Supplementary Material
Learning Local Implicit Fourier Representation for Image Warping

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1 Evaluation Detail

Asymmetric-scale SR We report peak signal-to-noise ratio (PSNR) for network evaluation on Set5 [1], Set14 [14], B100 [7], and Urban100 [4]. We use 48×48 patches for inputs [6] and bicubic resizing in Pytorch [10] for arbitrary-scale down-sampling during a training phase. RCAN [15] is used as an encoder without its upsampling module.

Homography transform For network evaluation, we propose Set5-Warping (Set5W), Set14-Warping (Set14W), B100-Warping (B100W), Urban100-Warping (Urban100W) datasets by applying homography transform to HR images from the existing Set5 [1], Set14 [14], B100 [7], and Urban100 [4] datasets. We report mask PSNR (mPSNR) [11] on DIV2KW [11], Set5W, Set14W, B100W, Urban100W. During training, we use bicubic resampling in [11] for arbitrary homography transform. Input patches of networks have a maximum size of 48×48. EDSR-baseline [6] and RRDB [13] are used as encoders without their upsampling modules.

ERP perspective projection We train our LTEW to represent homography transform and perform ERP perspective projection to verify the generalization ability without extra training. For network evaluation, we use street view panoramas in the Google StreetLearn dataset [2, 5, 8] and a full-circle panorama beside 'Namib Dune' taken by NASA's Curiosity Mars Rover [9].

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2 Visual comparison with state-of-the-art methods

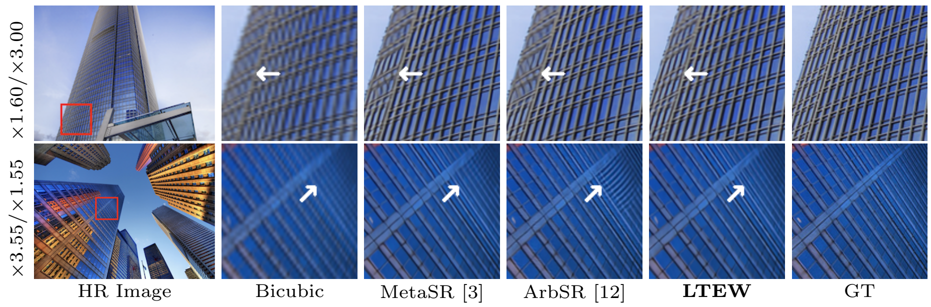


Fig. 1. Qualitative comparison to other **asymmetric-scale SR** within **in-scale**. RCAN [15] is used as an encoder for all methods.

Fig. 2. Qualitative comparison to other **asymmetric-scale SR** within **out-of-scale**. RCAN [15] is used as an encoder for all methods.

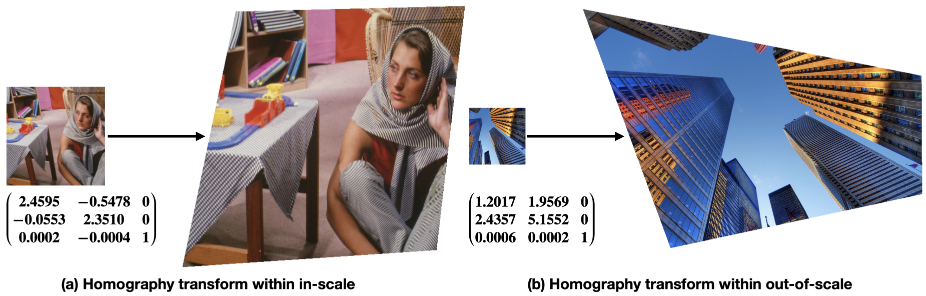
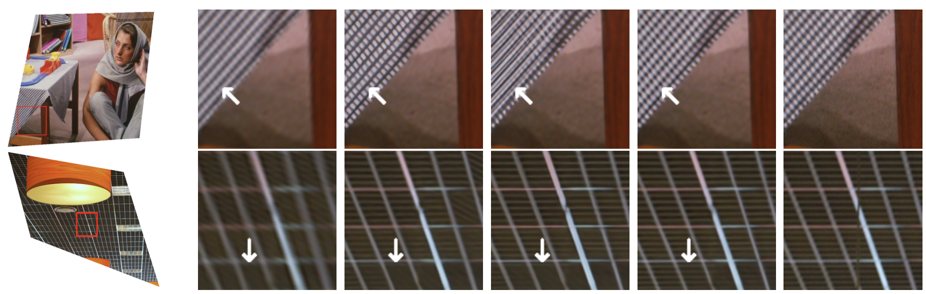
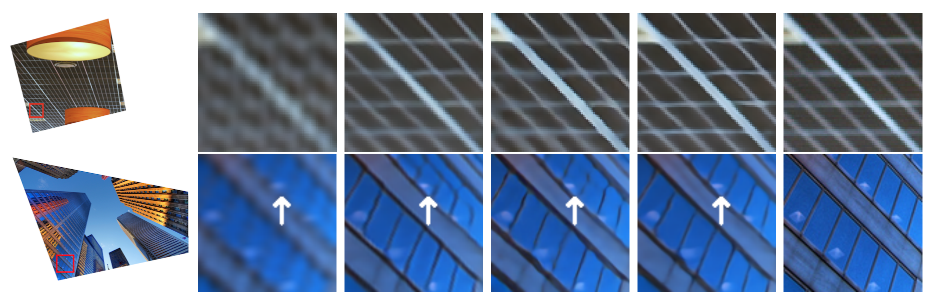


Fig. 3. Homography transform example within **in-scale** and **out-of-scale**.



HR Image | Bicubic | RRDB [13] | SRWarp [11] | **LTEW** | GT

Fig. 4. Qualitative comparison to other **homography transform** within **in-scale**. RRDB [13] is used as an encoder for all methods.



HR Image | Bicubic | RRDB [13] | SRWarp [11] | **LTEW** | GT

Fig. 5. Qualitative comparison to other **homography transform** within **out-of-scale**. RRDB [13] is used as an encoder for all methods.

Fig. 6. Qualitative comparison to other **homography transform** within **out-of-scale**, especially for a large magnification ratio (≃8). RRDB [13] is used as an encoder for all methods.

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