

# Neural Graph Mapping for Scalable Dense SLAM with Loop Closure

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## Abstract

*Existing neural field-based SLAM methods typically employ a single monolithic field as their scene representation. This prevents efficient incorporation of loop closure constraints and limits scalability. To address these shortcomings, we propose a neural mapping framework which anchors lightweight neural fields to the pose graph from an off-the-shelf SLAM system. Our approach shows the ability to integrate large-scale loop closures, while limiting necessary reintegration. Furthermore, we verify the scalability of our approach by demonstrating successful building-scale mapping taking multiple loop closures into account during the optimization, and show that our method outperforms existing state-of-the-art approaches on large scenes in terms of quality and runtime. Our code is available open-source at [https://github.com/roym899/neural\\_graph\\_mapping](https://github.com/roym899/neural_graph_mapping).*

## 1. Introduction

Simultaneous localization and mapping (SLAM) using cameras, often referred to as visual SLAM, has been a long standing problem in computer vision [6, 9, 14]. In particular, dense visual SLAM aims to construct a detailed geometric representation of the environment [27] enabling various applications, such as, occlusion handling in augmented reality [27], planning and collision checking in robotics [1], or camera localization [17, 22]. Often volumetric scene representations are employed as they are well-suited for online data integration. Traditional volumetric representations use grid-based structures [26], often incorporating acceleration approaches like octrees [7, 10, 19] or voxel hashing [28] in practice. However, incorporating loop closure constraints in volumetric maps is difficult [31, 42] compared to sparse keypoint-based maps, which can easily be deformed.

Recently, neural fields have emerged as a memory-efficient volumetric scene representation due to their amenability to differentiable rendering-based optimization [35]. Building on the first neural field-based SLAM method

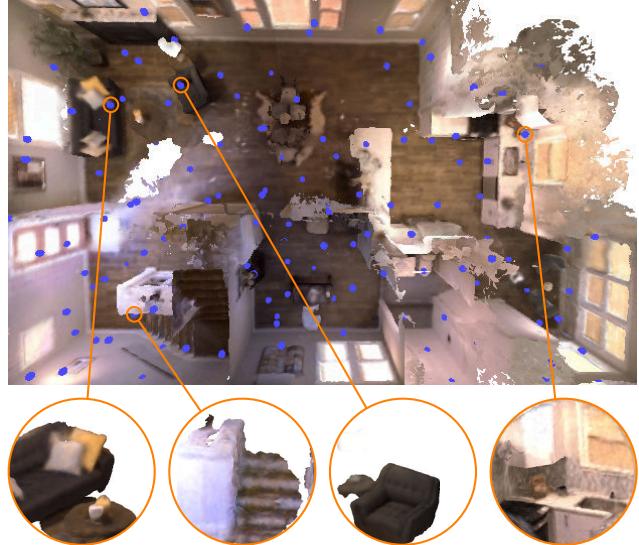


Figure 1. We propose to represent a scene by a set of neural fields (centers indicated by blue spheres) anchored to keyframes in a pose graph with each field capturing the scene within a sphere surrounding it. This allows to dynamically extend the scene while also incorporating loop closure deformations into the volumetric scene representation without requiring full reintegration.

by Sucar et al. [34], various adaptations of this method have been proposed. These adaptations primarily focused on enhancing optimization speed by altering network architecture, sampling scheme, and rendering formulation. Nevertheless, the majority of existing neural field-based SLAM methods [12, 34, 40, 45, 46] remain constrained by their monolithic data structure (i.e., a single fixed-size architecture). In that regard, neural fields share the same limitation as other volumetric scene representations, that is, after data has been integrated, the volumetric scene cannot easily be deformed to take loop closure constraints into account.

To address this issue, we propose to represent the scene by an extendable set of lightweight neural fields (see Fig. 1). These fields are anchored to keyframes within a pose graph, collectively forming the volumetric map while maintaining the ability to deform as the keyframe poses change upon

loop closure. Our design allows to combine the benefits of sparse pose graph-based SLAM methods while maintaining a volumetric scene representation that remains consistent with the pose graph without requiring costly full reintegration of previous sensor data. Furthermore, our method eliminates the necessity for fixed scene boundaries common among existing neural-field-based SLAM methods. It achieves this by allocating additional fields dynamically as new parts of the scene come into view.

To summarize, our contributions are

- a novel, scalable SLAM framework that combines the robust, accurate tracking and efficient loop closure handling of sparse visual SLAM with the differentiable-rendering-based dense mapping of neural scene representations,
- a multi-field scene representation in which neural fields are anchored relative to a pose graph allowing for large-scale map deformations while limiting necessary reintegration, and
- a thorough comparison to multiple state-of-the-art methods on scenes of varying scales; including a novel set of sequences for the larger Replica scenes that allow to benchmark robustness and scalability.

## 2. Related Work

### 2.1. Neural Field-Based Scene Representations

Neural fields are parametrized differentiable functions that map coordinates to quantities at that point in space. Initially, neural fields were trained using 3D supervision and were used to represent shape as occupancy [4, 20] or signed distance fields (SDFs) [29]. Shortly after, neural radiance fields (NeRFs) were introduced that were trained using only 2D supervision through differentiable volumetric rendering [21]. Subsequent to this work, a variety of further research efforts have been conducted, which are reviewed in [43].

Focusing on surface reconstruction, multiple works proposed SDF-based representations replacing the density-based approach in NeRFs. Azinović et al. [2] use a heuristic rendering model that allows to optimize SDFs yielding improved surface reconstructions; however, their model is not occlusion-aware. An occlusion-aware approach for unbiased SDF-based volume rendering was proposed in [41].

Focusing on training and inference speed, Müller et al. [24] showed significant speed-ups by employing a multi-resolution hash encoding in which learnable features in a hash table are used instead of a fixed Fourier encoding to lift the low-dimensional, low-frequency input point to a high-dimensional, high-frequency embedding. Rosu and Behnke [32] further proposed to replace the multi-resolution voxel grid with a multi-resolution permutohedral lattice due to its better scalability to higher dimensions. We adopt this approach as the positional encoding for each field.

Fewer works have investigated the use of multiple neu-

ral fields. In Block-NeRF [36] multiple fields are combined to represent whole neighborhoods. However, the field positions are predefined. In Nerflets [44] fields of varying size are composed to achieve an editable scene representation. NeRFuser [8] proposes methods for registering and blending multiple NeRFs. Finally, vMAP [15] uses multiple fields to represent individual objects highlighting the potential of vectorizing neural field evaluations. The latter is also employed in this work.

### 2.2. Neural Field-Based SLAM

iMAP [34] was the first SLAM method using a multilayer perceptron (MLP) as the underlying scene representation. During optimization previous keyframes have to be continuously reintegrated to avoid forgetting. Subsequently, various modifications of this approach have been proposed aiming to alleviate this forgetting issue and improve run-time.

NICE-SLAM [46] addresses the forgetting issue by employing a hierarchical feature grid combined with a fixed, pretrained decoder MLP. By adopting an SDF-based field combined with efficient learnable positional encodings, ESLAM [12] and Co-SLAM [40] demonstrate significantly improved optimization times. Specifically, ESLAM uses a tri-plane [3] encoding, whereas Co-SLAM uses the aforementioned multi-resolution voxel hash encoding [24]. Co-SLAM further complements the hash encoding with one-blob encodings [23] to improve scene completion. However, none of the above approaches support integration of loop closure constraints, limiting their applicability to larger scenes, in which accumulation of drift is unavoidable.

In work developed concurrently to ours, NEWTON [18] also uses multiple fields posed relative to a pose graph. They employ a spherical inverse depth NeRF formulation in which each field in principle covers the entire scene. Synthesized views from multiple fields are merged through alpha compositing. This approach is well-suited for novel view synthesis; however, generalizes poorly to mesh extraction and other geometric queries in which the blending weights are not well-defined. Instead, in our work, each field covers a Euclidean ball around it allowing general geometric queries as well as novel view synthesis.

In another concurrent work, Tang et al. [37] propose MIPS-Fusion also representing the scene by multiple fields and performing global bundle adjustment at the level of fields. Notably, both MIPS-Fusion and NEWTON are limited to a small number ( $\sim 10$ ) of fields, where fields can be interpreted as submaps. In contrast, our formulation allows training and maintenance of hundreds of fields and can therefore incorporate local and global pose graph deformations in a more fine-grained way.

