

CompenNet++: End-to-end Full Projector Compensation

- Supplementary Materials -

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1. Introduction

In this supplementary material, firstly, we show the detailed CompenNet++ parameters in §2. Then, more camera-captured full projector compensation results are shown in §3.

2. CompenNet++ Parameters

The detailed parameters of CompenNet can be found in [2]; affine θ_{aff} and TPS θ_{TPS} parameters are discussed in §3.3. **Network design.** We show the detailed CNN parameters of grid refinement network \mathcal{W}_{θ_r} in Tab. 1.

Table 1: Parameters of the grid refinement network \mathcal{W}_{θ_r} . It consists of a UNet-like [4] structure with a residual connection, it generates a refined sampling grid that samples the input image directly. Both input and output are two-channel image sampling grids with the same size as the projector input image. Note **Conv** and **TransConv** stand for convolutional and transposed convolutional layers; ReLU layers after each Conv/TransConv layer are omitted. The last activation layer is a leaky ReLU and its output is clamped to $(-1, 1)$.

Layer	Input size	Output size	Filter size	Stride	Padding
Conv1	$256 \times 256 \times 2$	$128 \times 128 \times 32$	3×3	2	1
Conv2	$128 \times 128 \times 32$	$64 \times 64 \times 64$	3×3	2	1
TransConv1	$64 \times 64 \times 64$	$128 \times 128 \times 32$	3×3	2	0
TransConv2	$128 \times 128 \times 32$	$256 \times 256 \times 2$	3×3	2	0
Leaky ReLU (slope = 0.1)	$256 \times 256 \times 2$	$256 \times 256 \times 2$	-	-	-

3. Camera Captured Full Projector Compensation Results

In the following figures, we show more qualitative comparisons of TPS [1] w/ SL, TPS textured w/ SL, Pix2pix [3] w/ SL, CompenNet [2] w/ SL, proposed CompenNet++ w/o refine and proposed CompenNet++ on four different surfaces. The 1st to 3rd columns are the camera-captured projection surface, desired viewer perceived image and camera-captured uncompensated projection, respectively. The rest columns are the compensation results of different methods. Each image is provided with two zoomed-in patches for detailed comparison. **In the first figure, notice the holes due to SL decoding error in the red zoomed-in patch of the 2nd surface (pillow) and the blue zoomed-in patch of the 3rd surface (curves)**, this issue is better addressed by the proposed CompenNet++, where geometric and photometric compensation are jointly optimized.

We list 32 high-resolution comparison images below due to the 20MB limit of the supplementary material. The source code, benchmark and high-resolution experimental results are available at <https://github.com/BingyaoHuang/CompenNet-plusplus>.

References

- [1] Anselm Grundhöfer and Daisuke Iwai. Robust, error-tolerant photometric projector compensation. *IEEE TIP*, 2015. 1
- [2] Bingyao Huang and Haibin Ling. End-to-end projector photometric compensation. In *CVPR*, 2019. 1
- [3] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. *CVPR*, 2017. 1
- [4] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *MICCAI*. Springer, 2015. 1

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