Supplementary Material for “Local-to-Global Registration for Bundle-Adjusting Neural Radiance Fields”

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A.1. Time Consumption

In all experiments, we always use the same initial conditions for all methods (fixed random seeds). For each object of synthetic scenes, we perturb the camera poses with additive noise as initial poses. Note that the way we add noise differs from [1], which perturbs ground-truth camera poses using left multiplication (transform cameras around the object’s center). Transformed cameras almost still face the object’s center, and the distances between the cameras and the object are almost unchanged. In contrast, we perturb ground-truth camera poses using right multiplication (transform cameras around themselves), thereby perturbing camera viewing directions (not always toward the object’s center) and camera positions (including the distances from them to the object), respectively.

The 6-DoF perturbation is parametrized by \( T = [R|t] \in SE(3) \), where \( R \in SO(3) \), \( t \in \mathbb{R}^3 \), and \( R \) is generated by exponential map \( \exp(r) \) from the Lie algebra \( \mathfrak{so}(3) \) to the Lie group \( SO(3) \). The additive rotation noise \( r \in \mathfrak{so}(3) \) and translation noise \( t \in \mathbb{R}^3 \) are distributed as \( r \sim N(0, n_r I) \) and \( t \sim N(0, n_t I) \), where the multiplier \( n_r \) and \( n_t \) are scene-dependent and given in Table 2.

A.2. Camera Pose Perturbation

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perturbed/optimized
camera
poses
ground
truth
camera
poses
translational
error
Figure 2. Visual comparison of ablation study about optimized camera poses (Procrustes aligned) for hotdog object. Full L2G-NeRF successfully aligns camera frames while w/o \( L_{\text{global}} \) gets stuck at suboptimal poses.

initial
w/o \( L_{\text{global}} \)
Ours

Figure 4. Visualization of ablation study about registration for room scene (Procrustes aligned). Results from L2G-NeRF highly agree with S/M [4] (colored in black), whereas w/o \( L_{\text{global}} \) results in suboptimal alignment.

w/o \( L_{\text{global}} \)
Ours
reference NeRF

Figure 3. Ablation study of NeRF on hotdog synthetic object. The image synthesis and the expected depth are visualized with ray compositing in the top and bottom rows, respectively. Full L2G-NeRF achieves comparable rendering quality to the reference NeRF (trained using ground-truth poses), while ablation w/o \( L_{\text{global}} \) renders artifacts due to suboptimal registration.

w/o \( L_{\text{global}} \)
Ours
reference NeRF

Figure 5. Ablation study of NeRF on room real-world scenes from unknown camera poses. While L2G-NeRF can jointly optimize poses and scenes, L2G-NeRF produces high fidelity results, which is competitive to reference NeRF trained using S/M poses. Ablation w/o \( L_{\text{global}} \) diverges to wrong poses and hence produces ghosting artifacts.

<table>
<thead>
<tr>
<th>Scene</th>
<th>Camera pose registration</th>
<th>View synthesis quality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rotation (^\circ) ↓</td>
<td>Translation ↓</td>
</tr>
<tr>
<td>Synthetic objects</td>
<td>Global Local L2G BARF w/o ( L_g ) Ours</td>
<td>0.15 3.63 0.55 23.82 0.46 0.33 0.61 0.32</td>
</tr>
<tr>
<td>Real-World scenes</td>
<td>Global Local L2G BARF w/o ( L_g ) Ours</td>
<td>7.02 3.63 0.55 23.82 0.46 0.33 0.61 0.32</td>
</tr>
</tbody>
</table>

Table 5. Quantitative results of ablation study about bundle-adjusting neural radiance fields. L2G-NeRF outperforms the local registration method (ablation w/o \( L_{\text{global}} \)) and global registration method (BARF) on the average evaluation criteria of both synthetic objects and real-world scenes, which reveals the advantage of our local-to-global registration process. Translation errors are scaled by 100.

