

GAMES Webinar

面向超高分辨率图像视频的实时增强研究

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研究背景



大华4K监控



海康4K监控



华为P40



iPhone 13



4K车载监控



大疆 Phantom 4



2020年5月，B站4K视频投稿正式开放



2020年7月，微博4K视频功能全面开放



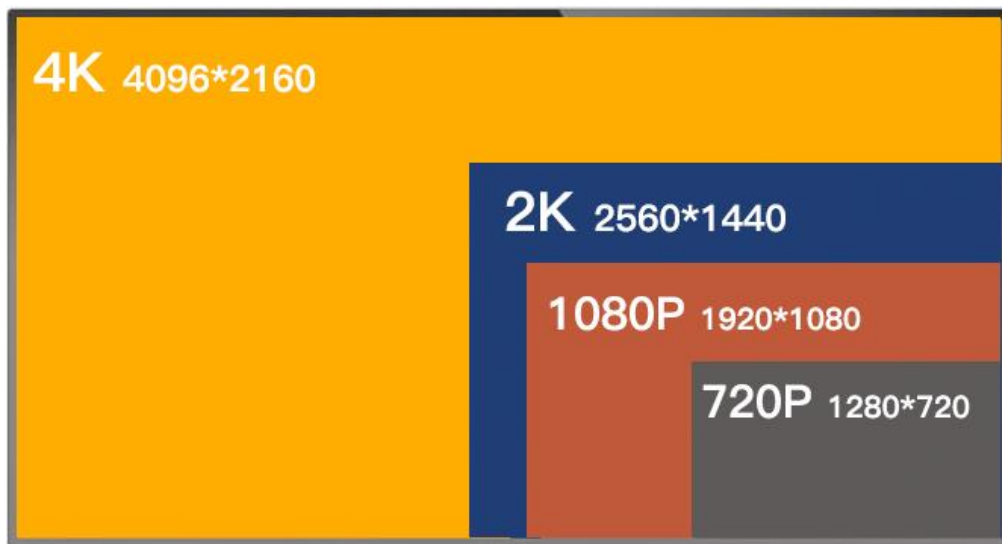
航拍城市4K视频：雨雪雾霾、模糊...



华为Meta40 Pro, 4K模式：模糊、低光照

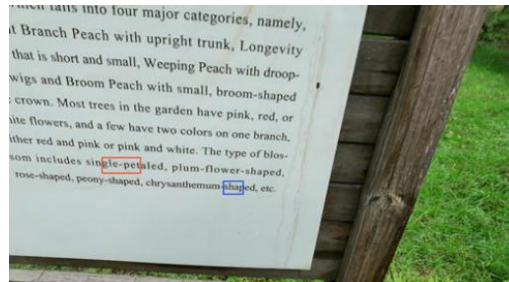
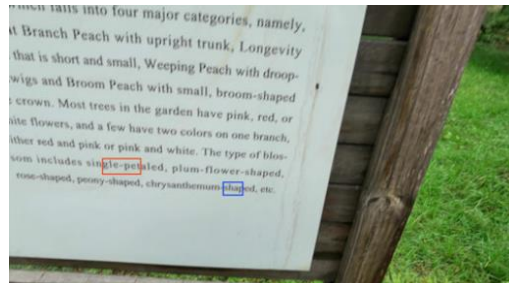
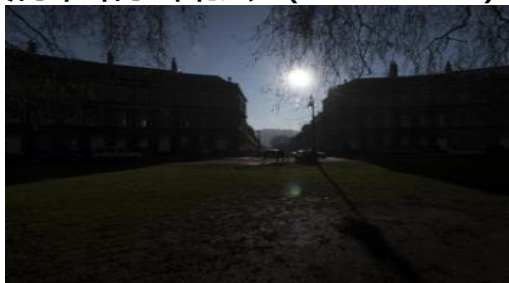
难点问题

- 针对低分辨率图像 (e.g., COCO, GoPro, DVD, RESIDE) 训练和设计的基于深度学习的图像重建模型通常无法有效推广到更高分辨率的场景。
 - ✓ 模型大小/运行速度通常使用与像素数成线性关系的GPU内存/时间
 - ✓ 需要更多参数覆盖更大感受野来考虑更高分辨率的场景空间关系
 - ✓ 超高分辨率训练集的缺失



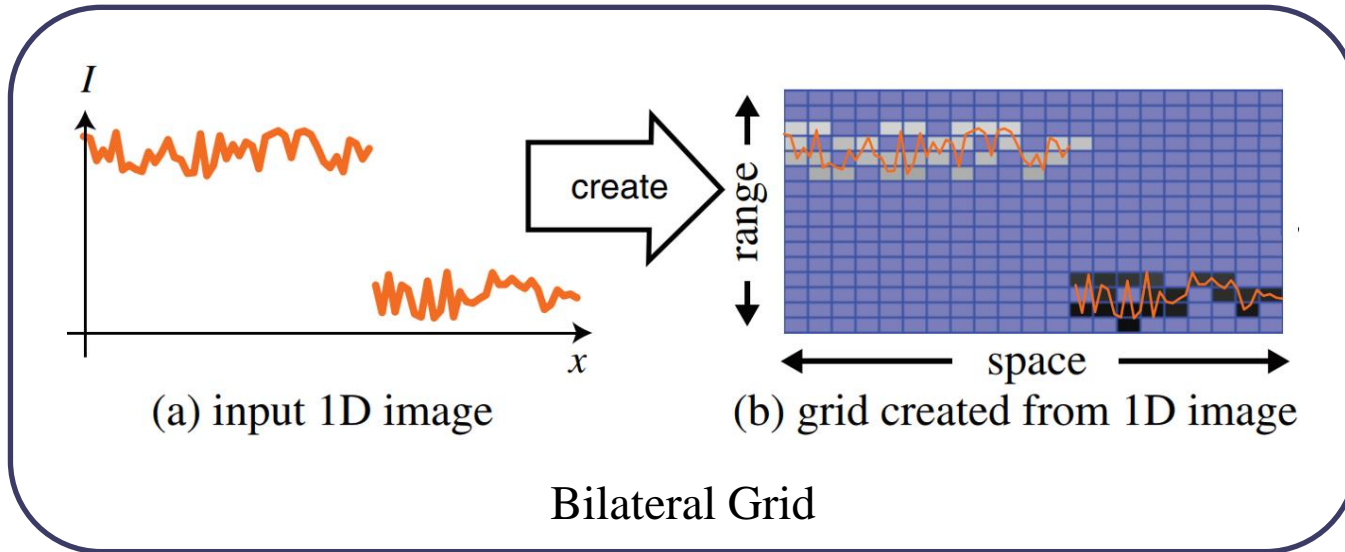
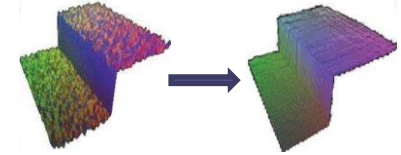
提纲

- 基于**双边网格学习**的4K超高分辨率增强模型
 - 多引导双边网格学习的去雾模型 (CVPR 2021)
 - 协同双边网格学习的HDR重构模型 (ICCV 2021)
- 基于**多尺度多分片并行**的4K超高分辨率视频去模糊 (ICCV 2021)
- 基于**网络架构自主搜索**的实时图像去模糊 (ICCV 2021)
- 基于**级联曲线估计**的屏下摄像图像增强 (TIP 2022)



双边网格 (Bilateral Grid)

双边滤波器:
$$BF[I]_{\vec{p}} = \frac{1}{W_{\vec{p}}} \sum_{\vec{q} \in S} G_{\sigma_s}(\|\vec{p} - \vec{q}\|) G_{\sigma_r}(\|I_{\vec{p}} - I_{\vec{q}}\|) I_{\vec{q}}$$



● Property

- 3D representation of 2D image
- Edge-aware operation
- Fast

● Applications

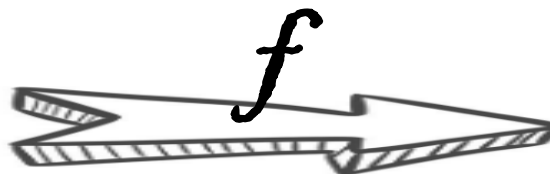
- Edge-aware painting (Chen et al. TOG 2016)
- Tone-mapping (Gharbi et al. TOG 2017)
- Style Transfer (Xia et al. ECCV 2020)

