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# Supplementary Material

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Video Results

**1 1 Introduction**

2 The supplementary material comprehensively explains our methods and presents detailed exper-  
3 iment results. In the methods section (Sec 2), we delve into various components of the multiview  
4 segmentation process. We discuss the COLMAP [8] data structure for finding corresponding points  
5 in 3D space from 2D pixel coordinates (Sec 2.1), the rationale behind calculating nearest points after  
6 projecting 3D points onto 2D planes (Sec 2.2), the importance of maintaining a same number of  
7 points annotations across views (Sec 2.3), and the speed loss associated with Grounded-SAM [2]  
8 (Sec 2.4), which motivates our design of converting text prompts to points prompts. Additionally, we  
9 describe the points sampling strategy for text prompts (Sec 2.5) and the patch sampling strategy for  
10 perceptual loss in the scene object removal part (Sec 2.6). The Experiments section (Sec 3) presents  
11 detailed experiment results, including an overview of all scenes and their respective editing outcomes  
12 (Sec 3.3). We also discuss the mask refinement strategy for LaMa processing (Sec 3.1) and provide  
13 implementation details (Sec 3.2).

**14 2 Methods**

**15 2.1 2D to 3D Matchness (COLMAP data structure)**

16 This section explains how to find the corresponding 3D position of 2D pixels through COLMAP’s  
17 [8] sparse reconstruction. Specifically, given a set of 2D pixels  $\mathcal{P}_{2D}$  picked by users indicating the  
18 unwanted objects on only one image, our ultimate goal is to spread  $\mathcal{P}_{2D}$  to all views while ensuring  
19 that the generated point annotations always indicate the target precisely. We address the above  
20 problem by projecting the target objects’ sparse point cloud in 3D space to all 2D image planes. To  
21 find the sparse point cloud indicated by  $\mathcal{P}_{2D}$ , we first utilize SAM (Segment-Anything [4]) to obtain  
22 an initial mask from points prompt  $\mathcal{P}_{2D}$ , then query COLMAP [8] sparse reconstruction with 2D  
23 pixel coordinates in the initial mask to get their corresponding 3D coordinates.

24 Specifically, we can obtain three files *cameras.bin*, *images.bin*, and *points3D.bin* from COLMAP  
25 [8] sparse reconstruction <sup>1</sup>. The *images.bin* and *points3D.bin* files provide a one-to-one mapping  
26 between the reconstructed sparse point cloud and 2D pixel coordinates as follows:

