

一键卸妆与视频超分辨率：腾讯优图ICCV

2017分享

沈小勇

腾讯优图

goodshenxy@gmail.com

About Me (<http://Xiaoyongshen.me>)

- BS, MS from ZJU and PhD from CUHK
 - Supervisors: Prof. Ligang and Prof. Jiaya
 - Three years research in CG and five years in CV
- Senior researcher in Youtu
 - Lead the research group
- My research is mainly on
 - Image filtering and restoration, matting, deblur, etc.
 - Motion and depth estimation, segmentation
 - Image classification, object detection and semantic segmentation, etc.

1 关于优图实验室-概览

优图团队立足于社交网络大平台，借助社交业务积累的海量人脸、图片、音乐等数据，专注在人脸、图像、音乐、语音、机器学习等领域开展技术研究，并积极推动研究成果在业务中落地产生价值。



人脸识别



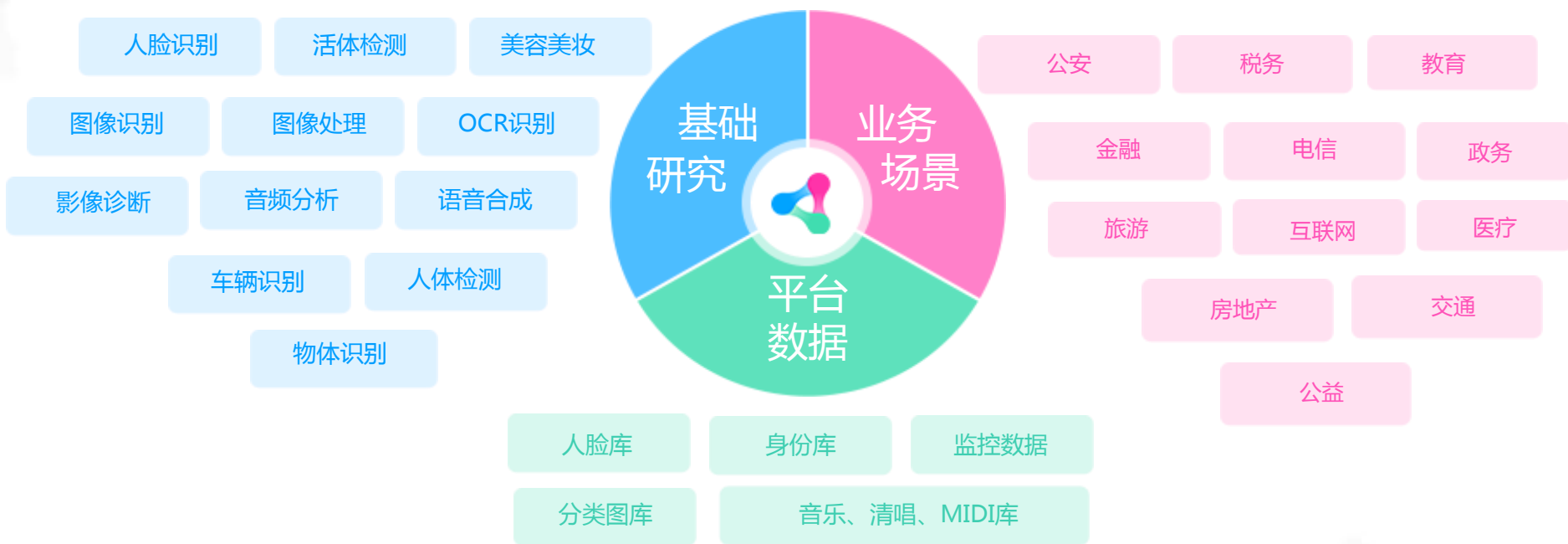
图像识别



音频识别

- 2017年4月，在国际MegaFace海量人脸识别数据库刷新世界记录
- 2017年3月，在国际LFW人脸数据库上刷新世界纪录
- 2017年3月，在国际ICDAR 2015文本检测项目中刷新世界纪录
- 2016年，优图实验室获得“腾讯行业贡献奖”
- 2015年，优图哼唱识别技术获得“腾讯年度微创新奖”
- 2015年10月，在国际音频比赛MIREX的哼唱识别比赛中，取得总成绩世界第一，并刷新其中一项世界纪录
- 2015年4月，在国际Pascal VOC2012物体分类赛刷新世界纪录
- 2014年11月，腾讯优图人脸检测刷新FDDB世界纪录
- 2014年，人脸识别获得腾讯公司年度“重大技术突破奖”
- 2014年，联合上海交通大学获得上海市科技进步二等奖
- 2013年，优图压缩获得腾讯公司年度“重大技术突破奖”
- 2012年，优图电商联合团队获得腾讯公司级别“卓越运营奖”

1 关于优图实验室-概览



研究、场景、数据三者融合

1 关于优图实验室-最新技术突破

2017年3月

在ICDAR 2015比赛中刷新 Focused Scene Text挑战的 Text Localization项目世界纪录

Method	Recall	Precision	Hmean
Tencent YouTu	89.53 %	94.26 %	91.84 %
CNN based mo...	89.17 %	94.63 %	91.82 %
RRPN-4	87.31 %	95.19 %	91.08 %
MSRA_v1	88.58 %	93.67 %	91.06 %
SRC-B-Machine...	87.07 %	93.28 %	90.07 %
Baidu IDL	87.11 %	92.83 %	89.88 %
CAS_HotEye_ver2	84.31 %	94.17 %	88.97 %
XvBaoBao	85.37 %	91.46 %	88.31 %
CAS_HotEye	86.65 %	89.99 %	88.29 %

2017年3月

在LFW无限制条件下人脸验证测试中，优图提交的最新成绩为**99.80%**，提升了上次99.65%的成绩，再次在这一测试中刷新纪录。

Faceall ⁷¹	0.9940 ± 0.0010
JustMeTalk ⁷²	0.9887 ± 0.0016
Facevisa ⁷⁴	0.9955 ± 0.0014
pose+shape+expression augmentation ⁷⁵	0.9807 ± 0.0060
ColorReco ⁷⁶	0.9940 ± 0.0022
Asaphus ⁷⁷	0.9815 ± 0.0039
Daream ⁷⁸	0.9968 ± 0.0009
Dahua-FaceImage ⁸⁰	0.9978 ± 0.0007
Easen Electron ⁸¹	0.9968 ± 0.0009
Skytop Gaia ⁸²	0.9630 ± 0.0023
CNN-3DMM estimation ⁸³	0.9235 ± 0.0129
Samtech Facequest ⁸⁴	0.9971 ± 0.0018
XYZ Robot ⁸⁷	0.9895 ± 0.0020
THU CV-AI Lab ⁸⁸	0.9973 ± 0.0008
PingAn Tech ⁸⁹	0.9960 ± 0.0031
dlib ⁹⁰	0.9938 ± 0.0027
Aureus ⁹¹	0.9920 ± 0.0030
YouTu Lab, Tencent ⁶³	0.9980 ± 0.0023

Table 0. Mean classification accuracy \bar{a} and standard error of the mean $\sigma_{\bar{a}}$.

2017年4月

在国际权威海量人脸识别数据库 **MegaFace**中，以**83.290%**的最新成绩在100万级别人脸识别测试中拔得头筹

Rank-1 Identification Accuracy with 1 Million Distractors

Algorithm	Date Submitted	Set 1
YouTu Lab (Tencent Best-Image)	04/08/2017	83.290%
DeepSense V2	1/22/2017	81.298%
Vocord-deepV1.2	12/1/2016	80.258%
GRCCV	12/1/2016	77.677%
SphereFace - Small	12/1/2016	75.766%

优图与ICCV

计算机视觉顶级会议ICCV 2017 腾讯优图入选12篇论文

人工智能 腾讯科技 2017-10-18 16:04

★ 收藏

0 评论

← 分享

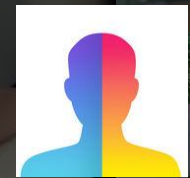
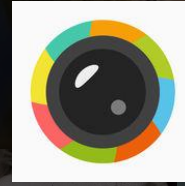
腾讯科技讯 被誉为计算机视觉领域三大顶级会议之一的ICCV（另外两个为CVPR、ECCV）近日揭晓收录论文名单，腾讯优图共有12篇论文入选，居业界实验室前列，其中3篇被选做口头报告（Oral），该类论文仅占总投稿数的2.1%（45/2143）。



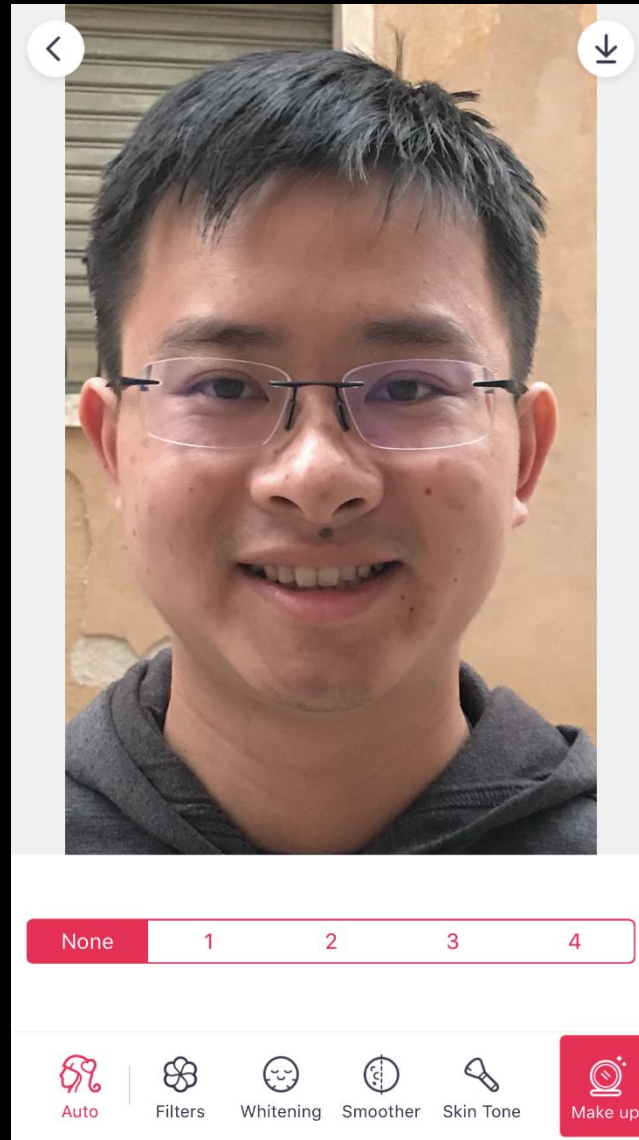
本届 ICCV 共收到2143篇论文投稿，其中621篇被选为大会论文，录用比例29%。其中有45篇口头报告（Oral）和56篇亮点报告（Spotlight）。今年参会人数预计将超过3000人，可见其火爆程度。

Makeup-Go: Blind Reversion of Portrait Edit

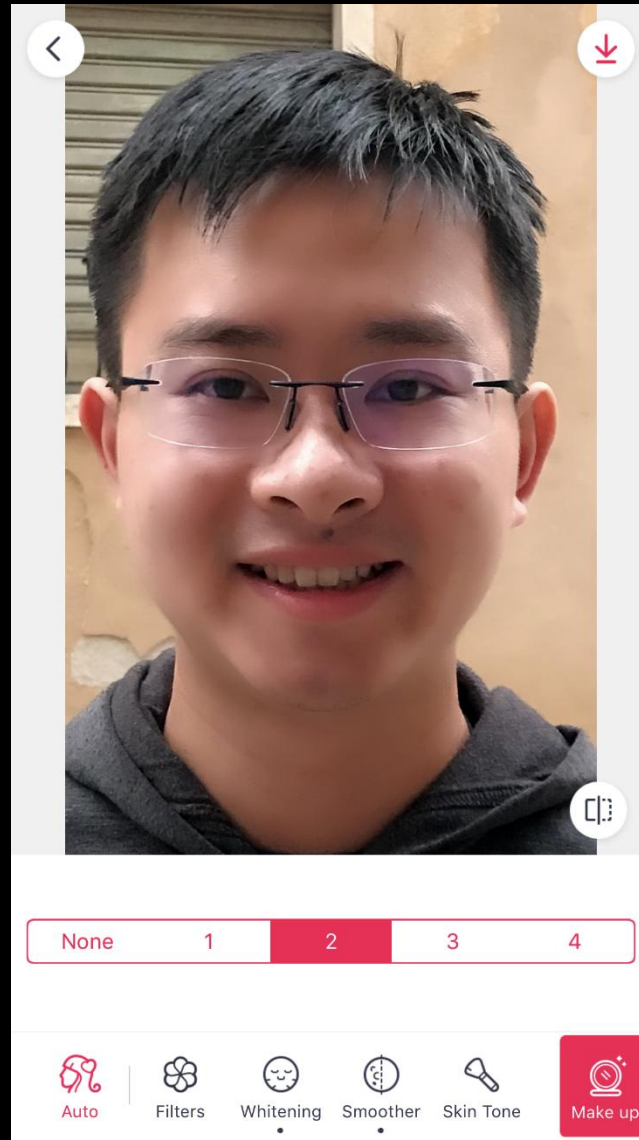
Popular Digital Editing Tools



A Digital Edit Example

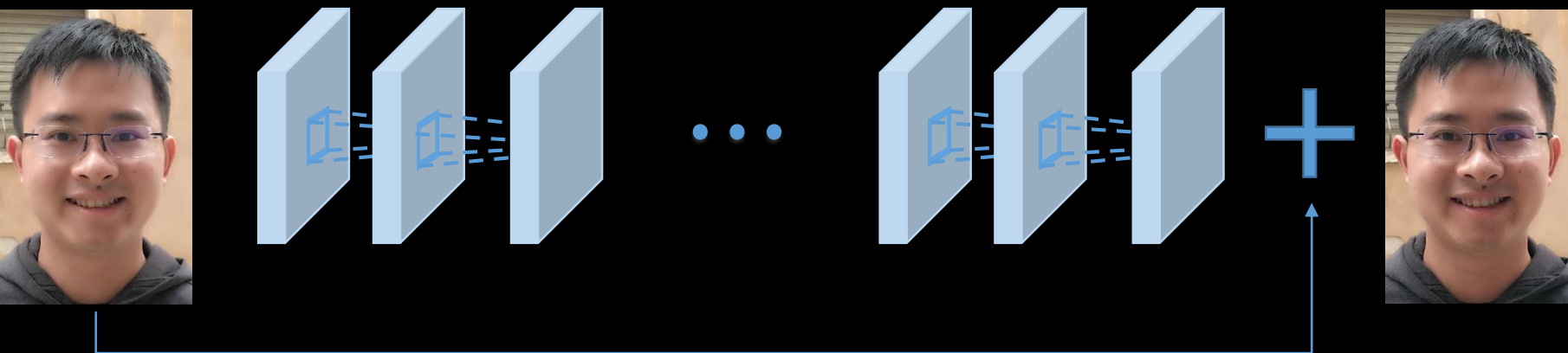


A Digital Edit Example



What is the difficulty of this task?