A.3. Convergence

We analyze the convergence of joint optimization on the Ship scene. We first set the base rotation noise multiplier \( n_r \) as 0.01 and the base translation noise multiplier \( n_t \) as 0.1, then linearly increased them by a common factor of \( \{n_c\}_{n_c=2}^9 \). As shown in Fig. 1, BARF fails to converge with \( n_c=4 (n_r=0.04, n_t=0.4) \) while L2G-NeRF fails to converge with \( n_c=8 (n_r=0.08, n_t=0.8) \). Moreover, we also analyze the influence of individual noise. Let \( n_r=0 \), BARF and L2G-NeRF can handle the largest \( n_t \) of 0.6 and 1.1, respectively. Let \( n_t=0 \), BARF and L2G-NeRF can handle the largest \( n_r \) of 0.16 and 0.25, respectively. In more noisy cases (such as random init), all methods cannot converge.
A.4. Tuning Parameters

We set the multiplier $\lambda$ of the global alignment objective to $1 \times 10^2$ for both the neural image alignment experiment and learning NeRF from imperfect camera poses with synthetic object-centric scenes. To further solve the challenging problem of learning NeRF in forward-facing LLFF scenes from unknown poses, we float the multiplier $\lambda$ between $1 \times 10^2$ and $1 \times 10^5$ (summarized in Table 3) to achieve preferable results for specific scenes. As shown in Table 4, a larger $\lambda$ encourages the model to emphasize geometric constraints more, achieving better accuracy but worse robustness (fails to converge on the Flower scene).

B. Ablation Studies

We propose a local-to-global registration method that combines the benefits of parametric and non-parametric methods. The key idea is to apply a pixel-wise alignment that optimizes photometric reconstruction errors...
Figure 8. Additional visual comparison of the optimized camera poses (Procrustes aligned) for the *mic* and *drums* objects. L2G-NeRF successfully aligns all the camera frames while baselines get stuck at suboptimal solutions.

Figure 9. Additional novel view synthesis results of NeRF on real-world scenes (LLFF dataset) from unknown camera poses. L2G-NeRF can optimize for neural fields of higher quality than baselines, while achieving the comparable quality of the reference NeRF model that is trained under the camera poses provided by S/M [4].

Figure 10. Visual comparison of the optimized camera poses (Procrustes aligned) for the *t-rex* real-world scene. L2G-NeRF successfully recovers the camera poses from *identity* transformation, which achieves fewer errors than BARF.
Figure 11. Visual comparison of optimized camera poses (Procrustes aligned) for the challenging toys scene captured under large displacements (hierarchical camera poses). L2G-NeRF successfully aligns all camera frames, which highly agrees with S/M camera poses (colored in black), while BARF gets stuck at suboptimal solutions.

Figure 12. Results of NeRF on toys scene. L2G-NeRF achieves comparable synthesis quality to the reference NeRF (trained under S/M camera poses). But BARF fails to recover the proper geometry, which results in artifacts.

Figure 13. Visual comparison of optimized camera poses for the challenging foods scene captured under sparse views. Results from L2G-NeRF highly agree with S/M, whereas BARF results in suboptimal alignment.

Figure 14. Results of NeRF on foods scene. L2G-NeRF outperforms BARF and even achieves better performance than reference NeRF in the scene where S/M [4] struggles with finding accurate registration from sparse views.

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<th>View synthesis quality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rotation (°) ↓</td>
<td>PSNR ↑</td>
</tr>
<tr>
<td></td>
<td>Naïve</td>
<td>BARF</td>
</tr>
<tr>
<td>Toys</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Foods</td>
<td>5.30</td>
<td>10.99</td>
</tr>
</tbody>
</table>

Table 6. Quantitative results of bundle-adjusting neural radiance fields on real-world scenes captured using an iPhone under large displacements (toys) or sparse views (foods). L2G-NeRF outperforms baselines and even achieves better performance than reference NeRF that trained under S/M poses in the Foods scene, which is hard for S/M to find accurate camera poses. Translation errors are scaled by 100.