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```
# images.bin: Images indexed by all images with item
Image = {POINTS2D[] as (X, Y, POINT3D_ID)}
# points3D.bin: Points3D indexed by all 3D points with item
Point3D = {TRACK[] as (IMAGE_ID, POINT2D_IDX)}
# Thus, we can find Point3D by:
Point3D=Points3D[POINT3D_ID]=Points3D[Images[IMAGE_ID][POINTS2D]]
```

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<sup>1</sup>COLMAP output formats

28 **2.2 Calculation of Nearest Points**

29 COLMAP [8] only provides sparse reconstruction, making it impossible to establish a connection  
30 from 2D to 3D for arbitrary image pixels. To tackle this limitation, we propose using the nearest  
31 points to the input points belonging to COLMAP’s reconstruction. This approach offers two potential  
32 solutions: 1) Querying the 3D coordinates for all points in the initial mask region and sorting them  
33 based on the distance between their corresponding 2D pixel positions and the input points prompt.  
34 Subsequently, the 3D points are projected back to the 2D image planes, and the projected 2D pixels  
35 are selected based on the sorting results. 2) Alternatively, the points in the initial mask region are  
36 sorted, and a certain number of 2D points are selected first. Then, their 3D points are queried and  
37 projected back to the 2D planes.

38 We adopt the first strategy as the second one carries potential risks. If the camera angle changes  
39 significantly, there may be no corresponding pixel to the selected points in the initial mask. As a  
40 result, these points would lose their annotations for such a view, as they would be "out of the image."  
41 In contrast, the first strategy selects the nearest points after projecting the points back to the 2D planes  
42 from 3D space. This approach avoids the aforementioned problem by simply filtering out invalid 2D  
43 pixel coordinates after the projection from 3D. An example of this corner case is illustrated in Fig 1.



Figure 1: Comparison of two nearest points strategies. The left image displays the user prompt, while the first strategy (middle, project first) ensures annotations for extreme view angles. However, the second strategy (right, sort first) loses all annotations.

44 **2.3 Number of Points Annotation for Each View**

45 As discussed, we project the sparse point cloud of the target objects onto the 2D image plane to obtain  
46 accurate point annotations for all scene views. However, why do we only select a certain number of  
47 projected 2D points as input for SAM [4] rather than using all projected 2D points? This decision  
48 is because using all projected 2D points as input may result in an inaccurate mask, as many points  
49 may be interpreted as multiple instances for segmentation. Fig 2 illustrates an example of using all  
50 projected 2D points as SAM input. To avoid mask ambiguity, annotating several points that indicate  
51 the unwanted objects is sufficient, and there is no need to generate many points.

52 **2.4 Grounded-SAM speed loss**

53 This section presents evidence for why we chose to convert the text prompt to points prompt. As  
54 shown in Figure 3, directly using the same text input to predict masks for all views using Grounded-  
55 SAM [2] runs at a speed of approximately seven seconds per frame, while using points prompt  
56 accelerates the process to two frames per second. This speed improvement is because points prompt  
57 only requires projection calculations (pure matrix) and SAM prediction, whereas Grounded-SAM [2]  
58 also requires Grounding-DINO [5] prediction. Additionally, the detection ability of Grounding-DINO  
59 [5] is unreliable for all views. Therefore, we recommend switching from text input to points prompt  
60 to obtain higher-quality masks in less time.

61 **2.5 Points Sampling Strategy for Text Prompt**

62 Recall that we introduced our points sampling strategy for the text prompt, which involves selecting  
63 three points from the initial mask: top left, bottom right, and centre. We slightly revised the code by  
64 switching the corner points from top left and bottom right to top right and bottom left. However, this



Figure 2: Comparison of two strategies for selecting the number of points. The second row (using all projected 2D points as input for SAM [4]) shows a serrated edge, while the first row (keeping the number of points the same as the user input) exhibits a smooth mask edge.

