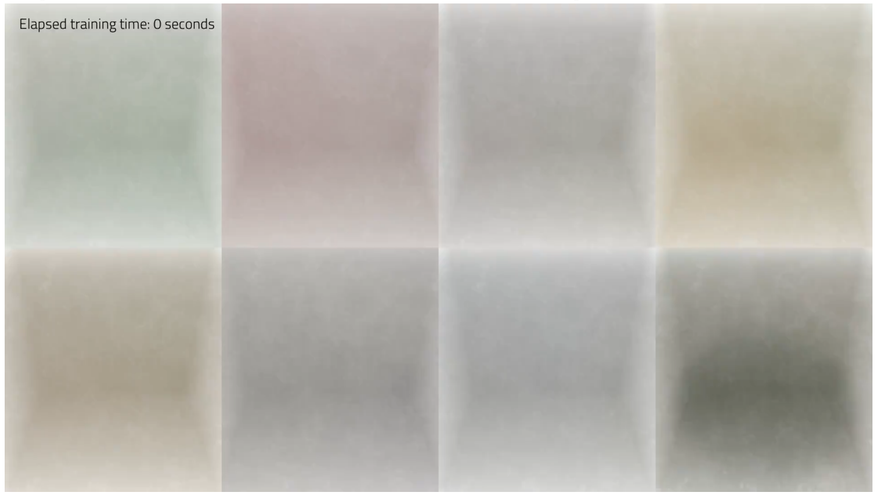
[1] NeuS: Learning Neural Implicit Surfaces by Volume Rendering for Multi-view Reconstruction, Wang et al., 2021

Neural Scene Representations

Follow-up Works

- Surfaces: NeuS [1]

- Speed: Instant Neural Graphics Primitives [2]



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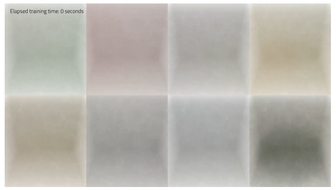

- Quality: Zip-NeRF [3]

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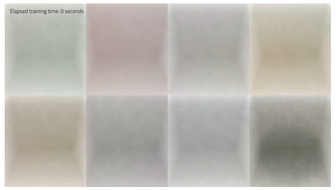

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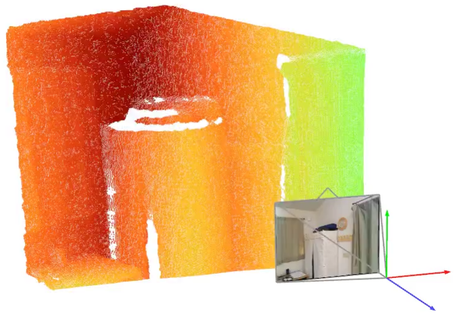
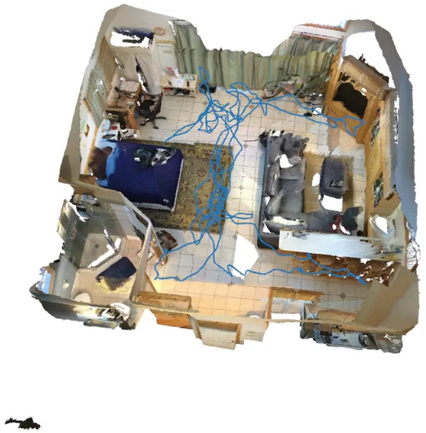
Neural SLAM

SLAM with Neural Scene Representations

Dense Visual SLAM

- Visual Simultaneous Localization and Mapping (SLAM)
  - Estimate camera trajectory of a moving camera from its image stream
  - Sparse keypoint-based maps
- Dense visual SLAM
  - Estimate dense 3D scene representation during localization (e.g., mesh)
  - RGB-D data
  - Volumetric scene representation
    - Classic approaches use voxel grids to represent 3D scene





iMAP

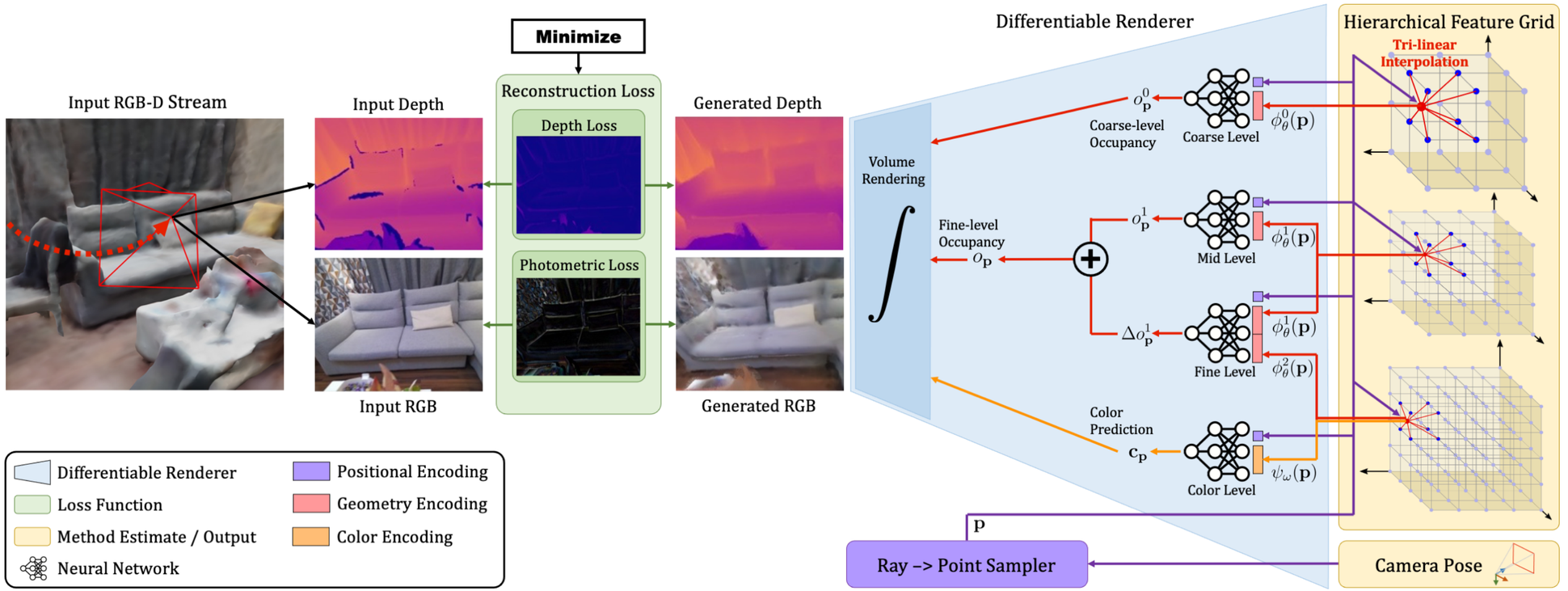
- First work demonstrating SLAM using neural field as scene representation
- Alternates between frame-to-map alignment and map refinement
- Compared to NeRF
  - Removed view-direction dependency
  - Smaller neural network
  - Depth supervision