Existing CNN Cannot Remove Make-up

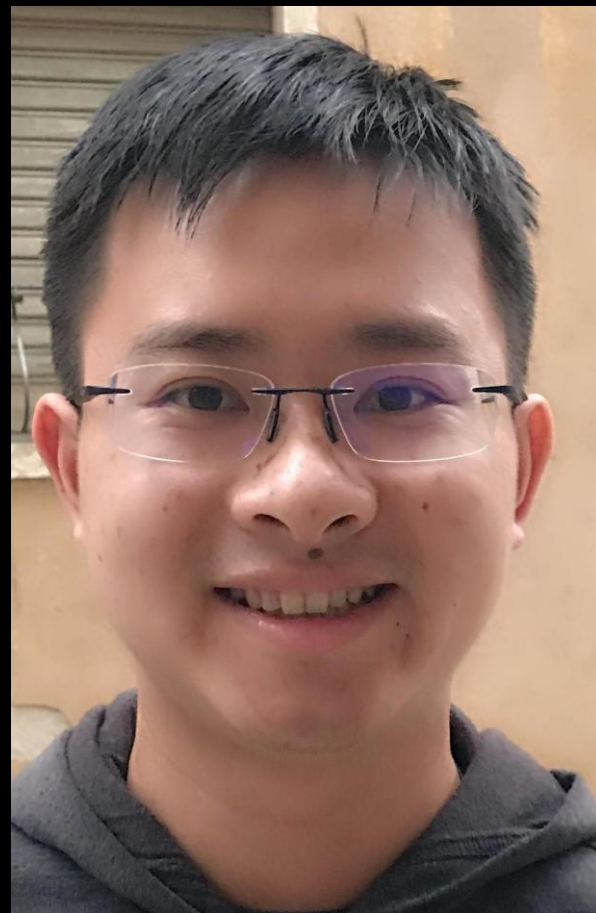


Kim, Jiwon, Jung Kwon Lee, and Kyoung Mu Lee. "Accurate image super-resolution using very deep convolutional networks." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2016.

Result of Applying CNN to Remove Make-up

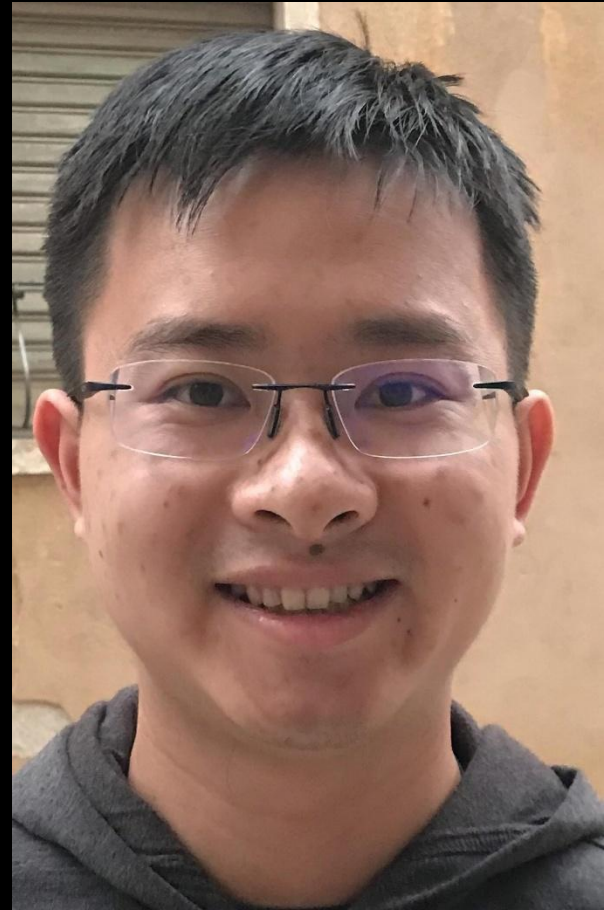


Input



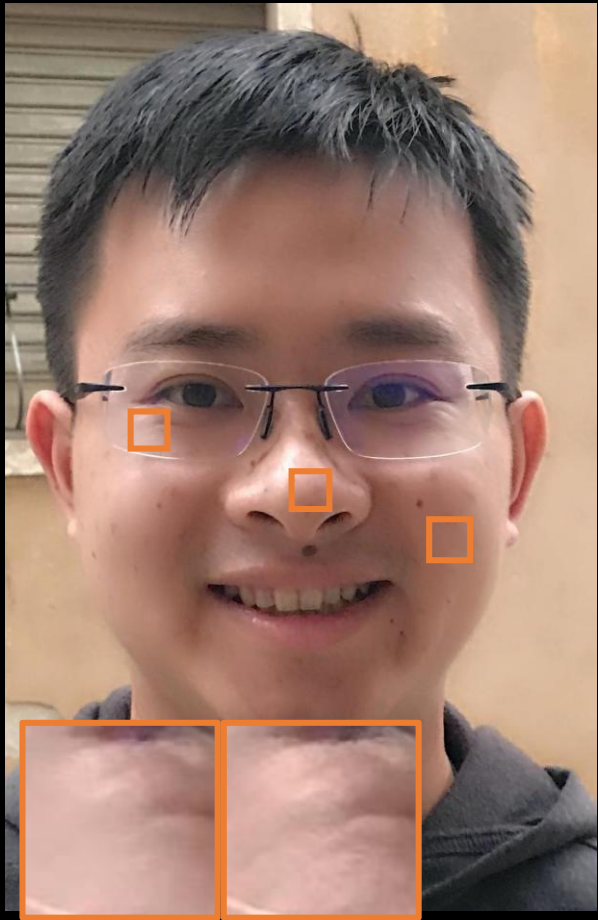
Output

Result of Applying CNN to Remove Make-up

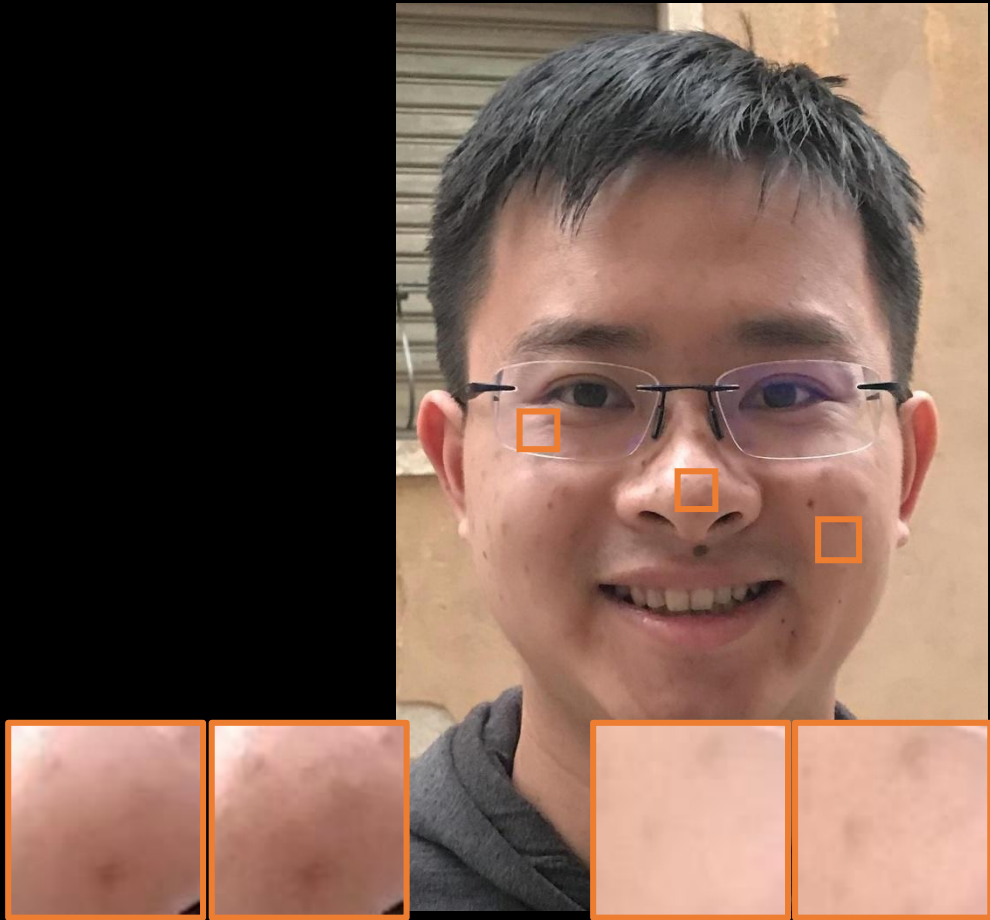


Gr0ntpTtuth

Result of Applying CNN to Remove Make-up



Output



Ground Truth

Why cannot existing CNN achieve this goal?

Component Domination Effect

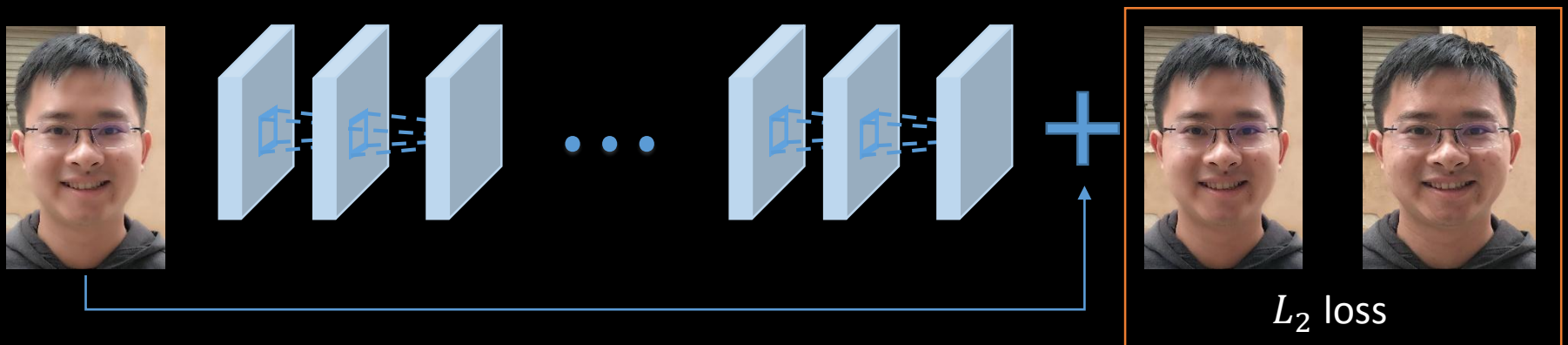
Analysis of the Loss

$$L = \|F(x) - y\|_2^2$$

x : input image patch

$F(x)$: network output (vectorized)

y : ground truth patch (vectorized)

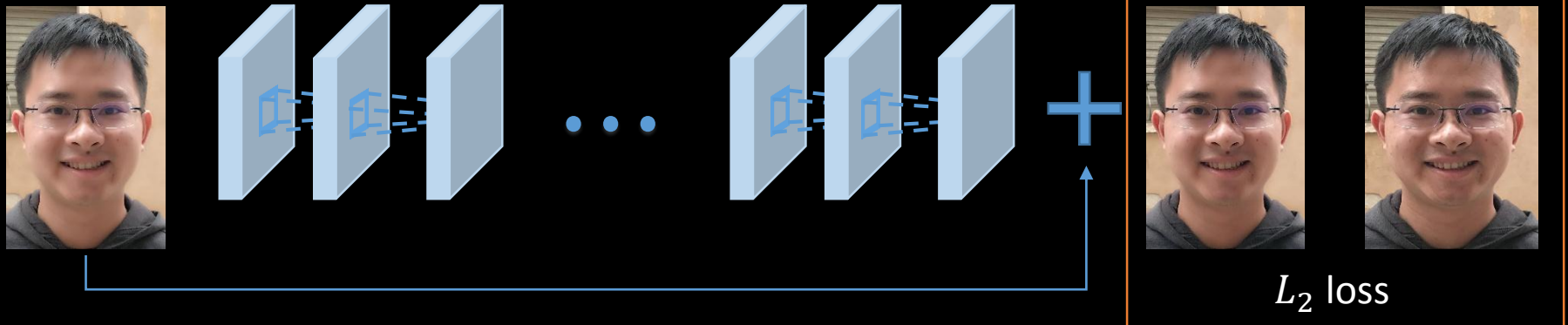


PCA Components of the Loss

$$L = \|U^T F(x) - U^T y\|_2^2$$

U : PCA matrix

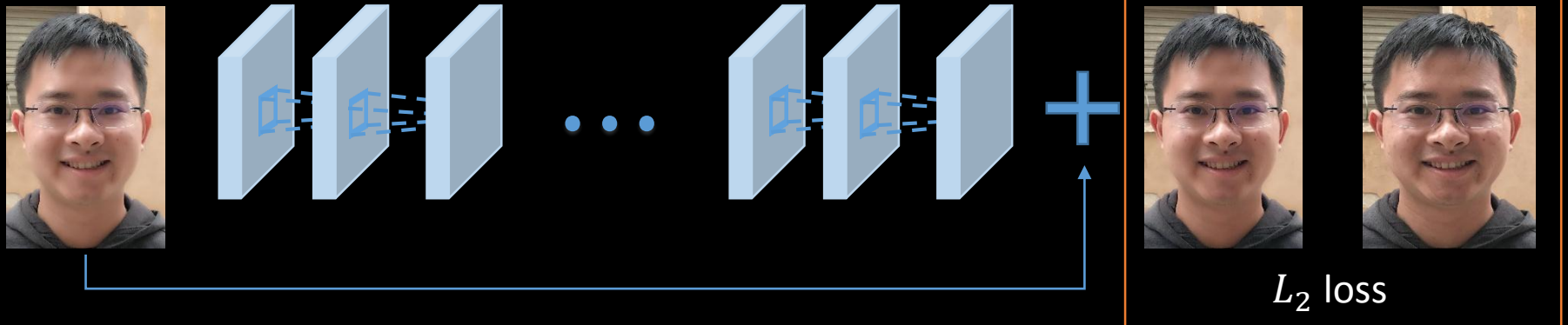
$$UU^T = I$$



PCA Components of the Loss

$$L = \left\| f_1(x) - u_1^T y \right\|_2^2 + \left\| f_2(x) - u_2^T y \right\|_2^2 + \dots + \left\| f_d(x) - u_d^T y \right\|_2^2$$

$$f_i(x) = u_i^T F(x), i = 1, 2 \dots, d$$



PCA Components of the Loss

$$L = \left\| f_1(x) - u_1^T y \right\|_2^2 + \left\| f_2(x) - u_2^T y \right\|_2^2 + \dots + \left\| f_d(x) - u_d^T y \right\|_2^2$$

$$f_i(x) = u_i^T F(x), i = 1, 2, \dots, d$$



$u_1^T y$

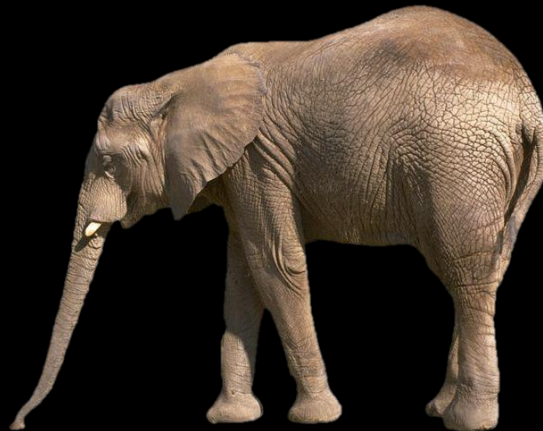
PCA Components of the Loss

$$L = \left\| f_1(x) - u_1^T y \right\|_2^2 + \left\| f_2(x) - u_2^T y \right\|_2^2$$