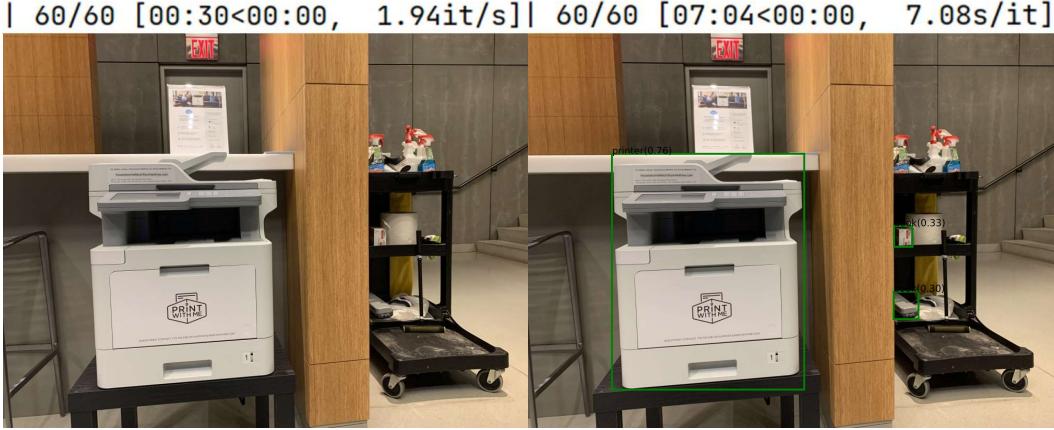


Figure 3: Comparison of two strategies for predicting masks with a text prompt. The progress bars above indicate that the switch strategy (left) is significantly faster than the non-switch strategy (right). The images below illustrate an example of the detection failure (bottom right) of the book by Grounding-DINO [5].

approach is unsuitable for complex scenes where unwanted objects result in slim, irregular masks. In such cases, the centre point calculation may be inaccurate, as shown in Fig 4. We can omit the centre point and use two corner points only to tackle this problem. Moreover, using the corner points directly can introduce problems, as points on the boundary are ambiguous for SAM [4] when predicting masks. Similarly, we use the centre point only to handle this issue.

## 2.6 Patch Sampling Strategy for Perceptual Loss

As perceptual loss [3] operates at the image level, we make it compatible with Neural Radiance Fields [6] training by sampling patches from the image. The patch sampling strategy used in SPIn-NeRF [7] involves downsampling the image by a factor of 16 to determine the patch shape. However, this approach can fail to adequately handle small mask regions, especially when the mask shape is smaller than the downsampled shape, as illustrated in an extreme example in Fig 1. To address this issue, we

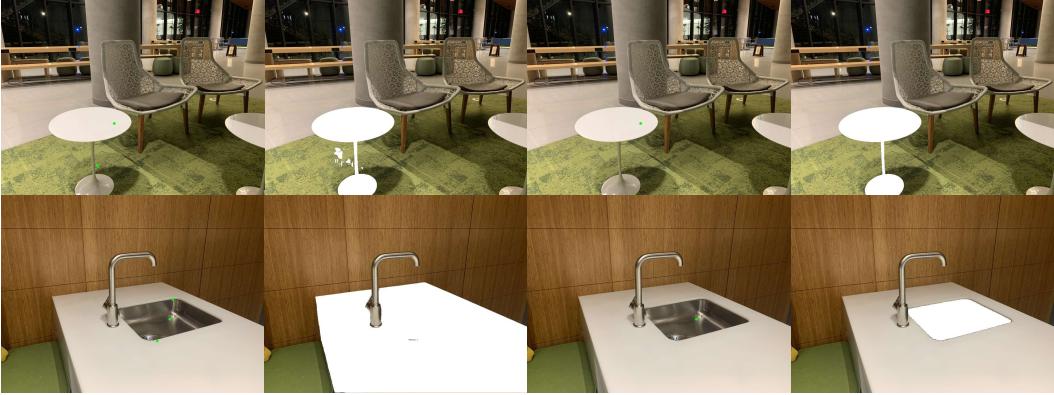


Figure 4: Comparison of two corner cases discussed in Sec 2.5. Each image pair, from left to right, displays points annotation and predicted masks. The left two columns depict the coarse sampling strategy, while the right two columns represent the improved version. The first row provides an example of an inaccurate centre point, and the second row demonstrates the ambiguous results when boundary points are applied.

76 propose a new sampling strategy that downsamples the mask area by a factor of 4 to determine the  
 77 patch shape rather than relying on the original image shape. Additionally, we enforce a minimum  
 78 patch length of 32 and a maximum length of 64. If these constraints still prove inadequate in handling  
 79 extreme situations, we skip applying perceptual loss for that specific image.

### 80 3 Experiments

#### 81 3.1 Mask Refine for LaMa

82 In this section, we focus on explaining our mask refinement method. As mentioned in SPIn-NeRF [7],  
 83 applying masks that precisely match the unwanted objects can lead to unexpected outcomes when  
 84 using the 2D inpainting network LaMa [9]. Specifically, LaMa [9] tends to preserve the silhouettes  
 85 or edge shadows of the objects when the mask shape provides some "knowledge" about the masked  
 86 area (Fig 5). In practice, we employ slightly more generous masks to achieve plausible inpainting  
 87 results, such as dilation or scaling. However, this refinement process must be cautiously approached,  
 88 as enlarging the mask can make it more challenging for LaMa [9] to generate reasonable priors.

89 In SPIn-NeRF [7], they employ a dilation operation with a  $5 \times 5$  kernel for 5 iterations. However, this  
 90 approach is too coarse for our scenes with various characteristics. For example, the mask may become  
 91 too large after dilation and include areas that should remain if the target region is relatively small.  
 92 Also, masks with highly irregular shapes can lose their original form, such as crossing slim chair legs.  
 93 In addition, there may exist noises for complicated scenes or ambiguous prompts. However, dilation  
 94 alone will magnify noises in the mask image. To address these issues, we provide three parameterized  
 95 mask refinement operations that can be customized by users. These operations include dilation  
 96 with adjustable kernel size and iteration steps, contour equidistant expansion with flexible scaling  
 97 steps, and a filtering mechanism to keep a specified number of masks in an image and eliminate  
 98 segmentation noise.

99 We have carefully fine-tuned the above operations for the scenes used in our experiments to ensure  
 100 that the refined mask is suitable for LaMa [7] inference while minimizing changes to the segmentation  
 101 results.

#### 102 3.2 Implementation Details

103 All our experiments are conducted on a single RTX 3090 or A5000 GPU. We evaluated our method  
 104 and the SPIn-NeRF [7] approach on all 20 scenes. We tested both the vanilla NeRF [6] and TensoRF  
