Supplementary Material *for* SCP-Diff: Photo-Realistic Semantic Image Synthesis with Spatial-Categorical Joint Prior

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1 Toolkit

For access to our fully anonymous code toolkit, please visit: https://anonymous.4open.science/r/SCP-Diff-Toolkit/.

2 Implementation Details

Finetuning ControlNet. We initialize the Stable Diffusion branch of ControlNet [8] with SD 2.1 weights. During training, we set the text prompt to fixed strings, and those are: *City road scenes* for Cityscapes [4], *Photorealistic and diverse images depicting various scenes* for ADE20K [9], and *high quality, detailed* for COCO-Stuff [1]. This aims to ensure that the text prompt remains devoid of any semantic cues, with the sole source of semantics derived from the semantic label processed by the control branch and the noise priors.

Evaluation. During inference of the generated results from different datasets, the text prompt was kept the same as the training procedure. For evaluation of FID, we sampled 50,000 images for each group of experimental setting, noting that FID score is biased and the bias is depending on the number of images we use for calculation [3]. For evaluation of mIoU, we follow OASIS [5], using UperNet101 [6] for ADE20K, multi-scale DRN-D-105 [7] for Cityscapes, and DeepLabV2 [2] for COCO-Stuff.

3 Results

3.1 More Qualitative Results

We provide more qualitative results, with Fig. 1 and Fig. 2 for Cityscapes, Fig. 3 and Fig. 4 for ADE20K, Fig. 5 and Fig. 6 for COCO-Stuff.

References

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Fig. 1: Qualitative Results on Cityscapes dataset. (cont.)

Fig. 2: Qualitative Results on Cityscapes dataset. (cont.)

Fig. 3: Qualitative Results on ADE20K dataset. (cont.)

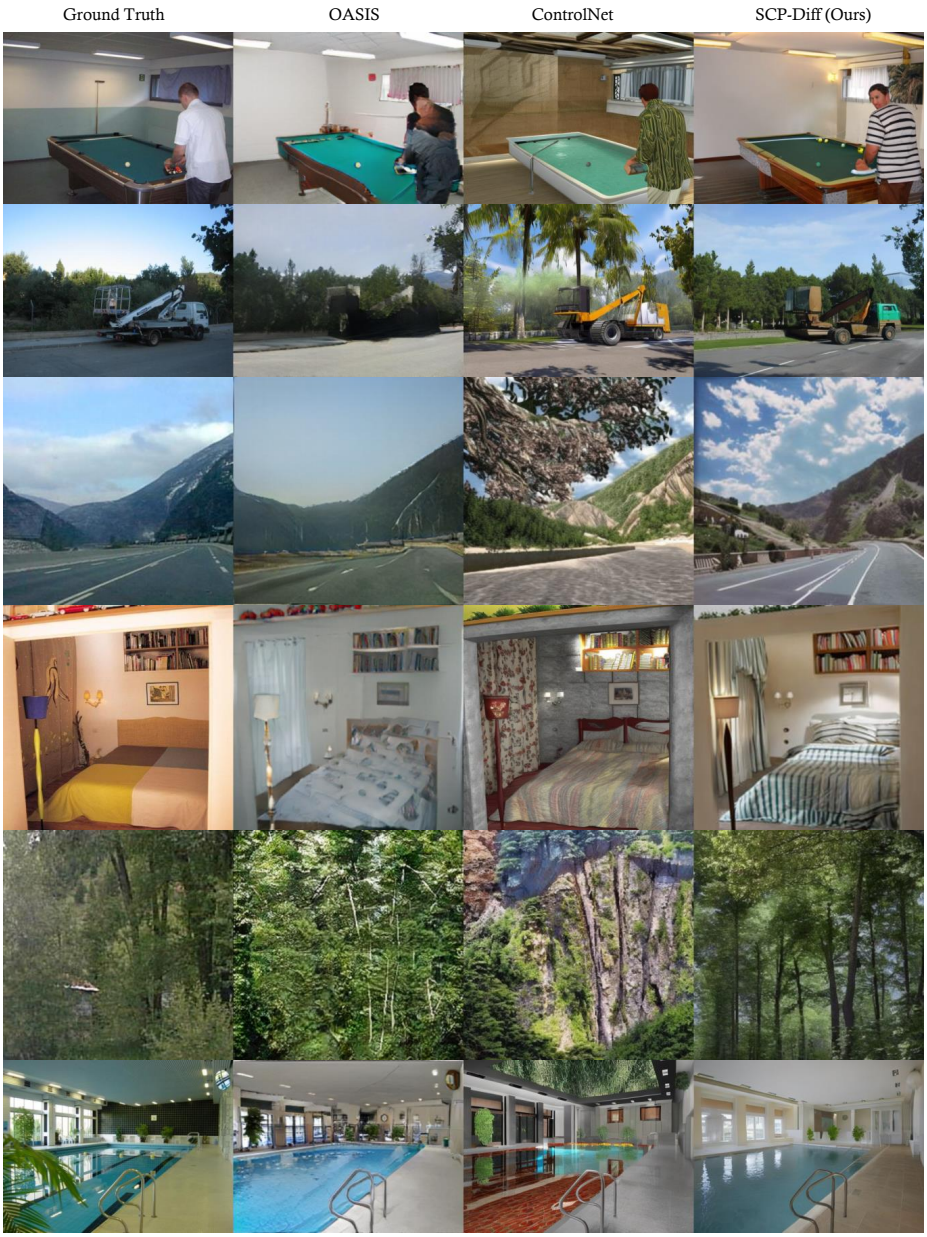

Fig. 4: Qualitative Results on ADE20K dataset. (cont.)

Fig. 5: Qualitative Results on COCO-Stuff dataset. (cont.)

Fig. 6: Qualitative Results on COCO-Stuff dataset.