$$f_i(x) = u_i^T F(x), i = 1, 2 \dots, d$$



$u_1^T y$



$u_2^T y$

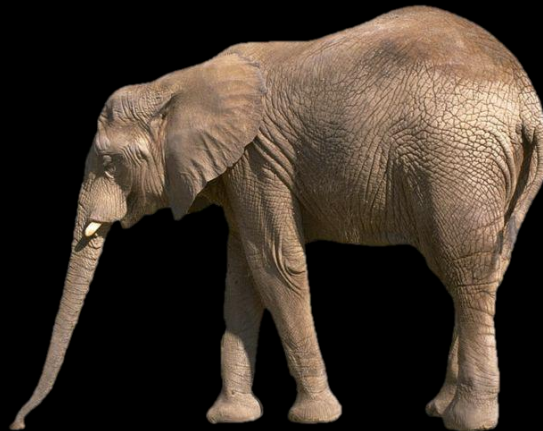
PCA Components of the Loss

$$L = \left\| f_1(x) - u_1^T y \right\|_2^2 + \left\| f_2(x) - u_2^T y \right\|_2^2 + \dots + \left\| f_d(x) - u_d^T y \right\|_2^2$$

$$f_i(x) = u_i^T F(x), i = 1, 2, \dots, d$$



$u_1^T y$



$u_2^T y$

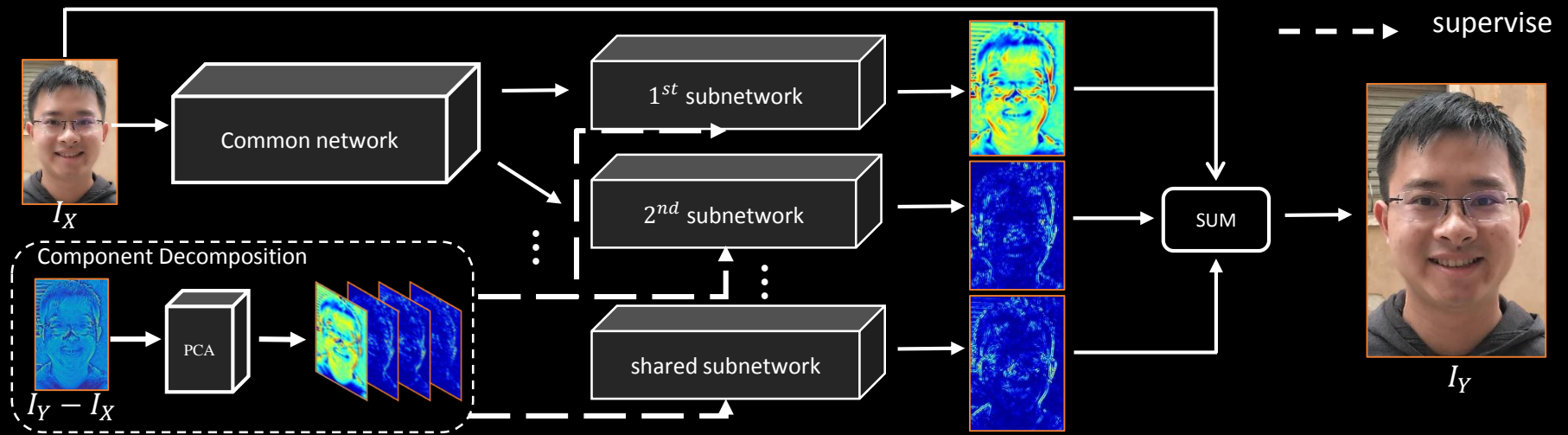
...



