

Learning Local Implicit Fourier Representation for Image Warping

Jaewon Lee¹ Kwang Pyo Choi² Kyong Hwan Jin¹
Image Processing Laboratory (IPL), DGIST, Korea¹
Samsung Electronics, Korea²



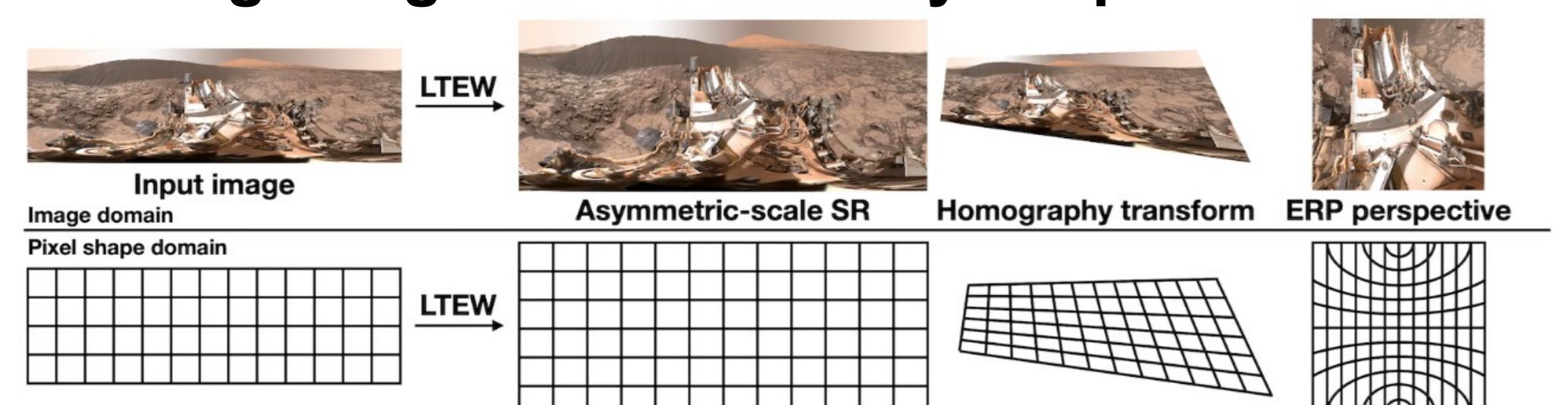
Paper

Code

Introduction

Image warping

Image warping aims to reshape images defined on **rectangular grids** into **arbitrary shapes**



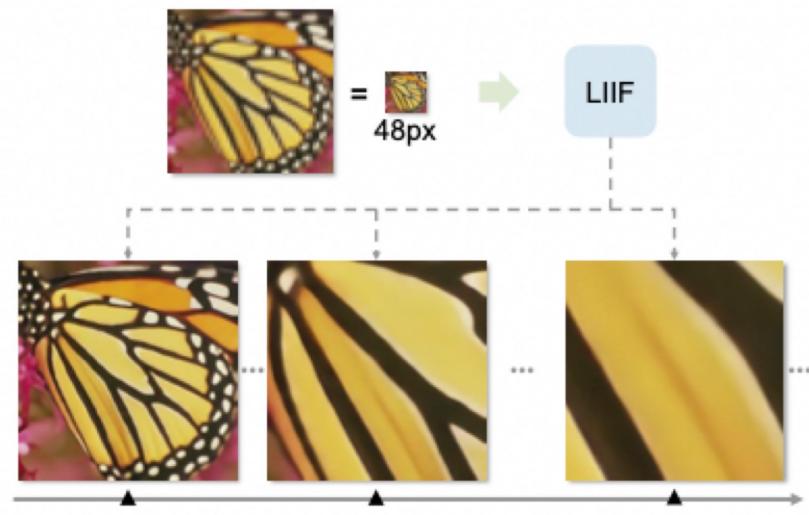
Motivation 1 – interpolation-based approach