- Limitation: continuous reoptimization of previous areas required to prevent forgetting

iMAP: Implicit Mapping and Positioning in Real-Time, Sucar et al., 2021

NICE-SLAM

- Replaces single MLP by combination of feature grid and frozen, pretrained decoder
  $\rightarrow$ No more forgetting, better scalability



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RGB-D Sequences

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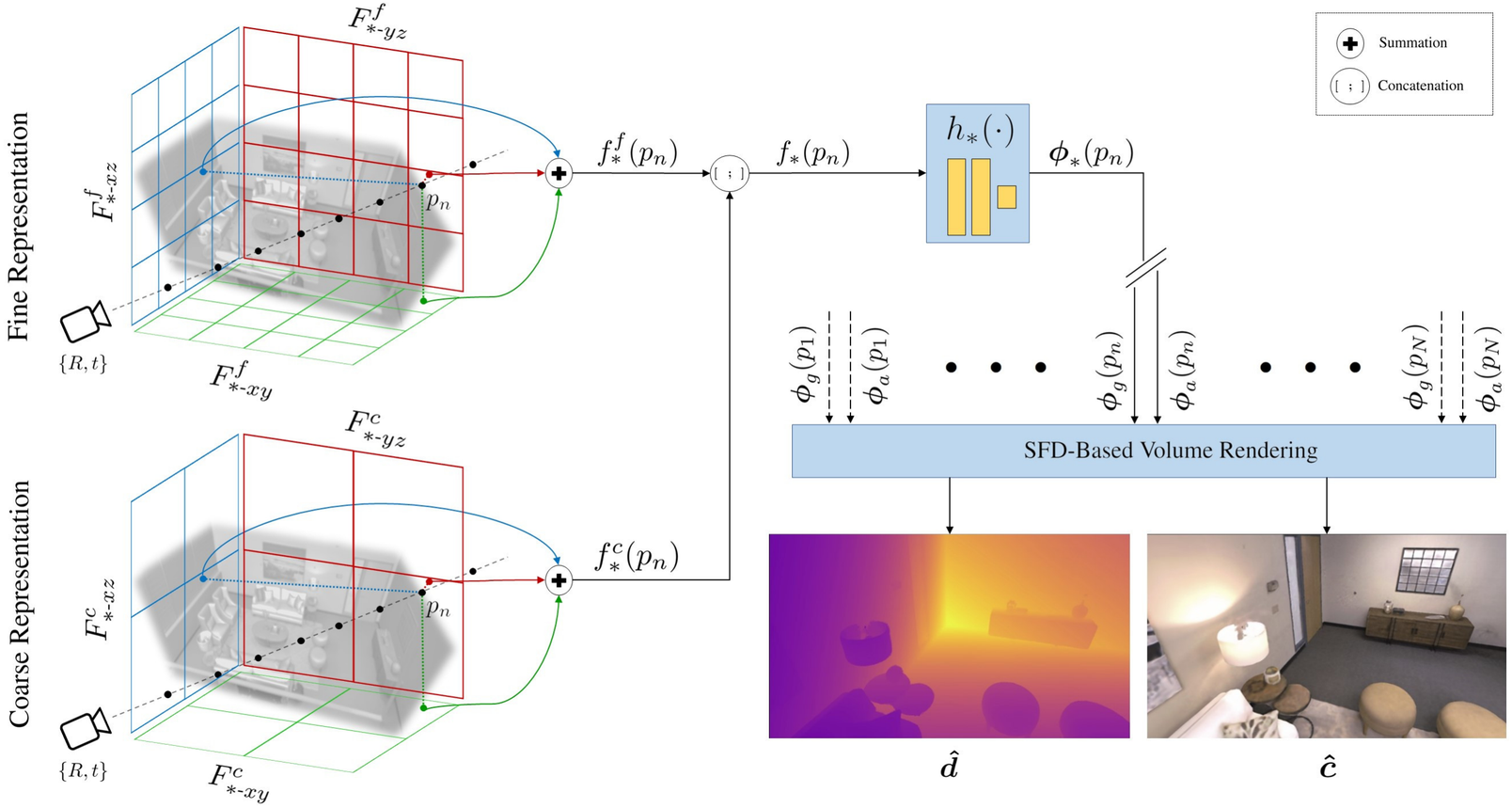
Follow-up Works