$u_d^T y$

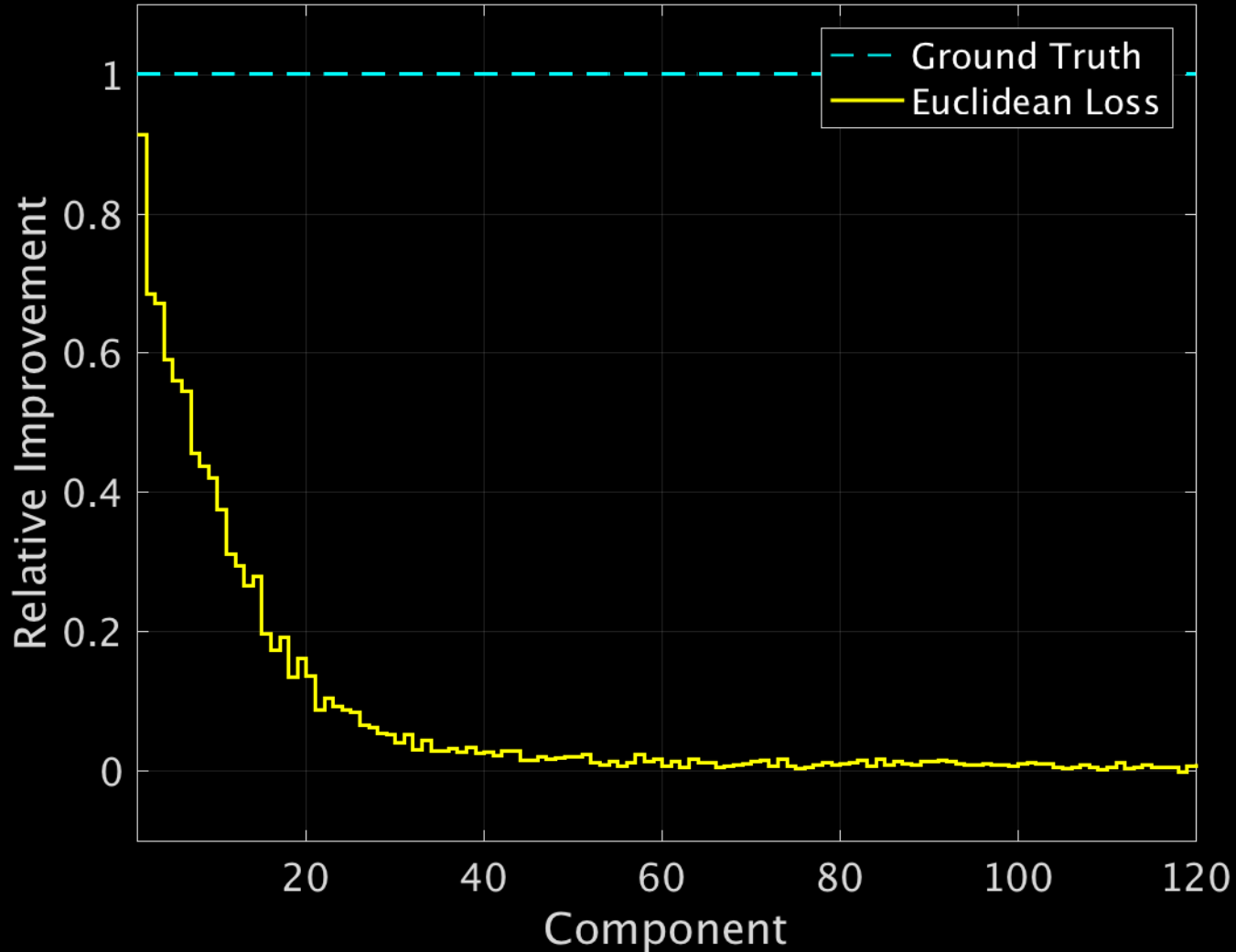
Our Framework

Component Regression Network



Experimental Results

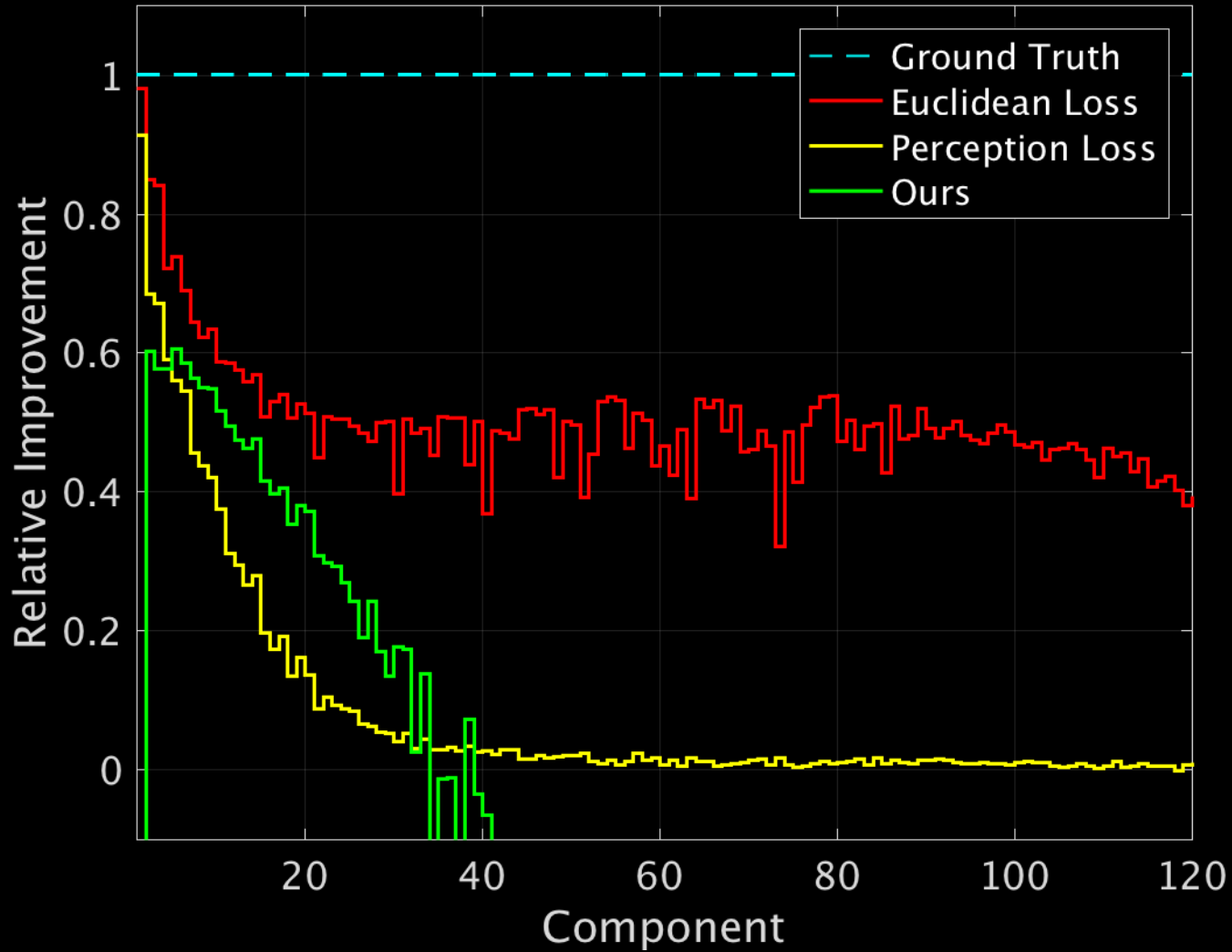
Component-level Comparison

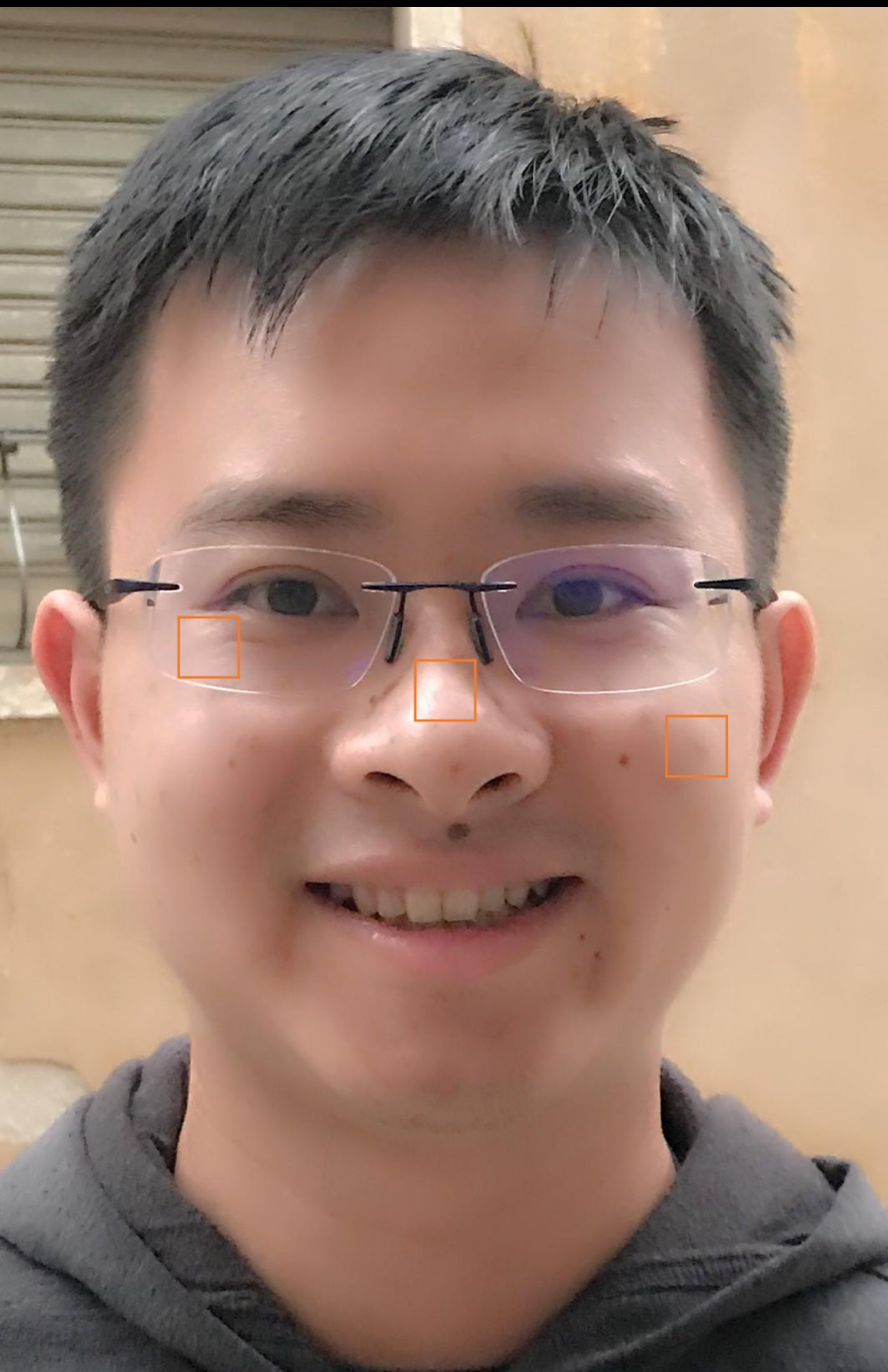


Component-level Comparison

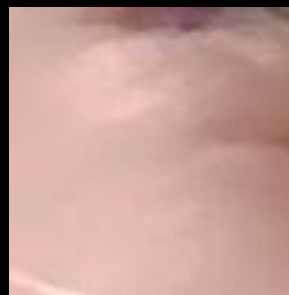


Component-level Comparison





Input Touched Image



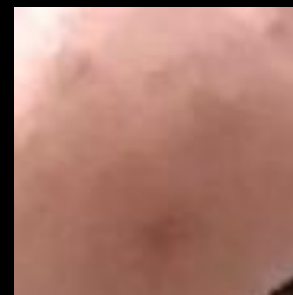


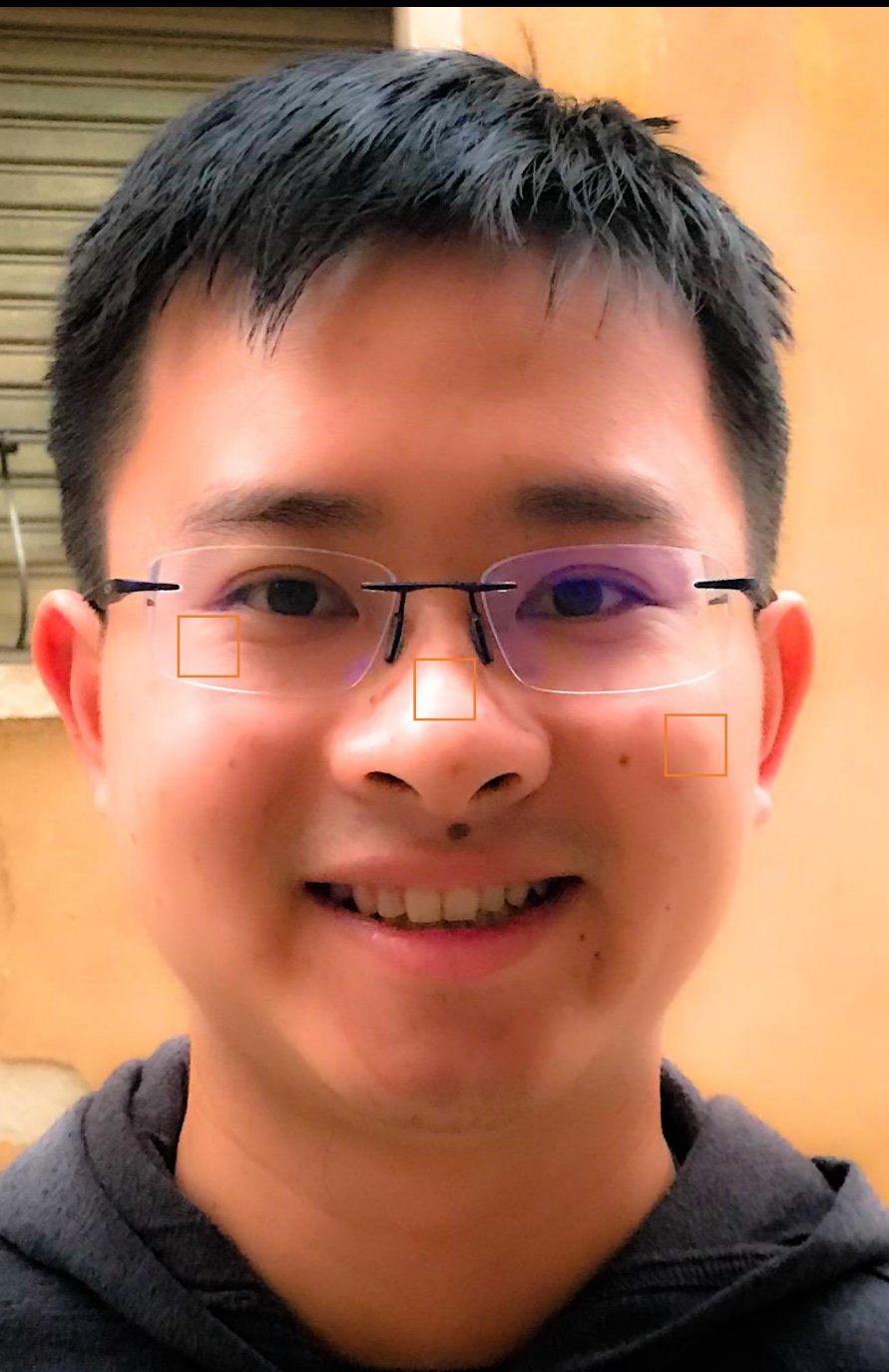
Our Result



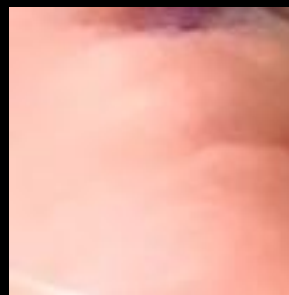


Ground Truth



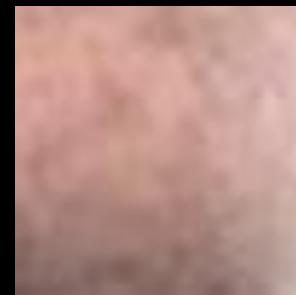
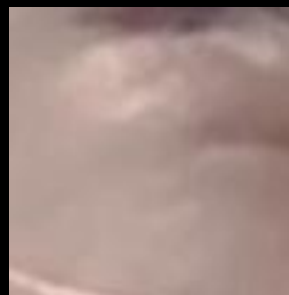


Overly Touched





Our result







Not-That-Good Result



Ground Truth



Touched

Not-That-Good Result



Ground Truth



Output

Summary

- We discovered the **component domination effect**.
- We proposed a **Component Regression Network** to tackle the problem.



Detail-revealing Deep Video Super-resolution

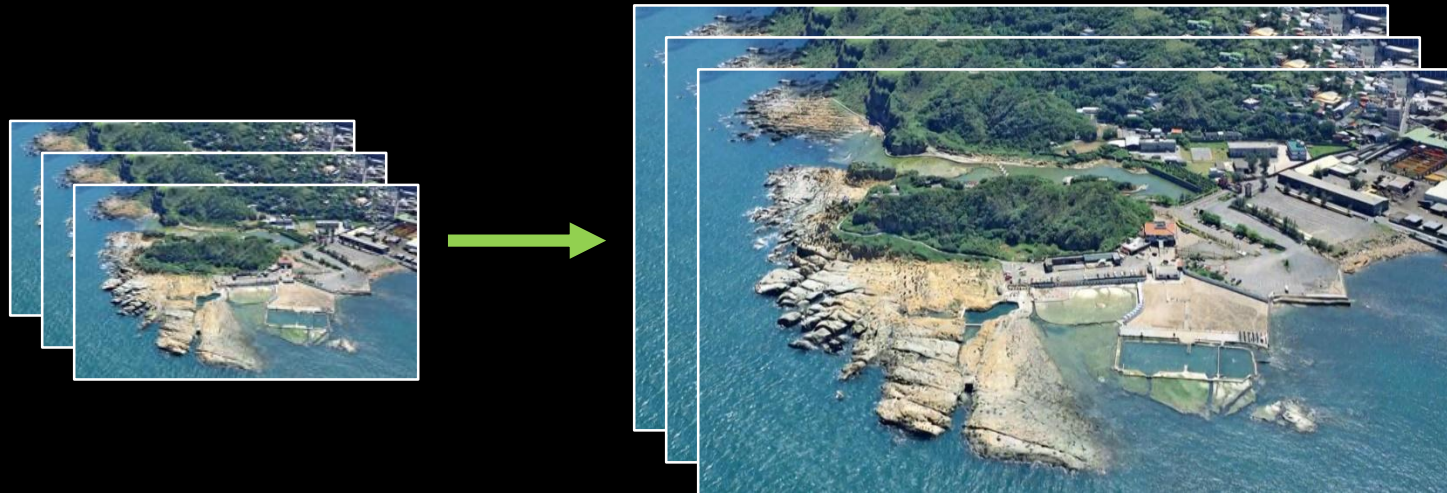
Motivation

- **Old and Fundamental**

- Several decades ago [Huang et al, 1984] → near recent

- **Many Applications**

- HD video generation from low-res sources



Motivation

- **Old and Fundamental**

- Several decades ago [Huang et al, 1984] → near recent

- **Many Applications**

- HD video generation from low-res sources
- Video enhancement with details



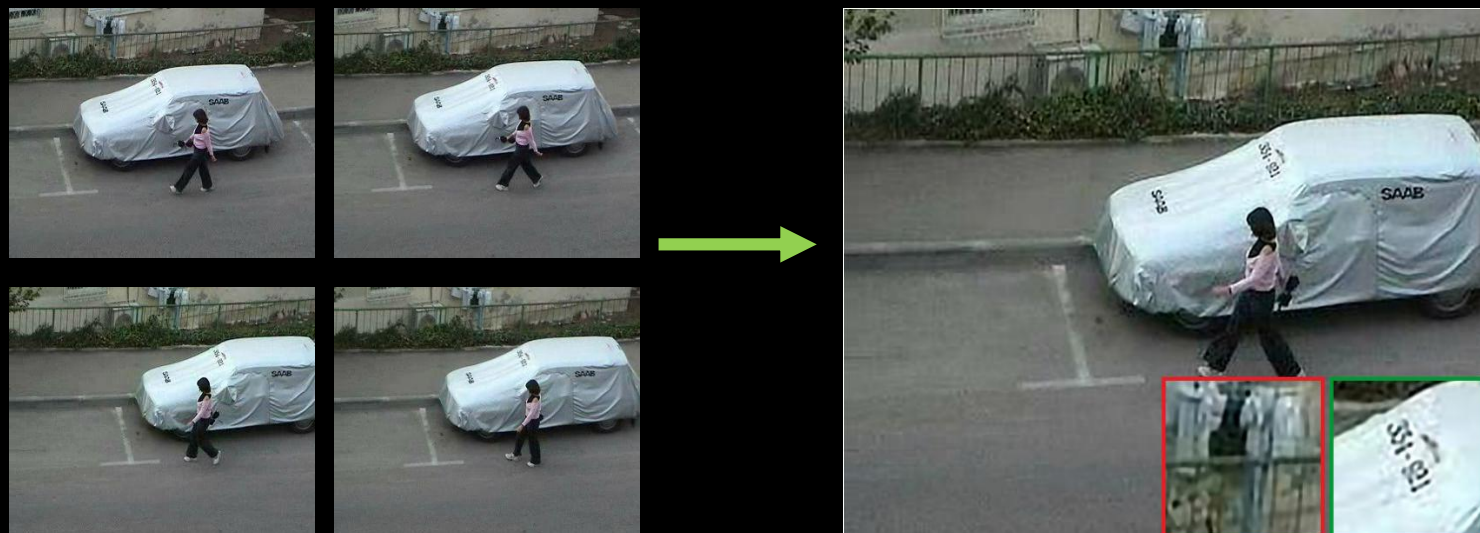
Motivation

- Old and Fundamental

- Several decades ago [Huang et al, 1984] → near recent

- Many Applications

- HD video generation from low-res sources
- Video enhancement with details
- Text/object recognition in surveillance videos



Previous Work

- **Image SR**

- **Traditional:** [Freeman et al, 2002], [Glasner et al, 2009], [Yang et al, 2010], etc.
- **CNN-based:** SRCNN [Dong et al, 2014], VDSR [Kim et al, 2016], FSRCNN [Dong et al, 2016], etc.

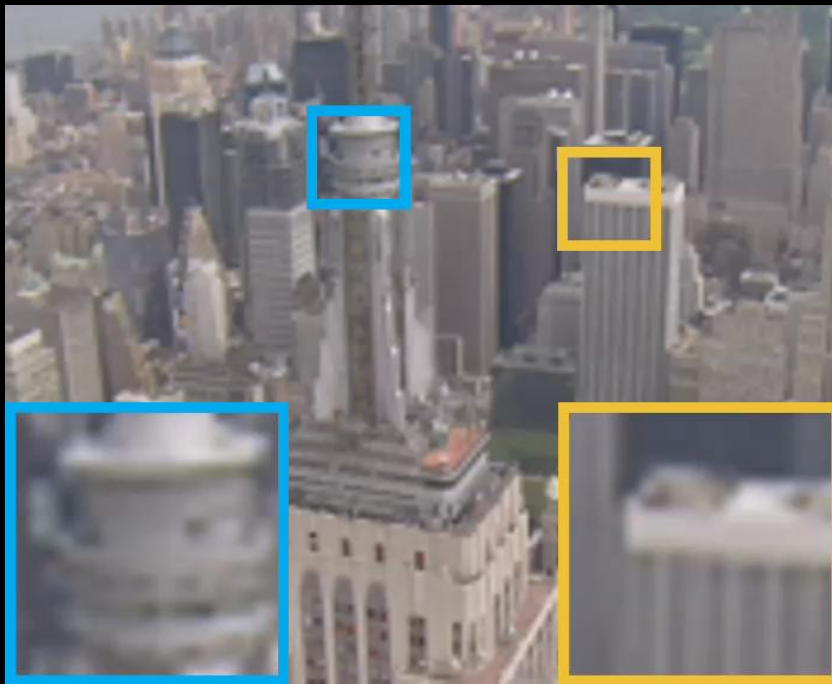
- **Video SR**

- **Traditional:** 3DSKR [Takeda et al, 2009], BayesSR [Liu et al, 2011], MFSR [Ma et al, 2015], etc.
- **CNN-based:** DESR [Liao et al, 2015], VSRNet [Kappeler, et al, 2016], [Caballero et al, 2016], etc.

Remaining Challenges

- **Effectiveness**

- How to make good use of multiple frames?



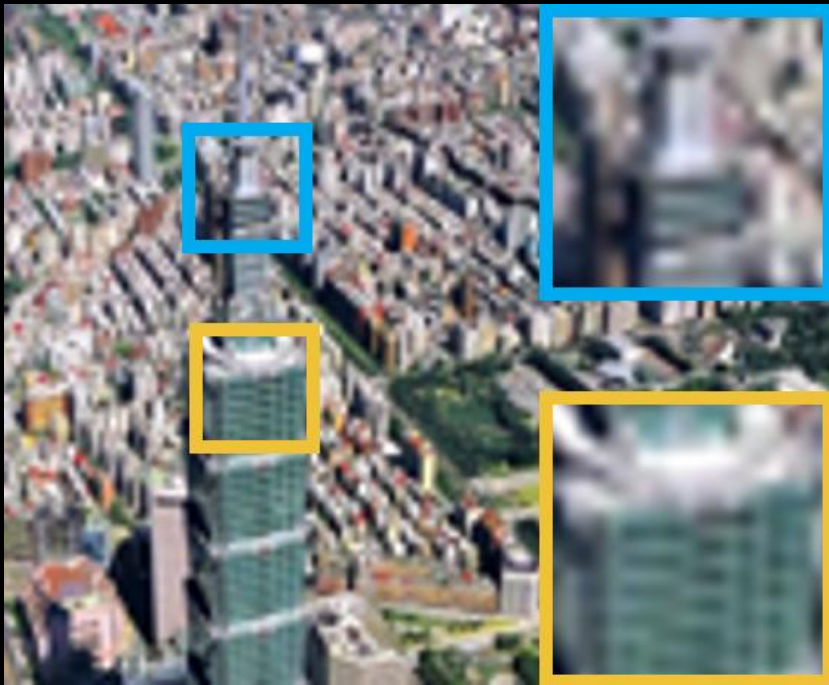
Bicubic x4

Misalignment
Large motion
Occlusion

Remaining Challenges

- **Effectiveness**

- How to make good use of multiple frames?
- Are the generated details real?