双边网格上采样

- 传统方法处理超高分辨率图像/视频

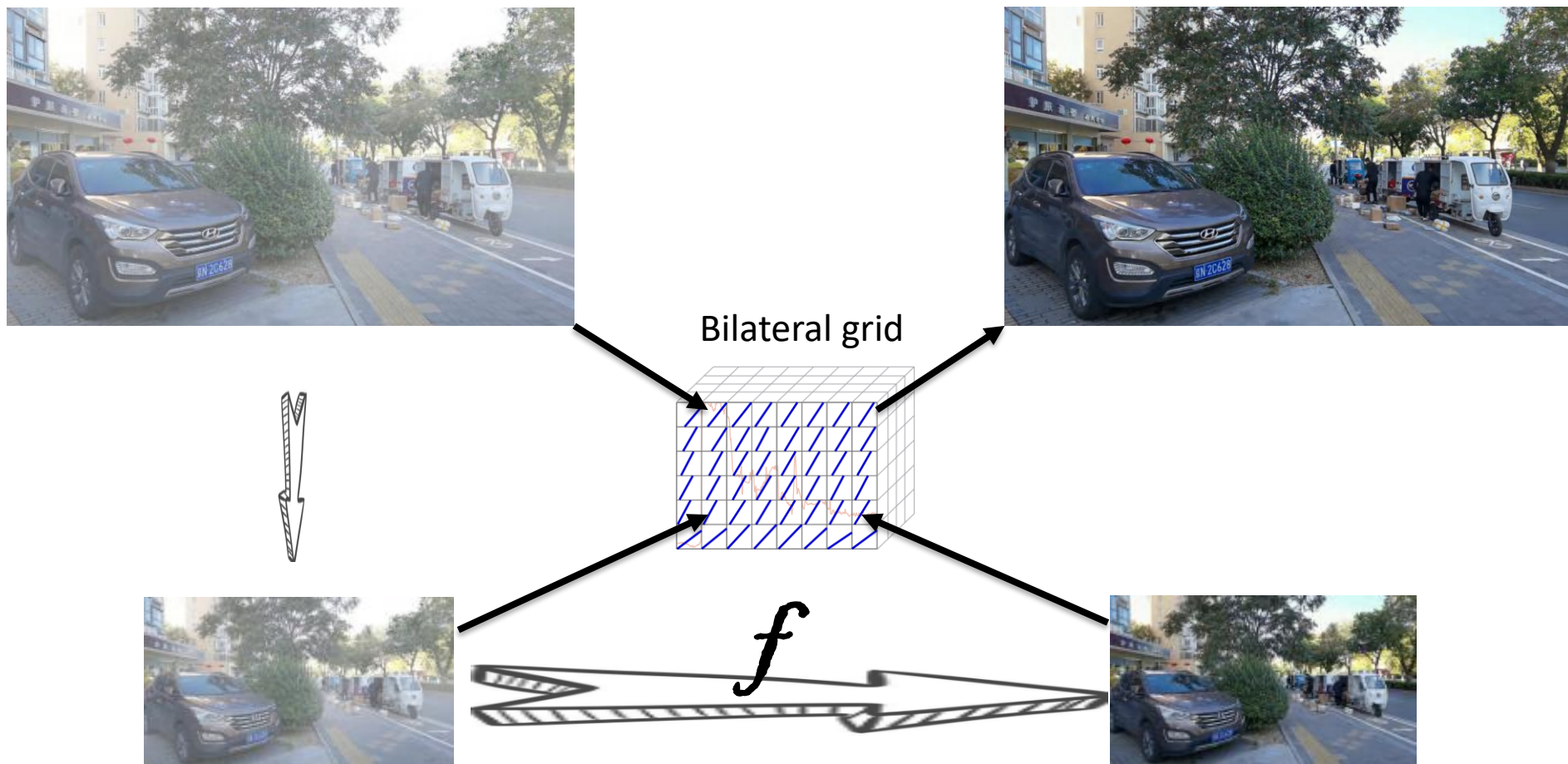
- ✓ Process on a low-resolution

- ✓ Up-sampling



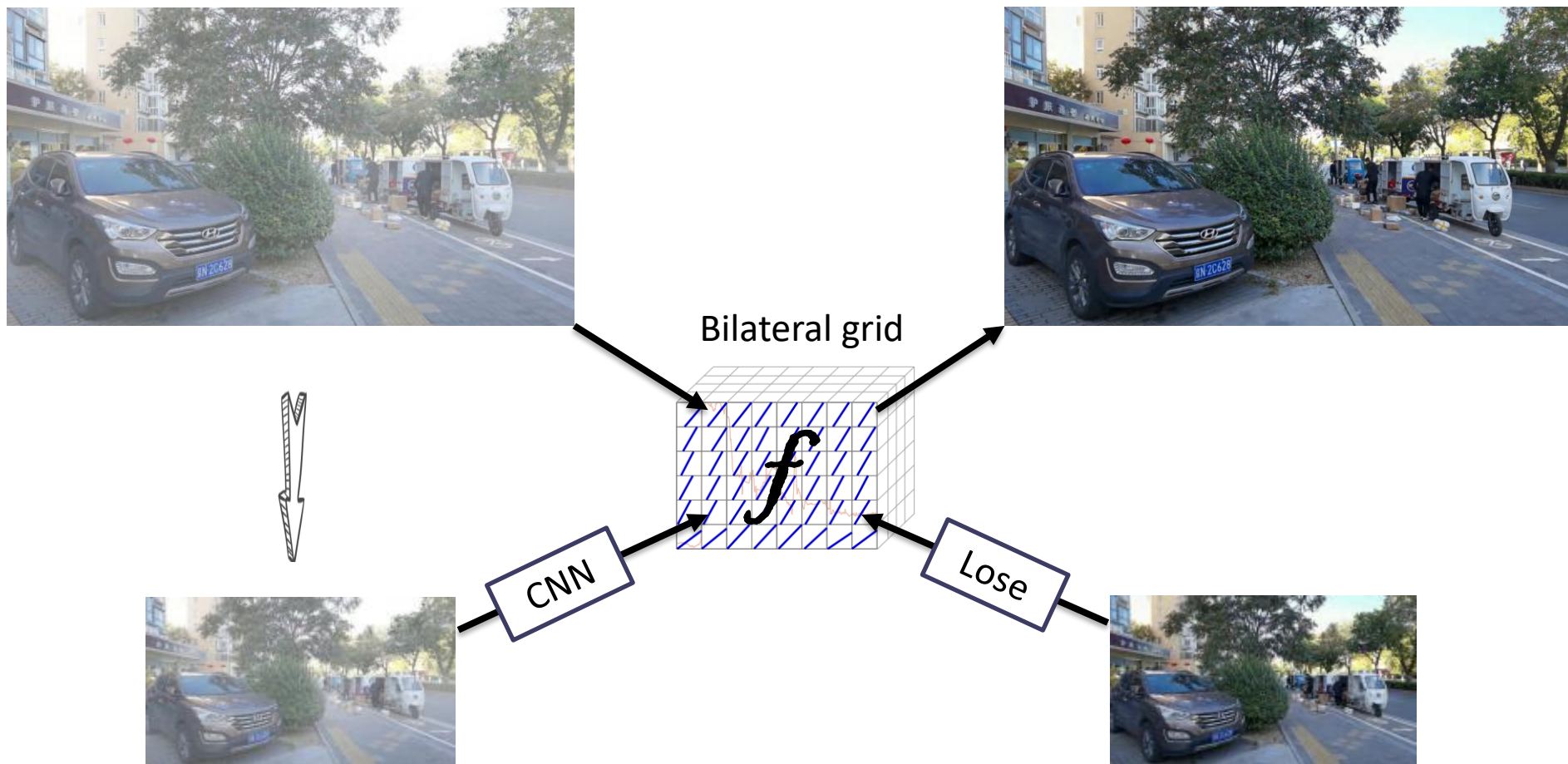
双边网格上采样

- Bilateral guided upsampling



双边网格学习

- Bilateral guided upsampling



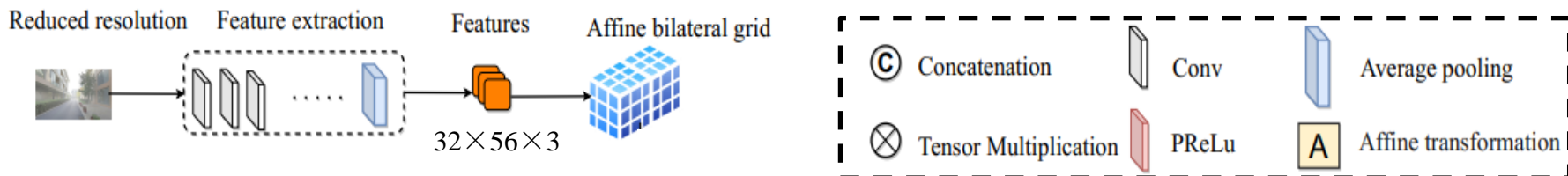
1. 超高分辨率图像去雾

研究动机 (CVPR'2021 Multi-Guided Bilateral Learning)

- 主流基于深度学习的图像去雾方法只能处理小于2K或者更低分辨率的图像，且测试耗费大量计算资源与运行时间。
- 传统双边网格学习方法直接从网格空间重建高分辨增强结果，造成信息损失较为严重，无法有效重建纹理互补的高分辨率特征。
- 4K UHD图像视频呈现快速增长，但是用于4K UHD的深度训练数据库依然较为缺失

1. 超高分辨率图像去雾

- 提出一种**多引导的双边网格学习策略**，在**低维双边网格空间**拟合分片仿射变换矩阵，针对4K (3840 × 2160) 分辨率图像可达到125fps处理速度。
- 利用不同颜色通道特征构建**边缘感知模块**，重建不同颜色通道之间纹理互补的高分辨率特征，用于恢复更清晰的对比度和细节边缘



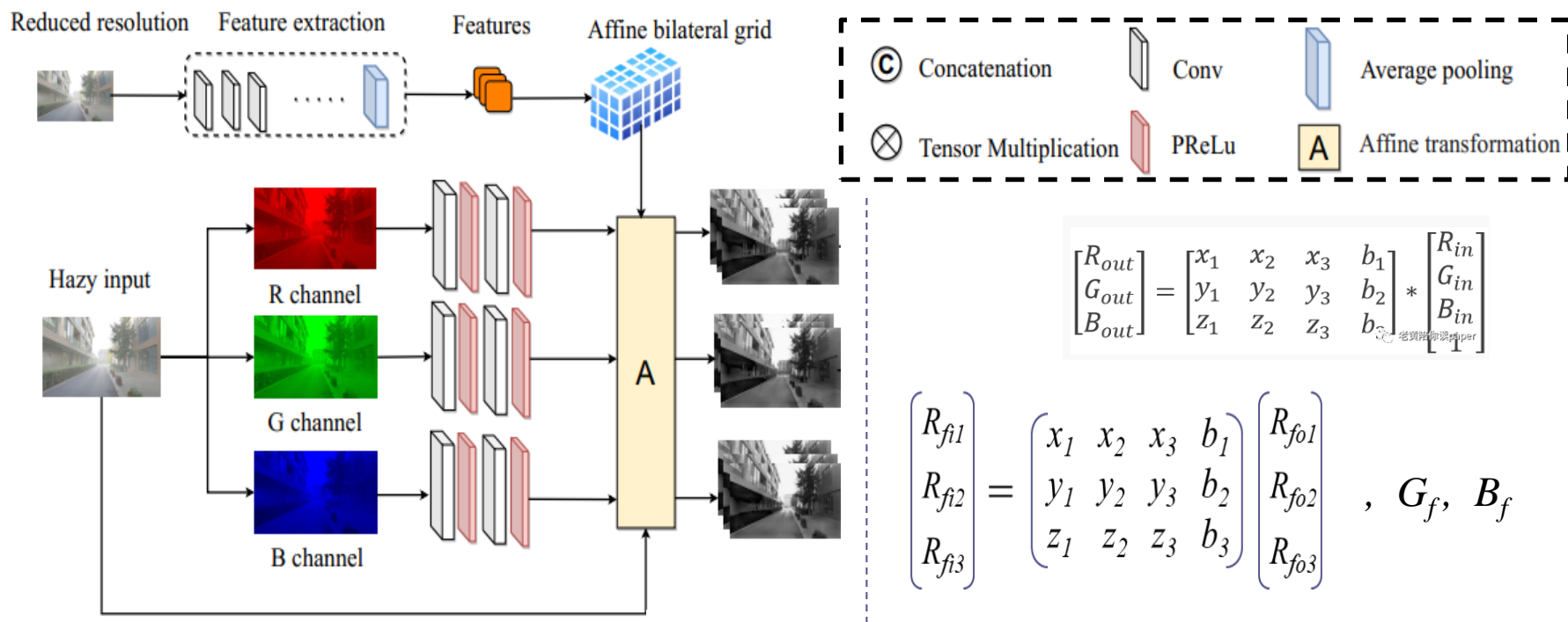
$$B_d[x', y', c'] \leftrightarrow F[x, y, c]$$

Affine bilateral grid: a $7 \times 8 \times 8$ bilateral grid, where each grid cell contains 12 numbers, one for each coefficient of a 3×4 affine transformation matrix.

借助于多引导双边网格学习的超高清图像去雾

1. 超高分辨率图像去雾

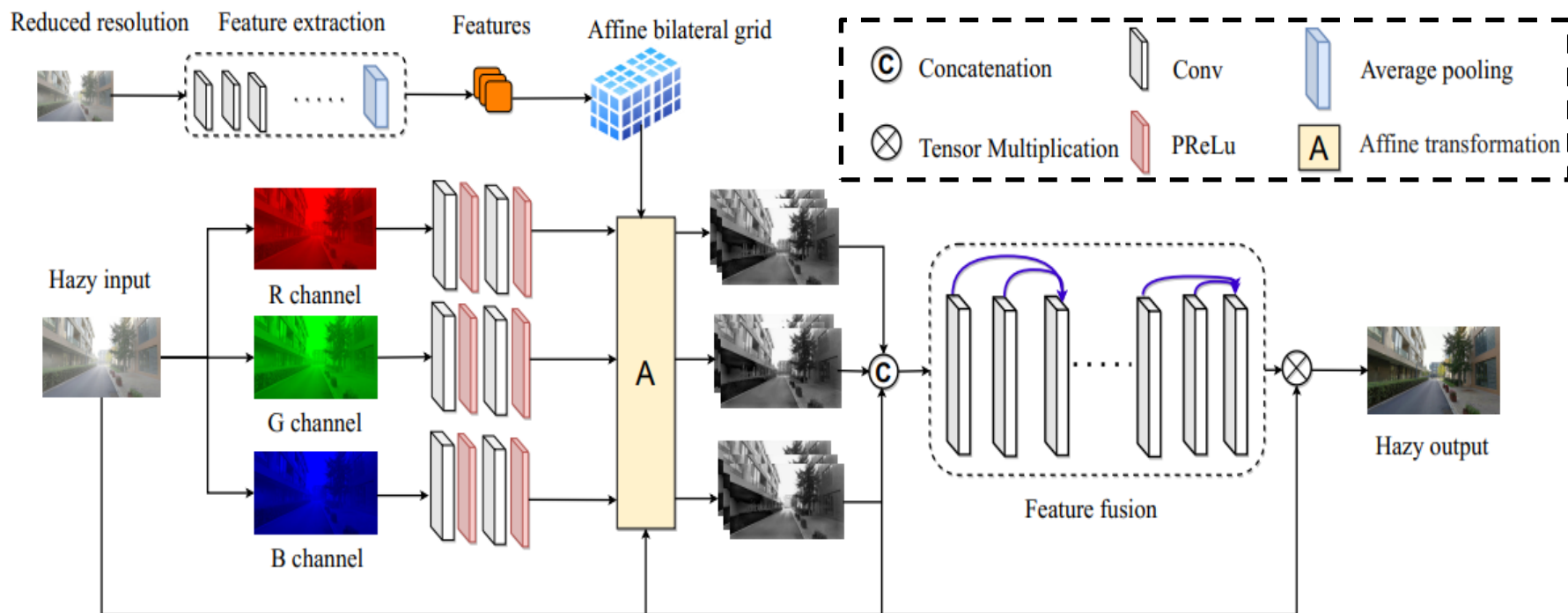
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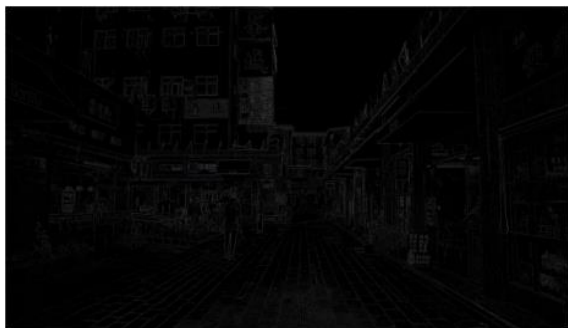
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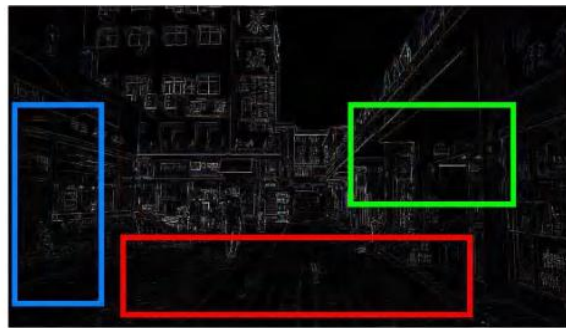
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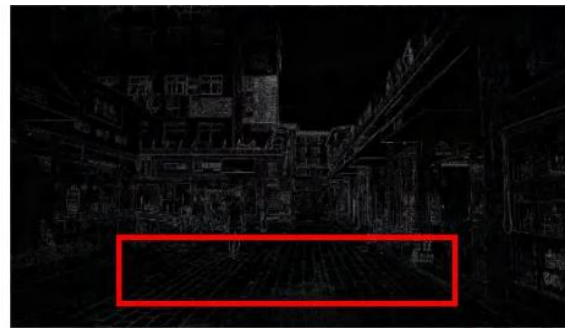
● 多引导 vs 单引导的双边网格学习



(a) Edge of hazy input



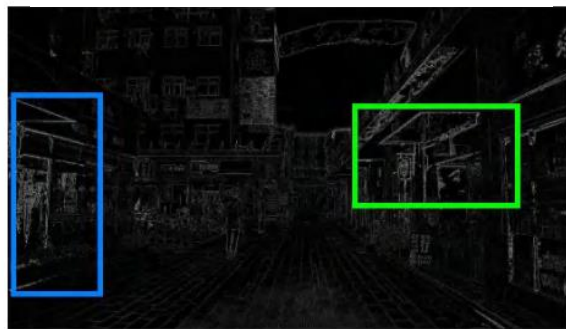
(b) Edge of single guided



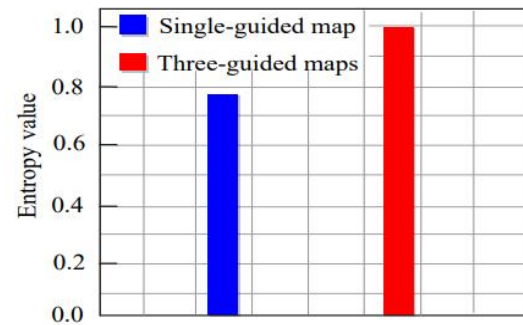
(c) Edge of multi-guided "R"



(d) Edge of multi-guided "G"