Limited **generalization** into a large-scale representation (out of training range)

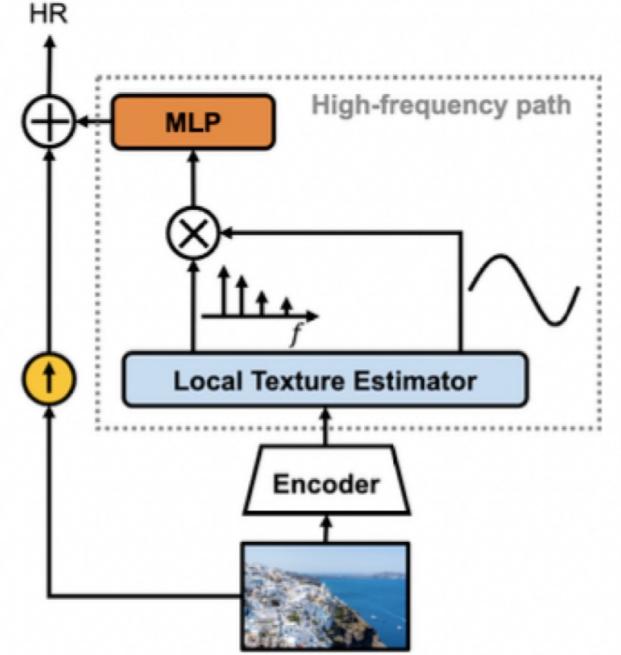


Motivation 2 – INR-based approach

- + Good generalization
- Spectral bias



- + Overcome spectral bias
- Spatial-invariant function



Local texture estimator for image warping

Method	SRWarp (21')	LIIIF (21')	LTE (22')	LTEW (ours)
Spatially-varying SR	✓	✗	✗	✓
Generalization	✗	✓	✓	✓
High-frequency detail	✓	✗	✓	✓

