2020 CVPR

Unified Dynamic Convolutional Network for Super-Resolution with Variational Degradations

Presenter：Chang-Ting Tsai
Thesis Advisor：Jian-Jiun Ding
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Outline

01 Introduction

02 Related work

03 Method

04 Result

PART

01 Introduction

Introduction

SISR (Single Image Super-Resolution)

LR (Low Resolution)

HR (High Resolution)

Introduction

SISR (Single Image Super-Resolution)

- Surveillance
- Medical diagnosis
- Astronomical observation

PART

02 Related work

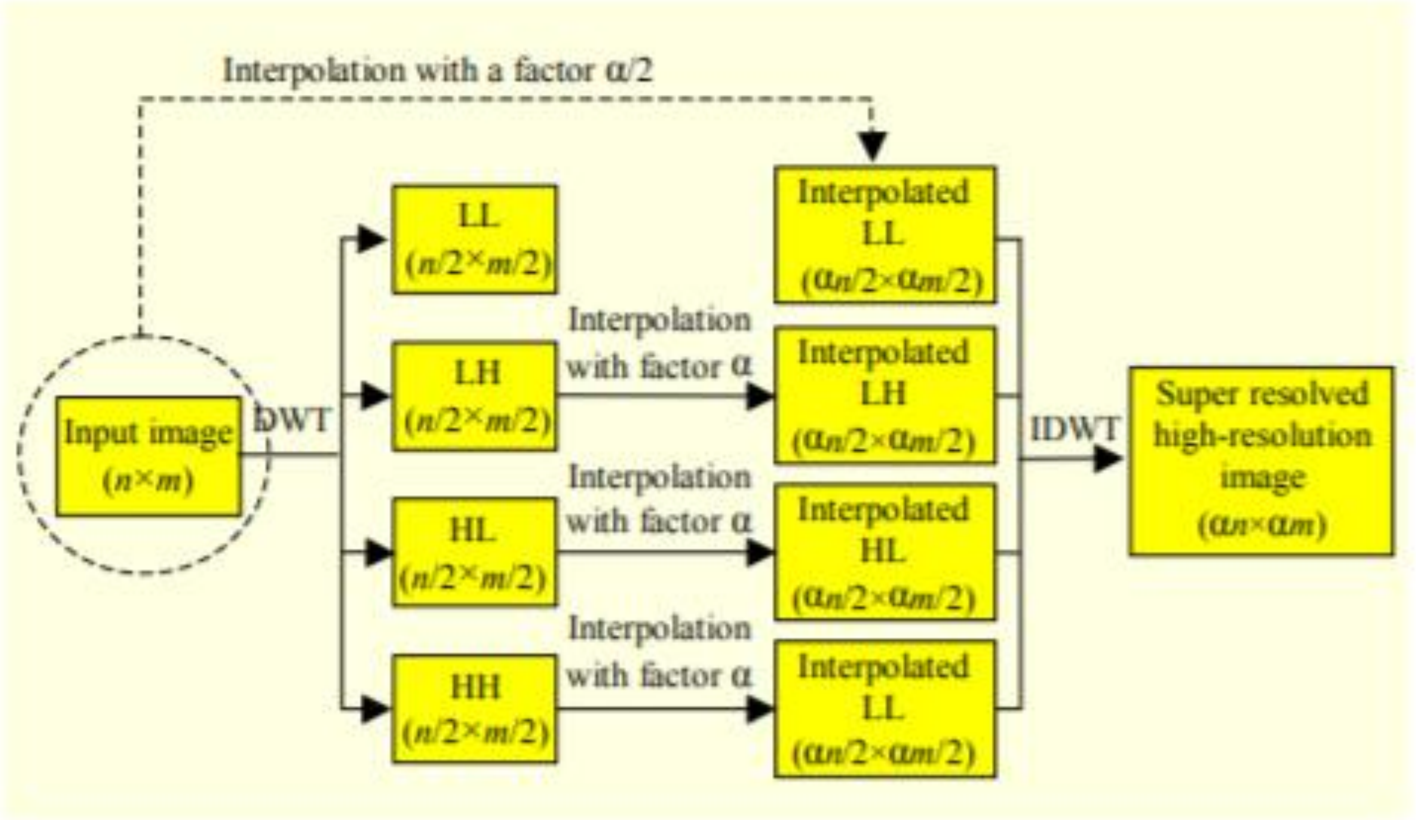
Related work

SISR (Single Image Super-Resolution)

- Non Learning Based
  - Discrete wavelet transform
- Learning Based (Deep learning)
  - SRCNN
  - FSRCNN