Finally, GO-SLAM [45] also incorporates loop closure constraints through extending DROID-SLAM [39] and biasing the optimization towards keyframes whose pose

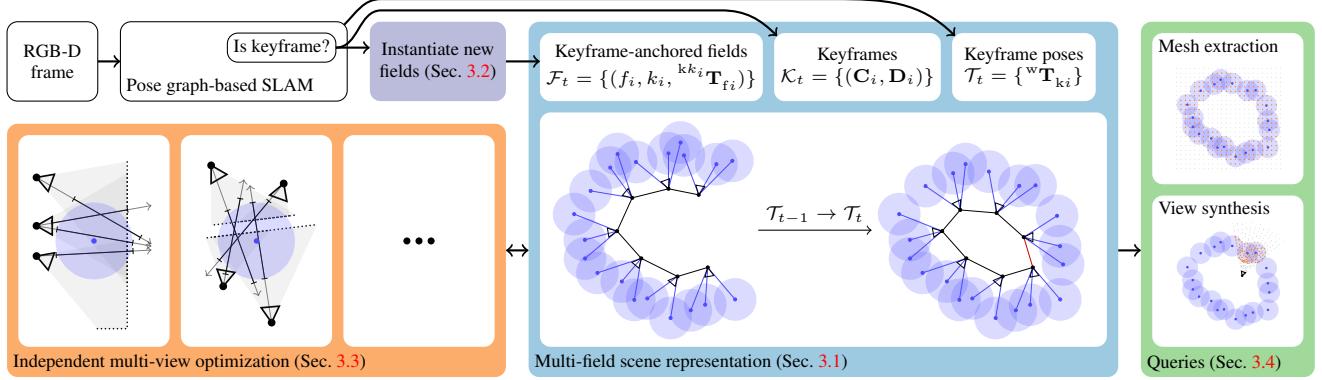


Figure 2. Neural graph map framework overview. Our framework can be used with any pose graph-based SLAM system and maintains a set of neural fields anchored relative to the keyframes of the SLAM system’s pose graph. Each field captures the scene in a ball surrounding it in local coordinates. The set of such fields represents a deformable volumetric scene representation that can easily adapt to and stay in sync with the pose graph. To enable efficient optimization and scalability the fields are optimized independently and in parallel. This design allows to average the output of overlapping fields in 3D leading to well-defined queries (e.g., mesh extraction and novel view synthesis).

changed the most. However, it still uses a single neural field. Instead we aim to reduce the need for reoptimization upon loop closure by anchoring fields to keyframes.

### 3. Method

We consider the problem of online mapping with an RGB-D camera without ground-truth poses. That is, given a stream of RGB-D frames  $\mathbf{F}_t = (\mathbf{C}_t, \mathbf{D}_t)$  composed of color images  $\mathbf{C}_t \in \mathbb{R}^{H \times W \times 3}$  and depth maps  $\mathbf{D}_t \in \mathbb{R}^{H \times W}$ , our goal is to build a dense scene representation at each step  $t$  taking into consideration the current and previously observed frames.

Figure 2 gives an overview of the proposed framework. Similar to other recent neural field-based mapping approaches [15, 18], our approach relies on an off-the-shelf keyframe-based SLAM system to provide a set of posed keyframes as well as the pose of the current frame.

#### 3.1. Multi-Field Scene Representation

Let  $\mathcal{K}_t = \{\mathbf{F}_i \mid i = 1, \dots, K_t\}$  and  $\mathcal{T}_t = \{{}^w\mathbf{T}_{ki} \in \text{SE}(3) \mid i = 1, \dots, K_t\}$  denote the set of keyframes and keyframe poses at time step  $t$ , respectively.

We propose to represent the scene by an extendable set of posed neural fields

$$\mathcal{F}_t = \{(f_i, k_i, {}^{kk_i}\mathbf{T}_{fi} = ({}^{kk_i}\mathbf{p}_{fi}, {}^{kk_i}\mathbf{R}_{fi})) \mid i = 1, \dots, F_t\}, \quad (1)$$

where each field

$$f_i : \mathbb{R}^3 \rightarrow \mathbb{R}^3 \times \mathbb{R} \quad (2)$$

$$\mathbf{x} \mapsto (\mathbf{c}, s)$$

maps a 3D point  $\mathbf{x}$  to the color  $\mathbf{c}$  and truncated signed distance  $s$  at that point (see Sec. 3.3 for further details). Each field is rigidly attached to a parent keyframe with index

$k_i \in \mathcal{I}(\mathcal{K}_t)$  (with  $\mathcal{I}$  denoting the set of indices) by a transform  ${}^{kk_i}\mathbf{T}_{fi} \in \text{SE}(3)$ , which can be decomposed into a translation  ${}^{kk_i}\mathbf{t}_{fi} \in \mathbb{R}^3$  and rotation  ${}^{kk_i}\mathbf{R}_{fi} \in \text{SO}(3)$ . To limit the complexity that each field stores, each field only captures the scene within a sphere of fixed radius  $r$  around its center.

In the following sections the proposed strategies to instantiate and anchor fields to the pose graph (Sec. 3.2), optimize the fields (Sec. 3.3), and query (e.g., for mesh extraction and view synthesis) the full scene representation (Sec. 3.4) are described. Finally, further architecture details are provided (Sec. 3.5).

#### 3.2. Field Instantiation

Whenever a new keyframe is added to the pose graph new fields are instantiated such that all observed 3D points  ${}^w\mathbf{x}_{kf}$  in the keyframe are covered by at least one field of radius  $r$ . An approximate two-stage algorithm is used (see Fig. 3). First, the uncovered 3D points  $\mathcal{X}_{unc} = \{\mathbf{x} \in {}^w\mathbf{x}_{kf} \mid \|\mathbf{x} - {}^w\mathbf{T}_{kk_i} {}^{kk_i}\mathbf{t}_{fi}\| > r \forall i = 1, \dots, F_t\}$  are found. Second, the space is divided into voxel cells with a side length of  $g = 2r/\sqrt{3}$ , such that a cell is fully covered by a field of radius  $r$  when the center of the field is at the center of the cell. New fields are instantiated in the center of all cells that contain a point from  $\mathcal{X}_{unc}$  and no field center. This scheme ensures that a minimum distance of  $g/2$  to existing fields is maintained; however, points in  $\mathcal{X}_{unc}$  might remain uncovered when fields move away from the cell centers through pose graph deformations. To alleviate the chance of uncovered points over time, the voxel grid is randomly shifted for every added keyframe.

#### 3.3. TSDF-Based Optimization

At each time step  $t$  a fixed number of optimization steps  $N_{it}$  are performed on up to  $N_f$  fields. During the optimization

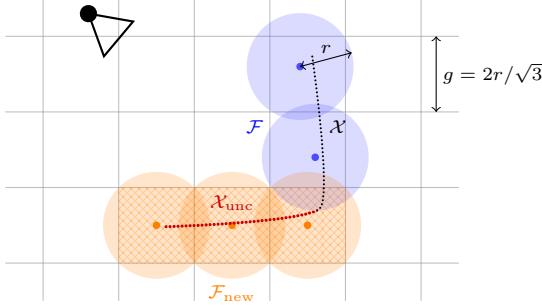


Figure 3. Grid-based instantiation scheme. A new keyframe (top-left) observes world points  $\mathcal{X}$  (black & red dots). The points  $\mathcal{X}_{\text{unc}}$  (red dots) that are not covered by any of the existing fields  $\mathcal{F}$  (blue circles) are determined. Cells that contain uncovered points and no existing field center (hatched orange) are used to instantiate new fields  $\mathcal{F}_{\text{new}}$  (orange circles). The new fields are positioned in the center of the uncovered cells and anchored to the keyframe.

the fields  $f_i$  are trained independently, allowing for efficient parallelization [15]. Therefore, we drop the field index  $i$  in the following.