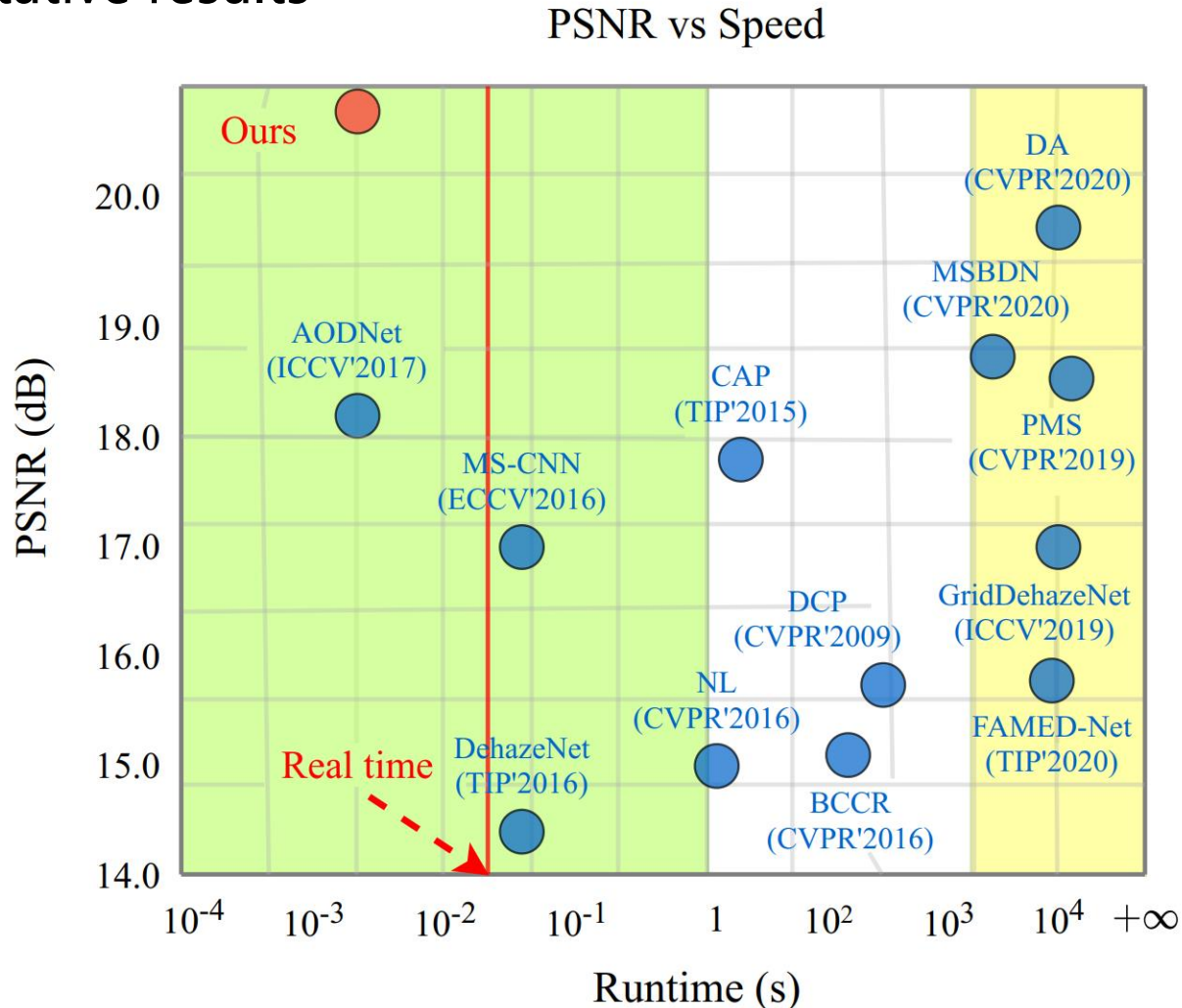
(e) Edge of multi-guided "B"



(f) entropies

1. 超高分辨率图像去雾

■ Quantitative results



TITAN RTX 24G



1. 超高分辨率图像去雾



Zhuoran Zheng, **Wenqi Ren***, Xiaochun Cao, Xiaobin Hu, Tao Wang, F. Song and X. Jia, *Ultra-high-definition image dehazing via multi-guided bilateral learning*, CVPR 2021

1. 超高分辨率图像去雾



(a) Input

(b) DCP [23]

(c) BCCR [34]

(d) CAP [53]

(e) NLD [7]

(f) AOD [26]



(g) DehazeNet [9]

(h) GridDehazeNet [32]

(i) PMS [14]

(j) MSBDN [16]

(k) DA [40]

(l) Ours



(a) Input

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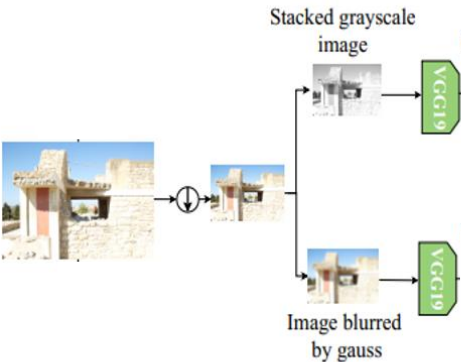
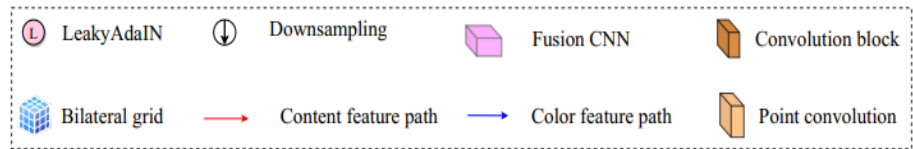
2. 超高分辨率高动态范围HDR重建

研究动机 (ICCV'2021 Collaborative Bilateral Learning)

- ✓ 单个低维的双边网格很难同时满足对于色彩、边缘、纹理等信息的拟合与建模。
- ✓ 低维双边网格的微弱噪声会引起高维重建结果中严重的伪迹效应。

2. 超高分辨率高动态范围HDR重建

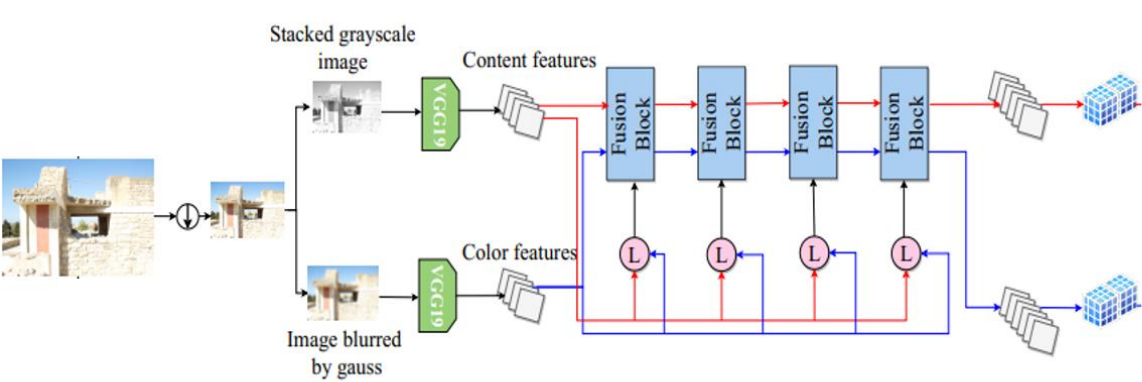
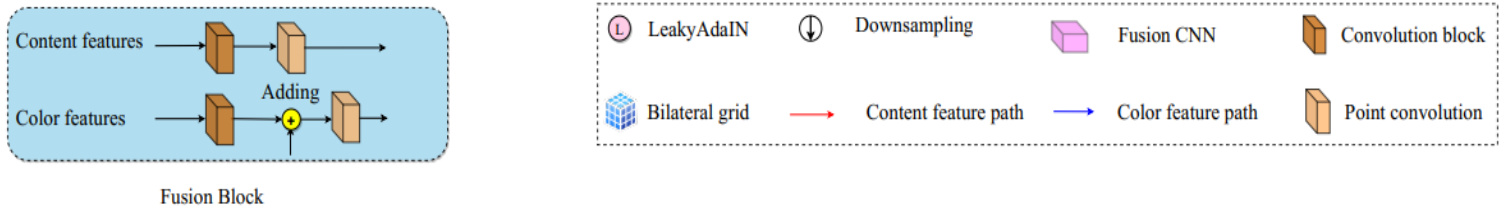
- 提出基于图像边缘/纹理双边空间和颜色双边空间协同学习的双路双边网格学习方法，同时达到实时4K HDR图像重建 (>160fps)
- 提出基于 LeakyAdaIN 的协同学习拟合数据分布特征
- 利用3D Tucker分解去除低维双边网格的噪音，减少恢复结果的伪影效应



纹理双边空间与颜色双边空间协同学习的高动态范围重建方法

2. 超高分辨率高动态范围HDR重建

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• Adaptive Instance Normalization:

$$\text{AdaIN}(x,y) = \sigma(y) \left(\frac{x - \mu(x)}{\sigma(x)} \right) + \mu(y).$$

• Leaky Adaptive Instance Normalization:

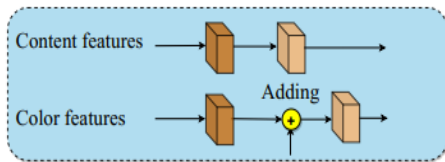
$$\text{LeakyAdaIN}(x,y) = s(p(y))\sigma(y) \left(\frac{x - \mu(x)}{\sigma(x)} \right) + s(p(y))\mu(y),$$

where $p(y)$ the global pooling and linear transformation of y , s is the sigmoid function

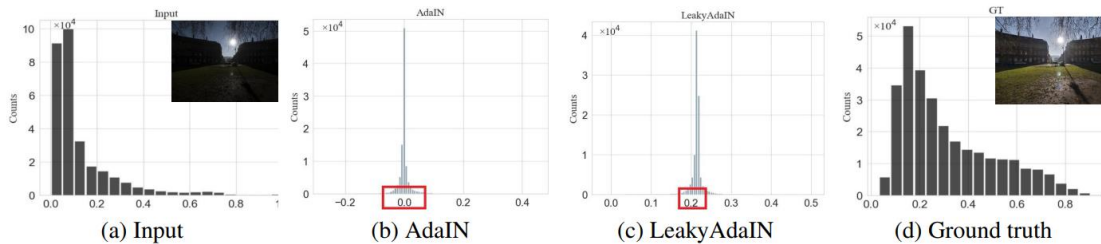
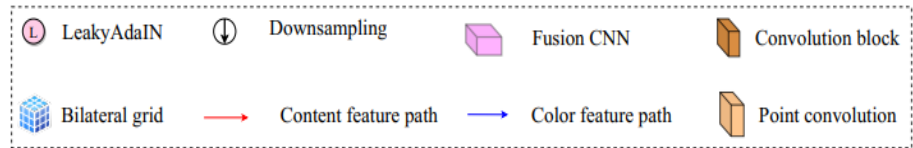
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Fusion Block



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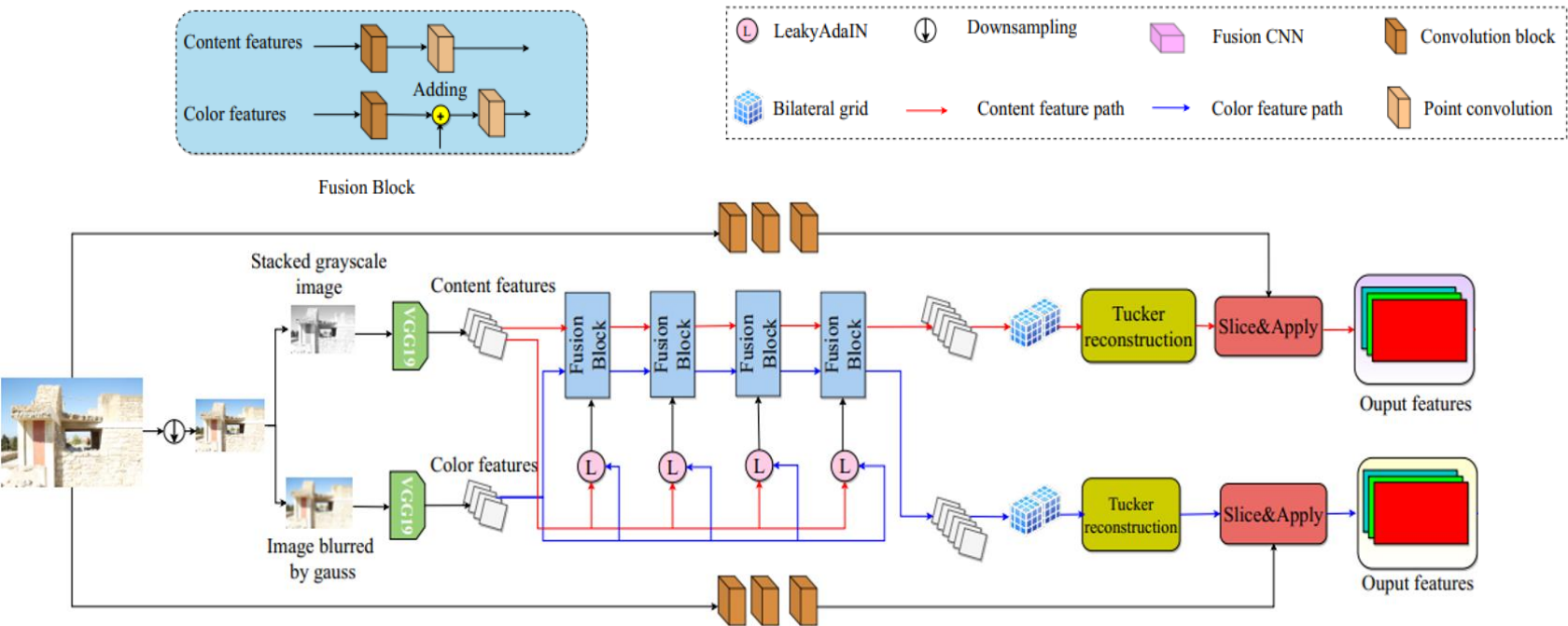
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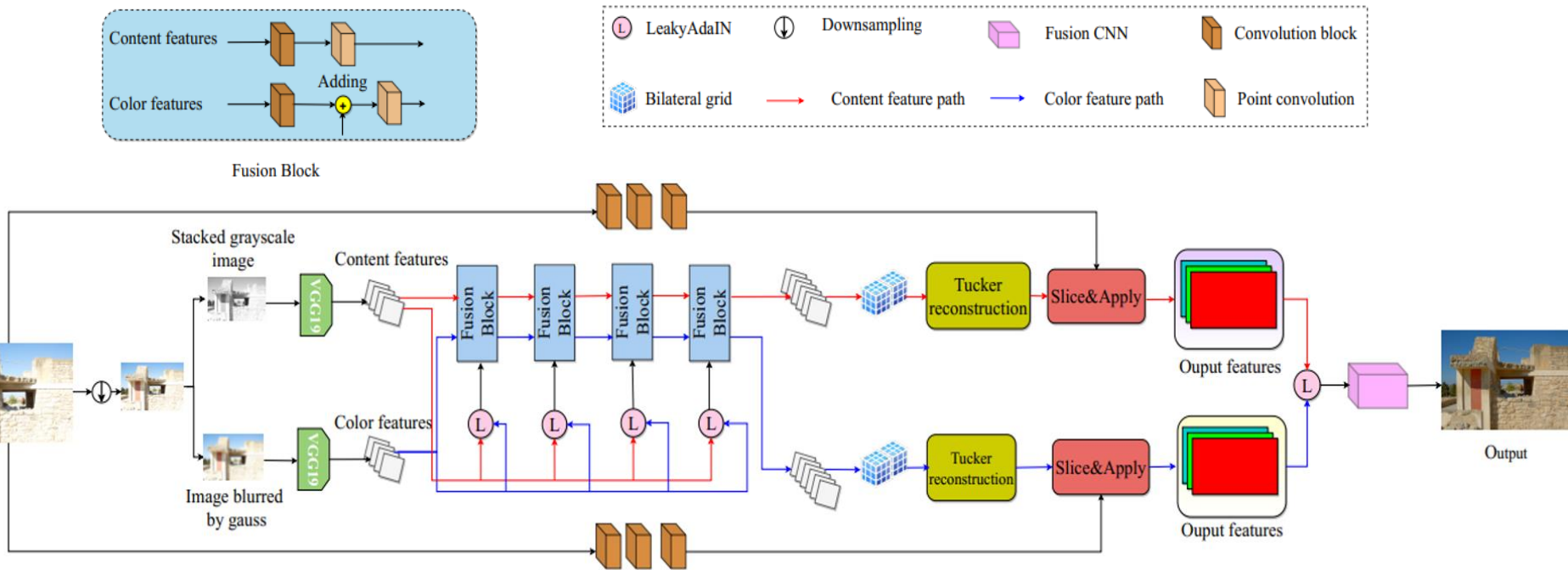
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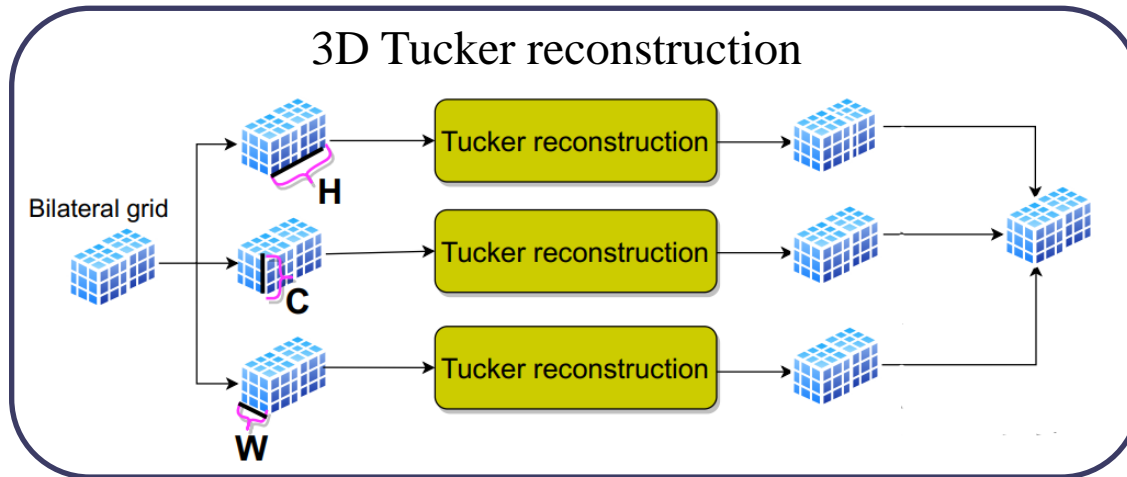
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2. 超高分辨率高动态范围HDR重建