- ESLAM [1]: triplane encoding



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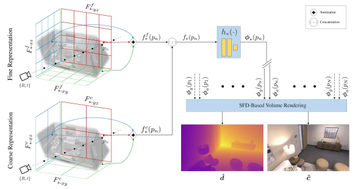
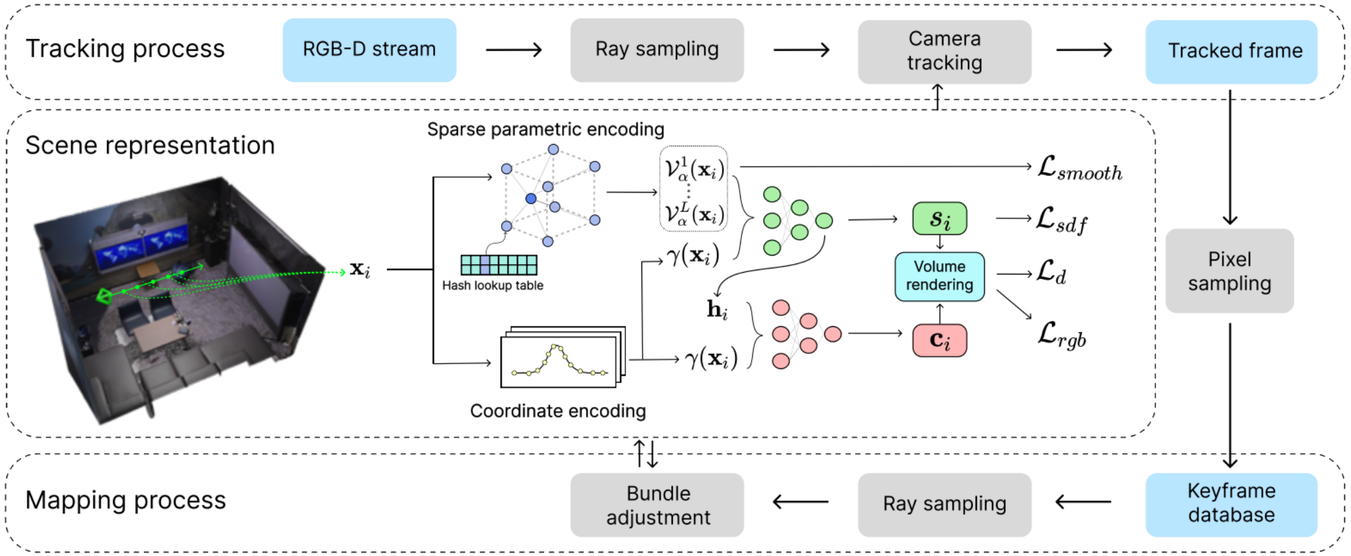


- Co-SLAM [2]: joint hash / coordinate encoding



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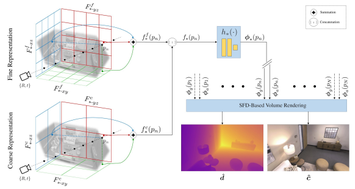

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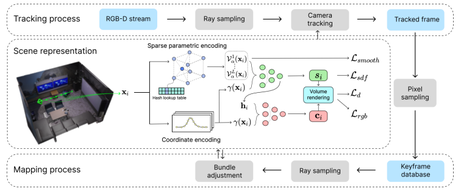
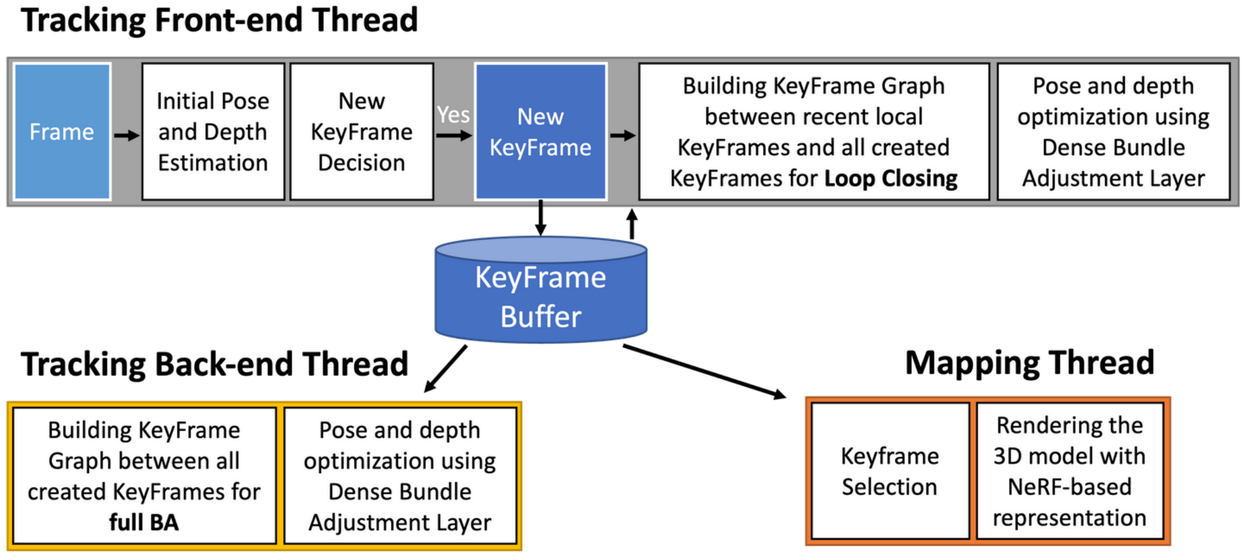