Bicubic x4

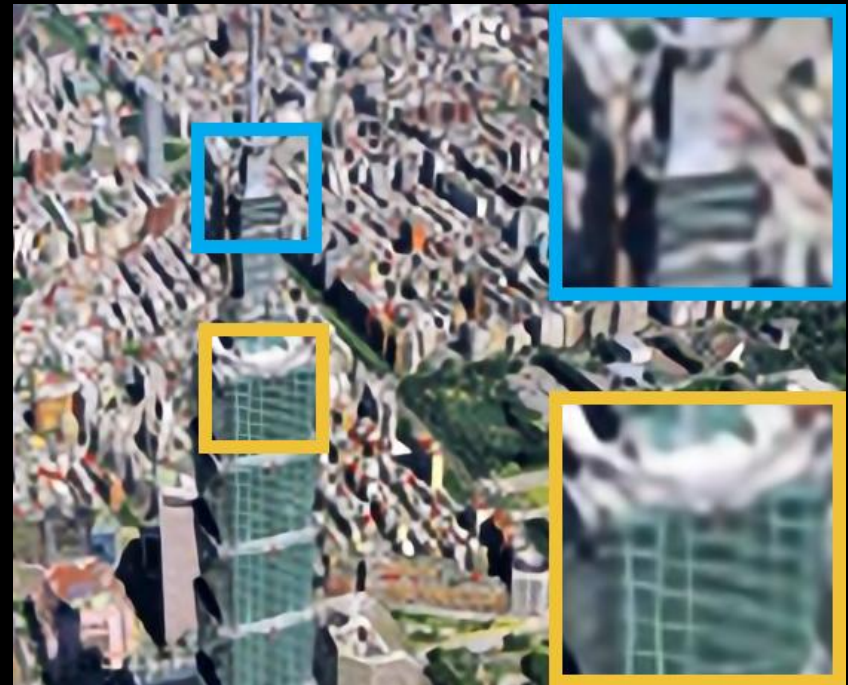
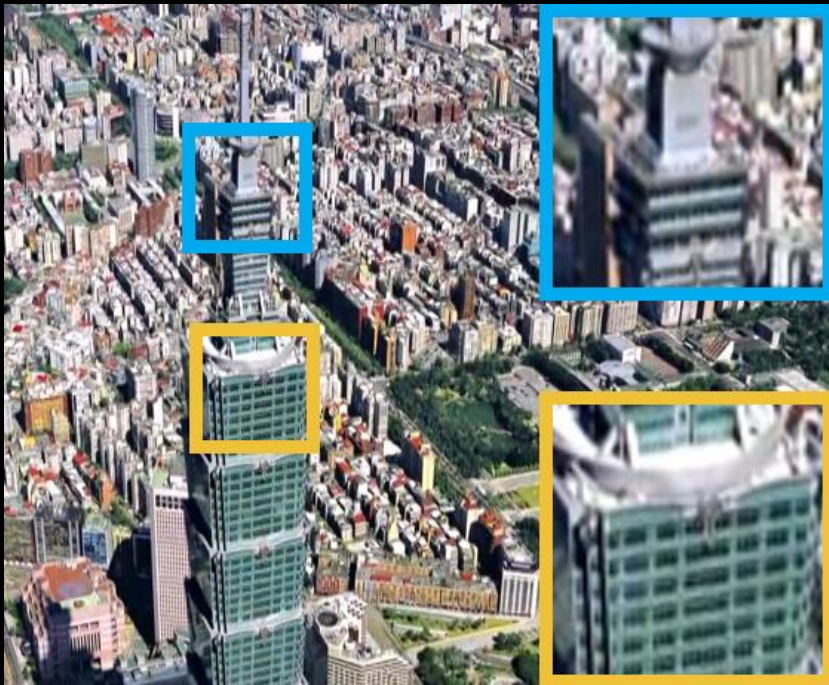


Image SR

Remaining Challenges

- **Effectiveness**

- How to make good use of multiple frames?
- Are the generated details real?



Truth

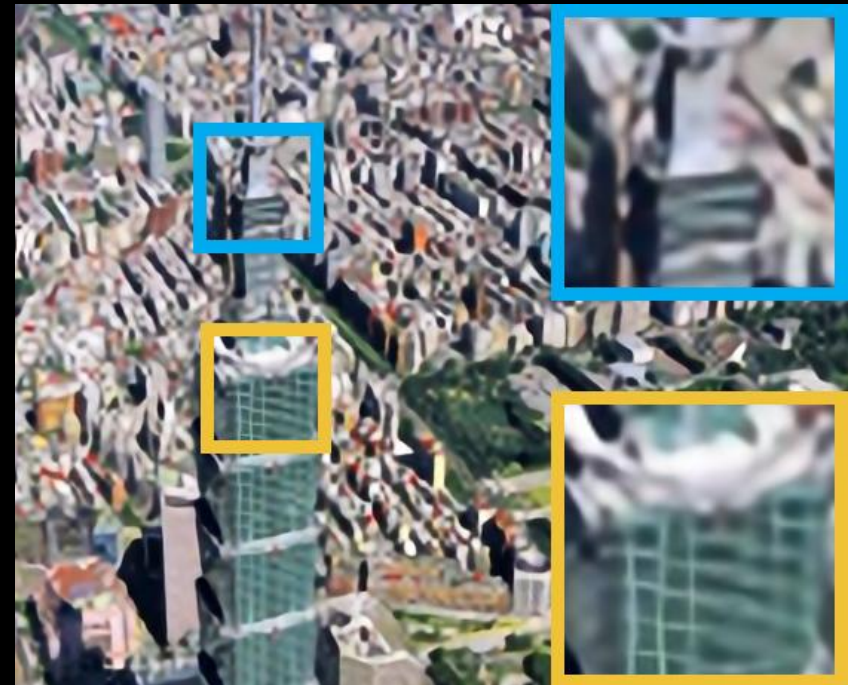


Image SR

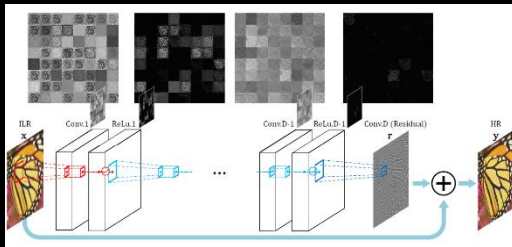
Remaining Challenges

- Effectiveness

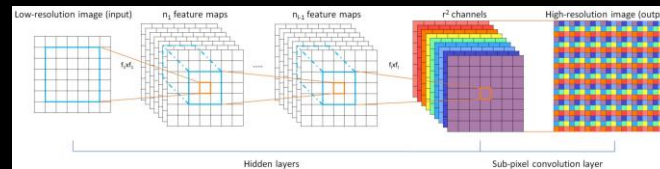
- How to make good use of multiple frames?
- Are the generated details real?

- Model Issues

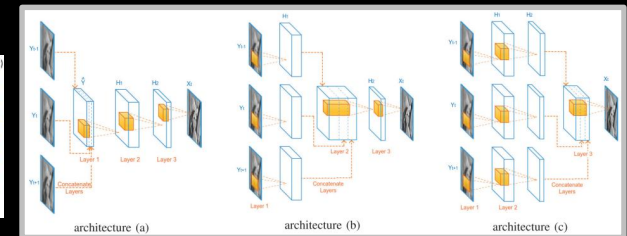
- One model for one setting



VDSR [Kim et al., 2016]



ESPCN [Shi et al., 2016]



VSRNet [Kappeler et al, 2016]

Remaining Challenges

- **Effectiveness**

- How to make good use of multiple frames?
- Are the generated details real?

- **Model Issues**

- One model for one setting
- Intensive parameter tuning
- Slow

Our Method

- **Advantages**

- Better use of sub-pixel motion
- Promising results both visually and quantitatively

- **Fully Scalable**

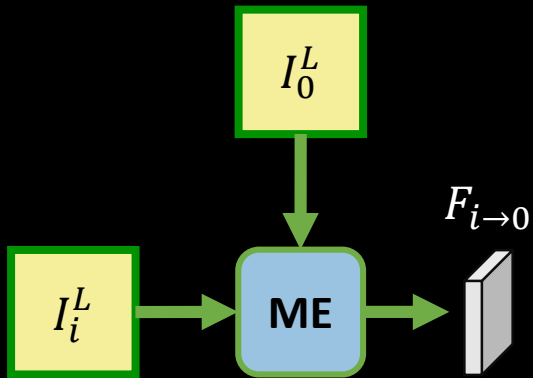
- Arbitrary input size
- Arbitrary scale factor
- Arbitrary temporal frames

Bicubic x4



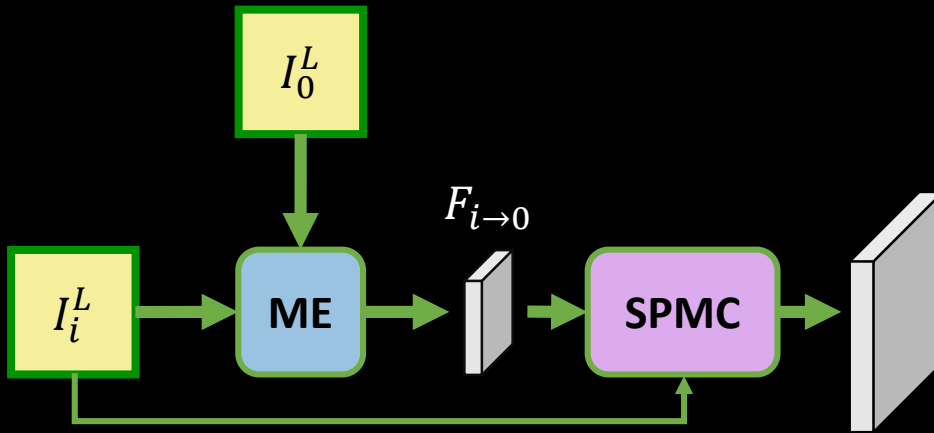
Our Method

- Motion Estimation



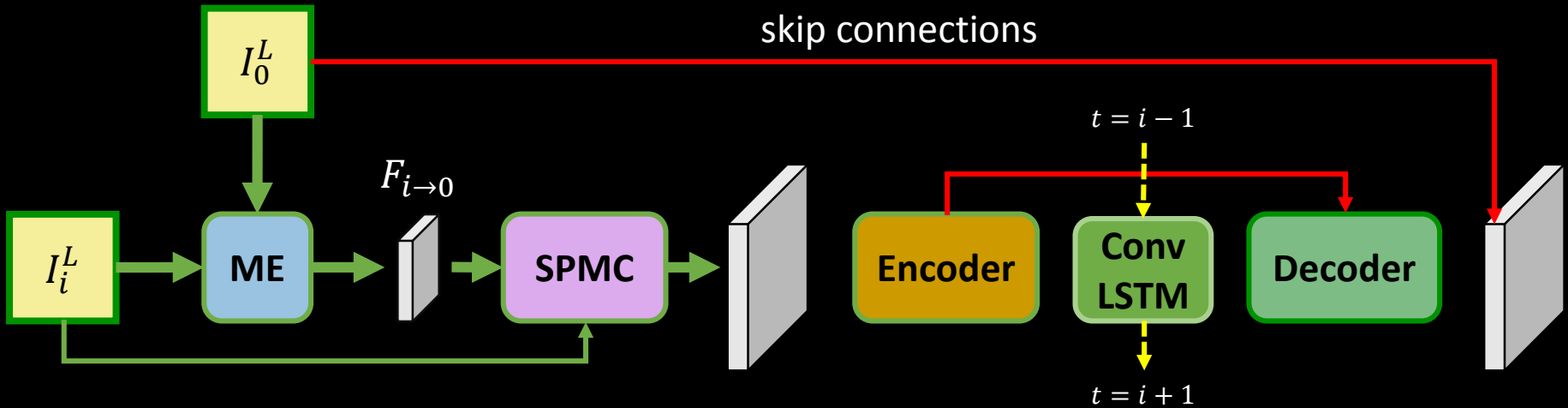
Our Method

- Sub-pixel Motion Compensation (SPMC) Layer

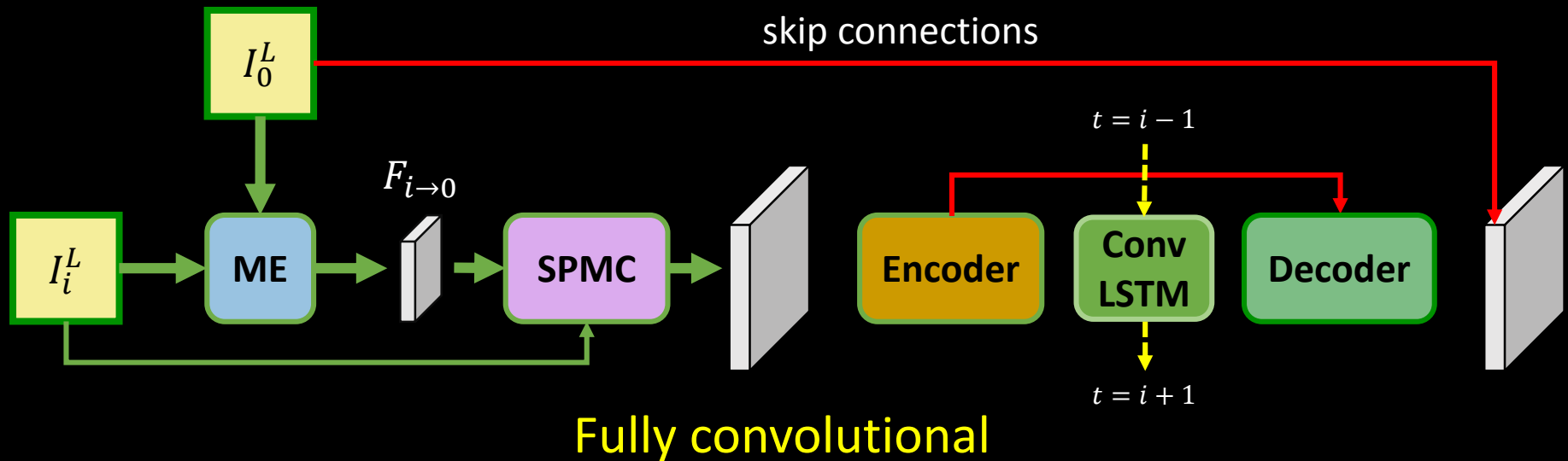


Our Method

- Detail Fusion Net

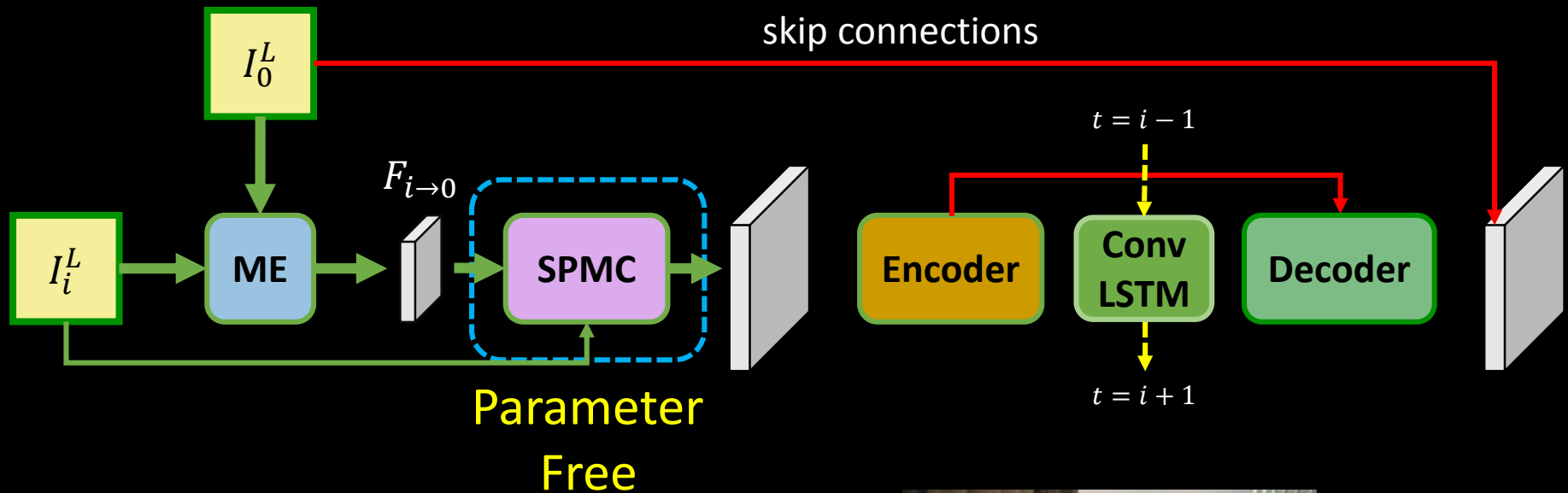


Arbitrary Input Size



Input size:

Arbitrary Scale Factors



2×

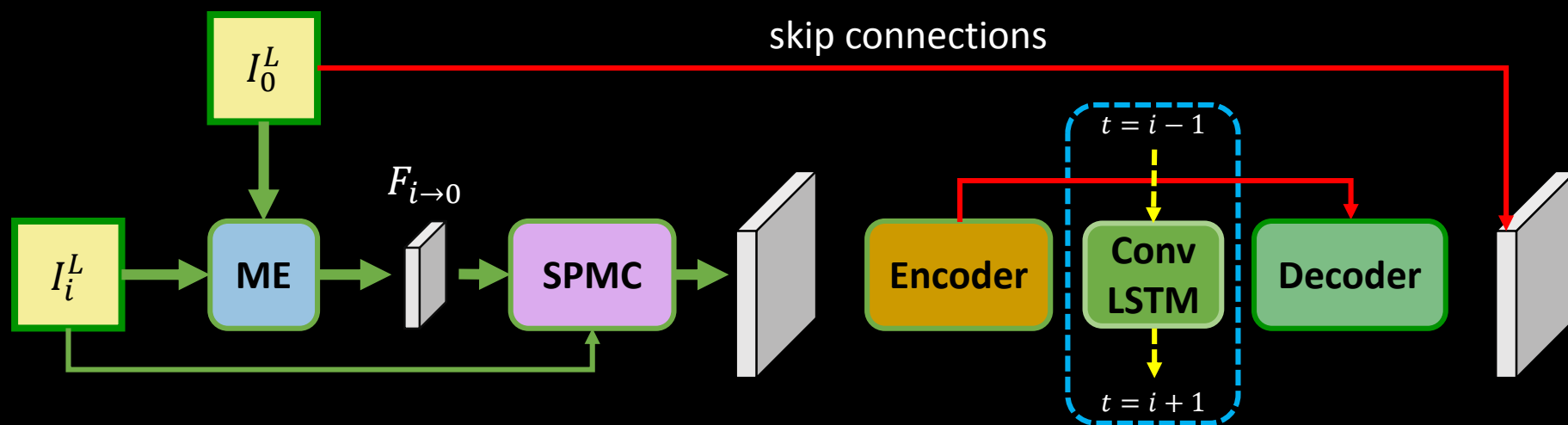


3×



4×

Arbitrary Temporal Length



3 frames



5 frames

Analysis

- Details from multi-frames



Output (identical)

3 identical frames

Analysis

- Details from multi-frames



Output (identical)

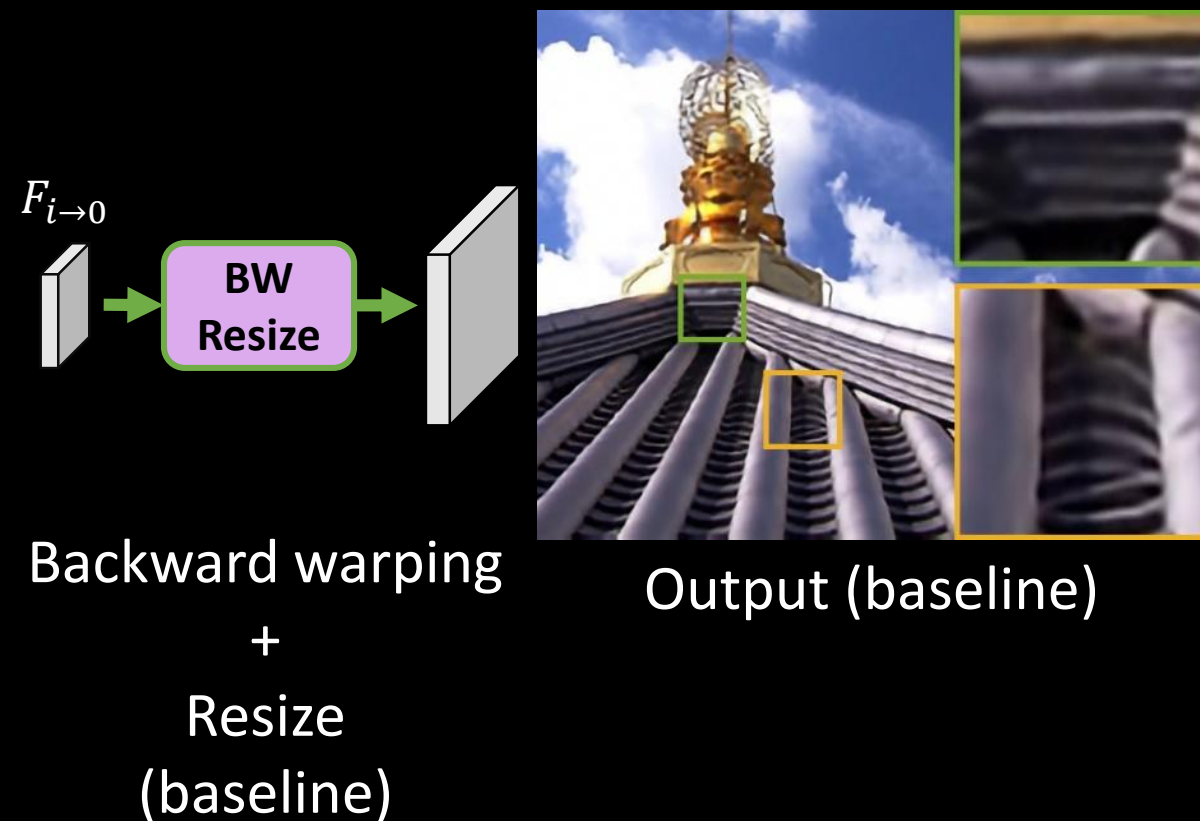


Output (consecutive)