- 协同双边学习方法可以有效地提取内容(边缘/纹理)细节和颜色分布。



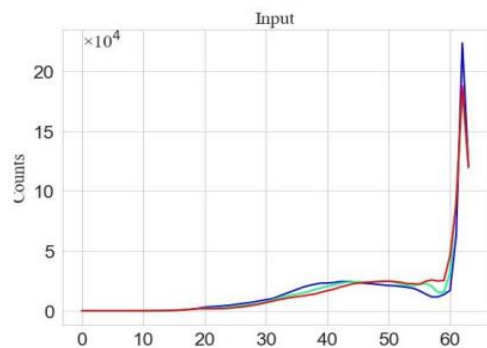
(a) Input



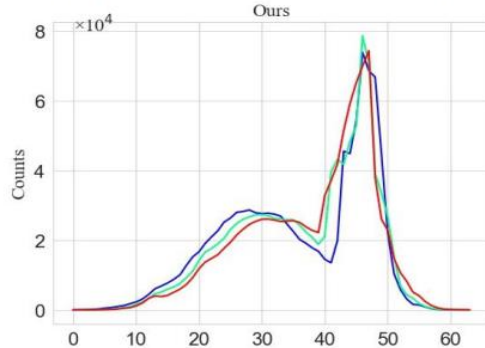
(b) Ours (texture)



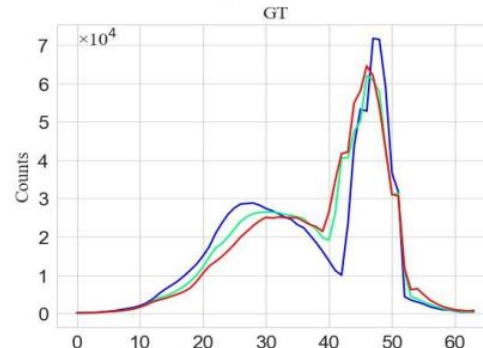
(c) GT



(d) Input



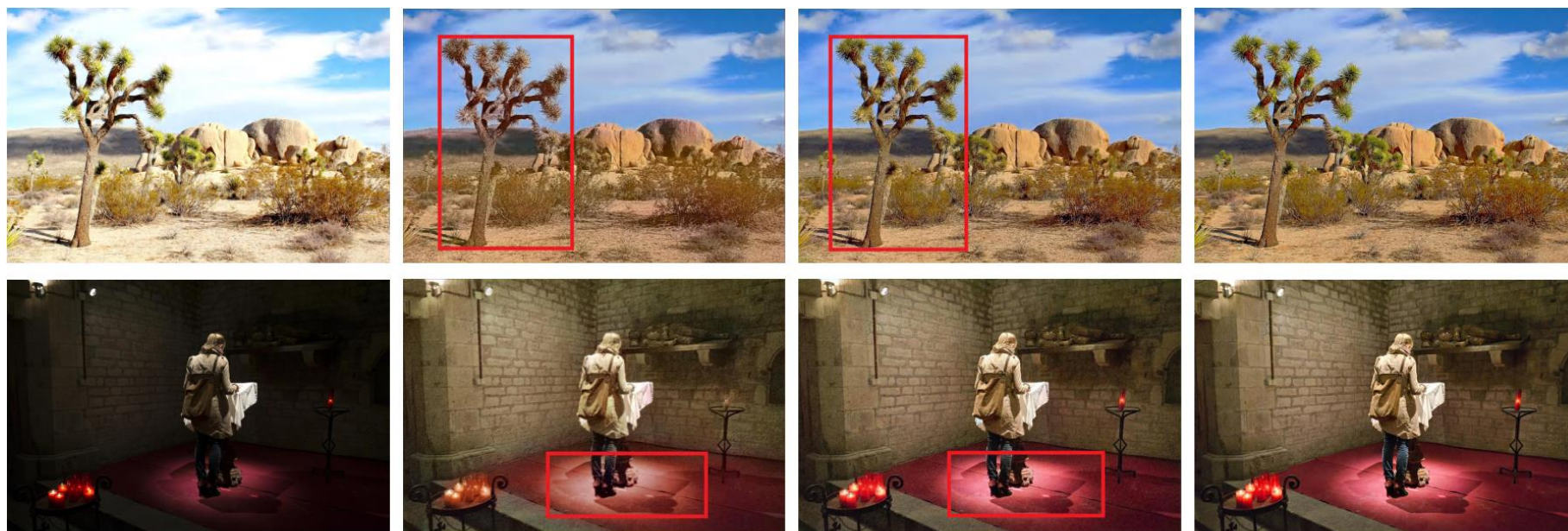
(e) Ours (color)



(f) GT

2. 超高分辨率高动态范围HDR重建

- 协同双边学习方法可以有效地提取内容(边缘/纹理)细节和颜色分布。



(a) Inputs

(b) Single path

(c) Ours

(d) Ground truths

2. 超高分辨率高动态范围HDR重建

- 3D Tucker 分解与重构可以去除恢复结果中的噪音、伪影等效应



PSNR/SSIM



22.52/0.73



21.01/0.70



23.32/0.78



$+\infty/1$



PSNR/SSIM



21.76/0.69



22.21/0.71



22.14/0.77



$+\infty/1$

(a) Inputs

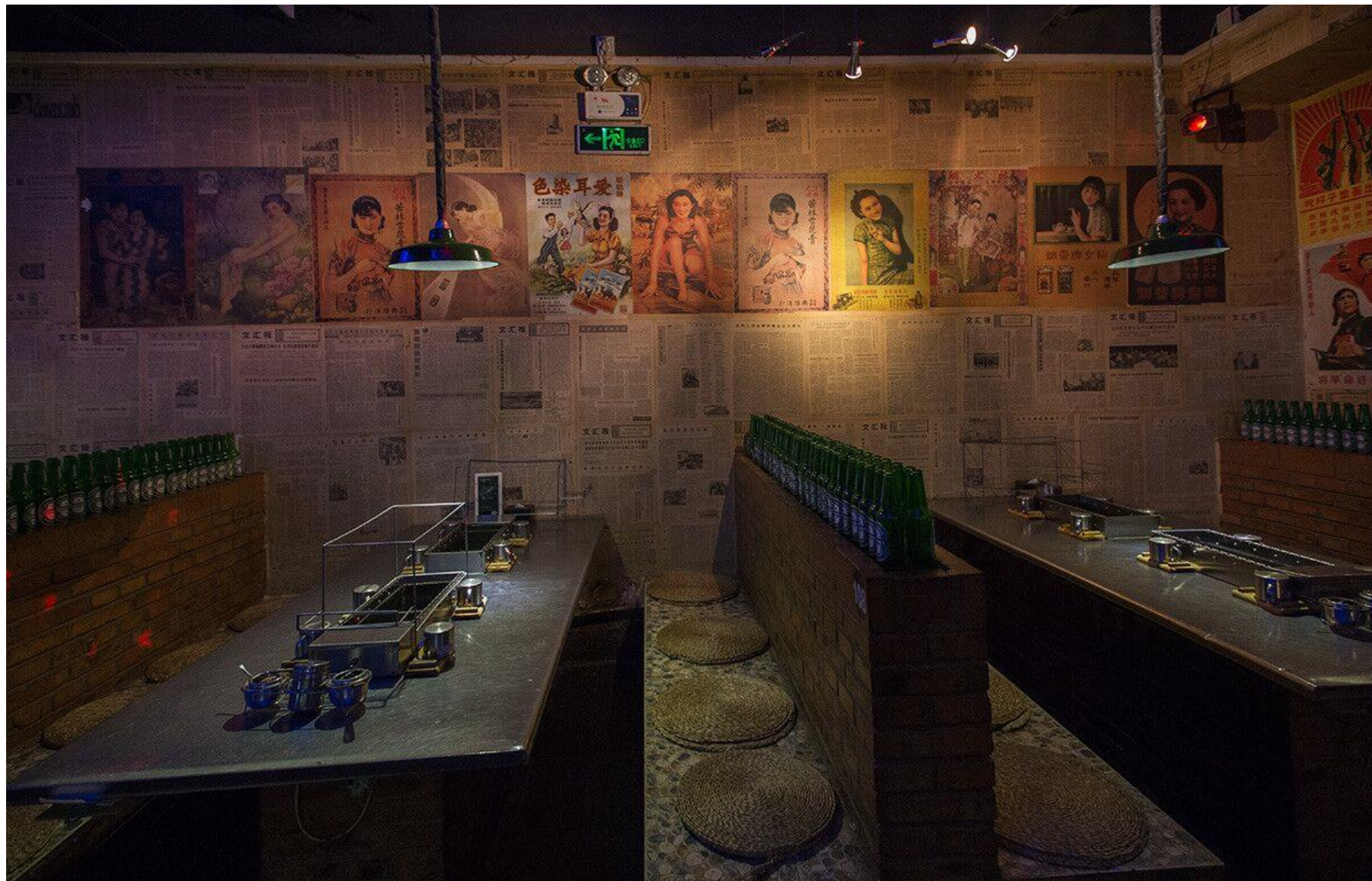
(b) w/o Tucker

(c) 1D Tucker

(d) Ours

(e) Ground truths

2. 超高分辨率高动态范围HDR重建



Zhuoran Zheng, **Wenqi Ren***, Xiaochun Cao, Tao Wang, and Xiuyi Jia, "UHD Image HDR Reconstruction via Collaborative Bilateral Learning", ICCV 2021

2. 超高分辨率高动态范围HDR重建



(a) Input

(b) LRCP

(c) ExpandNet

(d) HDRNet

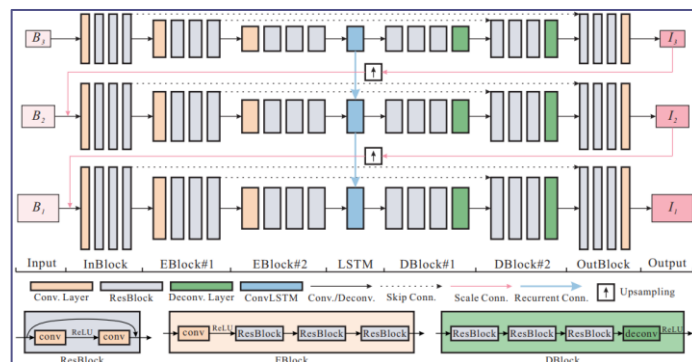
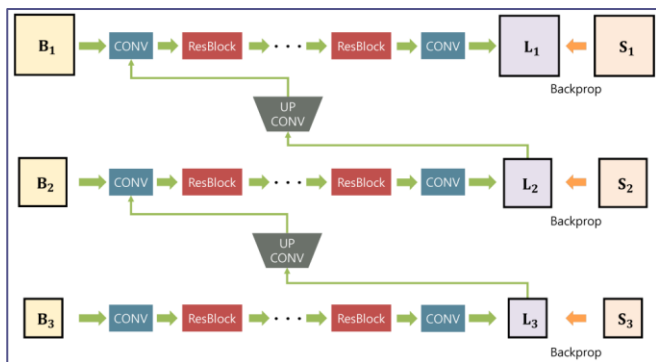
(e) 3DLUT