- GO-SLAM [3]: loop closure via reoptimization



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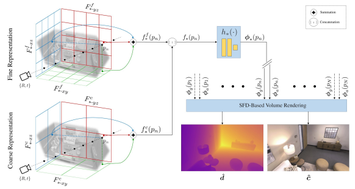

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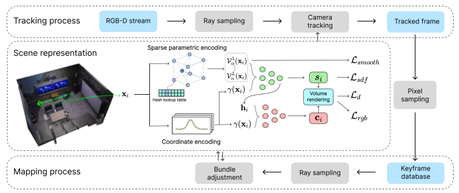

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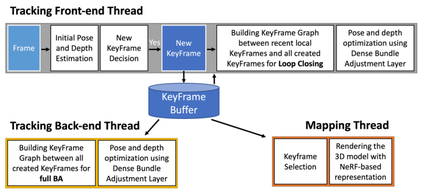

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Common Limitation: Monolithic Field

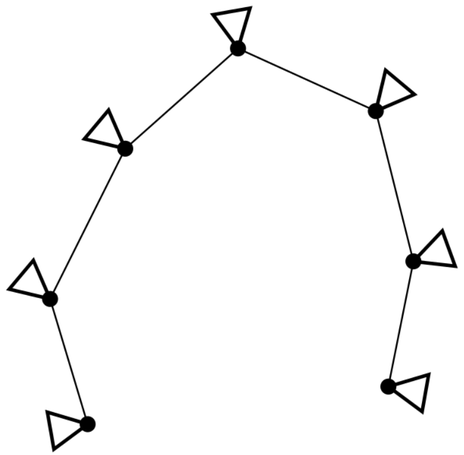
- All methods use a single monolithic data structure
- Expensive to optimize neural fields
- Sensor data gets baked into a data structure
  - Similar to classic voxel-based data structures
- Cannot easily deform volumetric scene representation on loop closure
  - GO-SLAM has to reintegrate all keyframes that have moved on loop closure
    $\rightarrow$ The larger the loop, the more reoptimization is required

Neural Graph Mapping

Efficient Loop Closure for Neural SLAM

Neural Graph Mapping

- Idea: attach lightweight neural fields to pose graph of sparse visual SLAM
- Each field captures scene within a fixed radius r



Neural Graph Mapping for Scalable Dense SLAM with Loop Closure, Bruns et al., 2024

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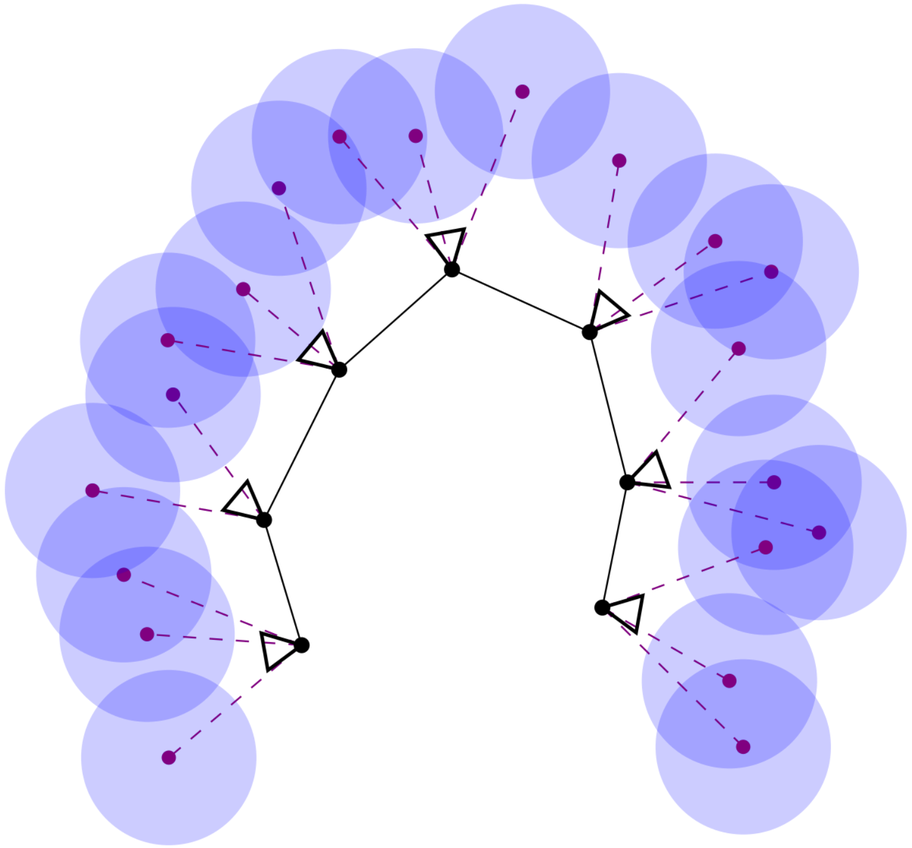