Related work

Discrete wavelet transform

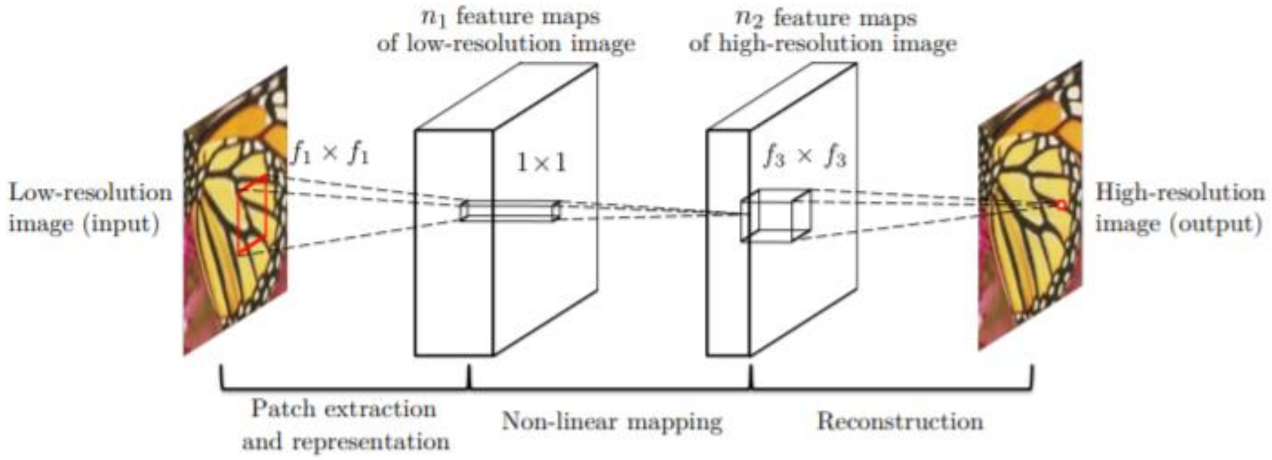


Related work

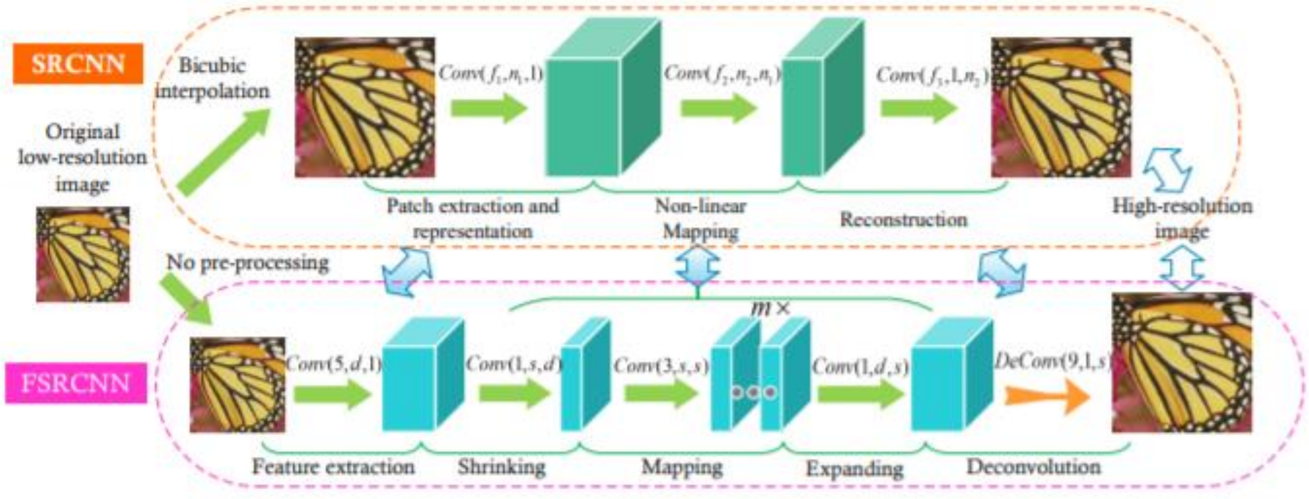
SRCNN

9 x 9 1 x 1 5 x 5

bicubic



FSRCNN



- Deconvolution
- Small kernel size
- Share parameter

PART

03 Method

Method

1. Problem Formulation
2. Proposed Model
3. Dynamic Convolution
4. Model Loss