(f) Ours

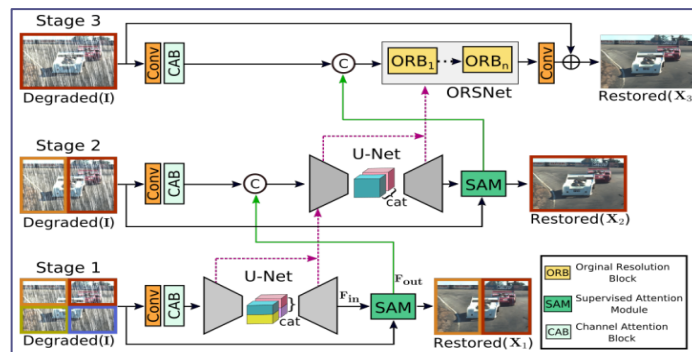
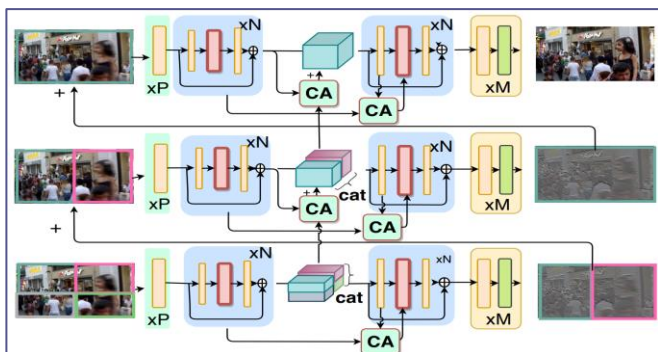
3. 超高分辨率图像/视频去模糊

研究动机 (ICCV'2021 Multi-Scale Separable Network)

- 多尺度网络可以有效模拟传统金字塔图像去模糊过程



- 多分片网络可以将网络集中在一个固定的小感知野内，提升恢复能力



3. 超高分辨率图像/视频去模糊

- 提出基于多尺度与多分片并行的视频去模糊架构，可实时处理4K超高分辨率模糊视频（30fps）
- 构建了非对称编解码结构，减少网络处理单元。
- 提出了分片并行处理策略，加速网络运行速度。

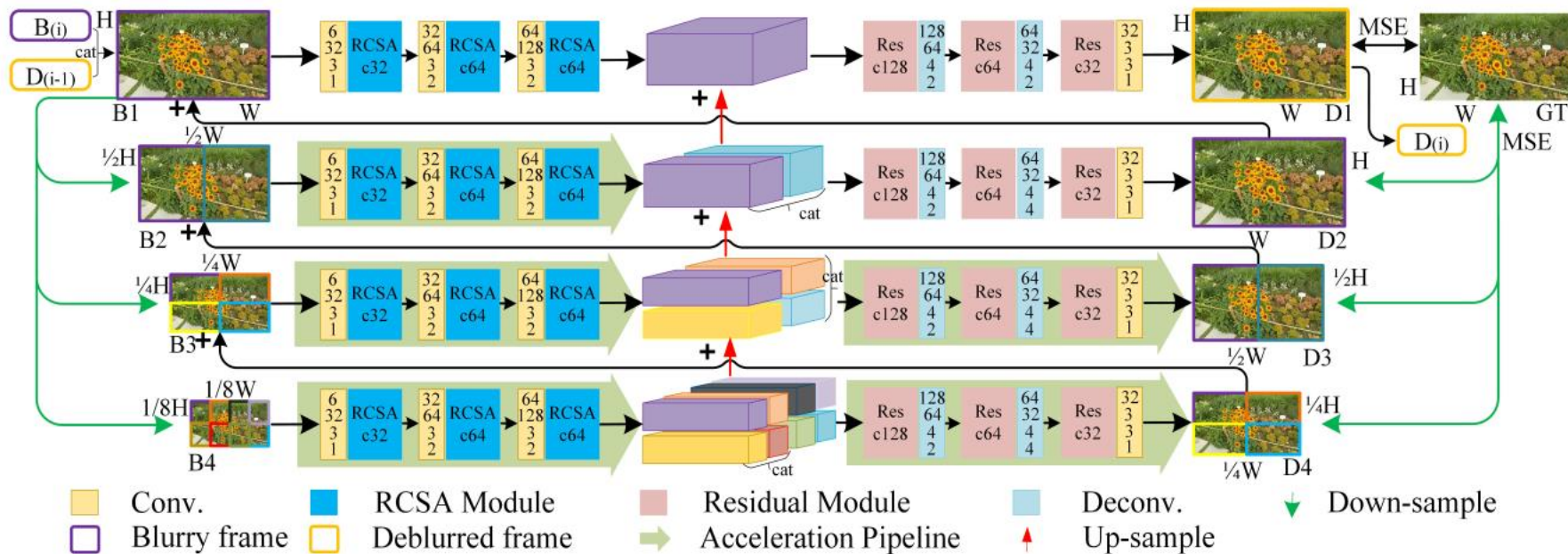


Figure 2. Our proposed UHDVD model and its some layer configurations. Symbol “+” is a summation akin to the target data

基于多尺度与多分片并行网络的超高清视频去模糊

3. 超高分辨率图像/视频去模糊

- 提出基于多尺度与多分片并行的视频去模糊架构，可实时处理4K超高分辨率模糊视频（30fps）
- 构建了非对称编解码结构，减少网络处理单元。
- 提出了分片并行处理策略，加速网络运行速度。

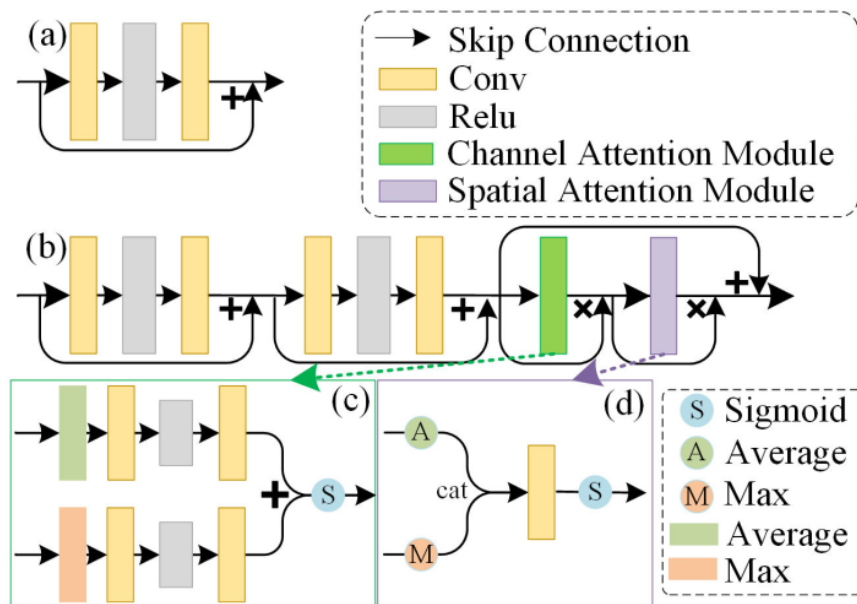


Figure 4. The structure of Residual module (a) and RCSA module (b) in UHDVD. (c) and (d) are CAM and SAM in RCSA module. Symbol “x” is point-wise multiplication and “+” is addition.

3. 超高分辨率图像/视频去模糊

- 提出基于多尺度与多分片并行的视频去模糊架构，可实时处理4K超高分辨率模糊视频（30fps）
- 构建了非对称编解码结构，减少网络处理单元。
- 提出了分片并行处理策略，加速网络运行速度。

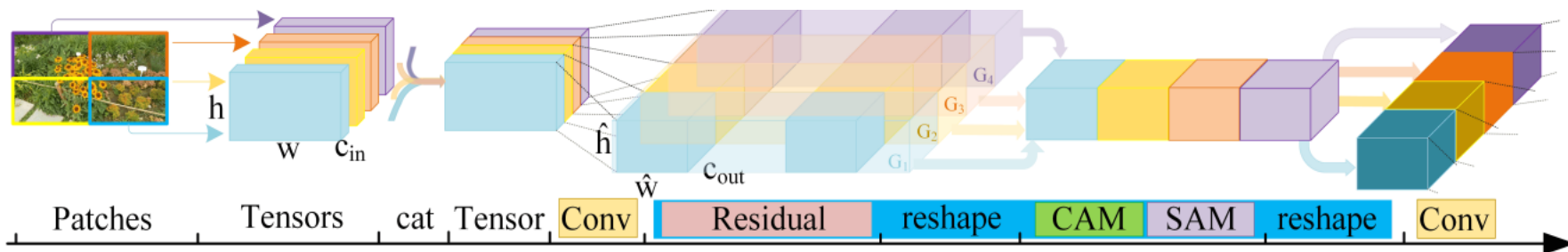
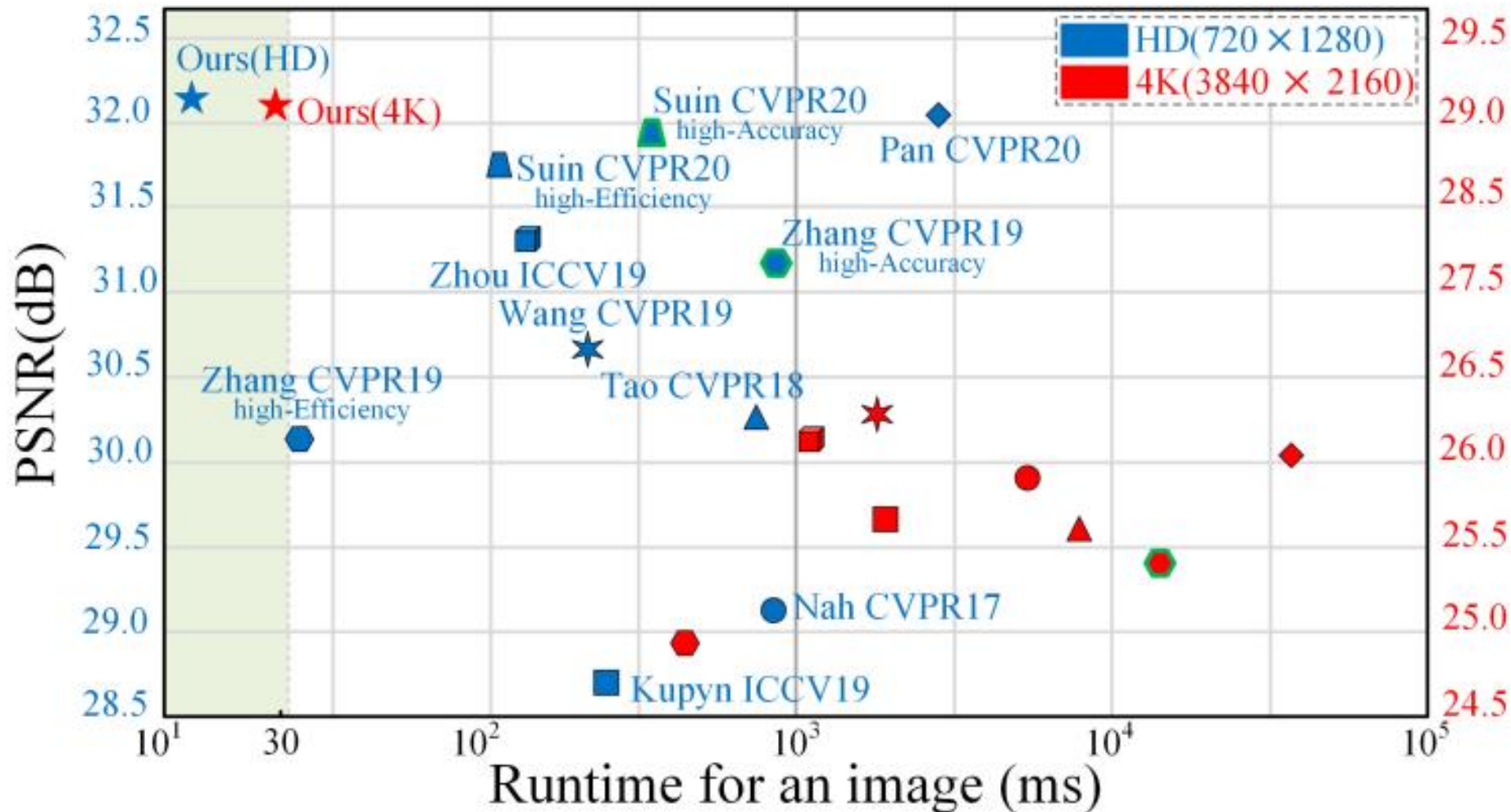


Figure 3. The separable-patch acceleration architecture. Taking the encoder branch of scale 3 before the second RCSA module as an example, where G_i is the group number in convolutional layers.

3. 超高分辨率图像/视频去模糊

- Quantitative results



3. 超高分辨率图像/视频去模糊

● Quantitative results

Methods		MSResNet [19]	SRN [48]	DeblurGAN-v2 [46]	DMPHN [23] Stack(4)/(1-2-4-8)	EDVR [26]	CDVD-TSP [24]	STFAN [22]	Ours
720P GoPro [19]	PSNR	28.45	30.10	29.55	31.20/30.25	26.87	31.67	28.63	<u>31.45</u>
	SSIM	0.917	0.932	0.934	0.945/0.935	0.843	0.928	0.863	0.923
	Time (ms)	747.8	731.7	293.6	1029.3/ <u>30.9</u>	384.6	4216.6	150.4	25.3
720P DVD [25]	PSNR	28.98	29.10	28.54	30.47/29.91	30.27	<u>32.13</u>	31.24	32.25
	SSIM	0.885	0.899	0.925	0.881/0.866	0.917	0.927	<u>0.934</u>	0.940
	Time (ms)	775.8	783.6	312.2	987.9/ <u>30.4</u>	289.2	4098.2	177.2	27.6
720P REDS [33]	PSNR	26.49	25.40	25.61	25.18/25.06	30.63*	26.29	25.49	<u>27.96</u>
	SSIM	0.742	0.734	0.731	0.724/0.724	0.850*	0.774	0.719	<u>0.827</u>
	Time (ms)	802.6	823.3	350.8	1069.9/ <u>29.3</u>	325.7	3765.6	155.7	26.9
2K Slow-Flow [35]	PSNR	27.70	<u>28.81</u>	28.75	28.29/27.94	26.42	28.64	28.23	29.03
	SSIM	0.817	<u>0.827</u>	0.817	0.813/0.807	0.797	<u>0.830</u>	0.825	0.834
	Time (ms)	2303.5	2677.1	833.6	3589.6/ <u>58.9</u>	1302.7	7491.5	326.0	38.5
4K 4KRD	PSNR	25.81	25.58	25.64	24.99/24.91	26.36	<u>26.43</u>	26.14	28.21
	SSIM	0.778	0.759	0.763	0.757/0.748	<u>0.803</u>	0.793	0.800	0.849
	Time (ms)	7543.4	8723.3	3283.4	10378.1/ <u>399.4</u>	2428.1	26922.9	953.2	57.9