Due to its well-defined isosurface for mesh extraction, we model the geometry as a truncated signed distance field (TSDF) adopting the TSDF-based rendering model from [2] and modify it to be occlusion-aware. Specifically, instead of directly converting signed distances to sample weights as done in [2, 40], we first convert them to occupancy probabilities. That is, given  $N_{\text{rs}}$  ray samples along a ray  $\mathbf{x}_i = \mathbf{o} + l_i \mathbf{d}, i = 1, \dots, N_{\text{rs}}$  with origin  $\mathbf{o}$  and direction  $\mathbf{d}$ , the colors and signed distances  $(\mathbf{c}_i, s_i) = f(\mathbf{x}_i)$  along the ray are computed. The signed distances are converted to occupancy probabilities using

$$o_i = 4\sigma\left(\frac{\eta s_i}{\tau}\right)\sigma\left(-\frac{\eta s_i}{\tau}\right), \quad (3)$$

where  $\sigma$  denotes the sigmoid function,  $\tau$  is the truncation distance, and  $\eta$  is a parameter that determines how quickly occupancy probability decays around the surface. Note that this definition ensures  $o_i = 1.0$  for  $s_i = 0.0$ . The ray's rendered color and depth are then computed via the weight  $w_i = o_i \prod_{j=1}^{i-1} (1 - o_j)$  as

$$\mathbf{c} = \sum_{i=1}^{N_{\text{rs}}} w_i \mathbf{c}_i \quad d = \sum_{i=1}^{N_{\text{rs}}} w_i l_i \quad (4)$$

assuming the ray's direction  $\mathbf{d}$  was scaled appropriately.

**Sampling Strategy** Each optimization iteration follows a three-stage sampling procedure. Specifically, we sample: (1) a subset of fields that will be optimized in the next iteration; (2) ray segments with supervision targets for each field; (3) query points along the ray segments. The sampling strategy is visualized in Fig. 4.

- Especially with larger scenes, it is important that recently added fields and those currently observed are optimized with a higher rate than out-of-view fields that have already been optimized before.

To achieve this, the currently observed fields  $\mathcal{F}_t^{\text{obs}} \subseteq \mathcal{F}_t$  are determined and sampled with a higher probability. Specifically, a total of  $N_f$  are sampled; half from the currently observed fields and the remaining ones from all fields  $\mathcal{F}_t$  discarding duplicates.

- To sample supervision targets, each sampled field  $i$  is approximated by a set of points  $\mathbf{q}_j^i, j = 1, \dots, N_{\text{approx}}$  sampled uniformly on the field's sphere of radius  $r$ . These points are projected into all keyframes. A field is considered visible in a keyframe, if at least one of the field's points  $\mathbf{q}_j^i$  is inside the keyframe's frustum and the projected depth of  $\mathbf{q}_j^i$  is smaller than the observed depth at the projected 2D point. This yields a set of keyframes  $\mathcal{K}_t^i \subseteq \mathcal{K}_t$ .  $N_{\text{rpf}}$  rays per field (i.e., target rays) are then sampled via the 2D bounding boxes of the projected points  $\mathbf{q}_j^i$  in the keyframes  $\mathcal{K}_t^i$ . For each target ray  $(\mathbf{o}, \mathbf{d})$  the closest point to the field center is computed as  $\mathbf{o} + l_c \mathbf{d}$  and only a ray segment  $[l_c - r, l_c + r]$  covering the sphere will be considered for optimization.
- Given a ray segment  $[l_{\min}, l_{\max}]$ ,  $N_{\text{uni}}$  samples are uniformly sampled across the segment, and  $N_{\text{dg}}$  samples are uniformly sampled in the truncation interval  $\tau$  around the observed depth, that is, in the interval  $[l_{\text{obs}} - \tau, l_{\text{obs}} + \tau]$ ; the full ray interval is used, if there is no depth measurement or  $l_{\text{obs}} \notin [l_{\min}, l_{\max}]$ . This yields a total of  $N_{\text{rs}} = N_{\text{uni}} + N_{\text{dg}}$  samples per ray segment during optimization.

**Loss** Our loss is a weighted sum of four terms: color, depth, TSDF, and free-space. The weighting has been found experimentally to achieve a good trade-off between appearance and geometry quality.

The color loss is computed as the mean L1-norm of the difference between observed and estimated color

$$l_{\text{color}} = \frac{1}{|\mathcal{C}|} \sum_{(\mathbf{c}, \tilde{\mathbf{c}}) \in \mathcal{C}} \|\mathbf{c} - \tilde{\mathbf{c}}\|_1 \quad (5)$$

and the depth loss is computed as the mean Huber loss [11] between observed and estimated depth with  $\delta = 5$  cm

$$l_{\text{depth}} = \frac{1}{|\mathcal{D}|} \sum_{(d, \tilde{d}) \in \mathcal{D}} \text{Huber}_{\delta}(d, \tilde{d}), \quad (6)$$

where  $\mathcal{C}$  and  $\mathcal{D}$  are sets containing tuples of the observed and estimated color and depth, respectively.

Finally, the set of all query points  $\mathcal{X}$  is filtered into two sets  $\mathcal{X}_{\text{tsdf}}$  and  $\mathcal{X}_{\text{fs}}$  based on whether a query point's projected depth  $l_i$  is within the truncation distance  $\tau$  of the corresponding observed depth  $l_{\text{obs},i}$  or is more than  $\tau$  in front

of it, respectively. A query point's associated estimated signed distance  $\tilde{s}_i$  and its signed distance to the observed depth  $s_i = l_{\text{obs},i} - l_i$  are then used to compute the TSDF loss as

$$l_{\text{tsdf}} = \frac{1}{|\mathcal{X}_{\text{tsdf}}|} \sum_{i \in \mathcal{I}(\mathcal{X}_{\text{tsdf}})} (\tilde{s}_i - s_i)^2 \quad (7)$$

and the free-space loss as

$$l_{\text{fs}} = \frac{1}{|\mathcal{X}_{\text{fs}}|} \sum_{i \in \mathcal{I}(\mathcal{X}_{\text{fs}})} (\tilde{s}_i - \tau)^2. \quad (8)$$

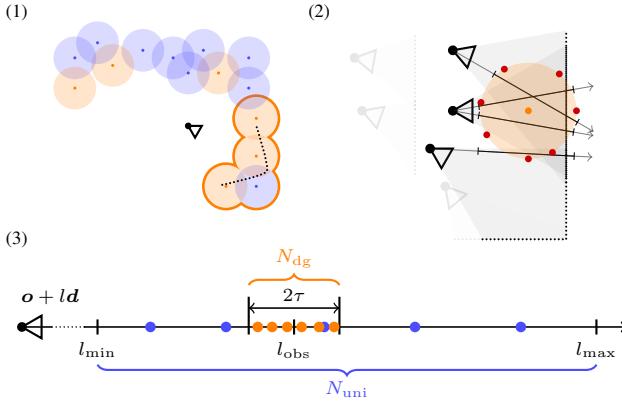


Figure 4. Multi-view sampling procedure. (1) A subset of fields (orange circles) to optimize in the next iteration is sampled with half the fields stemming from the currently observed fields (orange outline). (2) For each field, the observing keyframes (opaque frustums) are approximated based on whether samples on the field boundary (red dots) fall into the observed keyframe region. Ray segments to supervise the field are then sampled from the observing keyframes. (3) Each sampled ray segment  $[l_{\min}, l_{\max}]$  is approximated by a set of samples composed of  $N_{\text{uni}}$  uniform samples that cover the whole field and  $N_{\text{dg}}$  depth-guided samples distributed within the truncation distance  $\tau$  around the observed distance  $l_{\text{obs}}$ .

#### 3.4. Novel View Synthesis and Mesh Extraction

Due to the independent optimization described in Sec. 3.3 all fields will be supervised at least within a sphere of radius  $r$ . Therefore, overlapping regions will contain different colors and distances. To reduce transition artifacts at the boundary of fields, it is possible to query the  $k$  nearest fields within radius  $r$  and average the outputs based on the field distances (see supplementary material for details). For query points outside of all fields' spheres empty space is assumed, that is,  $s = 1$ .

**Novel View Synthesis** Since no ground-truth depth is available at inference time, a fixed far distance  $l_{\text{far}}$  is used. Samples are uniformly distributed within the ray interval  $[0, l_{\text{far}}]$  at the same density as the depth-guided samples, that is,  $N_{\text{rs,inf}} = l_{\text{far}}N_{\text{dg}}/(2\tau)$  ray samples are used during inference time.

**Mesh Extraction** To extract a mesh from our scene representation the marching cubes algorithm [16] with an unbiased isosurface level of 0 is used.

#### 3.5. Architecture Details

ORB-SLAM2 is used as the keyframe-based SLAM system in this work [25]. However, our proposed method is agnostic to the exact SLAM framework as long as a pose graph as described in Sec. 3.1 is available. We precomputed the ORB-SLAM results and will publish them in conjunction with our code to improve reproducibility.

Each field  $f_i$  is parameterized by a permutohedral hash encoding [32] followed by a linear layer with ReLU activation and another linear layer mapping to the output color and distance. We also experimented with other positional encodings, such as Fourier encoding [35], triplane encoding [3, 12], and voxel hash encoding [24]; however, the best results given the same time budget were achieved with the permutohedral hash encoding closely followed by the voxel hash encoding.