Method

Problem Formulation

Degradation：blurring, noise, downsampling

$$I_{LR} = (I_{HR} \otimes k) \downarrow_s + n$$

k：blur kernel

⊗：convolution

↓s：downsampling

n：noise

Method

Proposed model

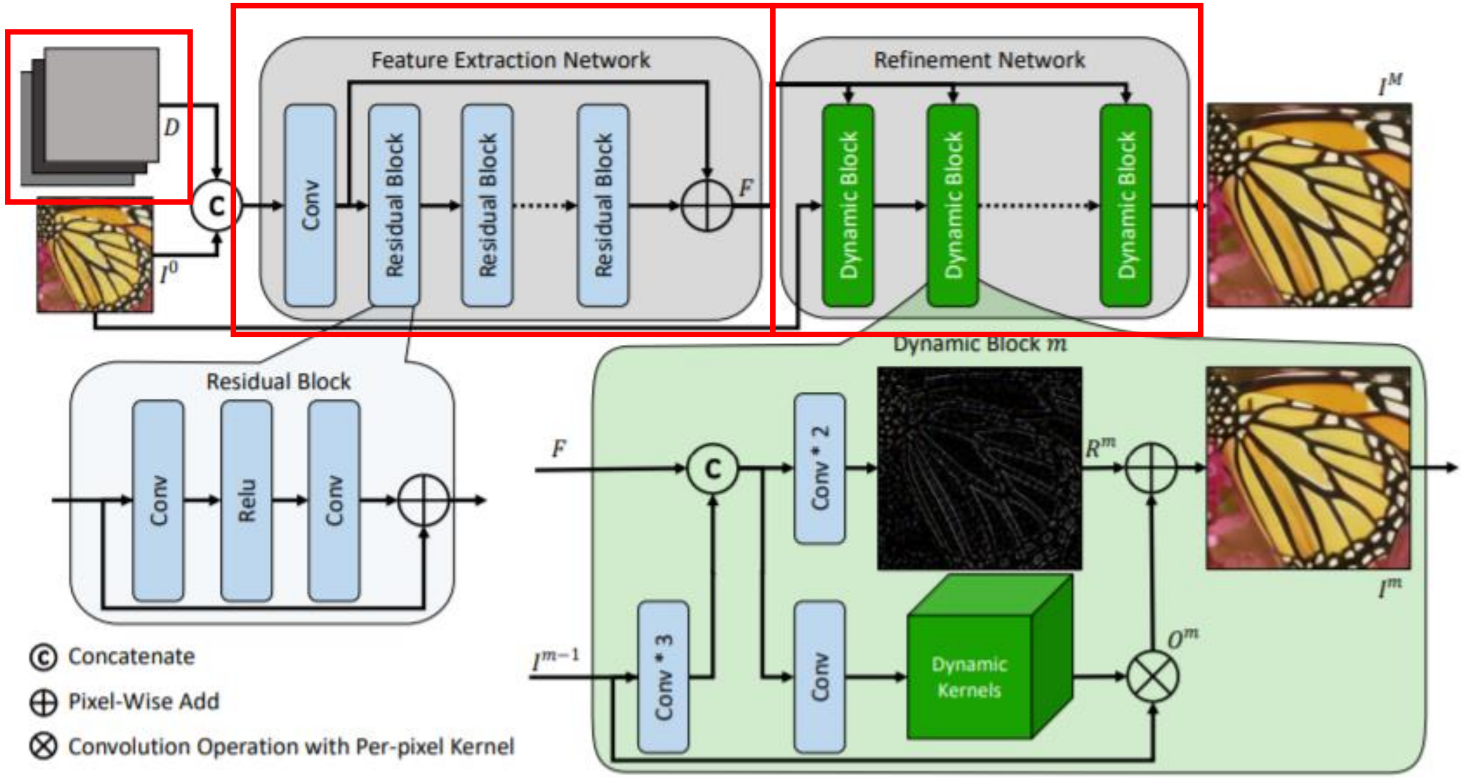


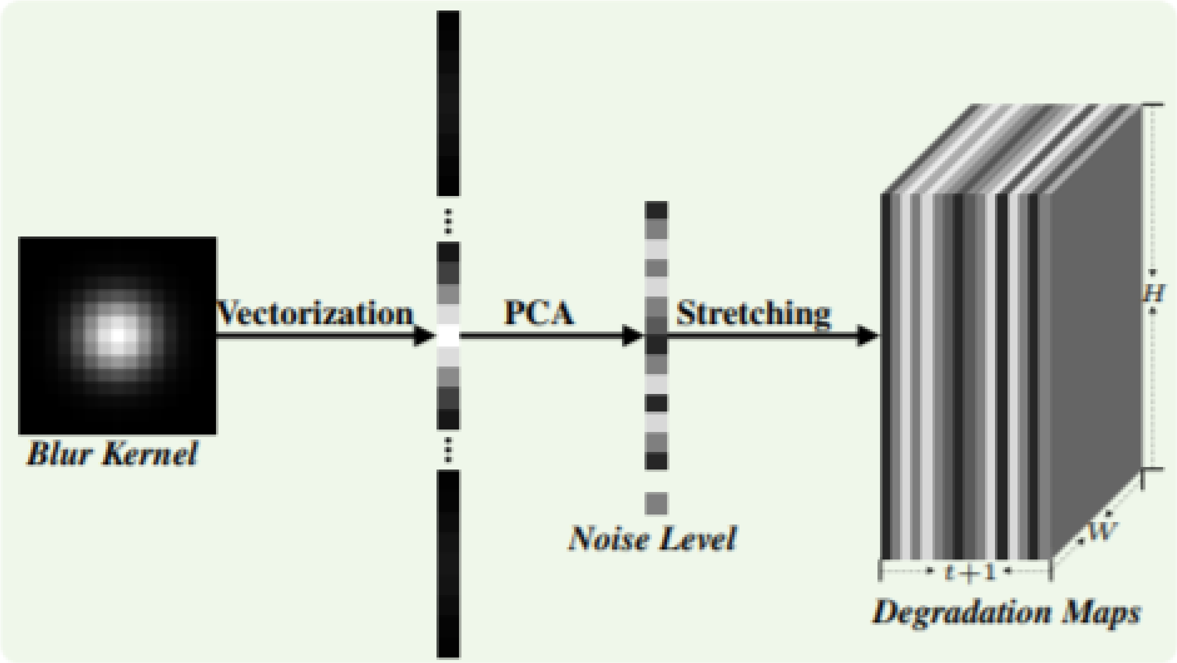
Figure 2. The network architecture of the proposed UDVD framework.