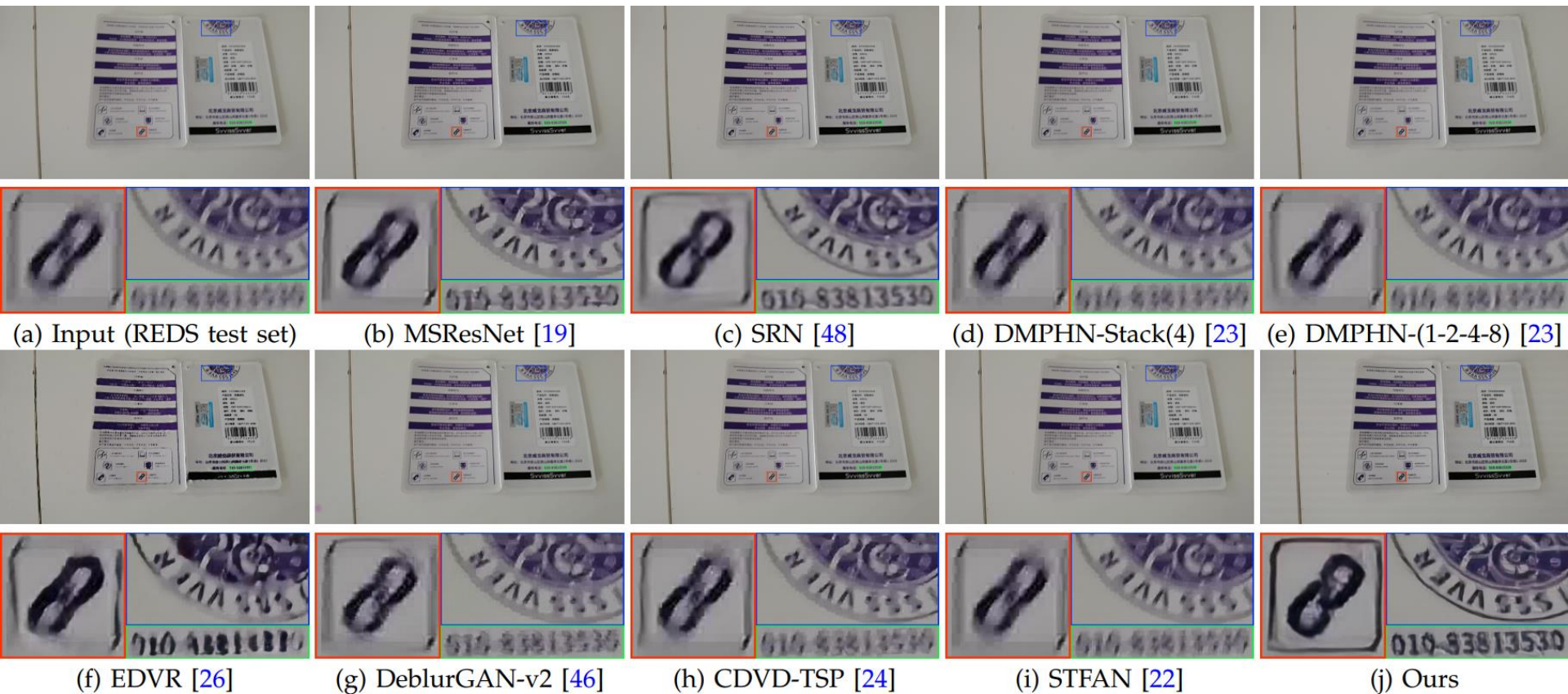
3. 超高分辨率图像/视频去模糊

- Qualitative results



3. 超高分辨率图像/视频去模糊

- Qualitative results



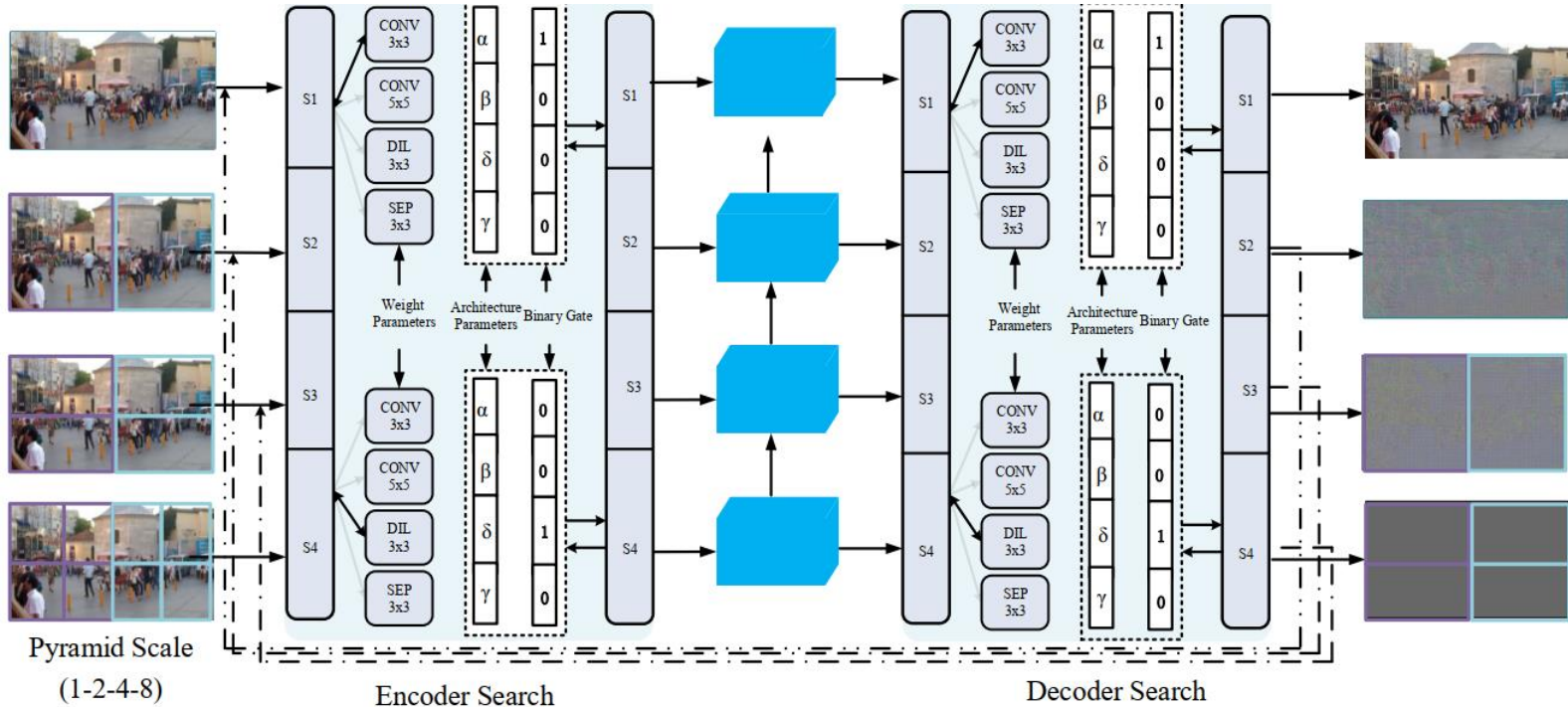
3. 超高分辨率图像/视频去模糊

研究动机 (ICCV'2021 Pyramid Architecture Search)

- ✓ 多尺度、多分片网络参数多为人工经验设定
- ✓ 网络参数量大，无法达到实时去模糊与准确去模糊的有效平衡点

3. 超高分辨率图像/视频去模糊

- 提出自动搜索多尺度（尺度/分片/卷积）模糊去除网络架构



- Pyramid variable: scale depth $1 \leq D \leq 4$;
- Pyramid variable: multi-patch hierarchy scheme $[1, p_2, \dots, p_N]$, p_N denotes the patch number at N scale;
- Conv operators: 3×3 convolution;
- Conv operators: 5×5 convolution;
- Dilation operators: 3×3 convolution with dilation rate of 2;
- Separable operators: 3×3 separable convolution;
- Zero operators: no connection and return zero;

3. 超高分辨率图像/视频去模糊

- 搜索策略一：不同层的网络参数完全共享 ($PyNAS_s$)

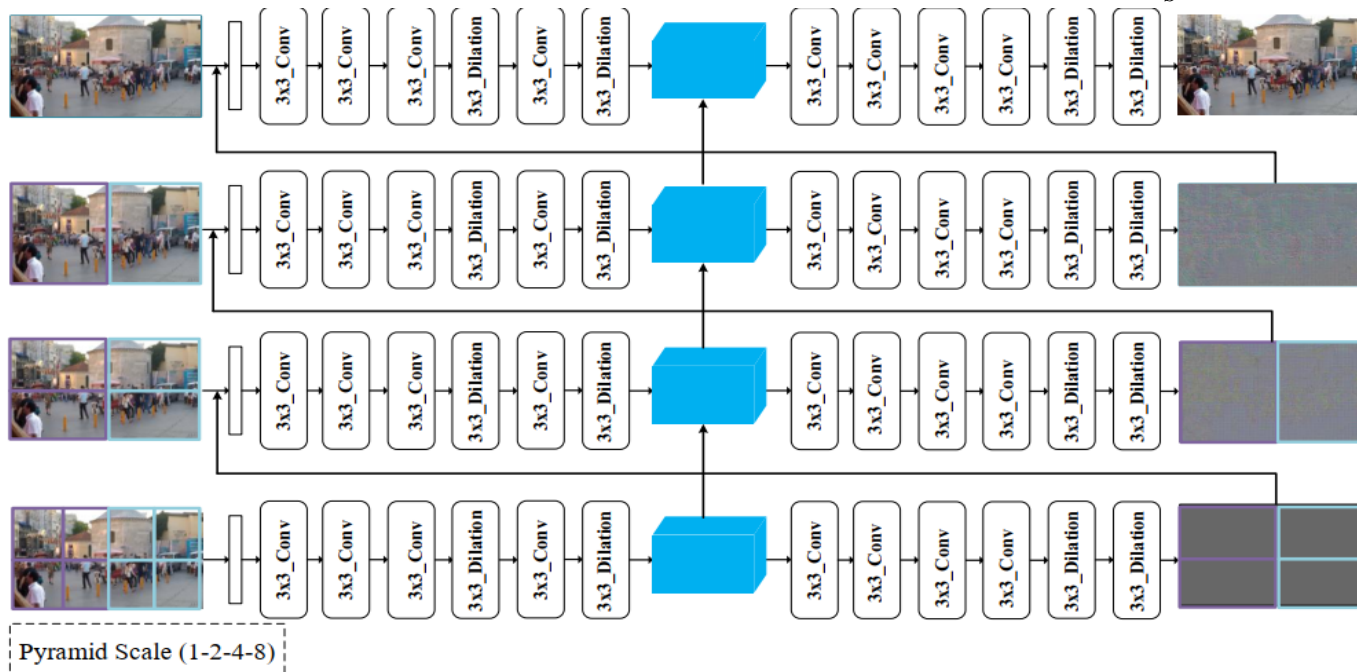


Figure 2. PyNAS_s: Our proposed pyramid architecture search (PyNAS) using the pyramid patch scheme (1-2-4-8) and scale depth (4). The non-overlap multi-patch hierarchy is used as the input of the network. PyNAS searches the whole encoder and decoder structure of each scale of the network from the operator candidates and the path binarization is exploited to search for the best operator.

- Pyramid variable: scale depth $1 \leq D \leq 4$;
- Pyramid variable: multi-patch hierarchy scheme $[1, p_2, \dots, p_N]$, p_N denotes the patch number at N scale;
- Conv operators: 3×3 convolution;
- Conv operators: 5×5 convolution;
- Dilation operators: 3×3 convolution with dilation rate of 2;
- Separable operators: 3×3 separable convolution;
- Zero operators: no connection and return zero;

3. 超高分辨率图像/视频去模糊

- 搜索策略二：不同层的网络参数相互独立 ($PyNAS_d$)

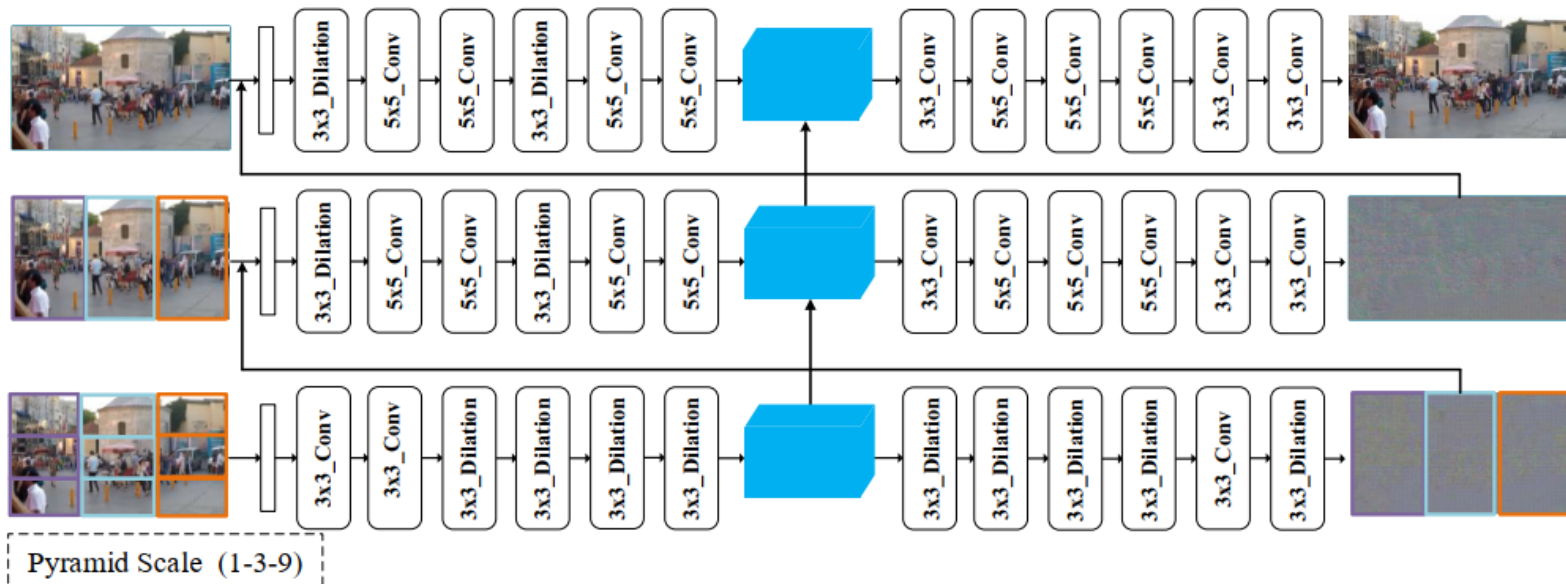


Figure 1. PyNAS_d: Our proposed pyramid architecture search (PyNAS) using the pyramid patch scheme (1-3-9) and scale depth (3). The non-overlap multi-patch hierarchy is used as the input of the network. PyNAS searches the whole encoder and decoder structure of each scale of the network from the operator candidates and the path binarization is exploited to search for the best operator. It is noteworthy that our PyNAS finds a better pyramid network architecture (1-3-9) using less inference time and shallower scale depth.