To efficiently evaluate and optimize multiple neural fields in parallel, optimization and evaluation is vectorized following [15]. One limitation imposed by PyTorch's [30] vectorization framework is that the batch size has to be the same for all evaluated networks. The design choices described in Sec. 3.3 are tailored to this limitation as they allow to sample the same number of rays per supervised field.

### 4. Experiments

To verify the proposed mapping approach, we report results following a reconstruction-based evaluation protocol similar to Wang et al.'s [40] (see supplementary for further details and experiments).

#### 4.1. Experimental Setup

**Datasets** We evaluate our method quantitatively on three synthetic datasets of varying difficulty: the Replica [33] sequences from iMAP [34], the dataset by Azinović et al. [2] (referred to as NRGDB dataset in the following), and three novel sequences on the larger Replica scenes (Replica-Big). The latter contains challenging trajectories with larger loops spanning multiple rooms. Further, we present qualitative results on two real-world datasets: ScanNet [5] and Kintinuous [42]. The latter contains a large-scale loop, whereas the tested ScanNet sequences typically contain one or two smaller loops.

**Metrics** We adopt most of metrics reported by Co-SLAM, but use completion ratio instead of depth L1, which is skewed by holes in the mesh and therefore less intuitive than the point set-based metrics. Completion ratio, defined akin to accuracy ratio, naturally completes the point set-based metrics. Therefore, we report the methods' accu-

Table 1. Quantitative mesh reconstruction quality on the synthetic dataset (**best** ●, second best ○).

|              | Replica       | NRGDB          |                |                |                |                |                |                |                | Replica-Big    |                |                |                |                |
|--------------|---------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
|              |               | Avg.*          | br             | ck             | gr             | gwr            | ki             | ma             | sc             | tg             | wa             | apt0           | apt1           | apt2           |
| NICE-S. [46] | Acc (cm)      | <b>2.38</b> ●  | 2.46           | 10.76          | 2.33           | 2.71           | 9.18           | 1.70○          | 4.55           | 8.37           | 7.37           | 15.98          | 17.56          | 23.39          |
|              | Acc. R. (%)   | <b>93.17</b> ● | 92.41○         | 65.34          | 93.87          | 93.63          | 57.29          | 95.06○         | 71.69          | 56.22          | 77.38          | 30.67          | 41.48          | 28.20          |
|              | Comp. (cm)    | 2.84○          | 4.82           | 14.21          | 3.91           | 3.19           | 12.82          | 3.36           | 10.69          | 8.02           | 5.39           | 12.73          | 11.59          | 19.77          |
|              | Comp. R. (%)  | 90.11○         | 86.18          | 53.58          | 86.66          | 87.64          | 50.04          | 84.06○         | 58.79          | 59.24          | 69.04          | 31.06          | 42.21          | 26.80          |
| Co-S.† [40]  | Acc (cm)      | 4.29           | <b>2.21</b> ●  | 4.73           | <b>1.89</b> ●  | <b>2.02</b> ●  | 7.40           | 1.74           | 3.30○          | 2.07           | 6.24           | 37.69          | 12.89          | 30.19          |
|              | Acc. R. (%)   | 87.02          | <b>93.24</b> ● | 75.16          | <b>95.17</b> ● | <b>94.84</b> ● | 77.72          | 93.98          | 78.01○         | 92.05○         | 84.92○         | 18.85          | 62.11          | 34.71          |
|              | Comp. (cm)    | 4.09           | <b>2.06</b> ●  | <b>8.76</b> ●  | 2.93○          | <b>2.41</b> ●  | 5.14○          | <b>2.75</b> ●  | <b>4.29</b> ●  | <b>2.83</b> ●  | <b>3.85</b> ●  | 17.91          | 7.07           | 17.75          |
|              | Comp. R. (%)  | 86.39          | 93.49○         | 63.17○         | 91.32○         | <b>93.96</b> ● | <b>78.19</b> ● | <b>86.41</b> ● | 70.90○         | <b>86.62</b> ● | <b>81.70</b> ● | 21.93          | 66.37          | 36.75          |
| GO-S. [45]   | Acc (cm)      | 2.89           | 3.89           | 4.08○          | 2.50           | 2.87           | 3.28○          | <b>1.54</b> ●  | 6.46           | <b>1.48</b> ●  | 5.46○          | 14.20○         | 8.92○          | 11.82○         |
|              | Acc. R. (%)   | 89.31          | 77.64          | 81.94○         | 91.46          | 86.87          | 84.74○         | <b>97.44</b> ● | 66.62          | <b>96.32</b> ● | 73.90          | <b>57.93</b> ● | 74.38○         | <b>80.22</b> ● |
|              | Comp. (cm)    | 6.18           | 9.25           | 29.60          | 9.50           | 4.50           | <b>5.11</b> ●  | 4.60           | 12.35          | 7.26           | 12.57          | <b>7.98</b> ●  | 5.19○          | 5.87○          |
|              | Comp. R. (%)  | 74.20          | 64.29          | 54.56          | 71.31          | 75.12          | 72.58          | 75.53          | 54.24          | 70.78          | 57.33          | <b>59.21</b> ● | 73.90○         | 81.06○         |
| Ours         | Acc (cm)      | 2.88○          | 2.26○          | <b>3.21</b> ●  | 1.90○          | 2.19○          | <b>2.19</b> ●  | 1.89           | <b>2.60</b> ●  | 2.05○          | <b>4.00</b> ●  | <b>10.14</b> ● | <b>5.26</b> ●  | <b>11.45</b> ● |
|              | Acc-Ratio (%) | 89.50○         | 90.58          | <b>87.81</b> ● | 94.60○         | 93.78○         | <b>96.18</b> ● | 93.01          | <b>93.45</b> ● | 91.50          | <b>85.97</b> ● | 56.09○         | <b>91.64</b> ● | 72.35○         |
|              | Comp. (cm)    | <b>2.36</b> ●  | 2.42○          | 9.03○          | <b>2.71</b> ●  | 2.44○          | 30.37          | 3.11○          | 4.67○          | 3.66○          | 4.64○          | 8.71○          | <b>2.48</b> ●  | <b>3.94</b> ●  |
|              | Comp. R. (%)  | <b>92.11</b> ● | <b>94.01</b> ● | <b>77.83</b> ● | <b>91.62</b> ● | 92.35○         | 73.03○         | 83.77          | <b>87.78</b> ● | 81.76○         | 81.07○         | 58.52○         | <b>96.26</b> ● | <b>82.70</b> ● |

\* Acknowledging the small differences on most Replica sequences, we only report the average here and include the full results in the supplementary material.

† We evaluated Co-SLAM without ground-truth initialization for fair comparison (see supplementary material for further discussion.)

racy, completion, accuracy ratio, and completion ratio at a 5 cm threshold. We further use F1-score to summarize reconstruction quality in a single metric [38]. Mathematical definitions are provided in the supplementary material.

**Baselines** We compare our method to three state-of-the-art neural field-based SLAM methods: NICE-SLAM [46], Co-SLAM [40], and GO-SLAM [45]. Co-SLAM is, to the best of our knowledge, the best available method in terms of quality and run-time at the time of writing. However, neither NICE-SLAM nor Co-SLAM can integrate loop closure constraints. GO-SLAM is, to our knowledge, the only other published neural field-based method that also incorporates loop closure constraints.

**Implementation Details** For all experiments we use the same parameters, most notably,  $r = 1$  m,  $N_{\text{it}} = 5$ ,  $N_f = 32$ ,  $N_{\text{rpf}} = 512$ ,  $N_{\text{uni}} = 8$ ,  $N_{\text{dg}} = 16$ , and  $k = 2$ . We adjust the truncation distance from  $\tau = 0.1$  m for synthetic data to  $\tau = 0.2$  m for real data to account for the increased depth noise. For ORB-SLAM2 we use the default parameters for the RGB-D setup increasing the number of extracted features in challenging scenes with low texture. All remaining parameters are provided in the supplementary material.

## 4.2. Reconstruction Quality Evaluation

Table 1 reports quantitative results on all datasets with Fig. 5 showing qualitative results on the Replica-Big and ScanNet datasets. Our method achieves state-of-the-art results on the smaller scenes (Replica, NRGDB), while outperforming existing methods on larger scenes (Replica-Big). While GO-SLAM achieves quantitatively similar results as our method on apt0 and apt2, we note that qualitatively our method shows better scene completion and robustness.