 105 [1] architectures using our implementation. Since the use of perceptual loss significantly increases  
 106 memory usage, we train our Ours-NeRF [6] model with perceptual loss using a batch size of 1,



Figure 5: Example of LaMa [9] inpainting results with (top) and without (bottom) mask refinement. Images in the second row demonstrate the effect of using masks without refinement, which precisely match the objects but result in the retention of object silhouettes.

107 while SPIIn-NeRF [7] and Ours-TensoRF [1] are trained with a batch size of 4. We follow the only  
 108 configuration provided by SPIIn-NeRF [7] to reproduce their results on all our scenes <sup>2</sup>.

109 Regarding the testing phase, the ground truth images provided by SPIIn-NeRF [7] after object deletion  
 110 do not indicate which images they corresponded to before deletion. Therefore, we rendered these  
 111 views using the camera parameters to generate the corresponding images for evaluation.

### 112 3.3 More Experiment Results

113 **Quantity** In this part, we give the detailed metrics tested in our experiments with all scene data  
 114 available as Table 1.

115 **Quality** In this part, we give our experiments' detailed original and edited image pairs with all  
 116 scene data available as Fig 6, 7 and 8.

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<sup>2</sup>SPIIn-NeRF GitHub



Figure 6: Original image (left), image with regions to be removed (middle), and images after removal from new views (right) for all scenes. (Begin)



Figure 7: Original image (left), image with regions to be removed (middle), and images after removal from new views (right) for all scenes. (Cont)



Figure 8: Original image (left), image with regions to be removed (middle), and images after removal from new views (right) for all scenes. (End)

Table 1: Experiment results for scene object removal. The first row indicates the scene name, and the first column indicates the method name. The abbreviations in the second column represent the loss modules used. 'dir' denotes training Neural Radiance Fields with LaMa [9] priors directly, 'dp' denotes partial depth, 'da' denotes all depth, and 'lips' denotes the use of perceptual loss. It is worth noting that perceptual loss is always applied with all-depth supervision enabled.

			2	3	4	7	10	12	book	trash	Mean
Ours-NeRF [6]	dir	PSNR↑	16.05	11.60	13.05	14.44	13.02	11.50	15.88	16.77	14.04
		FID↓	102.41	46.29	80.40	38.64	49.14	42.67	90.33	39.02	61.11
		LPIPS↓	0.8556	0.5730	0.7560	0.7246	0.6541	0.8084	0.5446	0.5510	0.6834
	da	PSNR↑	15.99	11.61	13.06	14.45	13.01	11.48	15.92	16.77	14.04
		FID↓	106.36	49.04	81.42	39.28	55.07	45.87	95.98	48.62	65.21
		LPIPS↓	0.8542	0.5759	0.7624	0.7315	0.6605	0.8132	0.5484	0.5682	0.6893
	dp	PSNR↑	16.07	11.59	13.10	14.60	13.26	11.53	16.16	16.97	14.16
		FID↓	111.16	47.94	77.93	40.40	49.37	46.18	91.72	52.97	64.71
		LPIPS↓	0.8643	0.5757	0.7843	0.7418	0.6775	0.8177	0.5560	0.6000	0.7022
	lips	PSNR↑	16.03	11.62	13.10	14.62	13.28	11.49	16.15	16.99	14.16
		FID↓	70.23	39.58	74.77	44.94	55.96	41.99	87.27	50.48	58.15
		LPIPS↓	0.8522	0.5532	0.7157	0.7157	0.6750	0.7593	0.5474	0.5917	0.6763
Ours-TensoRF [1]	dir	PSNR↑	15.91	11.40	13.04	14.41	12.88	11.37	15.84	16.62	13.93
		FID↓	90.05	37.04	80.09	37.55	43.84	38.38	64.63	34.66	<b>53.28</b>
		LPIPS↓	0.8039	0.5068	0.7200	0.6810	0.6179	0.7454	0.5167	0.5042	0.6370
	da	PSNR↑	15.92	11.41	13.05	14.51	13.15	11.37	16.03	16.85	14.04
		FID↓	91.64	38.70	82.86	37.37	49.12	39.72	94.61	80.29	64.29
		LPIPS↓	0.8071	0.5069	0.7298	0.6995	0.6496	0.7482	0.5234	0.5306	0.6494
	lips	PSNR↑	15.94	11.42	13.01	14.46	13.12	11.41	16.05	16.84	14.03
		FID↓	72.10	34.83	76.56	36.53	47.27	38.65	95.62	76.39	59.74
		LPIPS↓	0.7909	0.4941	0.6790	0.6606	0.6443	0.7192	0.5159	0.5143	<b>0.6273</b>
SPIn-NeRF [7]	dir	PSNR↑	16.78	12.05	14.92	15.35	12.72	12.47	17.77	16.73	<b>14.85</b>
		FID↓	94.80	93.80	73.19	26.41	62.10	55.37	105.74	48.76	70.02
		LPIPS↓	0.8636	0.5839	0.7285	0.7028	0.6971	0.8110	0.4388	0.6222	0.6810
	da	PSNR↑	16.54	12.00	14.93	15.31	12.71	12.45	17.84	16.74	14.82
		FID↓	93.94	93.11	76.07	29.10	54.14	53.19	113.91	47.08	70.07
		LPIPS↓	0.8687	0.5653	0.7299	0.6941	0.6880	0.8071	0.4394	0.6090	0.6752
	lips	PSNR↑	16.69	12.08	14.90	15.34	12.73	12.39	17.84	16.70	14.83
		FID↓	71.75	68.35	61.10	43.95	91.73	50.52	102.71	47.98	67.26
		LPIPS↓	0.8489	0.5472	0.6815	0.6552	0.7003	0.7518	0.4226	0.5972	0.6506

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