3 consecutive frames

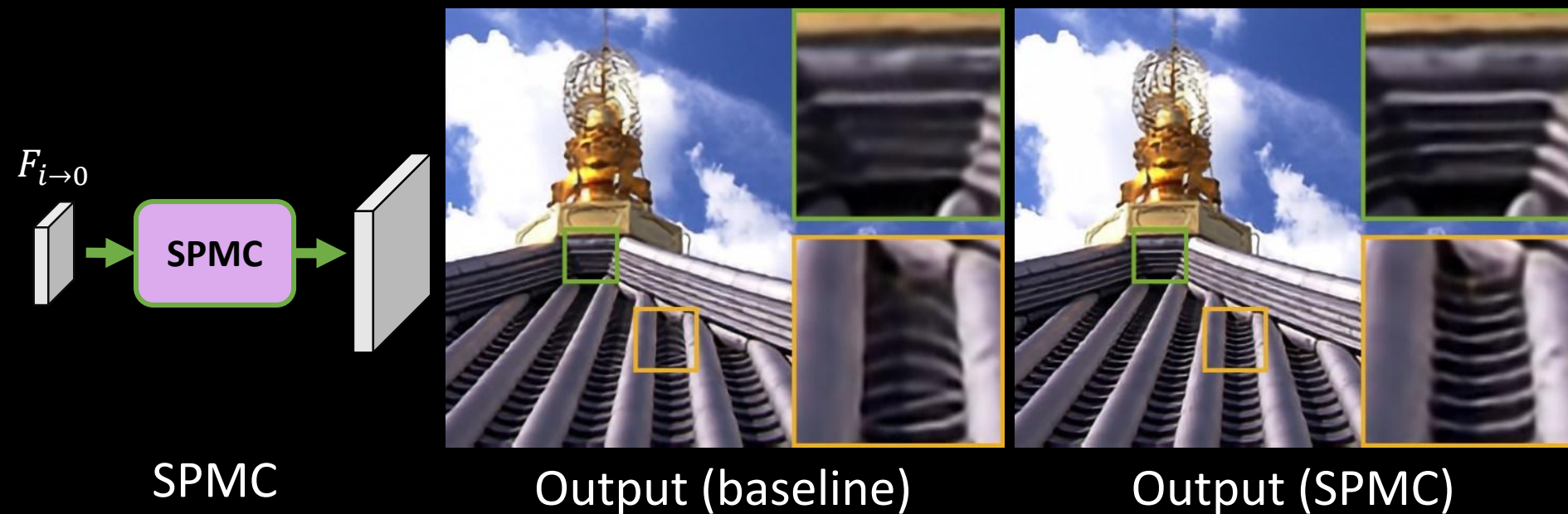
Analysis

- Ablation Study: SPMC Layer v.s. Baseline

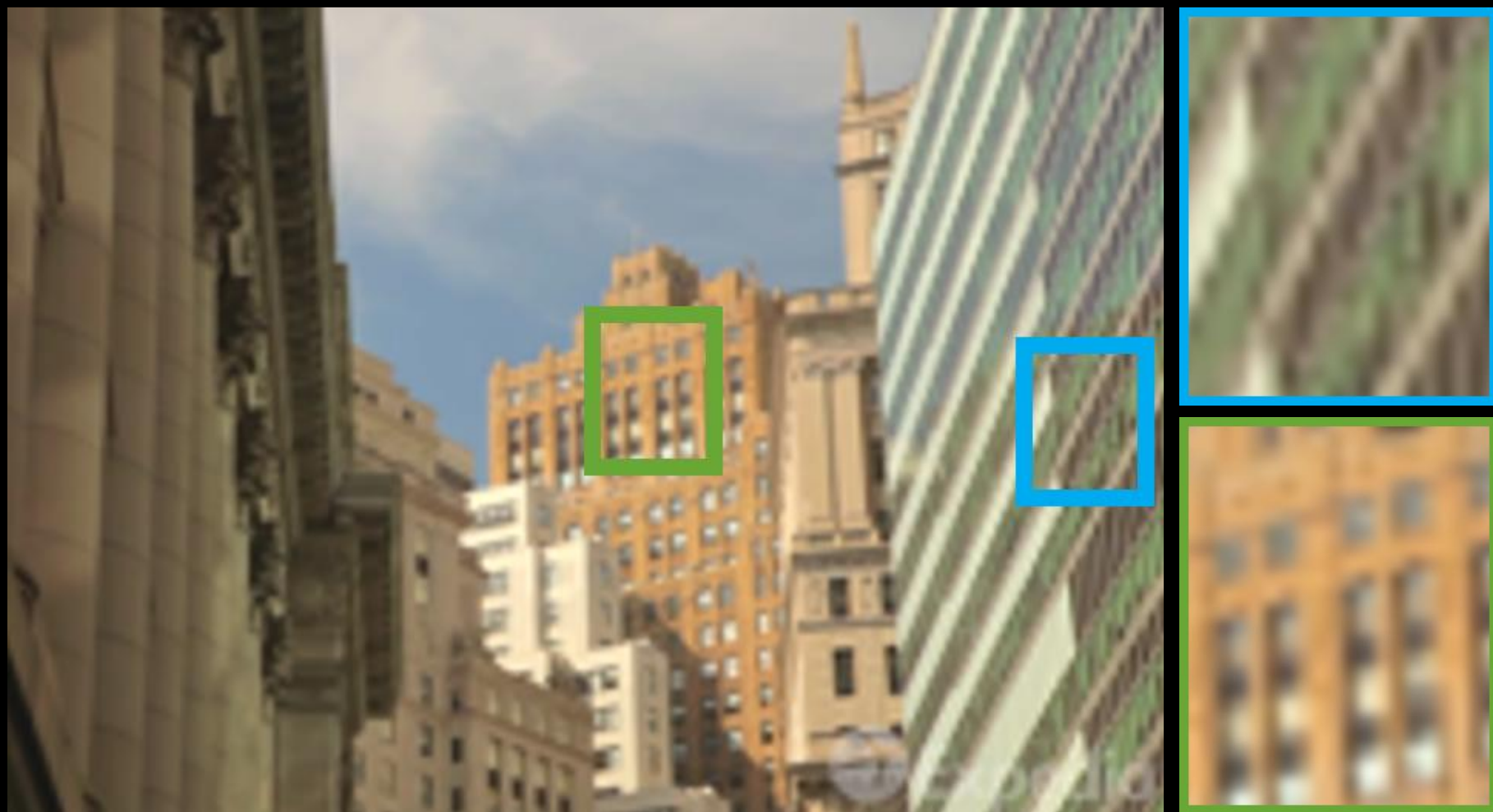


Analysis

- Ablation Study: SPMC Layer v.s. Baseline

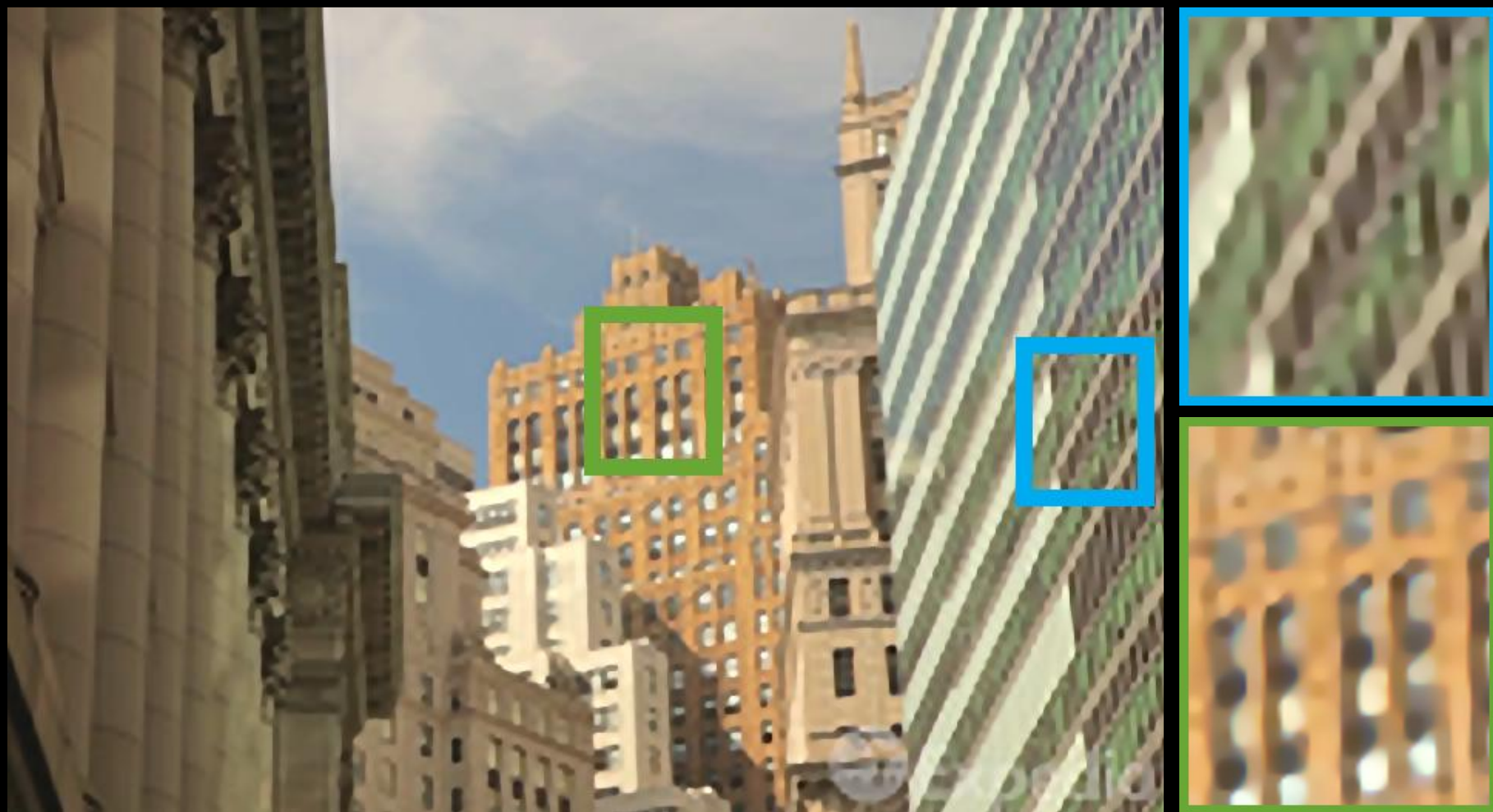


Comparisons

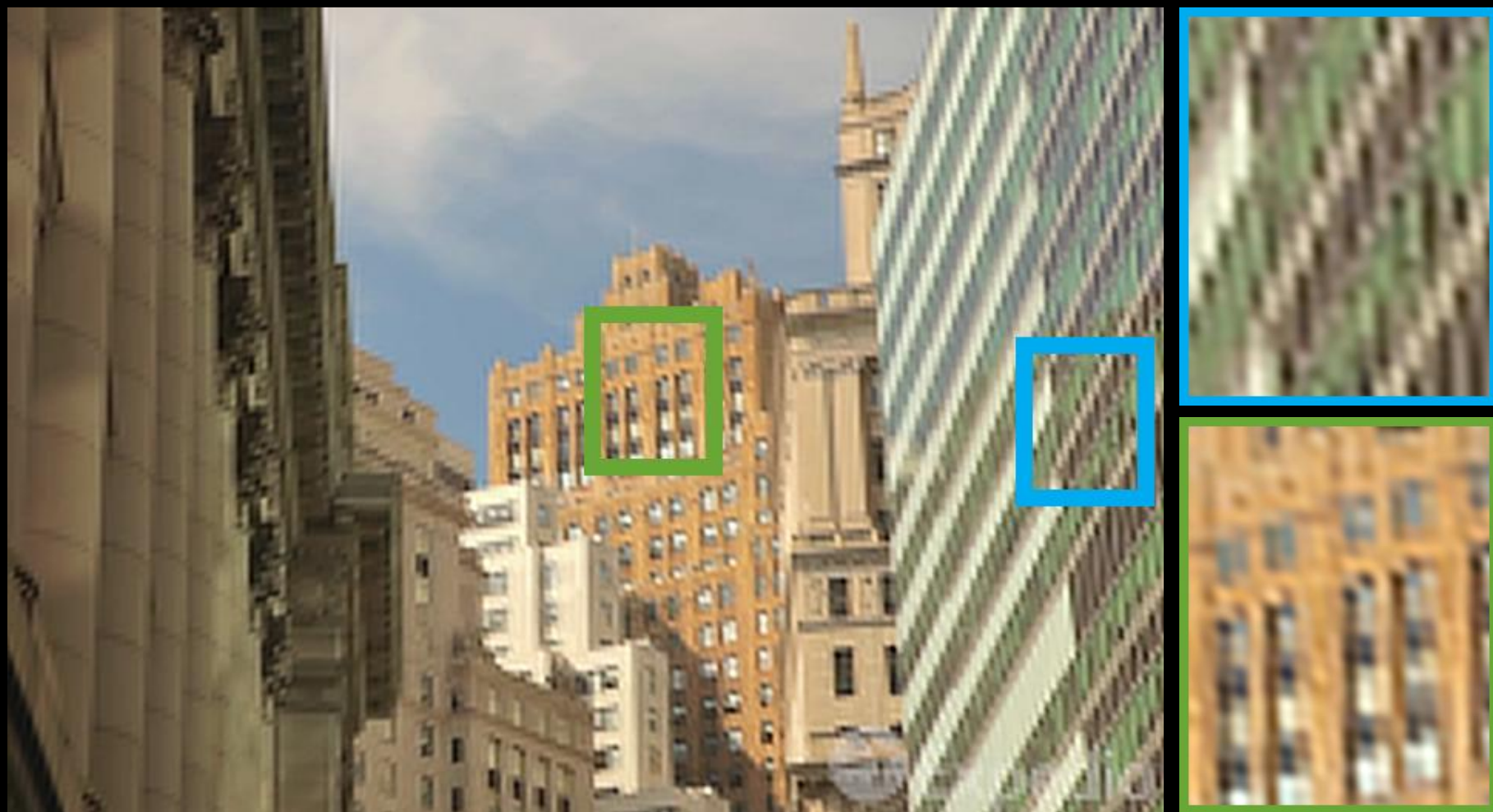


Bicubic x4

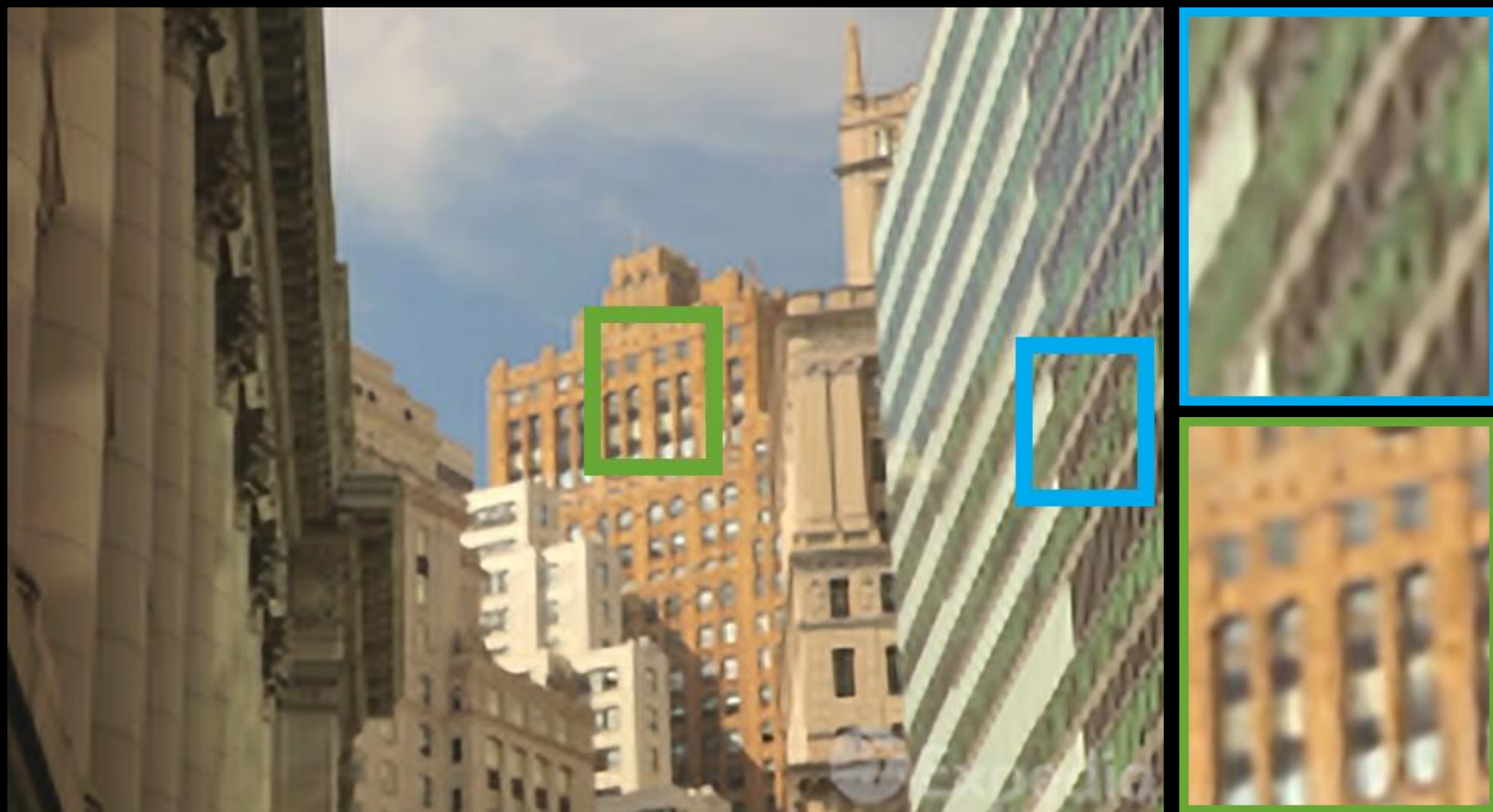
Comparisons



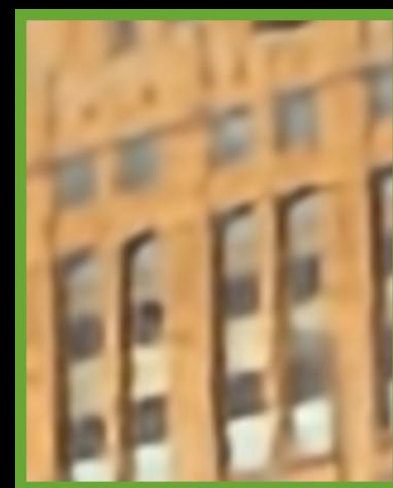
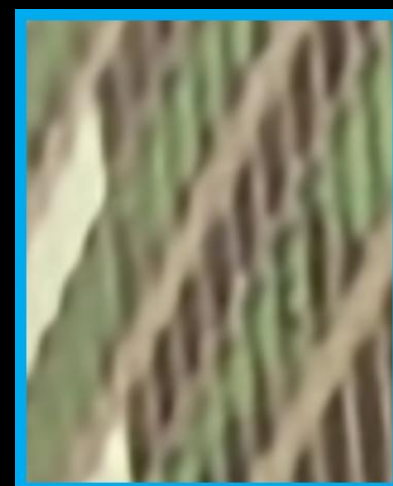
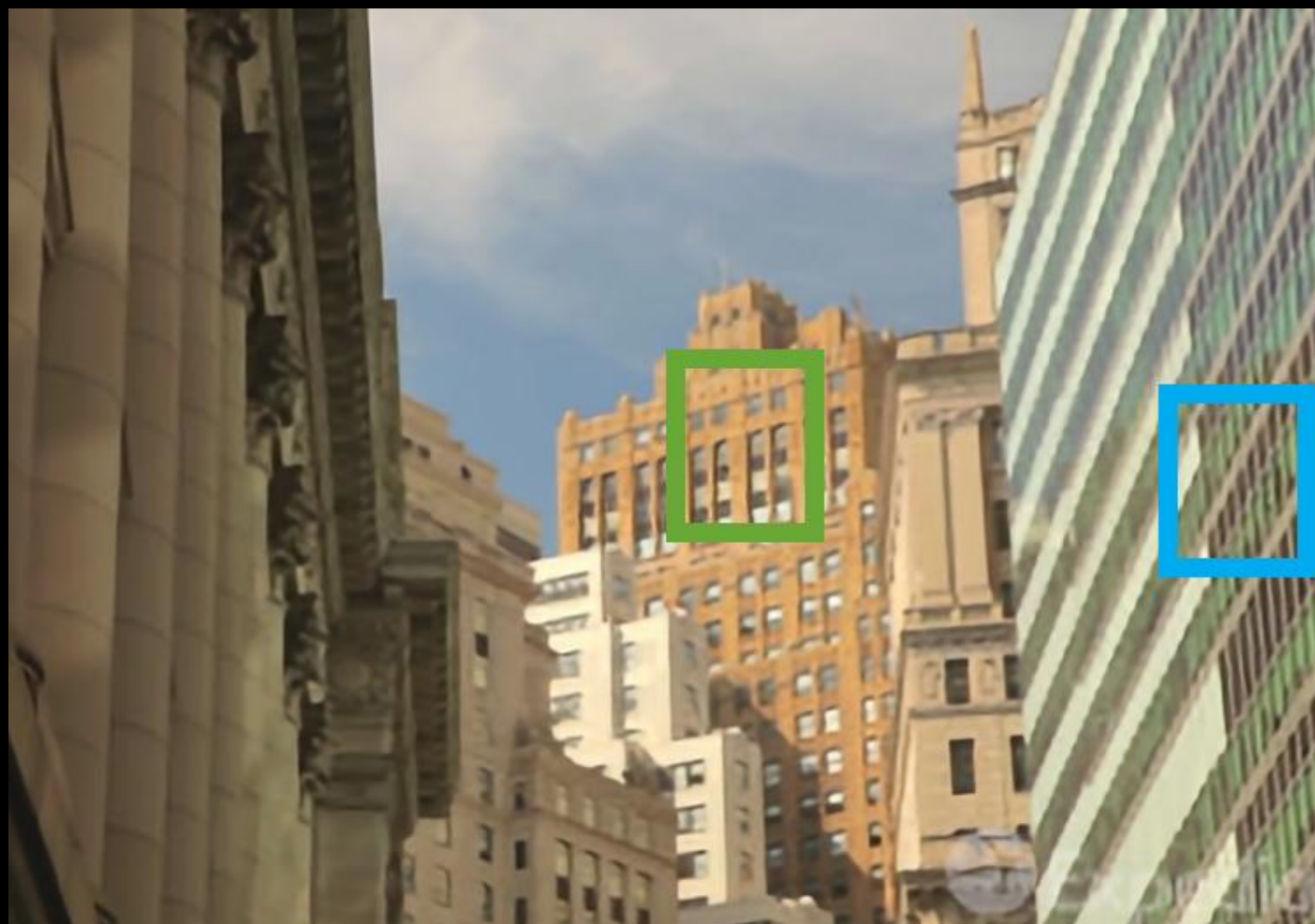
Comparisons