- Degradation map
- Feature extraction
- Refinement

Method

Degradation map

$$I_{LR} = (I_{HR} \otimes k) \downarrow_s + n$$



p x p

p^2 x 1

t x 1

(t+1) x 1

(t+1) x H x W

Method

Proposed model

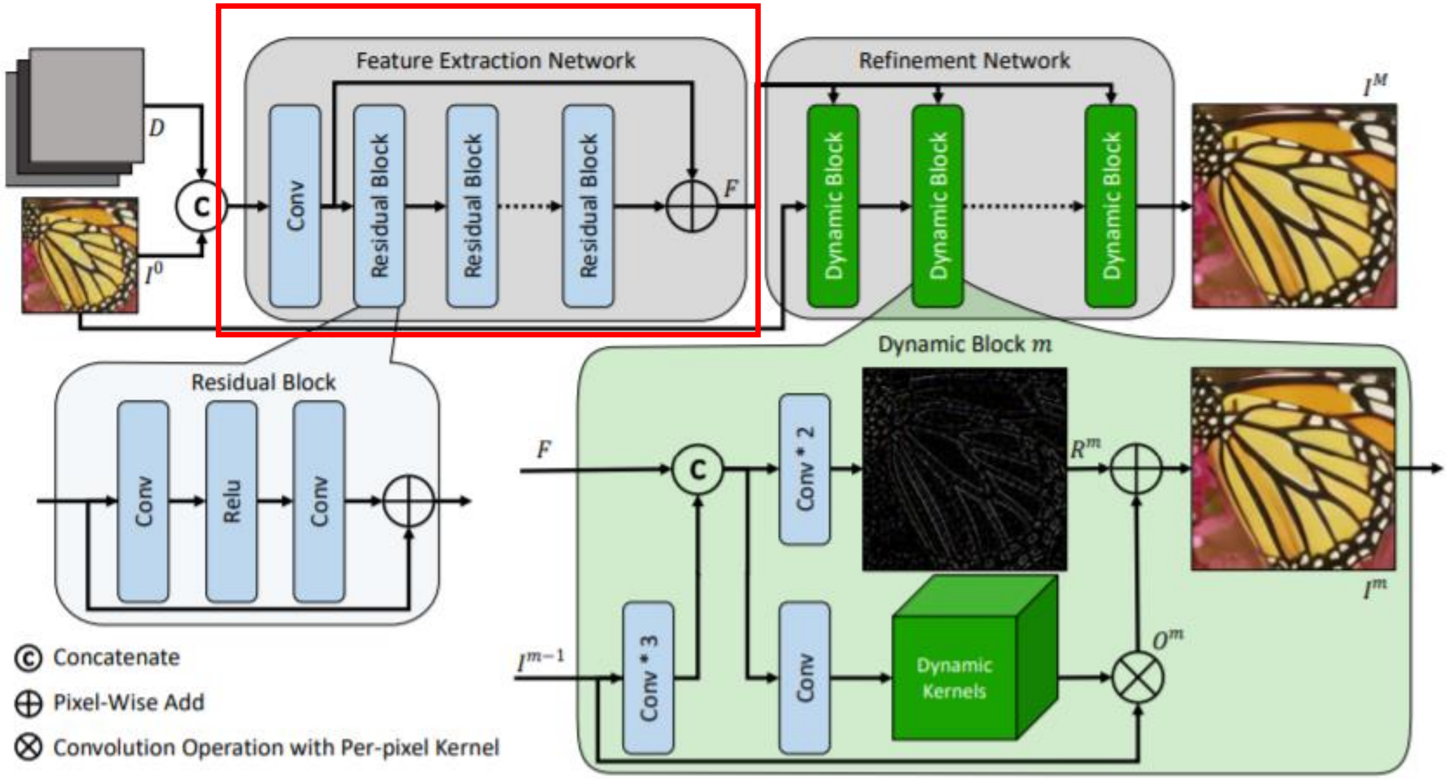
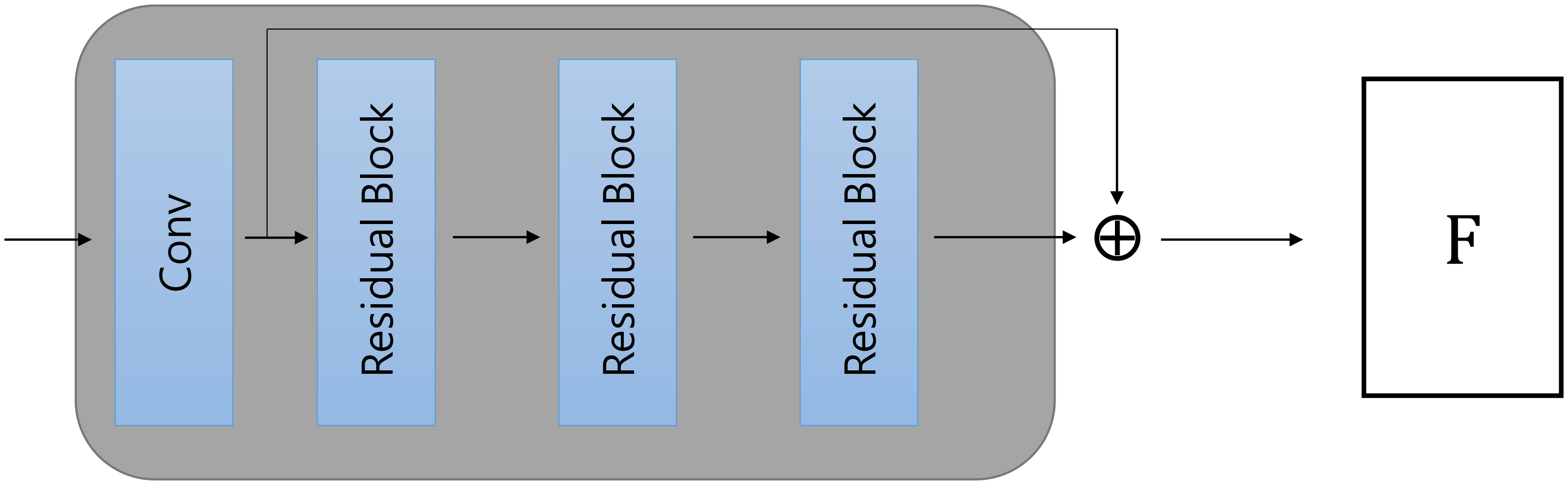


Figure 2. The network architecture of the proposed UDVD framework.