- Pyramid variable: scale depth $1 \leq D \leq 4$;
- Pyramid variable: multi-patch hierarchy scheme $[1, p_2, \dots, p_N]$, p_N denotes the patch number at N scale;
- Conv operators: 3×3 convolution;
- Conv operators: 5×5 convolution;
- Dilation operators: 3×3 convolution with dilation rate of 2;
- Separable operators: 3×3 separable convolution;
- Zero operators: no connection and return zero;

3. 超高分辨率图像/视频去模糊

● 提出自动搜索多尺度（尺度/分片/卷积）模糊去除网络架构

Table 1. Quantitative results on the GoPro test dataset. Size and Runtime are addressed in MB and Millisecond (*ms*). The reported time is only network inference time excluding the time of writing generated images to disk. We expand search space of the hierarchy multi-patch scheme to odd types (such as [1-3-9]). The best results are highlighted in bold and the second best is in underline.

GoPro dataset				
Models	PSNR	SSIM	Size	Runtime
Sun <i>et al.</i> [24]	24.64	0.8429	54.1	12000
Nah <i>et al.</i> [16]	29.23	0.9162	303.6	4300
Zhang <i>et al.</i> [32]	29.19	0.9306	37.1	1400
Tao <i>et al.</i> [25]	30.10	0.9323	33.6	1600
Zhang <i>et al.</i> [31]	30.25	0.9351	29.0	30
Yuan <i>et al.</i> [29]	29.57	0.9338	3.1	10
Ours (PyNAS _s)	<u>30.51</u>	0.9391	20.7	26
Ours (PyNAS _d)	30.62	0.9405	35.9	<u>17</u>

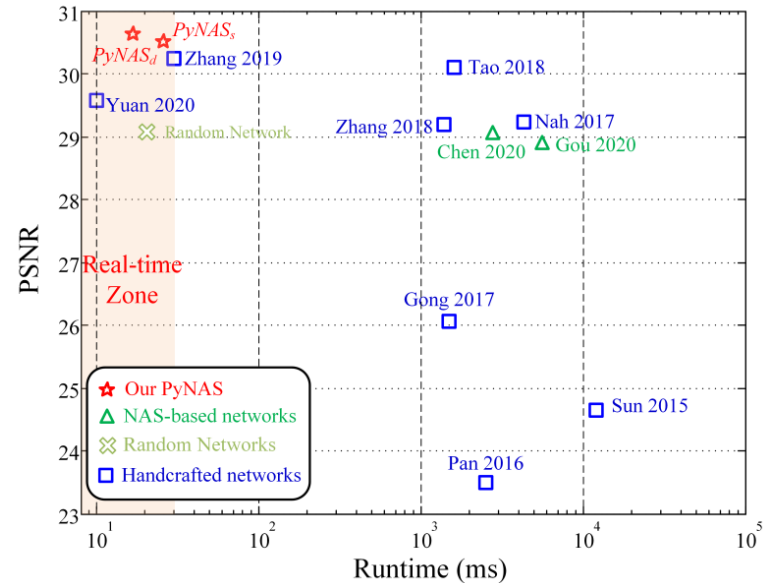


Table 2. Quantitative results (PSNR) on the VideoDeblurring dataset. Our models are trained on GoPro dataset and then generalized on the VideoDeblurring dataset.

GoPro dataset											
Models	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	Average
Input	24.14	30.52	28.38	27.31	22.60	29.31	27.74	23.86	30.59	26.98	27.14
PSDeblur	24.42	28.77	25.15	27.77	22.02	25.74	26.11	19.75	26.48	24.62	25.08
WFA [2]	25.89	32.33	28.97	28.36	23.99	31.09	28.58	24.78	31.30	28.20	28.35
Su <i>et al.</i> [22]	25.75	31.15	29.30	28.38	23.63	30.70	29.23	25.62	31.92	28.06	28.37
Zhang <i>et al.</i> [31]	29.89	33.35	31.82	31.32	26.35	32.49	30.51	27.11	34.77	30.02	30.76
Ours (PyNAS _d)	30.11	33.52	31.92	31.54	26.44	32.73	30.69	27.51	35.07	30.45	31.01

3. 超高分辨率图像/视频去模糊

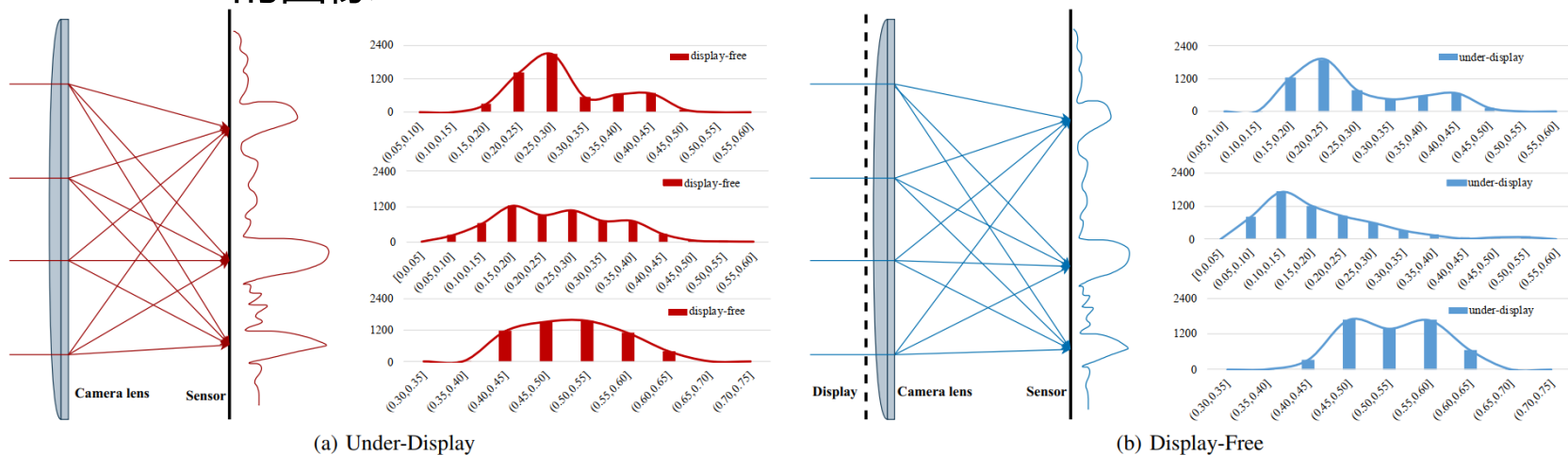
- 搜索发现
 - ✓ 1st, 2nd 尺度趋向于搜索到 large size kernel
 - ✓ 3rd, 4th 尺度趋向于搜索到 small size kernel
 - ✓ 所有的网络层都趋向于使用 dilation kernel
 - ✓ 共享搜索：尺度/分片跨度范围较小
 - ✓ 独立搜索：尺度/分片跨度范围较大
 - ✓ 删除掉不必要的skip/recurrent connections,
 - ✓ 减少 number of upsampling/deconvolution between convolutional features

4. 超高分辨率屏下摄像图像增强



研究动机 (Trans. IP'2022 UDC Image Enhancement)

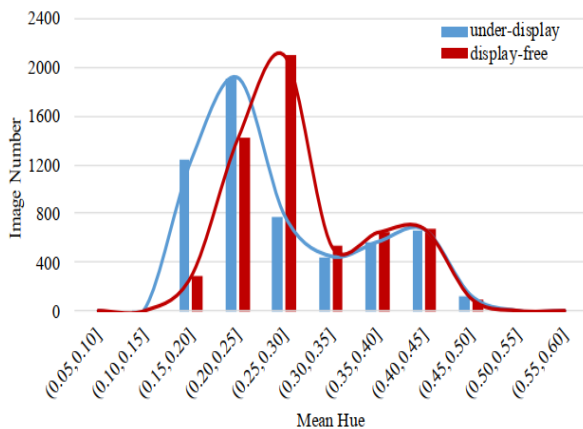
- 图像间的映射方法并非基于图像数据分布差异进行特定的增强曲线估计，无法用于像素级的自适应调整
- 由于真实图像不易获取，大多方法在合成数据集上进行模型训练，合成数据集图像种类有限，训练模型往往在真实场景中表现较差
- 屏下摄像图像增强问题处于初步探索阶段，局限于数量有限的成对数据集，其中一些方法由于网络参数量大，计算成本较高，无法直接处理分辨率大于 1080×720 的图像



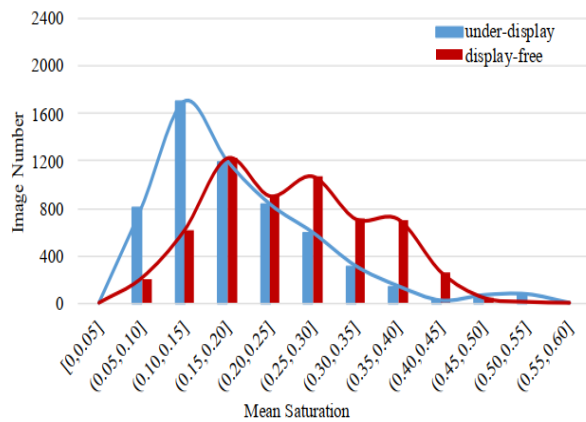
光线传输过程

4. 超高分辨率屏下摄像图像增强

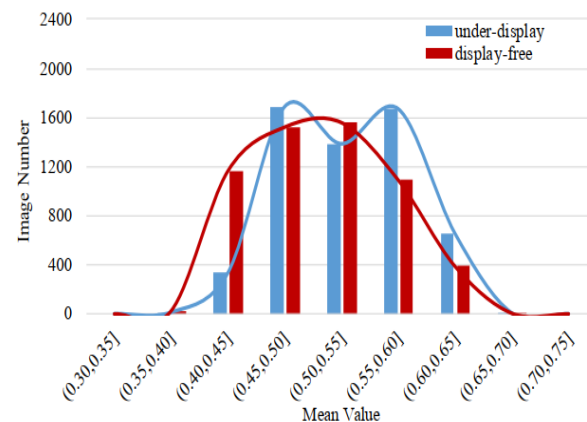
- 分析了 HSV 颜色空间各通道的统计特性



(a) Hue Channel



(b) Saturation Channel

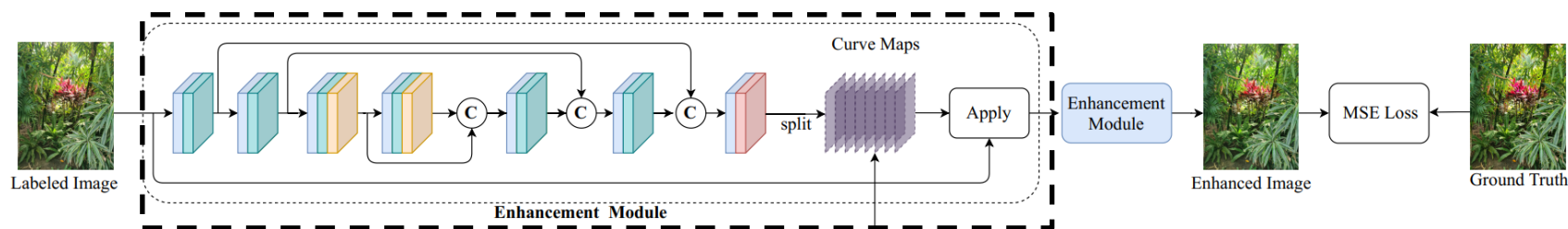


(c) Value Channel

HSV颜色空间各通道统计特性

4. 超高分辨率屏下摄像图像增强

- 分析了 HSV 颜色空间各通道的统计特性
- 设计增强曲线估计网络并进行级联，实现低质量图像迭代增强，拟合图像对之间的高阶映射关系



Pixelwise curve adjustment:

$$CE(I(x); \alpha) = I(x) + \alpha I(x)(1 - I(x)),$$

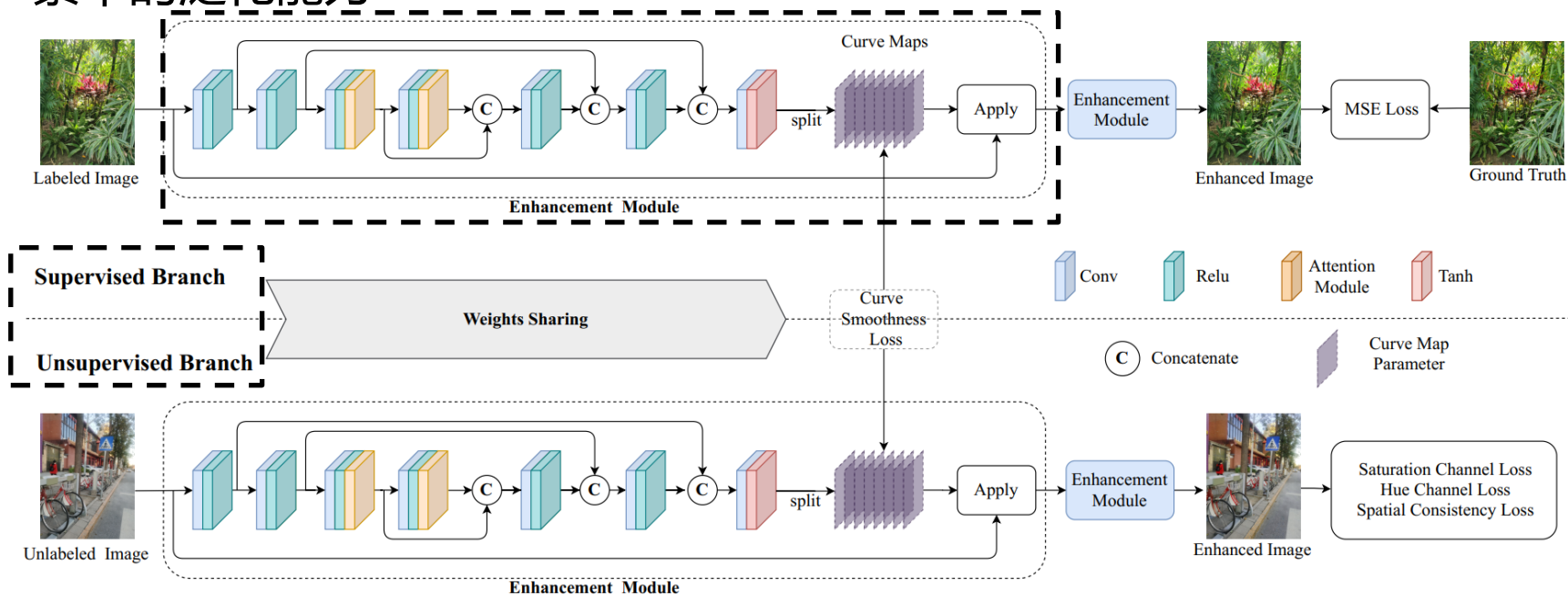
Iterative enhancement operation:

$$CE_n(I(x); \alpha) = CE_{n-1}(x) + \varphi_n(x)CE_{n-1}(x)(1 - CE_{n-1}(x)),$$

基于级联曲线估计的屏下摄像图像增强

4. 超高分辨率屏下摄像图像增强

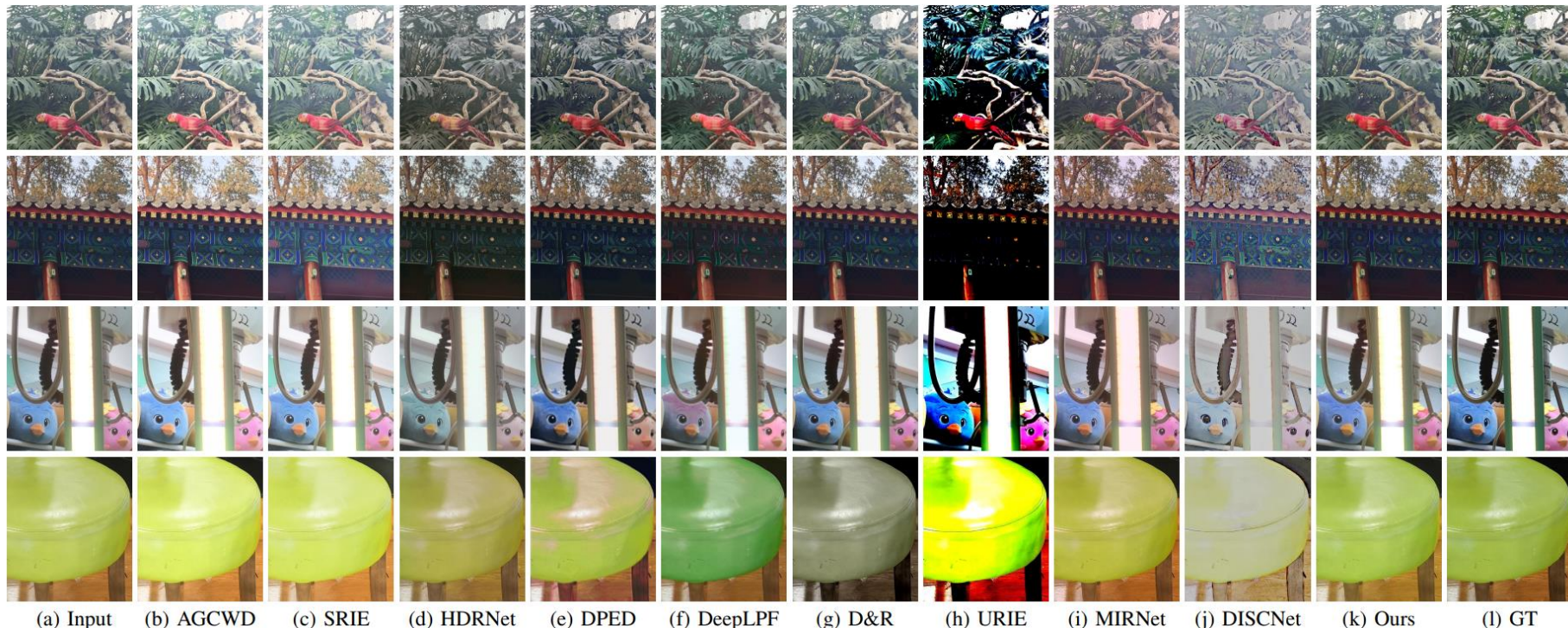
- 分析了 HSV 颜色空间各通道的统计特性
- 设计增强曲线估计网络并进行级联，实现低质量图像迭代增强，拟合图像对之间的高阶映射关系
- 采用半监督学习方式，缓解对大量配准数据对的需求，提高模型在真实场景中的泛化能力



基于级联曲线估计的屏下摄像图像增强

4. 超高分辨率屏下摄像图像增强

● Evaluation on Full-Reference Images

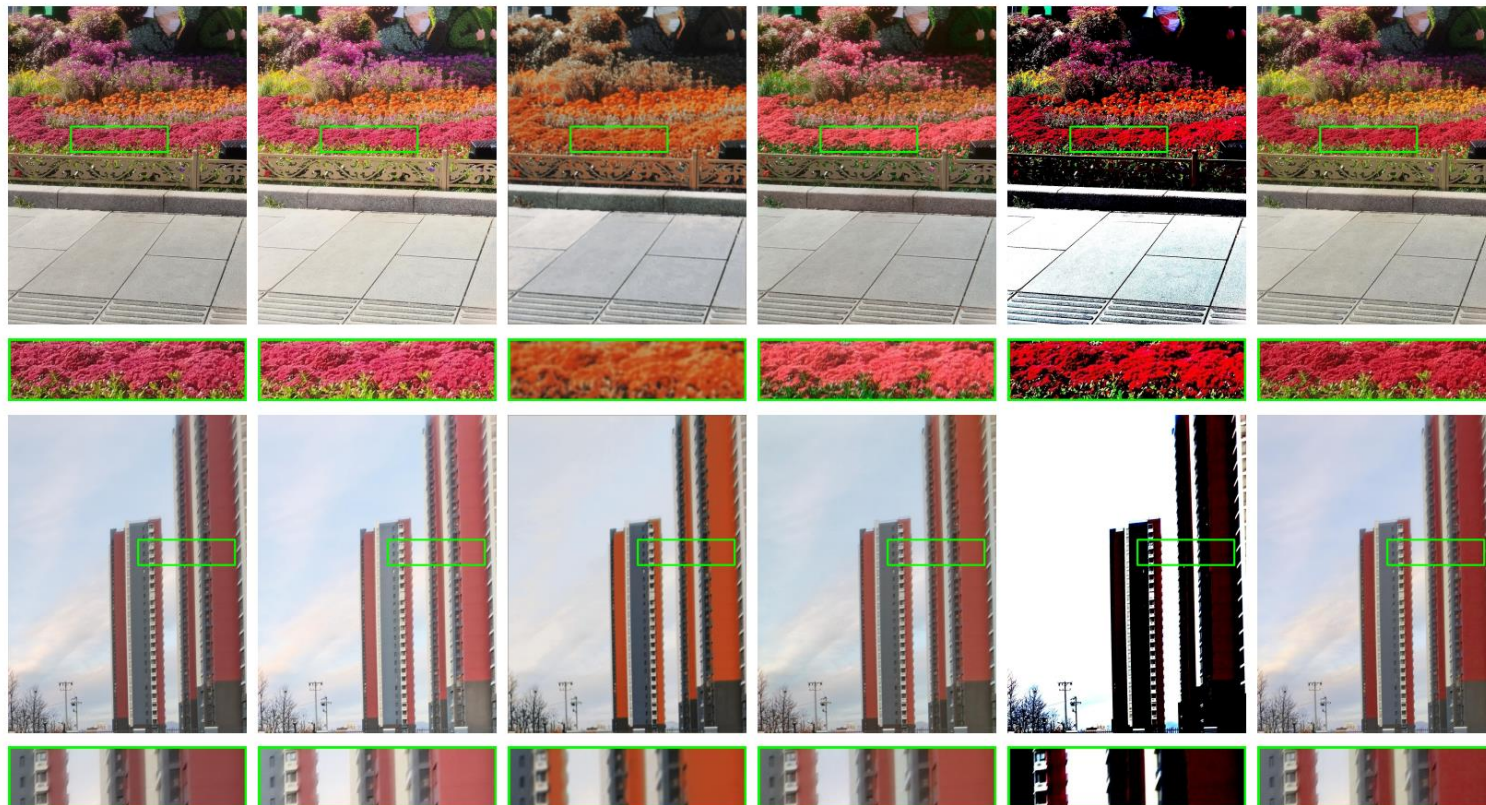


Methods	Input	AGCWD	SRIE	HDRNet	DPED	DeepLPPF	D&R	URIE	MIRNet	DISCNet	Ours
$SSIM_{rgb}$	0.906	0.838	0.825	0.900	0.809	0.853	<u>0.907</u>	0.412	0.909	0.675	0.909
$PSNR_{rgb}$	24.178	15.621	15.123	23.381	23.156	22.727	24.852	12.423	24.399	15.328	<u>24.602</u>
$SSIM_{hs}$	0.699	<u>0.702</u>	0.698	0.665	0.555	0.501	<u>0.702</u>	0.129	0.600	0.412	0.708
$PSNR_{hs}$	17.545	17.582	17.560	17.415	16.687	16.311	<u>17.780</u>	8.901	15.296	12.414	18.122
$SSIM_{gray}$	0.912	0.849	0.839	0.911	0.834	0.882	0.914	0.420	<u>0.915</u>	0.702	0.916
$PSNR_{gray}$	25.082	15.829	15.381	24.305	23.769	23.832	25.758	12.438	<u>25.523</u>	15.790	25.501

Jun Luo, **Wenqi Ren***, Tao Wang, Chongyi Li, and Xiaochun Cao. "Under-Display Camera Image Enhancement via Cascaded Curve Estimation", **TIP 2022**.

4. 超高分辨率屏下摄像图像增强

● Evaluation on Non-Reference Images



(a) Input

(b) SRIE

(c) DPED

(d) DeepLPF

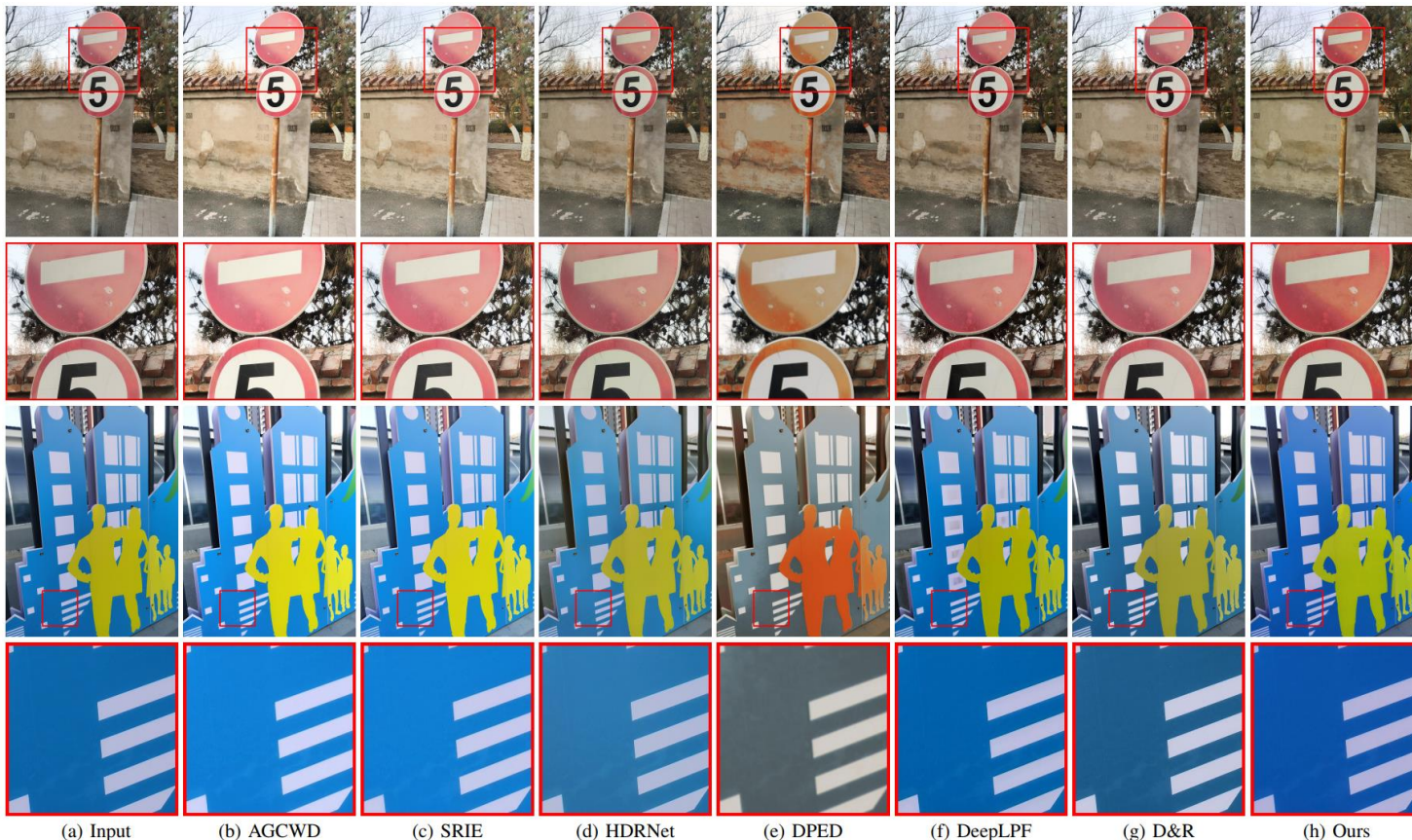
(e) URIE

(f) Ours

Methods	SRIE [36]	DPED [13]	DeepLPF [14]	URIE [16]	Ours
BIQI/SSEQ	34.01/43.61	53.71/52.16	39.16/45.86	36.00/44.43	33.24/ 43.33

4. 超高分辨率屏下摄像图像增强

● Evaluation on 4K UHD Images



CPU/GPU	AGCWD [35]	SRIE [36]	HDRNet [12]	DPED [13]	DeepLPF [14]	D&R [15]	URIE [16]	MIRNet [17]	Ours
1068 × 1224	0.060/-	1.73/-	-0.010	-4.20	-0.12	-0.24	-0.005	-0.94	-0.005
4K	0.576/-	19.1/-	-0.093	-45.45	-0.91	-1.54	-/-	-/-	-0.006

Jun Luo, **Wenqi Ren***, Tao Wang, Chongyi Li, and Xiaochun Cao. “Under-Display Camera Image Enhancement via Cascaded Curve Estimation”, **TIP 2022**.

谢谢大家
敬请批评指正

Code and datasets are available

<https://sites.google.com/view/wenqiren/homepage>