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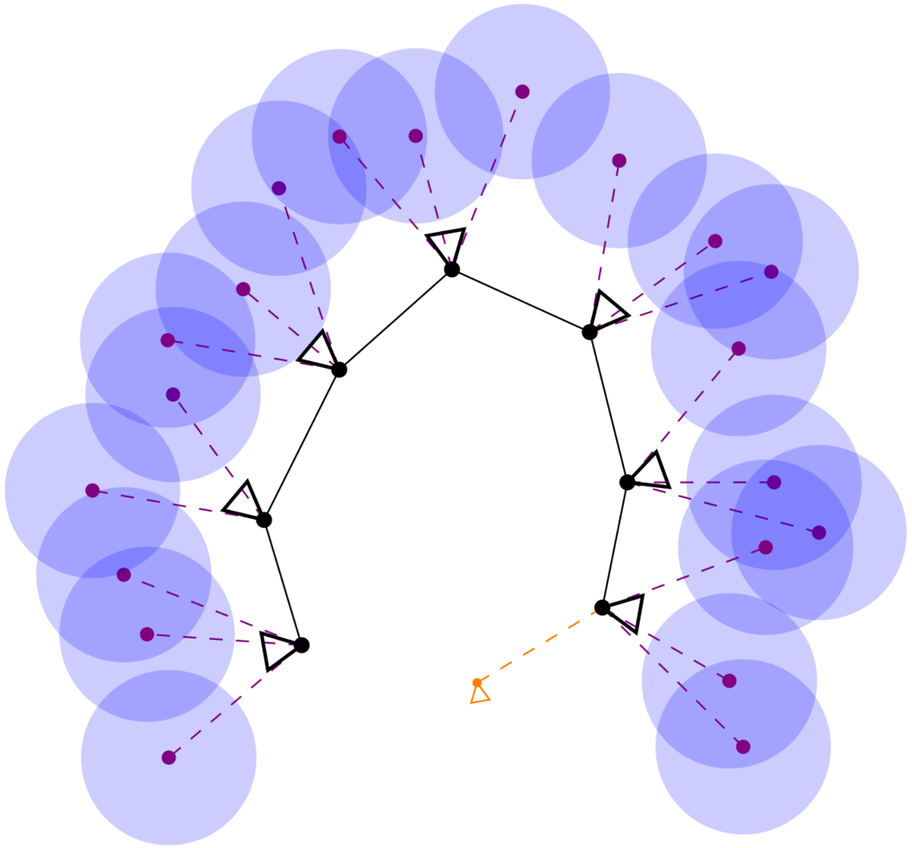

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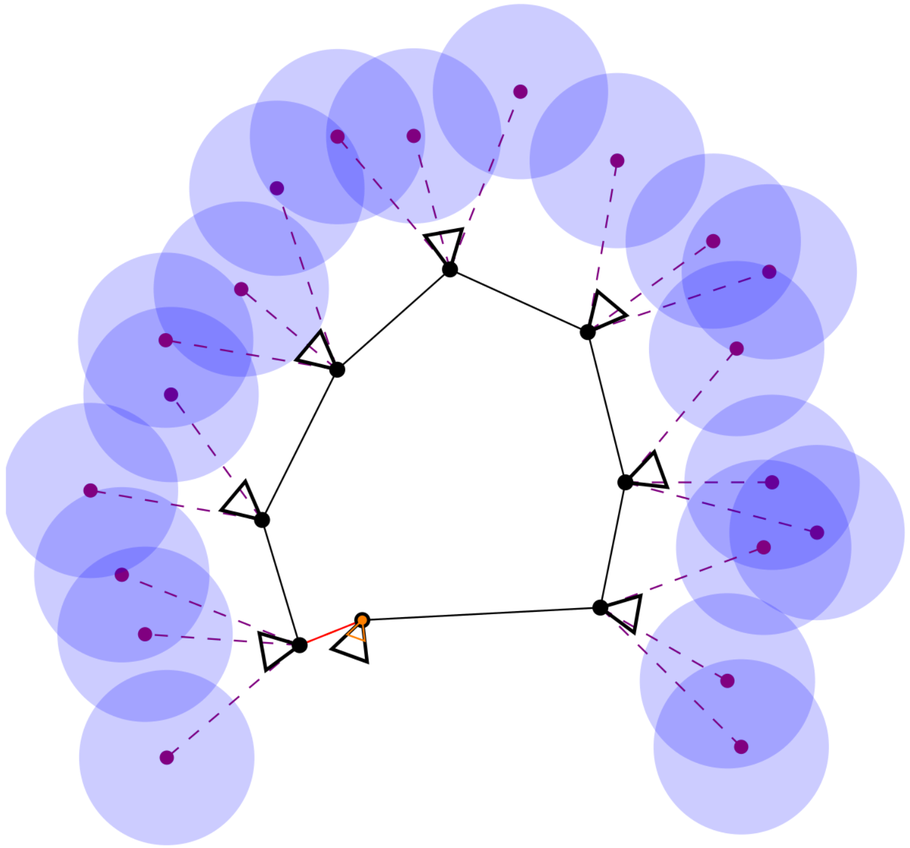