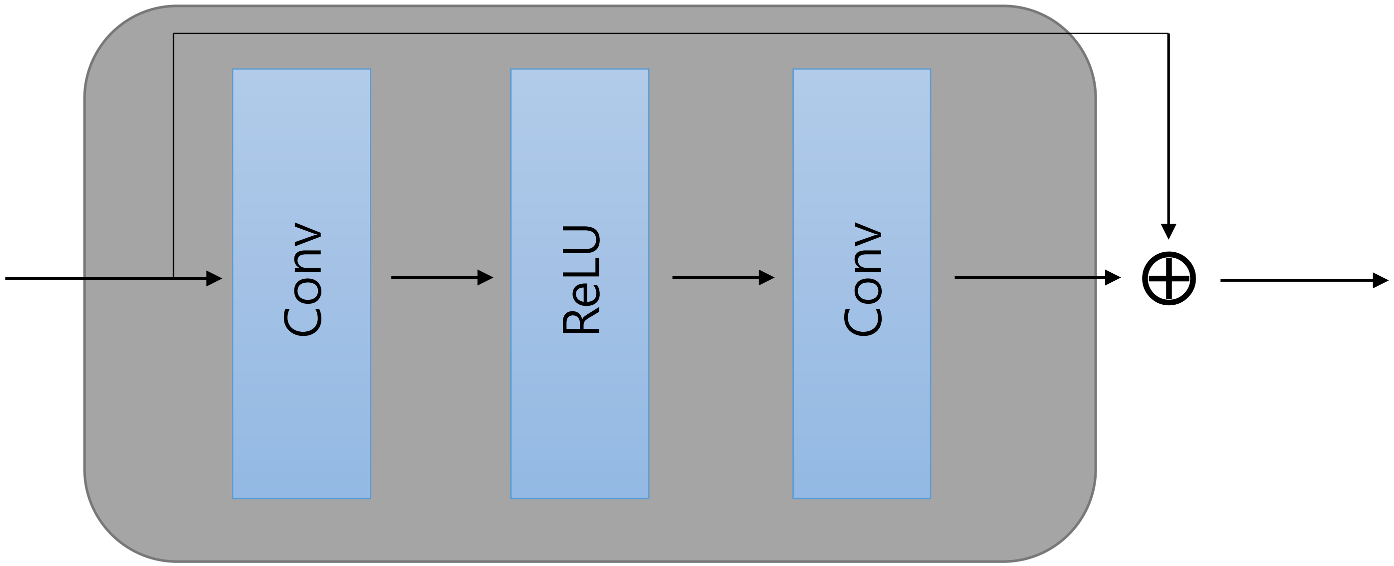
Method

Feature extraction



Method

Residual block



Method

Proposed model

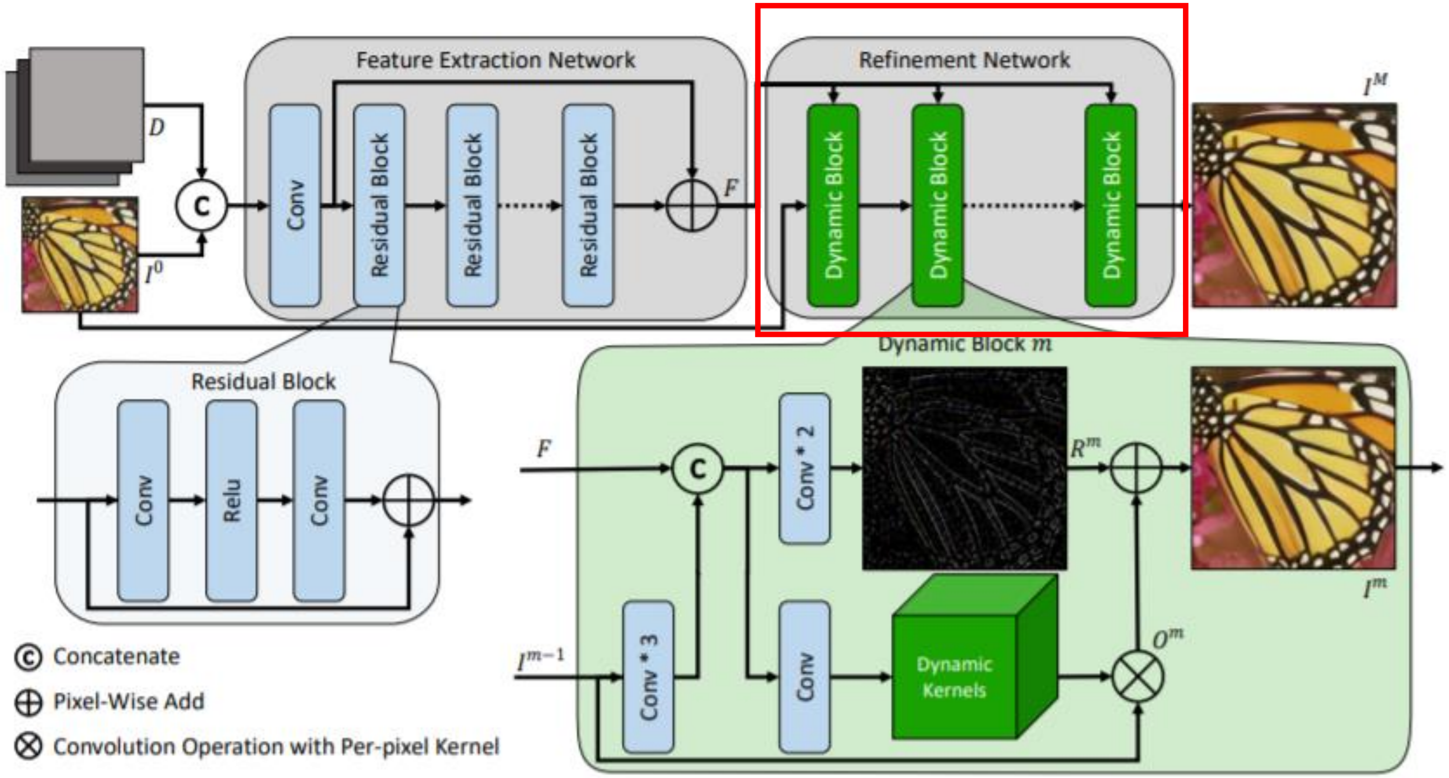


Figure 2. The network architecture of the proposed UDVD framework.