The qualitative comparison shows large differences in mesh quality on the Replica-Big dataset. Both NICE-SLAM and Co-SLAM drift off and cannot correct for the drift upon returning to previous frames. GO-SLAM also benefiting from loop closures successfully maps large parts; however, fails in the last section of apt0 and generally exhibits worse reconstruction quality.

Figure 6 shows results on the Kintinuous sequence before and after loop closure without additional optimization. Our framework allows to close the large-scale loop by only adjusting the field poses connecting the two corridors. GO-SLAM did not close the loop and Co-SLAM failed in the second corner (see supplementary material).

## 4.3. Run-Time and Model Size Analysis

Table 2. Run-time and model size comparison of all methods. Our method compares favorably in terms of processing time; however, is less efficient in terms of model size.

|           | FPS (Hz) | Model Size (MB) | F1-Score (%) |
|-----------|----------|-----------------|--------------|
| NICE-SLAM | 2.02     | 49.0            | 92.12        |
| Co-SLAM   | 11.44    | 8.1             | 94.39        |
| GO-SLAM   | 15.86    | 66.5            | 76.26        |
| Ours      | 17.07    | 73.6            | 92.38        |

In Tab. 2 we compare run-time<sup>1</sup> and model size of our method to the baselines on the room0 scene of the Replica dataset. Despite the overhead of parallelized training of multiple fields, our approach compares favorably in terms

<sup>1</sup>We report time per frame by benchmarking the execution time for the whole sequence and dividing it by the number of frames. Mesh extraction and other logging has been deactivated for all methods for fair comparison. All evaluations were run with an Intel Core i9-13900KF and NVIDIA GeForce RTX 4090.

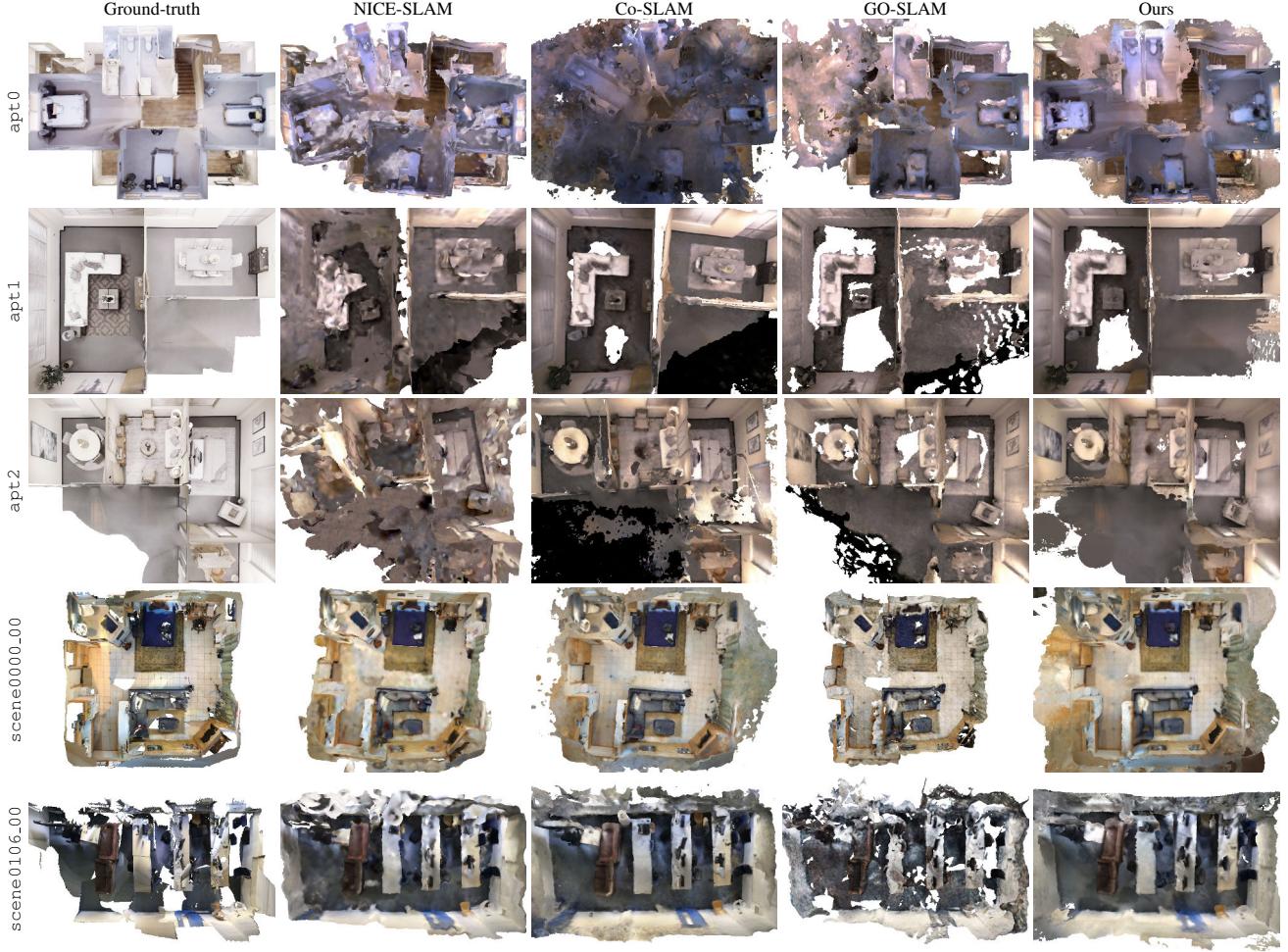


Figure 5. Qualitative comparison of final meshes extracted by all methods. Our method performs significantly better for large scale scenes while maintaining qualitative similar results as the otherwise best performing method Co-SLAM. The methods that incorporate loop closure (ours and GO-SLAM) perform significantly better on the larger scenes. Meshes have been trimmed to allow a better view into the rooms.

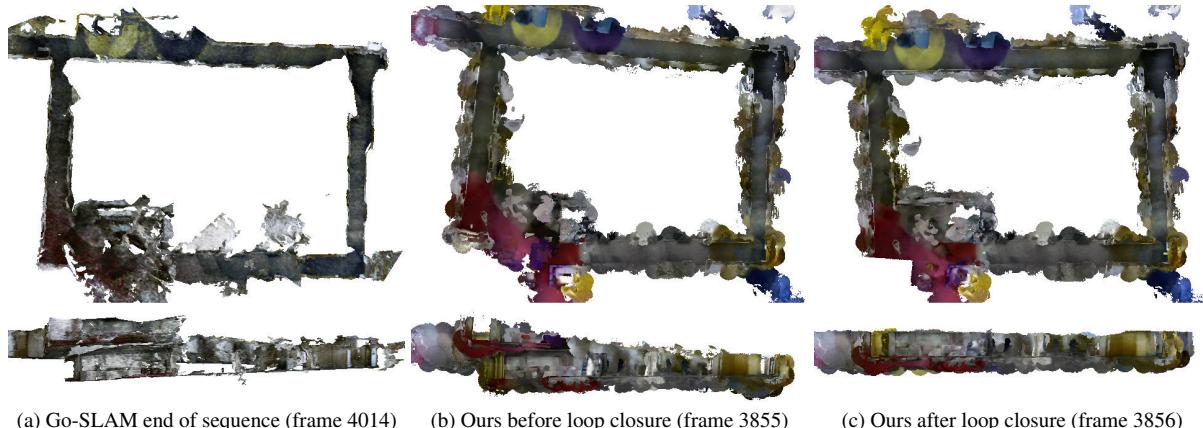


Figure 6. Qualitative results on the Kintinuous sequence (first row shows top view; second row shows side view). No additional optimization has been performed between extracting the two meshes for our method; only the field poses have changed successfully connecting the corridors (note the duplicate floors on the left of the side view in (a) and (b)). Meshes have been trimmed to allow a better view.

of run-time. In terms of model size our approach requires more parameters than the baselines, which we suspect is due to the less efficient hash table use, which depending on the field’s content will be unnecessarily large. Sharing hash tables among multiple fields might be a viable future direction to further reduce the model size.

**Field Radius and Hash Map Size** In Fig. 7 the memory requirement and F1-score for different field radii  $r$  and hash table sizes  $T$  is reported. In general, larger fields require larger hash maps to maintain the same quality. Our approach works across a wide range of  $r$ , but the ability to adapt to loop closures will be limited for larger  $r$ .