Method

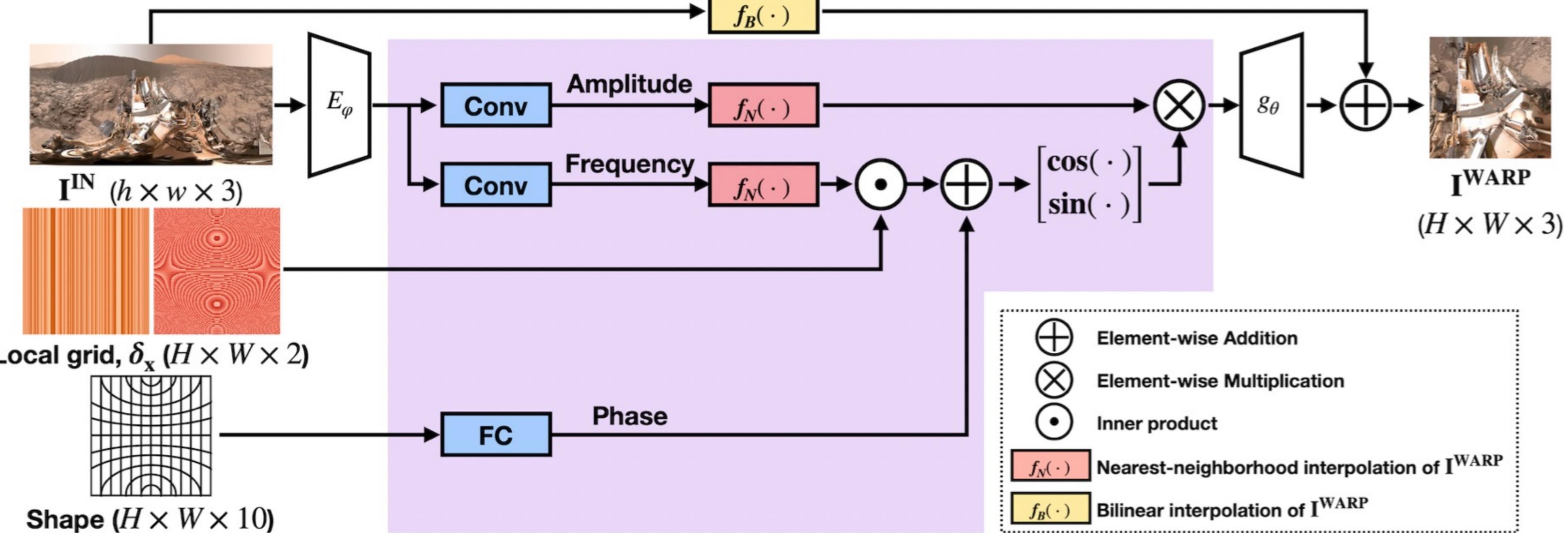


Image warping

Given an image $I^{IN}: X \rightarrow \mathbb{R}^3$, and a differentiable and invertible coordinate transformation $f: X \rightarrow Y$
we aim to represent a warped image $I^{WARP}: Y \rightarrow \mathbb{R}^3$

Local implicit representation function

$$I^{WARP}[y; \theta, \Psi] = \sum_{j \in J} w_j g_\theta(h_\psi(z_j, x - f(x_j)))$$

where $z = E_\varphi(I^{LR})$

However, LTE fails to represent warped images since F_j is a frequency response of an input image, instead of of a warped image.

Local texture estimator

$$h_\psi(z_j, \delta, c) = A_j \odot \begin{pmatrix} \cos(\pi(F_j \delta + h_p(c))) \\ \sin(\pi(F_j \delta + h_p(c))) \end{pmatrix}$$

Frequency Phase
Amplitude

Learning Fourier information with coordinate transformations

1. Local grid relationship

$$\begin{aligned} \delta_y &= y - f(x_j) = f(x) - f(x_j) \\ &= \{f(x_j) + J_f(x_j)(x - x_j) + \mathcal{O}(x^2)\} - f(x_j) \\ &\simeq J_f(x_j)(x - x_j) = J_f(x_j)\delta_x \end{aligned}$$