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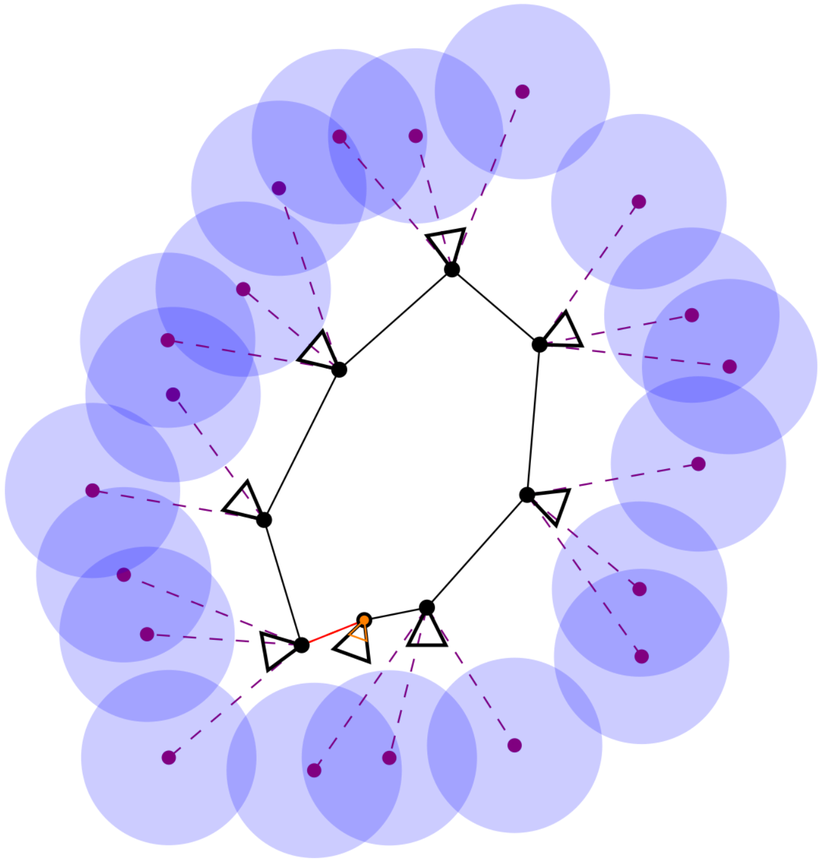

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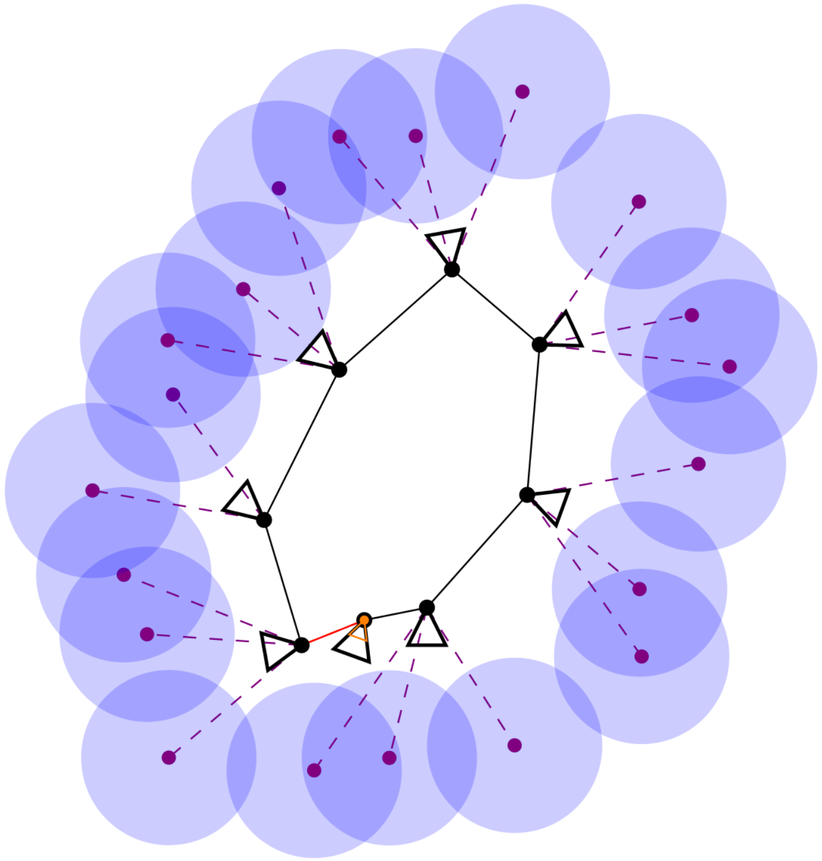