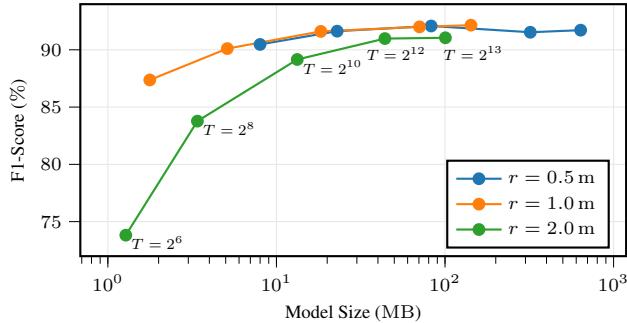


Figure 7. Impact of field radius  $r$  and hash table size  $T$  on model size and reconstruction quality. Larger radii lead to fewer fields and smaller model size. However, larger radii require larger hash tables to achieve similar quality.

**Batch Size and Iterations** Increasing the number of iterations per frame or the batch size will directly influence run-time and quality. In Fig. 8 the processing time per frame and F1-score is reported for various settings. Notably, our approach maintains high reconstruction quality even at frame rates of over 50 Hz.

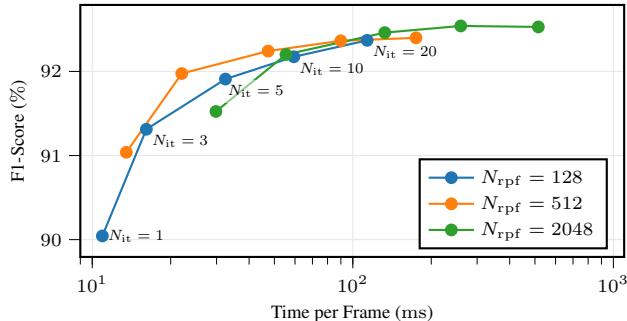


Figure 8. Impact of number of iterations per frame  $N_{it}$  and number of rays per field  $N_{rpf}$  (i.e., batch size per field) on run-time and reconstruction quality.

#### 4.4. Ablation Study

**Multi-View Supervision** In Fig. 9 we compare optimization with targets sampled from all keyframes as described

in Sec. 3.3 to targets sampled from a single view only. In the latter case, optimization alternates between a random previous keyframe and the latest keyframe. The figure shows that single-view supervision exhibits local forgetting effects, particularly notable when a previously seen wall is observed from the other side. Multi-view optimization avoids this local forgetting effect by combining previous and current observations in each optimization step.



Figure 9. Single-view supervision (left) leads to artifacts when the opposite side of a wall is observed. Multi-view supervision (right) significantly reduces this local forgetting effect.

**K-Nearest Neighbor Averaging** Figure 10 shows renderings of our model with varying values for  $k$  (see Sec. 3.4). For higher  $k$  visible transitions between fields are reduced and smoothed out. Note that due to our independent training scheme, all fields are trained in overlapping regions making averaging at the query point a viable strategy. While higher values for  $k$  lead to improved results, it also multiplies the number of queries required for rendering and mesh extraction (note that optimization time is unaffected by  $k$ ).



Figure 10. Comparison of rendered views with  $k = 1$ ,  $k = 2$ , and  $k = 4$ . By increasing the number of nearest neighbors taken into account, the number of visible field transitions decreases. These transitions are most visible in unobserved regions, such as the underside of the countertop shown here.

## 5. Conclusion

In this work, we presented a novel approach to volumetric mapping that anchors lightweight neural fields to the pose graph of a sparse visual SLAM system. This framework allows to incorporate loop closures into the volumetric map at near-zero cost improving robustness and scalability. Compared to existing works that support loop closure in a similar manner [18], our system allows well-defined geometric queries (such as mesh extraction) without relying on any space warping or image-space fusion. Compared to other monolithic mapping systems our approach offers benefits comparable to submap-based mapping approaches.

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# Neural Graph Mapping for Scalable Dense SLAM with Loop Closure

## Supplementary Material

### 6. Method Details

#### 6.1. K-Nearest Neighbors Queries

We compute the color and signed distance at a query point as the weighted average of the  $k$  nearest fields. Specifically, let  $\mathbf{x} \in \mathbb{R}^3$  denote the query point. Let  $\mathbf{c}_i, s_i, d_i, i = 1, \dots, k$  denote the returned color, signed distance, and distance to the field center for the  $k$  nearest fields for the query point  $\mathbf{x}$ . We compute weights based on the softmax of the negative distances, that is,

$$u_i = \frac{e^{-\xi d_i}}{\sum_{j=1}^k e^{-\xi d_j}}, \quad (9)$$

where  $\xi$  determines the transition speed. The combined color and signed distance are then computed as a weighted sum, that is,  $\mathbf{c} = \sum_{i=1}^k u_i \mathbf{c}_i$  and  $s = \sum_{i=1}^k u_i s_i$ .

We always use the  $k$  nearest fields even when only the closest field is within radius  $r$ . However, we set  $\xi$  sufficiently high such that the transition region becomes small and fields with  $d_i \gg r$  will have no significant contribution to the final value. This is a feasible strategy, since fields are optimized for all ray segments intersecting them even when the segment is terminating outside the sphere. Hence, each field will in practice capture a region larger than a sphere with radius  $r$ .

Figure 11 illustrates the effect of this weighted averaging for different values of  $\xi$ ,  $k$ , and with and without  $u_i = 0$  for  $d_i > r$  on a 2D toy example with three fields of fixed color. Note that the distance-weighted averaging leads to smooth transitions in the overlapping regions. When forcing  $u_i = 0$  for  $d_i > r$  transitions on the boundaries are unavoidable, hence we opt for the strategy described in the previous paragraph. For the experiments we use  $k = 2$  and  $\xi = 10$ .

#### 6.2. Parameters

In Tab. 3 we provide a full list of parameters, the used value to achieve the experimental results, and a brief description. Parameters were tuned manually and the same setting is used for all experiments (with the exception of  $\tau$ , which is increased for the real-world datasets).

### 7. Experiment Details

**Baseline Setup** All baselines are evaluated using the parameters published as part of the published code. For additional datasets for which no parameters were provided, the most similar dataset’s parameters were adopted (i.e.,

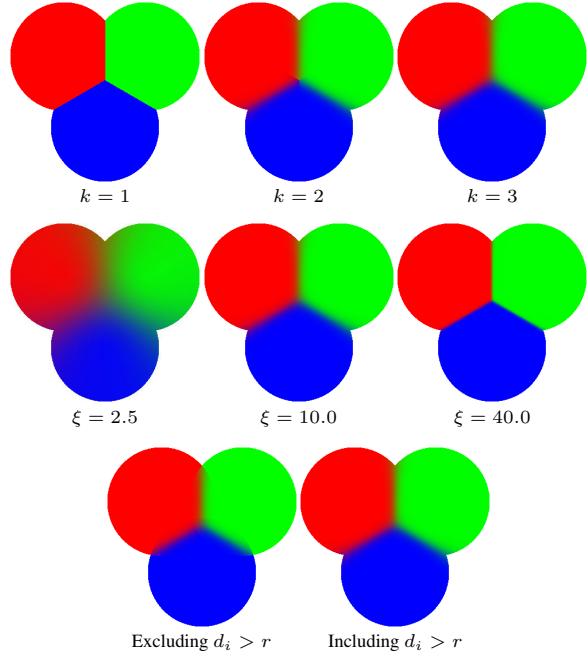


Figure 11. Visualization of  $k$ -nearest neighbor distance-based averaging. The top row shows the effect of varying  $k$ . The second row shows the effect of varying  $\xi$ . The last row shows the effect of excluding fields with distances  $d_i$  greater than the field radius  $r$  from the averaging.

for Replica-Big the provided setup for Replica is used; for Kintinous the setup for ScanNet). Scene boundaries were manually adjusted to cover the observed area with extra margin to account for errors in positioning.

In our experiments, we noticed that Co-SLAM [40] uses the ground-truth pose of the first frame to initialize the SLAM system, which leads to axis-aligned planes. We found that planes (such as walls, floors, and ceilings) which are axis-aligned are significantly better completed using the one-blob encoding [23] than generally-oriented planes. Therefore, for a fair comparison, we modified Co-SLAM’s implementation to start from a random orientation instead. We note that this mainly reduces qualitative scene completion, however, on one of the Replica scenes it leads to tracking issues and hence poor reconstruction results. Figure 12 shows an example of the scene completion capability of Co-SLAM with and without ground-truth initialization (i.e., with and without axis-aligned planes).