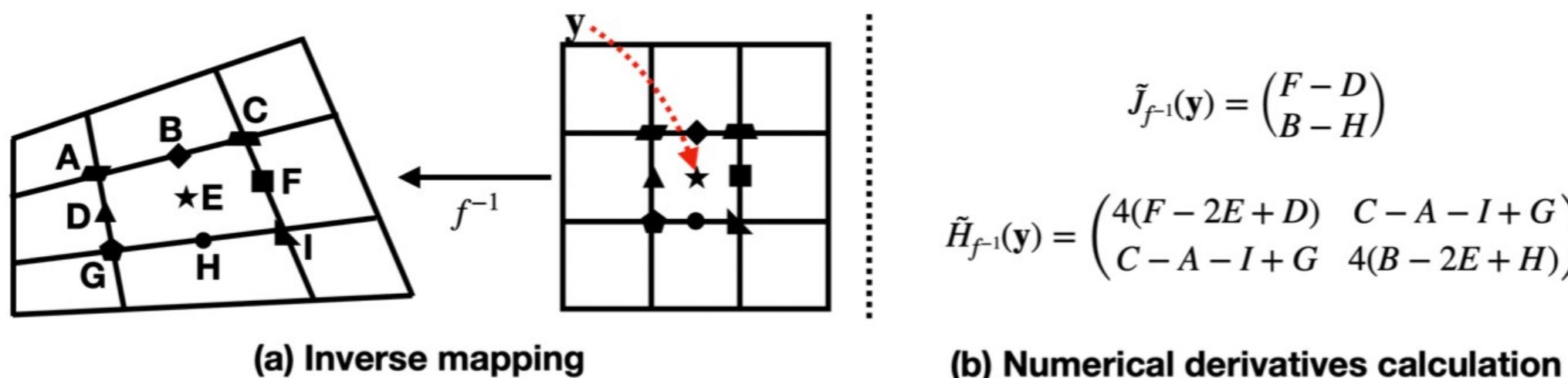
2. Frequency response of a warped image

$$F'_j \simeq J_f^{-T}(x_j)F_j.$$

3. Redefine the LTE (LTE Warp)

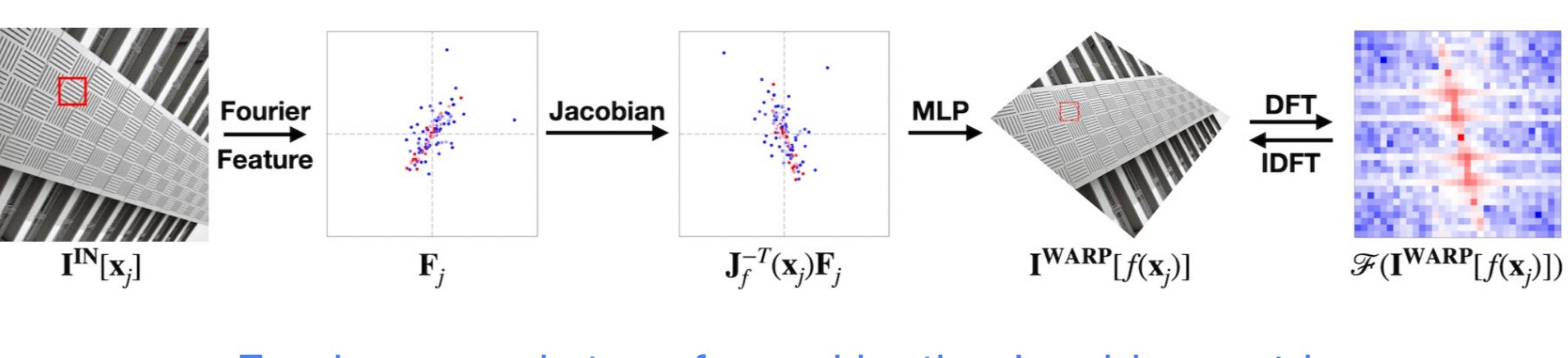
$$\begin{aligned} h_\psi(z_j, \delta_y, f) &= A_j \odot \begin{bmatrix} \cos(\pi < F'_j, \delta_y) \\ \sin(\pi < F'_j, \delta_y) \end{bmatrix} \\ &\simeq A_j \odot \begin{bmatrix} \cos(\pi < J_f^{-T}(x_j)F_j, J_f(x_j)\delta_x) \\ \sin(\pi < J_f^{-T}(x_j)F_j, J_f(x_j)\delta_x) \end{bmatrix} \\ &= A_j \odot \begin{bmatrix} \cos(\pi < F_j, \delta_x) \\ \sin(\pi < F_j, \delta_x) \end{bmatrix} \\ &= h_\psi(z_j, \delta_x). \end{aligned}$$