Comparisons

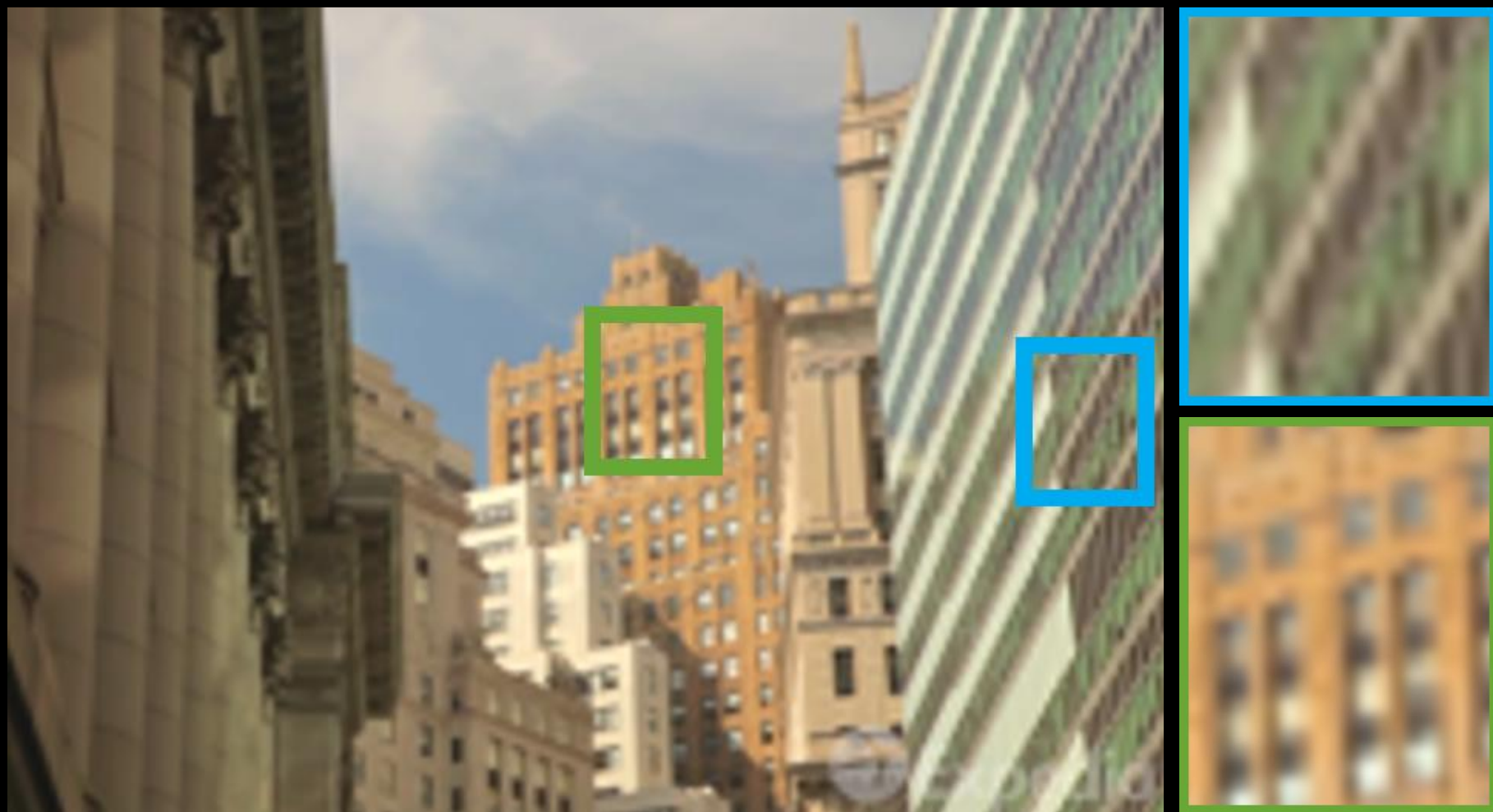


Comparisons



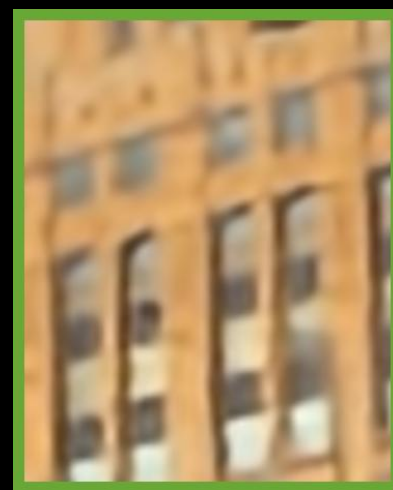
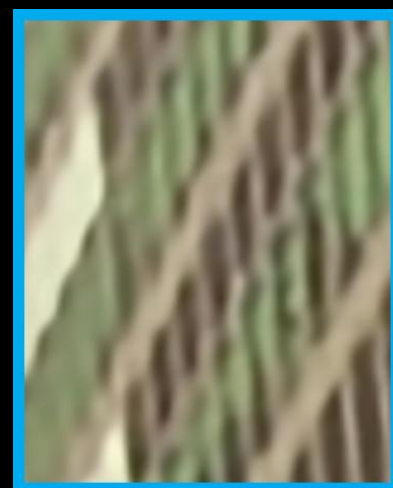
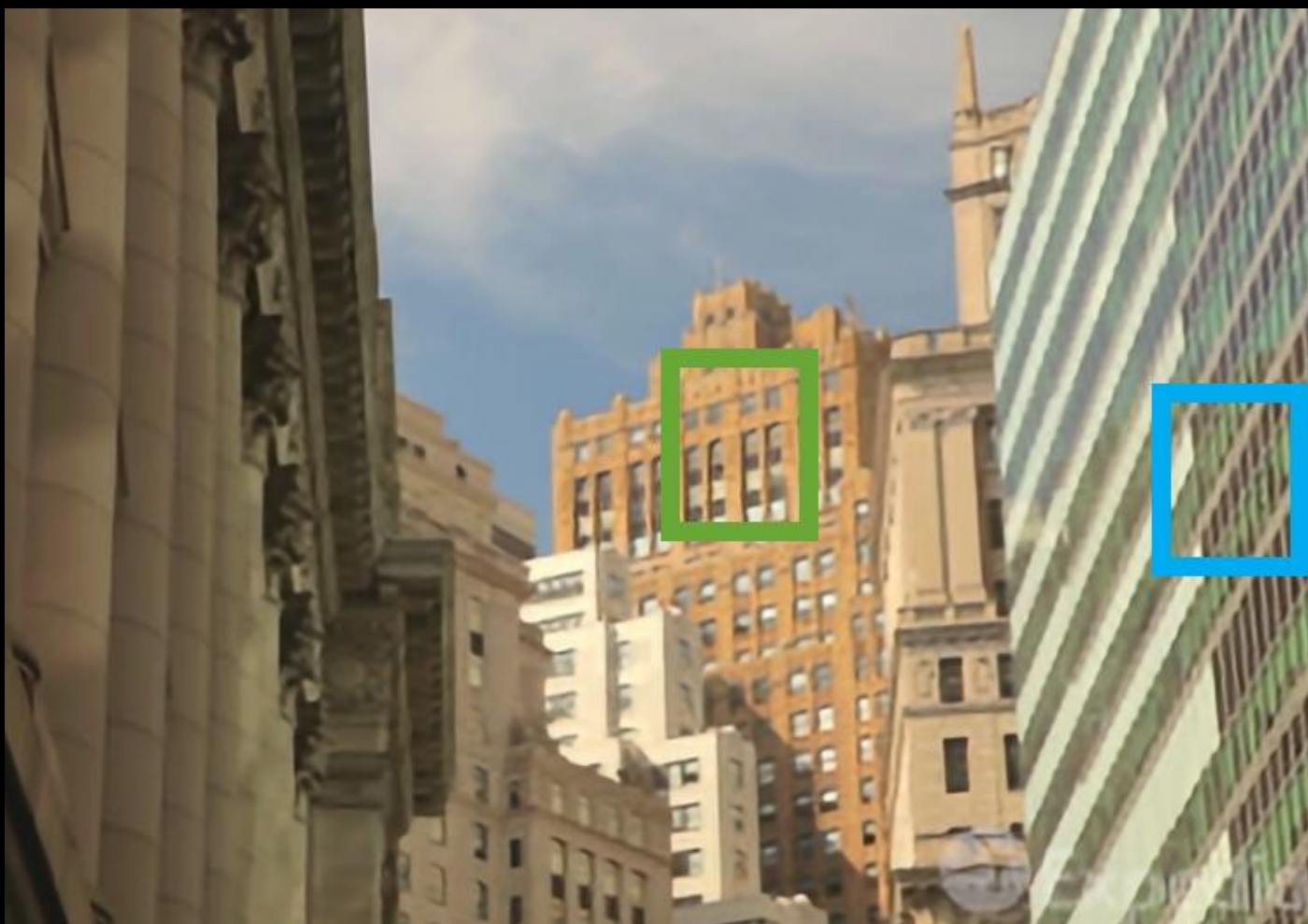
Ours

Comparisons



Bicubic x4

Comparisons

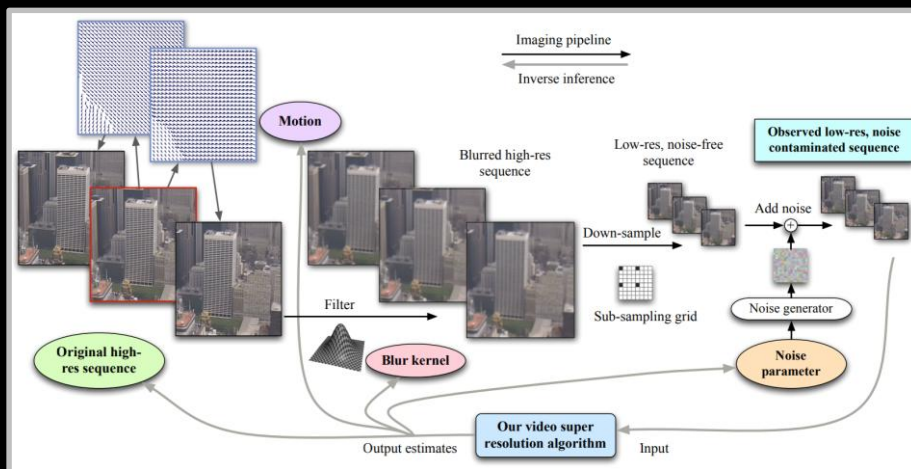


Ours

Running Time

Running Time

- BayesSR [Liu et al, 2011]



2 hour / frame

Frames: 31
Scale Factor: 4×

Running Time

- MFSR [Ma et al, 2015]

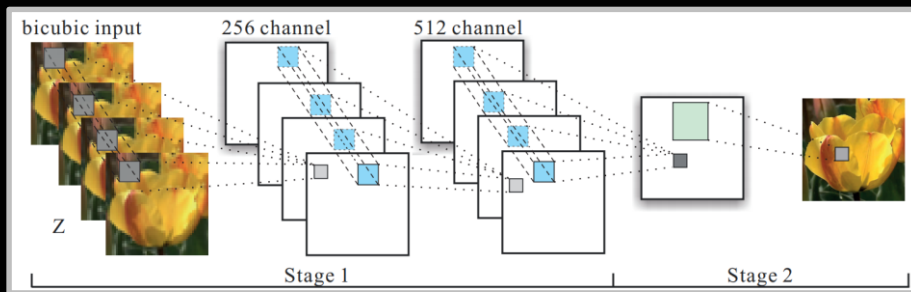


10 min / frame

Frames: 31
Scale Factor: 4×

Running Time

- DESR [Liao et al, 2015]

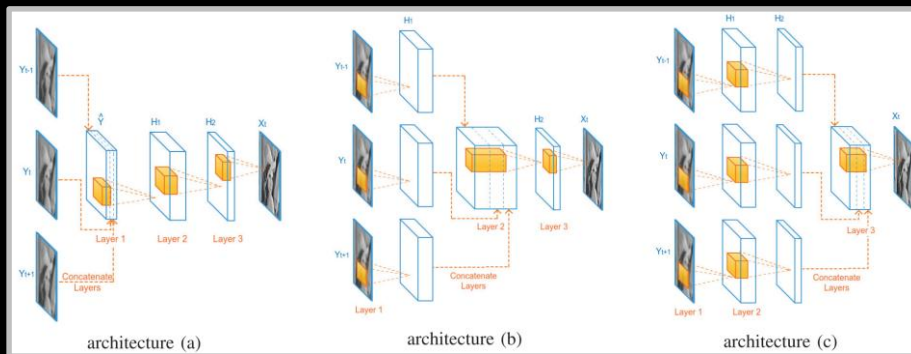


8 min / frame

Frames: 31
Scale Factor: 4×

Running Time

- VSRNet [Kappeler et al, 2016]



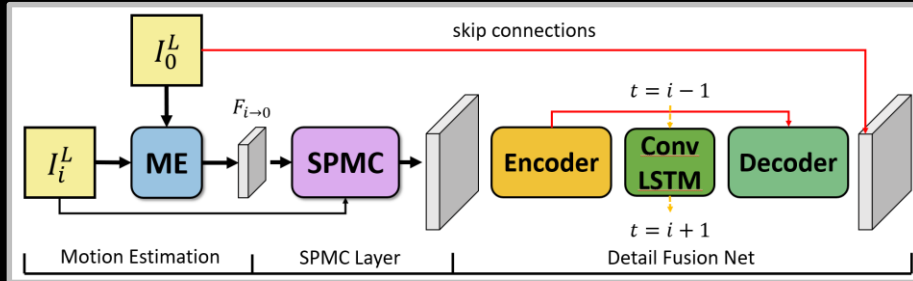
40 s / frame

Frames: 5

Scale Factor: $4\times$

Running Time

- Ours (5 frames)



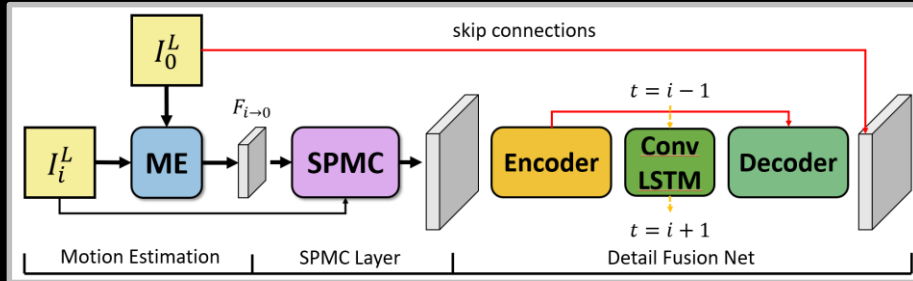
0.19_s / frame

Frames: 5

Scale Factor: 4×

Running Time

- Ours (3 frames)



0.14s / frame

Frames: 3

Scale Factor: 4×

More Results

Bicubic x4



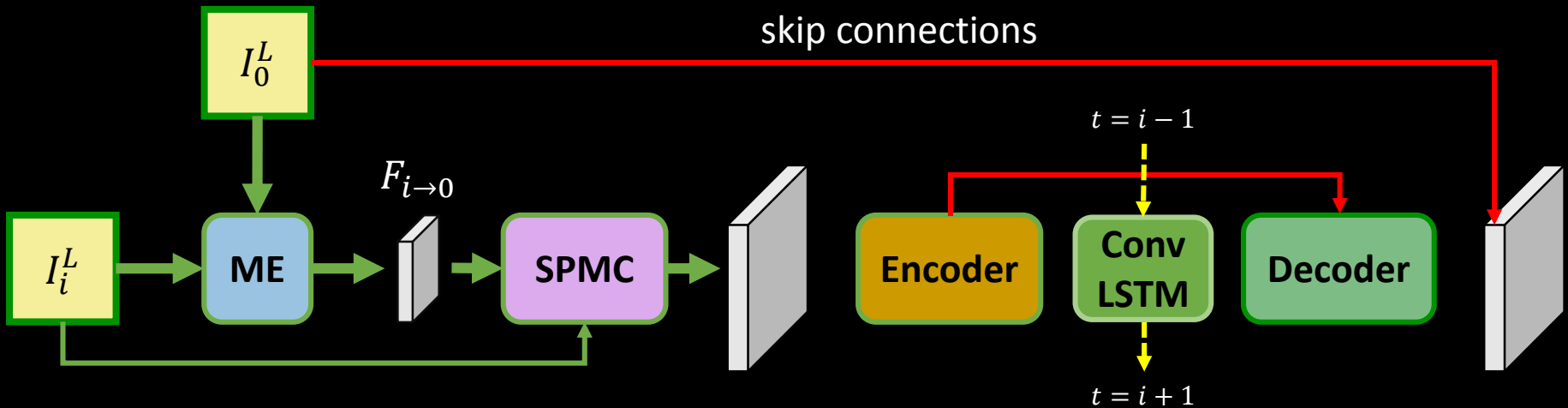
Bicubic x4



Bicubic x4



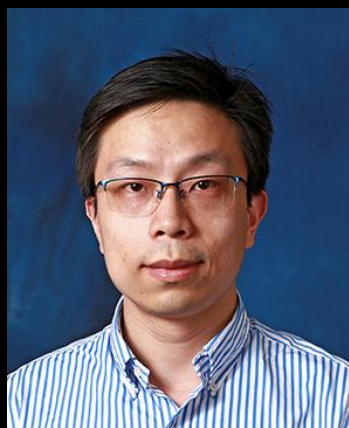
Summary



- End-to-end & fully scalable
- New SPMC layer
- High-quality & fast speed

腾讯优图X-Lab

- 成立于2017年，T5科学家领衔，负责前沿视觉技术研究与其它AI领域的融合
- 团队主要成员



贾佳亚 教授
杰出科学家



戴宇荣
专家研究员



沈小勇
高级研究员



我们需要

- 高级计算机视觉研究员
 - 负责计算机视觉算法的研究与产品落地，负责指导团队成员与实习生
 - 要求：博士或者优秀硕士
- 计算机视觉工程师
 - 计算机视觉算法的优化以及在云端，移动端的落地
 - 要求：两年以上相关开发经验
- 实习生
 - 要求：对计算机视觉具有浓厚兴趣，工程算法能力强者优先考虑



骁勇 

中国香港 沙田区



扫一扫上面的二维码图案，加我微信

Thank You