#### 7.1. Evaluation Protocol

Let  ${}^w\mathcal{M}_{\text{gt}}$  and  ${}^w\mathcal{M}_{\text{est}}$  denote the ground-truth mesh and estimated mesh respectively. We assume that  ${}^w\mathcal{M}_{\text{est}}$  has al-

Table 3. Overview of parameters.

| Parameter                | Value              | Description   |
|--------------------------|--------------------|---|
| $r$                      | 1 m                | Field radius  |
| $N_{\text{fields}}$      | 2                  | Number of fields optimized in parallel in each iterations   |
| $N_{\text{rpf}}$         | 512                | Number of ray segments sampled per field during optimization  |
| $N_{\text{uni}}$         | 8                  | Number of uniform samples distributed along each ray segment during optimization  |
| $N_{\text{dg}}$          | 16                 | Number of depth-guided samples distributed along each ray segment during optimization   |
| $\tau^*$                 | 0.1 m or 0.2 m     | Truncation distance; used for scaling depth-guided sampling and for capping the supervision range (i.e., dividing samples into free-space samples and TSDF samples) |
| $\eta$                   | 20.0               | Determines how fast occupancy probability decays around surfaces  |
| $k$                      | 2                  | Number of nearest neighbors used during evaluation  |
| $\xi$                    | 10.0               | Distance weighing determining transition speed between two fields   |
| $L$                      | 1                  | Number of MLP layers following the permutohedral encoding; excluding the final linear layer   |
| $T$                      | $2^{12}$           | Hash table size for permutohedral encoding  |
| $N_{\text{levels}}$      | 16                 | Number of resolution levels for permutohedral encoding  |
| $N_{\text{fpl}}$         | 16                 | Number of features per level for permutohedral encoding   |
| $r_{\text{coarse}}$      | 1.0                | Coarsest resolution for permutohedral encoding  |
| $r_{\text{fine}}$        | 0.0001             | Finest resolution for permutohedral encoding  |
| $\lambda_{\text{color}}$ | 1.0                | Weight of color loss  |
| $\lambda_{\text{depth}}$ | 1.0                | Weight of depth loss  |
| $\lambda_{\text{fs}}$    | 40.0               | Weight of free-space loss   |
| $\lambda_{\text{tsdf}}$  | 50.0               | Weight of TSDF loss   |
| $\delta$                 | 5 cm               | Huber loss threshold  |
| $\gamma$                 | $1 \times 10^{-3}$ | Learning rate used for Adam optimizer [13]  |
| $\lambda$                | $1 \times 10^{-5}$ | Weight decay used for Adam optimizer [13]   |

\* The truncation distance is increased for real-world datasets to account for the increase in depth noise.

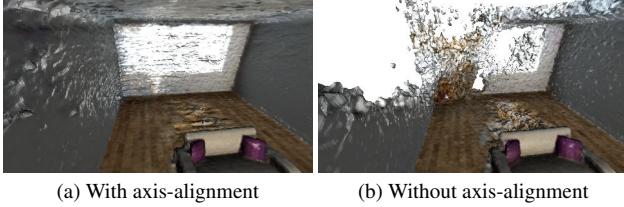


Figure 12. Co-SLAM result with and without ground-truth initialization. Ground-truth initialization leads to axis-aligned walls and floors, which in turn leads to significantly better scene completion.

ready been globally aligned with  ${}^w\mathcal{M}_{\text{gt}}$ , which is typically achieved by either aligning the first frame in the sequence or by aligning the trajectories using the Umeyama algorithm. Starting from  ${}^w\mathcal{M}_{\text{gt}}$  and  ${}^{\bar{w}}\mathcal{M}_{\text{est}}$  further preprocessing steps are performed before the evaluation metrics are computed.

1. Unobserved parts of the ground-truth mesh  ${}^w\mathcal{M}_{\text{gt}}$  are removed. In particular, we apply two removal steps. First, vertices falling more than 2 cm outside the scene bounding box are removed. The scene bounding box is computed as the intersection of a manually-set bounding box (used to exclude outliers in the depth map present in some scenes) and an automatically computed bounding box (based on the ground-truth trajectory and depth maps). Second, vertices that are not in front or up to 3 cm behind any rendered depth map are removed. These depth maps are rendered from the ground-truth trajectory and from additional virtual views manually placed to improve the evaluation of scene completion (same as in Co-SLAM [40]). This yields a culled ground-truth

mesh used for evaluation  ${}^w\mathcal{M}_{\text{gt}}^*$ .

2. To further equalize slight differences in alignment between different methods, we perform another alignment step using point-to-plane-based iterative closest point from  ${}^{\bar{w}}\mathcal{M}_{\text{est}}$ 's vertices to  ${}^w\mathcal{M}_{\text{gt}}$ 's vertices yielding an aligned estimated mesh  ${}^w\mathcal{M}_{\text{est}}^*$ .
3. The aligned estimated mesh  ${}^w\mathcal{M}_{\text{est}}^*$  follows the same removal process as the ground-truth mesh (see step 1 above) yielding the culled estimated mesh used for evaluation  ${}^w\mathcal{M}_{\text{est}}^*$ .

For the evaluation,  $N_{\text{samples}} = 200\,000$  points are uniformly sampled on both meshes yielding the point sets  $\mathcal{G} = \{\mathbf{x}_i \sim \mathcal{U}({}^w\mathcal{M}_{\text{gt}}^*) \mid i = 1, \dots, N_{\text{samples}}\}$  and  $\mathcal{E} = \{\mathbf{y}_i \sim \mathcal{U}({}^w\mathcal{M}_{\text{est}}^*) \mid i = 1, \dots, N_{\text{samples}}\}$ , where  $\mathcal{U}(\cdot)$  denotes the uniform distribution. The point sets are used to compute accuracy, completion, accuracy ratio, and completion ratio as

$$\text{Acc}(\mathcal{G}, \mathcal{E}) = \frac{1}{|\mathcal{E}|} \sum_{\mathbf{y} \in \mathcal{E}} \min_{\mathbf{x} \in \mathcal{G}} \|\mathbf{y} - \mathbf{x}\| \quad (10)$$

$$\text{Comp}(\mathcal{G}, \mathcal{E}) = \frac{1}{|\mathcal{G}|} \sum_{\mathbf{x} \in \mathcal{G}} \min_{\mathbf{y} \in \mathcal{E}} \|\mathbf{x} - \mathbf{y}\| \quad (11)$$

$$\text{AR}(\mathcal{G}, \mathcal{E}) = \frac{1}{|\mathcal{E}|} \sum_{\mathbf{y} \in \mathcal{E}} \left[ \min_{\mathbf{x} \in \mathcal{G}} \|\mathbf{y} - \mathbf{x}\| < \Delta \right] \quad (12)$$

$$\text{CR}(\mathcal{G}, \mathcal{E}) = \frac{1}{|\mathcal{G}|} \sum_{\mathbf{x} \in \mathcal{G}} \left[ \min_{\mathbf{y} \in \mathcal{E}} \|\mathbf{x} - \mathbf{y}\| < \Delta \right], \quad (13)$$

where  $[\cdot]$  denotes the Iverson bracket and  $\Delta = 5$  cm in our experiments. Since accuracy ratio and completion ratio can

Table 4. Comparison of mesh quality on Replica (best ●, second best ○).