Shape-dependent phase estimation



$$s(y) = [\tilde{J}_{f^{-1}}(y), \tilde{H}_{f^{-1}}(y)]$$

Fourier space visualization



Fourier space is transformed by the Jacobian matrix

Results

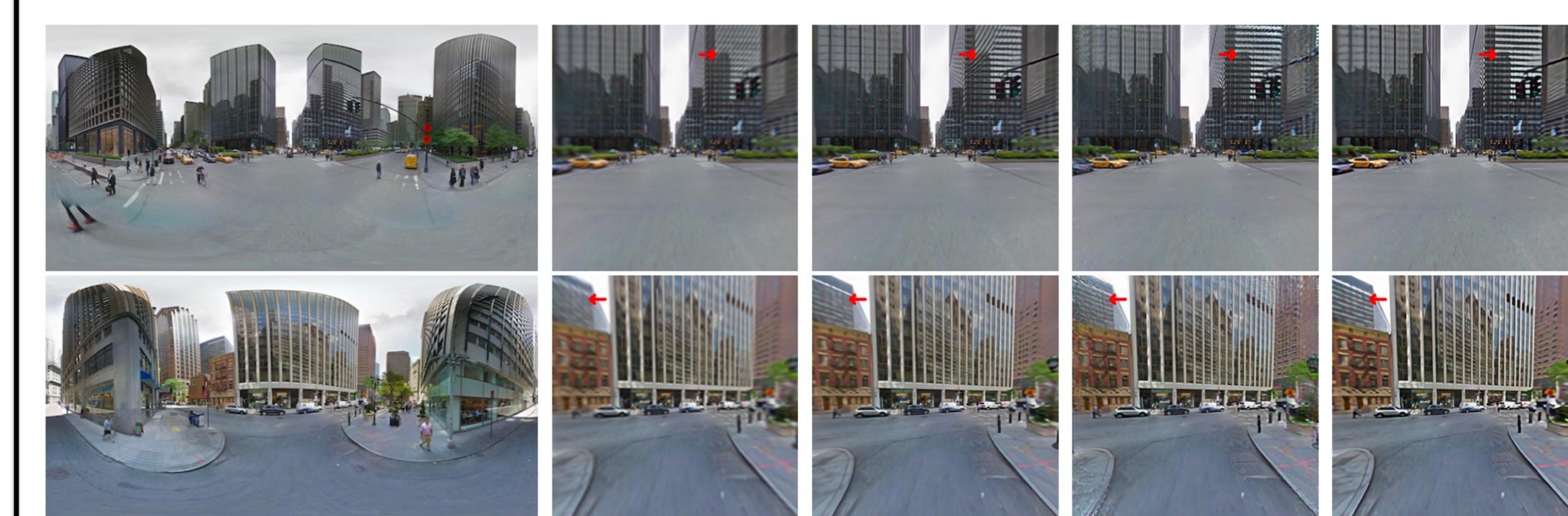
Quantitative comparison

Method	Set5			Set14			B100		Urban100			
	$\times 3$	$\times 7$	$\times 6.1$	$\times 8$	$\times 4$	$\times 7$	$\times 8$	$\times 3$	$\times 7$	$\times 6$	$\times 7.6$	$\times 3.1$
Bicubic	25.69	26.35	26.84	24.27	24.62	24.79	24.67	25.58	24.98	22.55	21.92	22.15
RCAN [51]	29.00	30.01	30.46	26.48	26.94	27.11	26.06	27.19	26.47	25.52	24.50	24.84
MetaSR-RCAN [19]	28.75	29.74	30.38	26.32	26.85	27.03	26.07	27.15	26.45	25.50	24.47	24.84
Arb-RCAN [46]	28.37	29.35	30.08	26.06	26.63	26.84	25.91	27.14	26.40	25.36	24.12	24.61
LTEW-RCAN (ours)	29.26	30.16	30.64	26.60	27.06	27.25	26.25	27.28	26.62	25.85	24.79	25.18

Homography transformation

Method	DIV2KW		Set5W		Set14W		B100W		Urban100W	
	isc	osc								
Bicubic	27.85	25.03	35.00	28.75	28.79	24.57	28.67	25.02	24.84	21.89
RRDB [48]	30.76	26.84	37.40	30.34	31.56	25.95	30.29	26.32	28.83	23.94
SRWarp-RRDB [42]	31.04	26.75	37.93	29.90	32.11	25.35	30.48	26.10	29.45	24.04
LTEW-RRDB (ours)	31.10	26.92	38.20	31.07	32.15	26.02	30.56	26.41	29.50	24.25

Qualitative comparison (ERP2Perspective)



Model complexity (x2 SR with 256x256 input)

Method	Training task	#Params.	Runtime	Memory	in-scale		out-of-scale	
					$\times 2$	$\times 3$	$\times 4$	$\times 6$
Arb-RCAN [46]	Asymmetric scale SR	16.6M	160ms	1.				