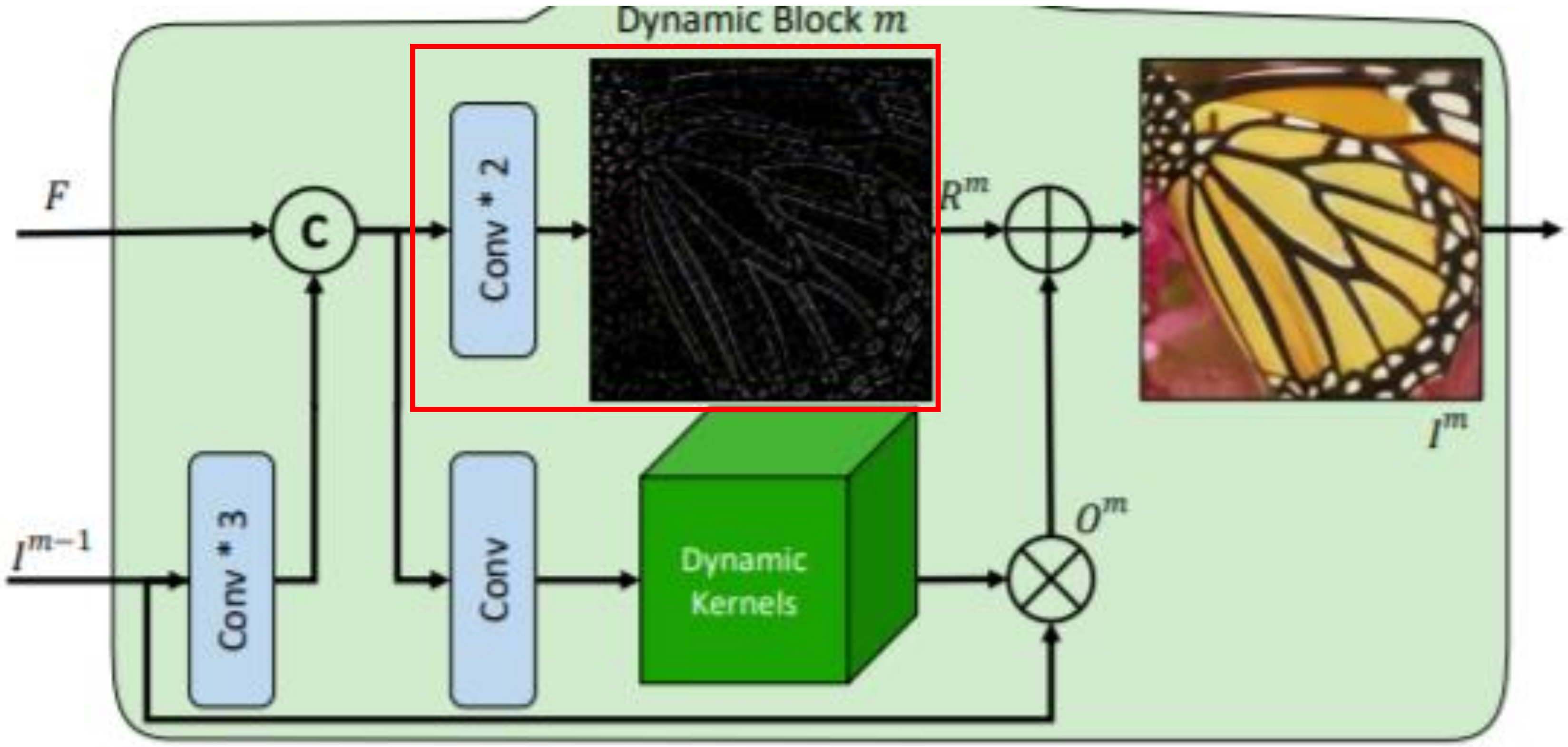
Method

Refinement

Generate high frequency detail

Feature

Image

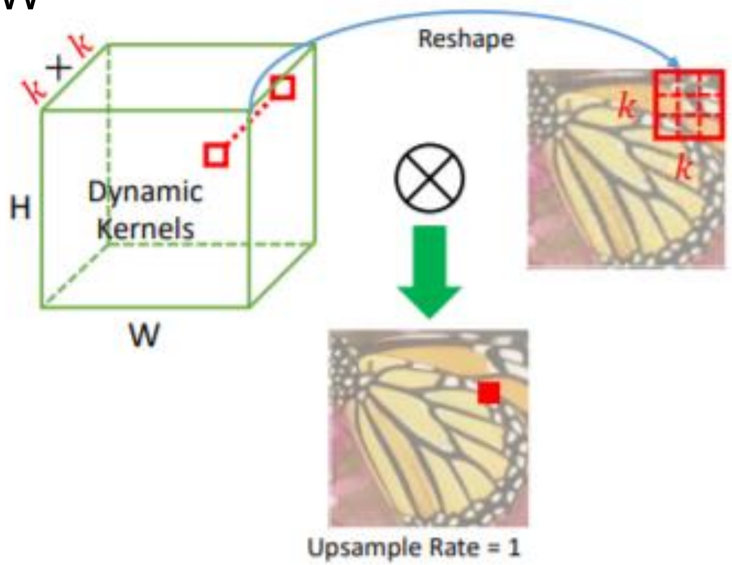


Method

Dynamic Convolution

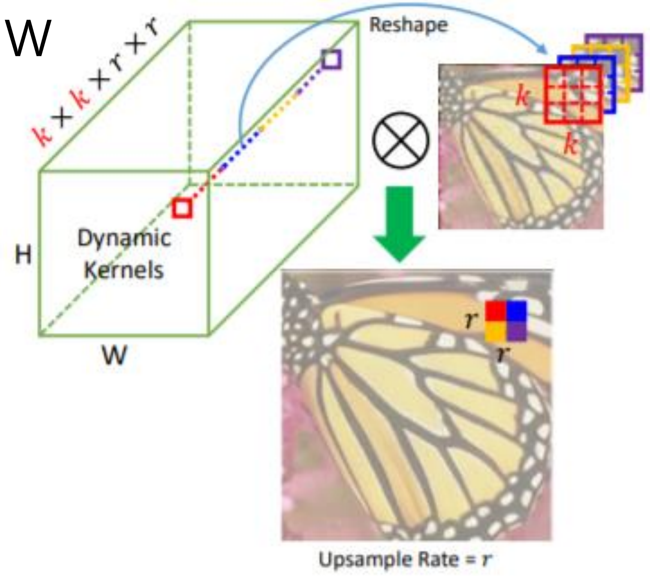
Typical

$(k^2) \times H \times W$



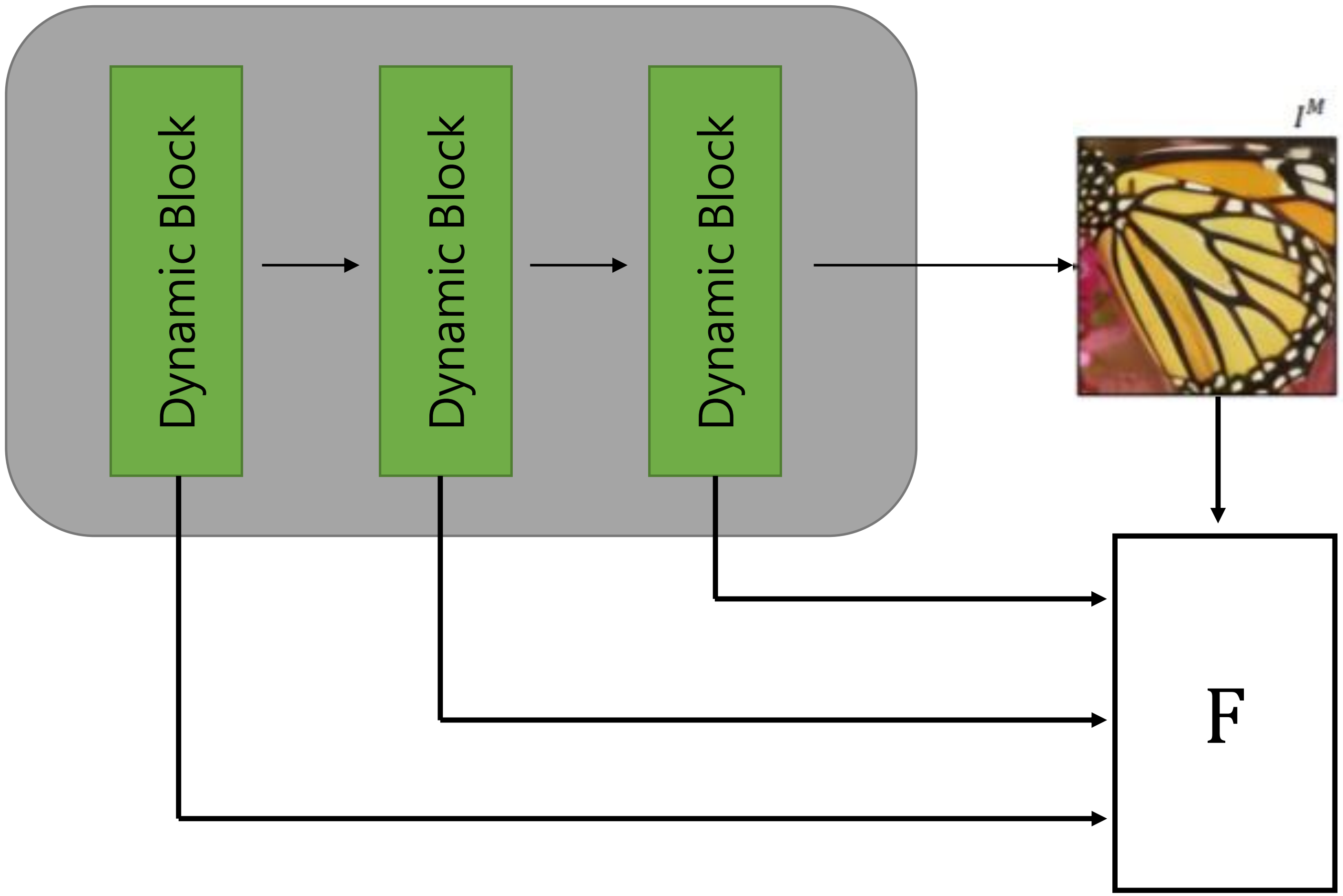
With upsampling

$(k^2 \times r^2) \times H \times W$



Method

Model loss



$$Loss = \sum_{m=1}^{M} F(I^M, I_{HR})$$