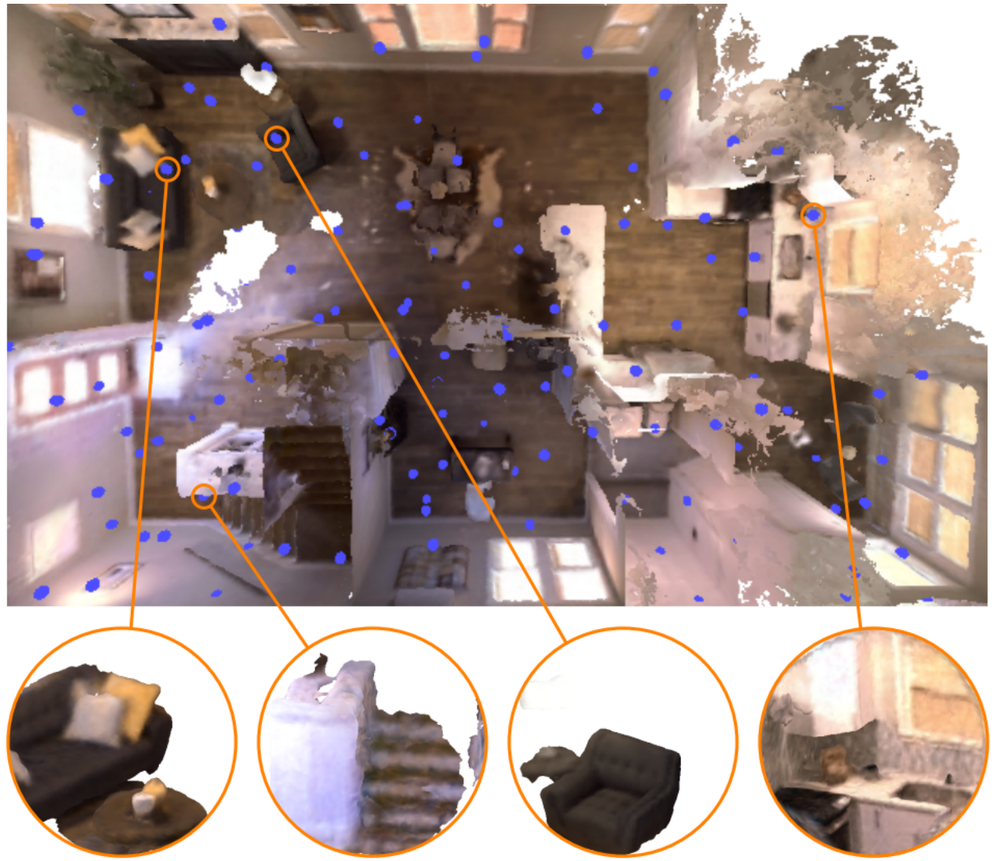

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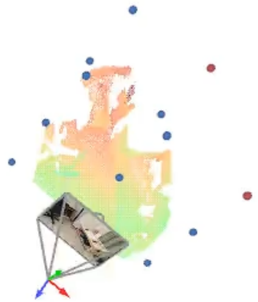
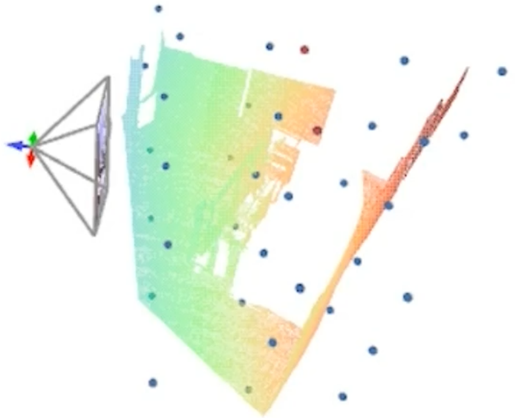
Neural Graph Mapping

Example

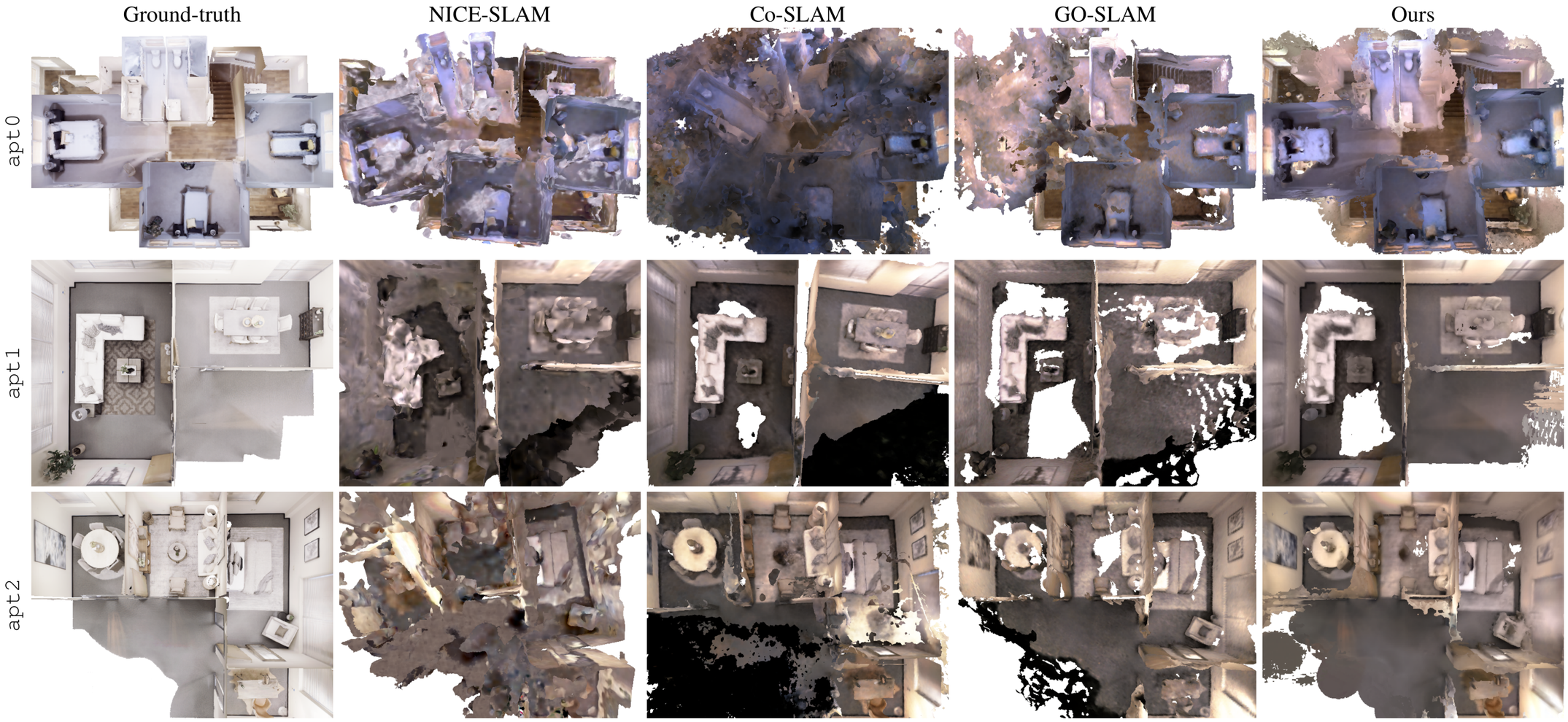


Another Example



Neural Graph Mapping

Comparison to Monolithic Approaches



Outlook

- Higher memory usage compared to monolithic neural field methods
  - How to reduce memory requirements?

- Neural field-based map not used for SLAM currently
  - How to combine sparse visual SLAM and dense visual SLAM?