|                | Replica         |                |                |                |                |                |                |                |                        |
|----------------|-----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|------------------------|
|                | room0           | room1          | room2          | offi0          | offi1          | offi2          | offi3          | offi4          | Avg.                   |
| NICE-SLAM [46] | Acc (cm)        | 2.47 ●         | 2.21 ●         | 2.17 ●         | 1.90           | 1.61 ●         | 3.13 ●         | 2.92 ●         | 2.60 ● <b>2.38</b> ●   |
|                | Acc.-Ratio (%)  | 93.38 ●        | 94.92 ●        | <b>93.75</b> ● | 94.87          | 95.30          | 89.78 ●        | 90.17 ●        | 93.21 ● <b>93.17</b> ● |
|                | Comp. (cm)      | 2.93           | 2.31 ●         | 2.77 ●         | 2.37           | 2.15           | 2.89           | 3.42           | 3.91                   |
|                | Comp. Ratio (%) | 90.90          | 93.57 ●        | 90.97 ●        | 92.58          | 92.15          | 88.78          | 86.20          | 85.72                  |
| Co-SLAM [40]   | Acc (cm)        | <b>1.99</b> ●  | 19.90          | <b>1.92</b> ●  | <b>1.55</b> ●  | <b>1.33</b> ●  | <b>2.76</b> ●  | <b>2.61</b> ●  | <b>2.22</b> ●          |
|                | Acc.-Ratio (%)  | <b>95.37</b> ● | 38.68          | 93.51 ●        | 96.15 ●        | 96.75 ●        | <b>90.92</b> ● | <b>92.04</b> ● | <b>92.70</b> ●         |
|                | Comp. (cm)      | 2.37 ●         | 17.47          | <b>2.08</b> ●  | <b>1.54</b> ●  | 1.68 ●         | 2.39 ●         | 2.73 ●         | <b>2.47</b> ●          |
|                | Comp. Ratio (%) | <b>93.43</b> ● | 40.03          | <b>93.16</b> ● | <b>96.04</b> ● | 94.57 ●        | <b>91.99</b> ● | <b>90.92</b> ● | <b>90.96</b> ●         |
| GO-SLAM [45]   | Acc (cm)        | 3.45           | <b>2.15</b> ●  | 2.90           | 1.88 ●         | 1.72           | 3.51           | 3.97           | 3.56                   |
|                | Acc.-Ratio (%)  | 84.59          | <b>96.04</b> ● | 89.50          | <b>96.31</b> ● | <b>97.55</b> ● | 84.49          | 79.64          | 86.34                  |
|                | Comp. (cm)      | 6.83           | 4.26           | 8.46           | 3.12           | 4.17           | 6.74           | 7.43           | 8.39                   |
|                | Comp. Ratio (%) | 69.44          | 82.89          | 72.65          | 85.21          | 82.89          | 69.40          | 63.81          | 67.33                  |
| Ours           | Acc (cm)        | 2.63           | 2.25           | 2.86           | 1.88 ●         | 2.07           | 3.45           | 4.92           | 2.98                   |
|                | Acc.-Ratio (%)  | 90.80          | 93.01          | 86.99          | 93.83          | 92.43          | 87.73          | 83.01          | 88.20                  |
|                | Comp. (cm)      | <b>2.25</b> ●  | <b>1.86</b> ●  | 3.57           | 1.67 ●         | 1.79 ●         | <b>2.34</b> ●  | <b>2.69</b> ●  | 2.67 ●                 |
|                | Comp. Ratio (%) | 93.23 ●        | <b>94.98</b> ● | 89.62          | 95.59 ●        | 93.34 ●        | 91.35 ●        | 89.40 ●        | 89.34 ● <b>92.11</b> ● |

be interpreted as precision and recall of the reconstruction, we further use the F1-score

$$F_1(\mathcal{G}, \mathcal{E}) = \frac{2}{\text{AR}(\mathcal{G}, \mathcal{E})^{-1} + \text{CR}(\mathcal{G}, \mathcal{E})^{-1}} \quad (14)$$

to summarize reconstruction performance in one metric.

## 8. Additional Results

**Detailed Replica Results** Table 4 shows per-scene results on the Replica dataset. On most scenes Co-SLAM achieves the best result; however, it fails on room1 leading to worse average results. We note that our contributions do not aim to improve scene reconstruction on small scenes and this experiment merely serves to highlight overall competitive results. That is, our method scales to large scale scenes by incorporating loop closure constraints, without significantly hurting small scene performance.

**Additional Qualitative Results** Figure 13 shows an extended comparison at the end of the Kintinous [42] sequence. Our method is the only one that successfully closes the loop. Co-SLAM drifts off significantly in the second corner failing to map subsequent parts successfully.

In Fig. 14, Fig. 15, and Fig. 16 qualitative results on the ScanNet, Replica, and NRGBD datasets are shown, respectively. In most scenes our approach performs close to the best performing method Co-SLAM, while outperforming NICE-SLAM and GO-SLAM. Co-SLAM achieves slightly more detailed and smoother results, which might be due to their more effective hash table use and the additional smoothness loss.



Figure 13. Qualitative comparison on the Kintinous dataset [42] at the end of the sequence. Three views are shown. Note that our method is the only one closing the loop successfully. The last row shows the corner in which Co-SLAM is failing (mapping a 90 degree corner as a U-turn).



Figure 14. Qualitative comparison of final meshes extracted by all methods on the ScanNet dataset [5]. Our method fails on scene0181\_00 due to tracking issues in the underlying SLAM system in a feature-less region.

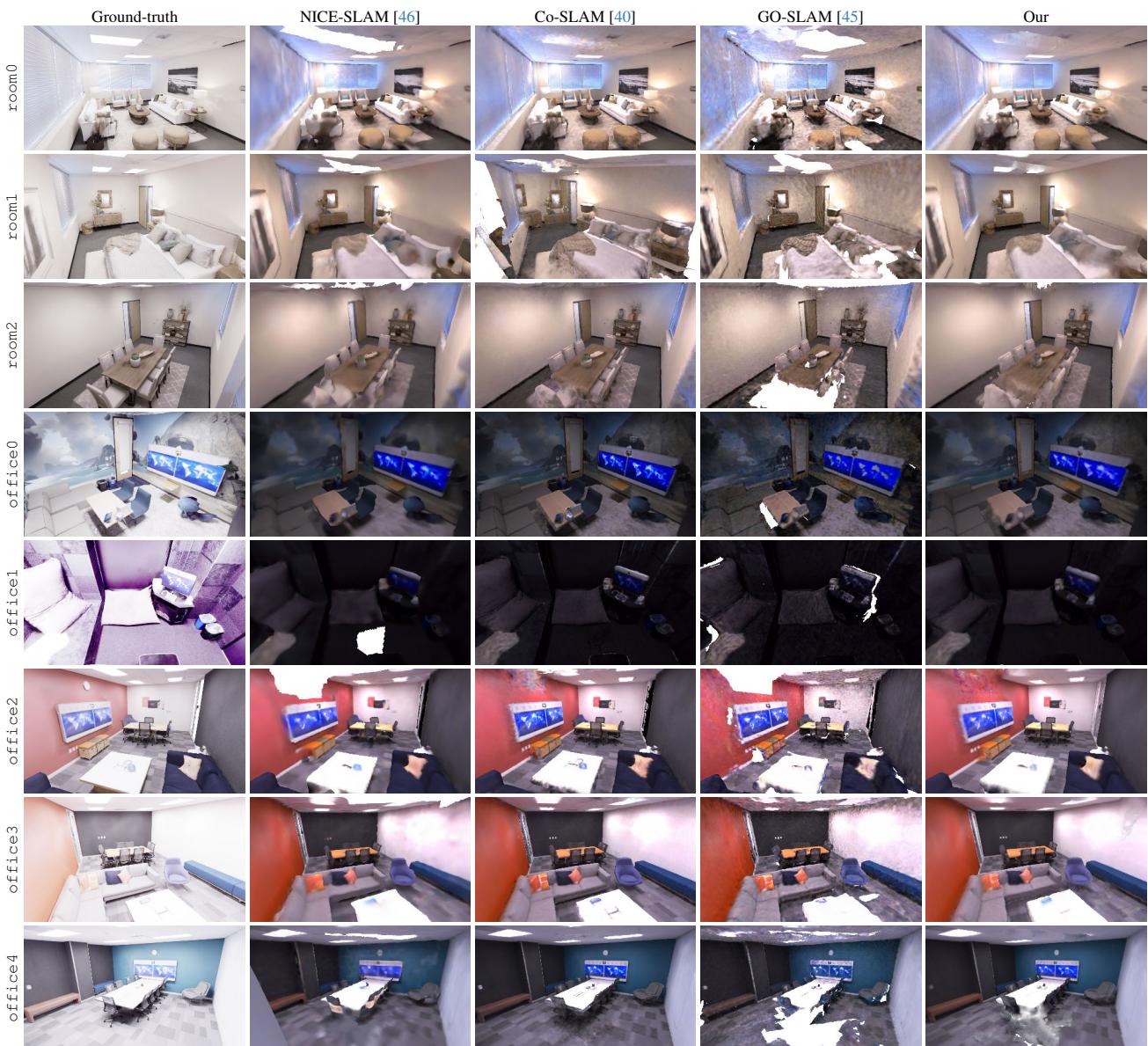


Figure 15. Qualitative comparison of final meshes extracted by all methods on the Replica dataset [33, 34].



Figure 16. Qualitative comparison of final meshes extracted by all evaluated methods on the NRGBD dataset [2].