B.1. Ablation on NeRF (3D): Synthetic Objects

We first investigate the ablation study of learning NeRF from imperfect camera poses. We experiment with 8 synthetic object-centric scenes [3]. The results in Fig. 3 and Table 5 show that L2G-NeRF achieves better performance than the ablation w/o \( \mathcal{L}_{\text{global}} \). Fig. 2 further illustrates that L2G-NeRF can achieve near-perfect registration while the ablation w/o \( \mathcal{L}_{\text{global}} \) suffers from suboptimal solutions.
B.2. Ablation on NeRF (3D): Real-World Scenes

We further explore the ablation study of employing NeRF to learn 3D neural fields in real-world scenes with unknown camera poses. We evaluate on the standard benchmark LLFF dataset [2]. Quantitative results are summarized in Table 5. The ablation w/o $L_{\text{global}}$ diverges to wrong poses (visualized in Fig. 4), producing ghosting artifacts (shown in Fig. 5). L2G-NeRF outperforms the ablation w/o $L_{\text{global}}$ and achieves high-quality view synthesis that is competitive to the reference NeRF.

B.3. Ablation on Neural Image Alignment (2D)

We further concretely analyze on the homography image alignment experiment and visualize the results in Fig. 6. Alignment with w/o $L_{\text{global}}$ results in distorted artifacts (cat ears) in the recovered neural image due to ambiguous registration. This is the consequence of w/o $L_{\text{global}}$’s attempt to directly optimize the pixel agreement metric, which minimizes photometric errors but does not obey the geometric constraint (global alignments). As L2G-NeRF discovers precise warps, it optimizes neural image with high fidelity.

C. Additional Results

C.1. NeRF (3D): Synthetic Objects

We report additional qualitative results of learning 3D NeRF from noisy camera poses for synthetic objects in Fig. 7. The baselines still perform poorly, while L2G-NeRF can achieve near-perfect registration (reflected in Fig. 8) and render images with comparable visual quality against reference NeRF that trained under ground-truth poses.

C.2. NeRF (3D): Real-World Scenes (LLFF)

We report additional qualitative results of learning NeRF for the standard LLFF dataset in Fig. 9, where camera poses are unknown. L2G-NeRF successfully recovers the 3D scene with higher fidelity than baselines. Fig. 10 shows that the recovered camera poses from L2G-NeRF agree more with those estimated from S/M methods than BARF.

C.3. NeRF (3D): Real-World Scenes (Ours)

We take one step further to experiment with images captured using an iPhone under challenging camera pose distribution. Fig. 11 and Fig. 13 indicate the advantage of L2G-NeRF in registering images captured under large displacements and sparse views, while baselines exhibit artifacts (Fig. 12 and Fig. 14) due to unreliable registration, which is reflected in Table 6. Moreover, the difficulty of registering from sparse views prevents S/M from finding accurate poses, which results in broken stripes on the synthesis of reference NeRF trained under S/M poses in foods scene. This further demonstrates the effectiveness of removing the requirement of pre-computed S/M poses. Fig. 11 and Fig. 13 show the largest displacements (hierarchical but adjacent camera poses) and the sparsest camera setting (9 views) of L2G-NeRF to register images in these scenes successfully, than which we can not handle a more challenging camera pose distribution.

C.4. NeRF (3D): Real-World Scenes (Shiny)

To analyze the influence of reflective surfaces, We present an example in Fig. 15 that models scenes [6] with reflections from identity initialization (L2G-NeRF converges, BARF fails in the guitars scene). Interestingly, global alignment loss increases by 4 to 10 times w.r.t. other datasets. This may be caused by inaccurate local registration in specular regions, and our convergence benefits from the global registration constraint. Specific methods (e.g., [5]) could be employed to handle reflective surfaces better.

References


Representing scenes as neural radiance fields for view synthesis. In *European conference on computer vision*, 2020. 1, 5