- Currently limited to indoor environments with depth data available
  - How to extend to outdoor environments?

- Neural SLAM in general requires lots of resources
  - Can we use meta-learning for few-shot mapping?

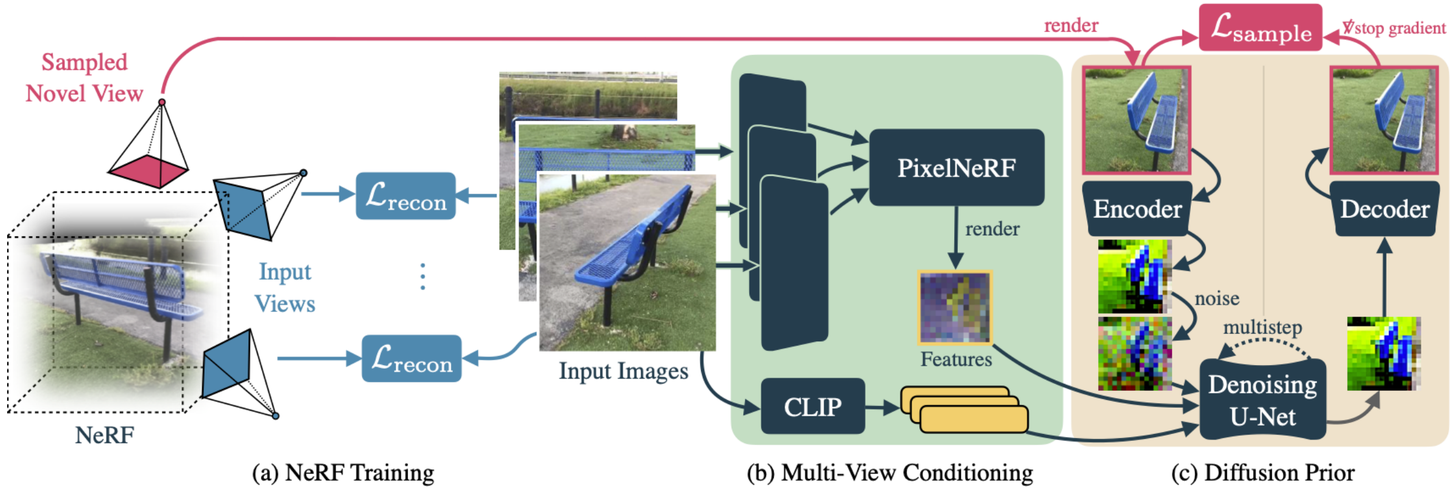
Outlook

Open Research Problems

Outlook

Learning vs Optimization

- Optimization-based approaches inherently limited to what is captured by sensors
  - Sufficient for elaborate sensor setups and human operator
  - However, far from human-level spatial understanding (infilling / etc.)
- Learning approaches might infill from partial observations
- How to combine strong generative model with partial observations?
  - Some work in this direction: ReconFusion



ReconFusion: 3D Reconstruction with Diffusion Priors, Wu et al., 2023

Outlook

Gaussian Splatting

- Represent scene by a set of 3D Gaussians instead of differentiable function
- Each Gaussian has
  - Shape: position + covariance
  - Opacity
  - Coefficients of spherical harmonics ($\rightarrow$ view-dependent color)
- Rasterization instead of volume rendering

  $\rightarrow$ Real-time (>100 FPS), high-resolution rendering

3D Gaussian Splatting for Real-Time Radiance Field Rendering, Kerbl et al., 2023
https://lumalabs.ai/featured

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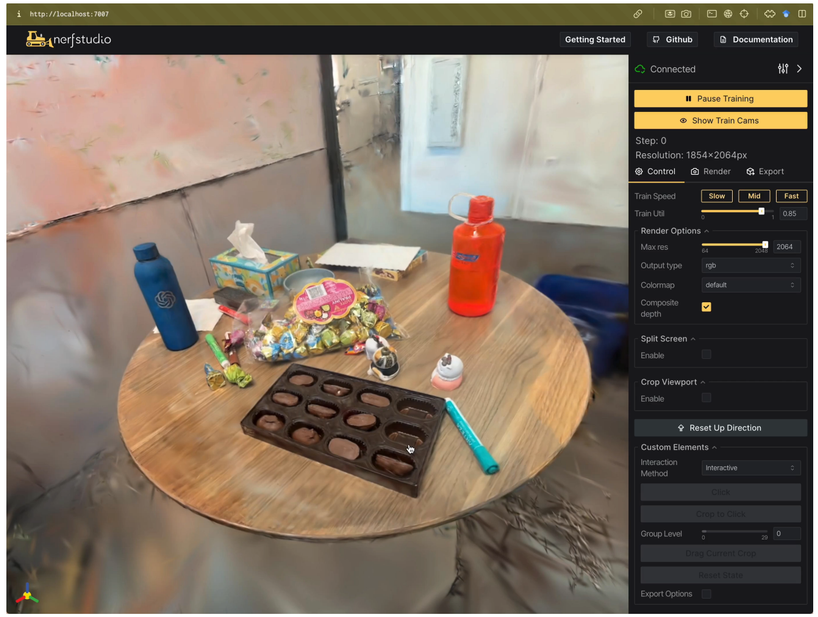
Outlook

Object-based / Interactive Map Decomposition

- Scenes learned in this way are not interactive
  - Objects are not separated; and not complete
  - Reflections are baked in
  - Shadows are baked in
- Some early work in this direction: LERF [1], GARField [2]



[1] LERF: Language Embedded Radiance Fields, Kerr et al., 2023
[2] GARField: Group Anything with Radiance Fields, Kim et al., 2024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