F：L2 loss, perceptual loss

PART

04 Result

Result

Dynamic kernel

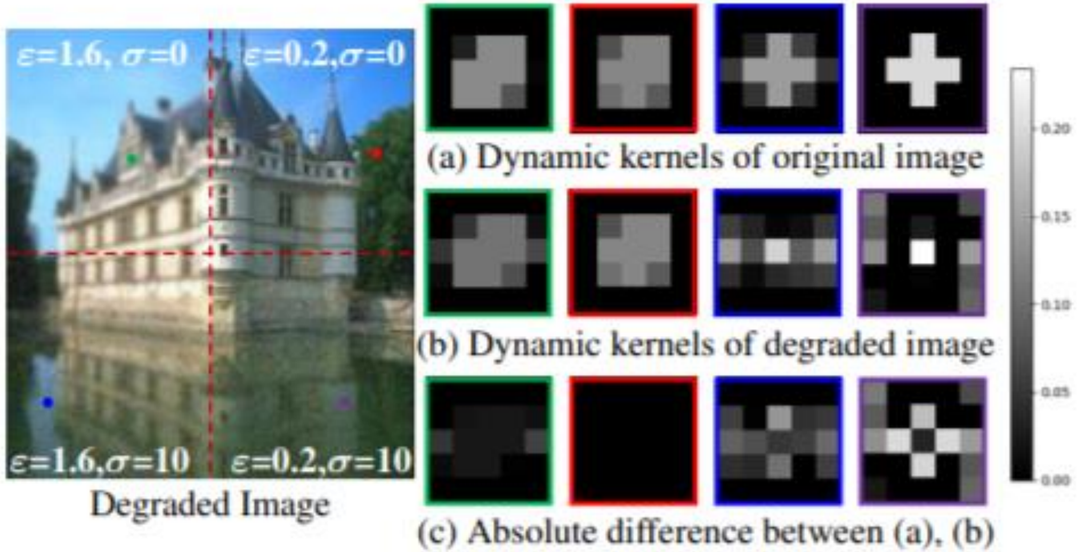


Figure 4. The predicted per-pixel kernels in second dynamic block of UDVD. (a) The kernels learned from lr image. (b) The kernels learned from image with spatially variant degradation of Gaussian blur kernel width ε and noise level σ. (c) The absolute difference between (a) and (b).

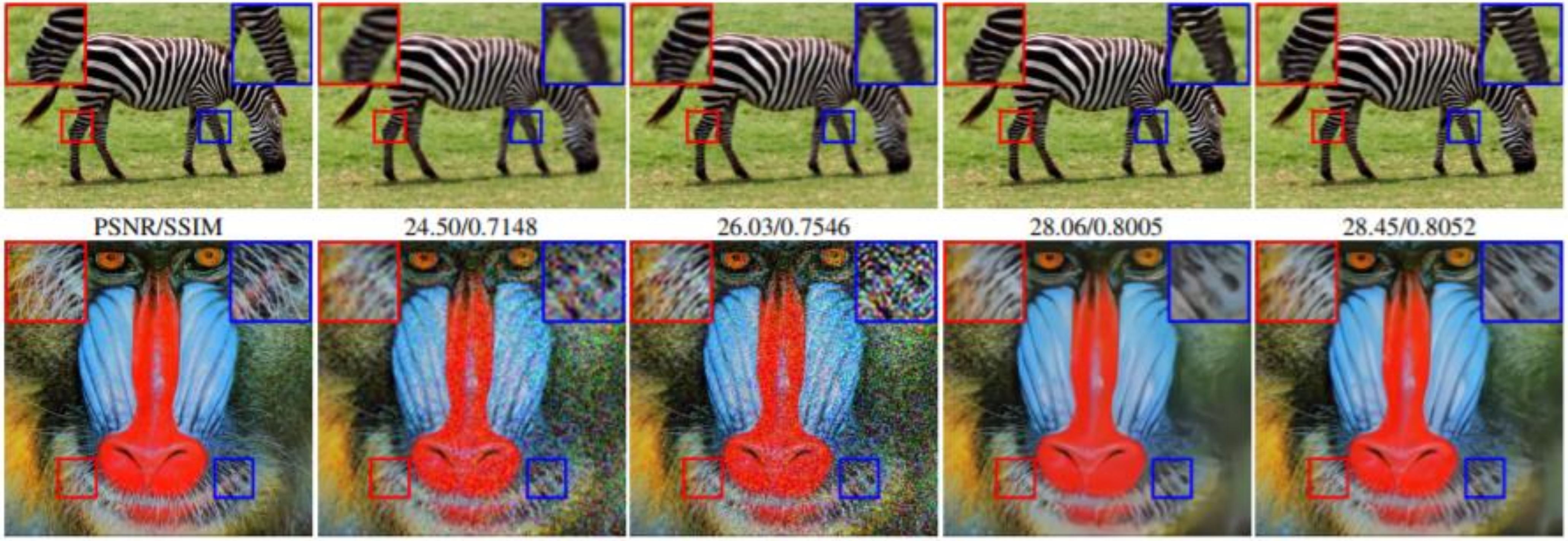
Result

Synthesis dataset

Methods	Kernel width	Noise level	Set5 ×2	Set5 ×3	Set5 ×4	Set14 ×2	Set14 ×3	Set14 ×4	BSD100 ×2	BSD100 ×3	BSD100 ×4
RDN [10]	0.2	15	26.23	25.57	24.48	25.44	24.40	23.45	25.03	24.04	23.13
RCAN [12]			26.05	25.46	24.83	25.3	24.29	23.64	24.95	23.92	23.33
IRCNN [17]			32.60	30.08	28.35	-	-	-	-	-	-
SRMD [20]			32.76	30.43	28.79	30.14	27.82	26.48	29.23	27.11	25.95
UDVD			32.96	30.68	29.04	30.43	28.14	26.82	29.38	27.27	26.08
RDN [10]	1.3	15	25.01	24.98	24.33	24.08	23.92	23.39	23.85	23.67	23.09
RCAN [12]			24.9	24.94	24.58	24.04	23.88	23.53	23.84	23.62	23.26
IRCNN [17]			29.96	28.68	27.71	-	-	-	-	-	-
SRMD [20]			30.98	29.43	28.21	28.34	27.05	26.06	27.52	26.45	25.63
UDVD			31.16	29.67	28.43	28.63	27.36	26.37	27.64	26.58	25.74
RDN [10]	2.6	15	23.18	23.28	23.07	22.34	22.40	22.31	22.44	22.52	22.35
RCAN [12]			23.13	23.29	23.24	22.34	22.41	22.42	22.47	22.5	22.48
IRCNN [17]			26.44	25.67	24.36	-	-	-	-	-	-
SRMD [20]			28.48	27.55	26.82	26.18	25.58	25.06	25.81	25.29	24.86
UDVD			28.73	27.80	26.98	26.48	25.87	25.33	25.93	25.41	24.96
RDN [10]	0.2	50	17.23	16.85	16.51	17.04	16.58	16.21	16.90	16.38	15.99
RCAN [12]			17.08	16.13	16.64	16.84	15.68	16.35	16.66	15.54	16.1
IRCNN [17]			28.20	26.25	24.95	-	-	-	-	-	-
SRMD [20]			28.51	26.48	25.18	26.70	25.01	23.95	26.13	24.74	23.86
UDVD			28.63	26.65	25.34	27.00	25.32	24.24	26.27	24.87	23.98
RDN [10]	1.3	50	16.97	16.70	16.41	16.75	16.45	16.14	16.64	16.29	15.95
RCAN [12]			16.82	15.98	16.54	16.55	15.56	16.28	16.42	15.47	16.06
IRCNN [17]			26.69	25.20	24.42	-	-	-	-	-	-
SRMD [20]			27.43	25.82	24.77	25.63	24.47	23.64	25.26	24.33	23.63
UDVD			27.54	25.99	24.92	25.88	24.75	23.91	25.36	24.45	23.74
RDN [10]	2.6	50	16.50	16.31	16.08	16.30	16.09	15.88	16.29	16.03	15.77
RCAN [12]			16.36	15.6	16.22	16.12	15.24	16.02	16.07	15.23	15.88
IRCNN [17]			22.98	22.16	21.43	-	-	-	-	-	-
SRMD [20]			25.85	24.75	23.98	24.32	23.53	22.98	24.30	23.68	23.18
UDVD			26.00	24.85	24.11	24.60	23.81	23.23	24.41	23.79	23.27

Result

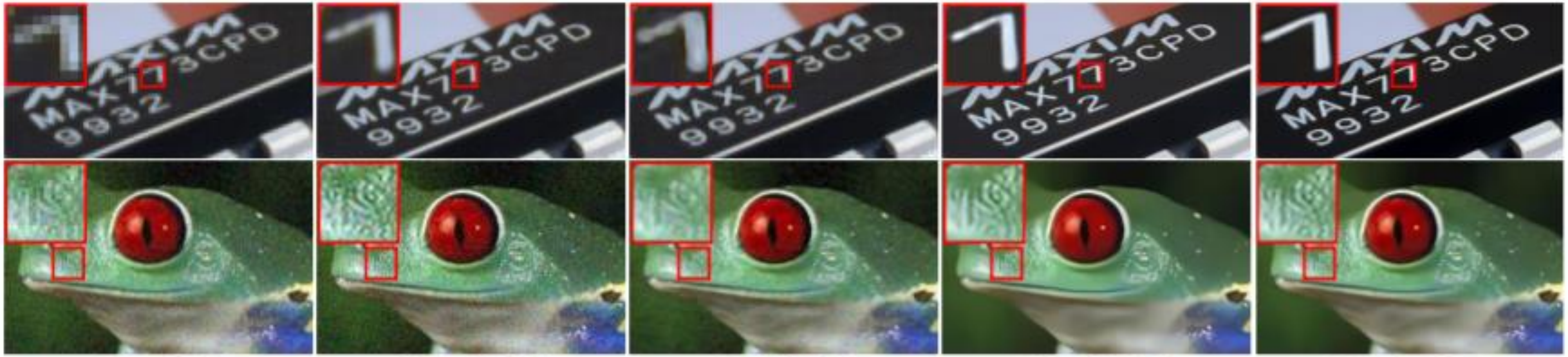
Synthesis dataset



(a) Ground Truth (b) Bicubic (c) RCAN [12] (d) SRMD [20] (e) UDVD(Ours)

Result

Real dataset



(a) Real LR (b) RCAN [12] (c) ZSSR [21] (d) SRMD [20] (e) UDVD(Ours)

Reference

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