图像视频压缩

图鸭信息科技有限公司

武俊敏

关于我们-图鸭科技

- 目前公司30多人，8位知名高校博士,20多位研发，来自上海交大，南京大学，浙江大学等，团队申请的专利80多项，发表的论文80多篇。

- Make video smaller & smarter

图片视频编解码

网络图片 / 视频数据传输的基础

300 DPI

26M

A4 大小图片 → 真彩色扫描 → 数据量

（不压缩）

图片和视频 — 新时代的文本

10 亿 / 天	71.7%	12.69 亿	80%
微信图片日均上传量（张）	2017年新闻格式图片占比	2017今日头条视频资讯日均播放量	游戏资源包中超过80%为图片和视频

视频压缩

视频类

网络视频**月度**覆盖超过**5亿**；人均视频时长超过**1小时／天**

直 播

2016年，网络直播平台**超过200个**，服务用户规模达 **3.3亿**

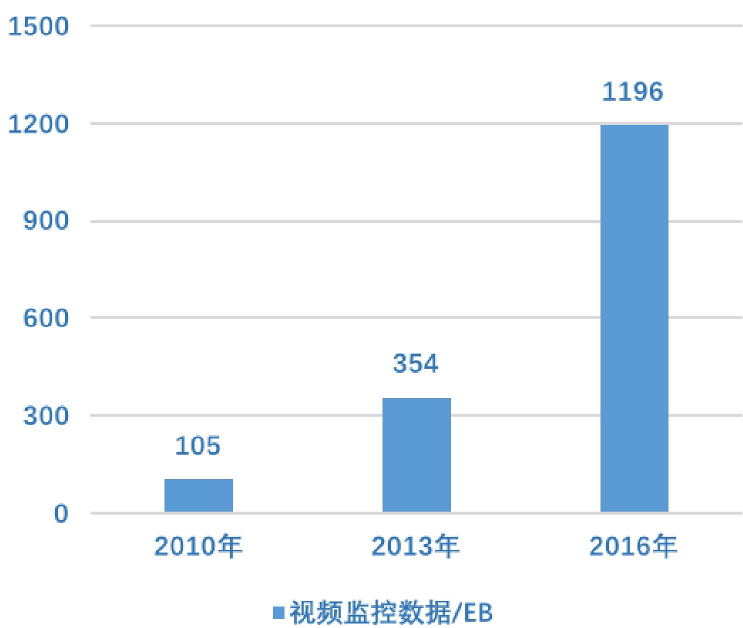
短视频

资讯和社交平台短视频数量**增势惊人；**短视频是社交和信息传递的延续，而非视频网站的补充。

监控市场

视频监控数据量庞大；高清 / 超高清化趋势，监控数据将以指数级增长

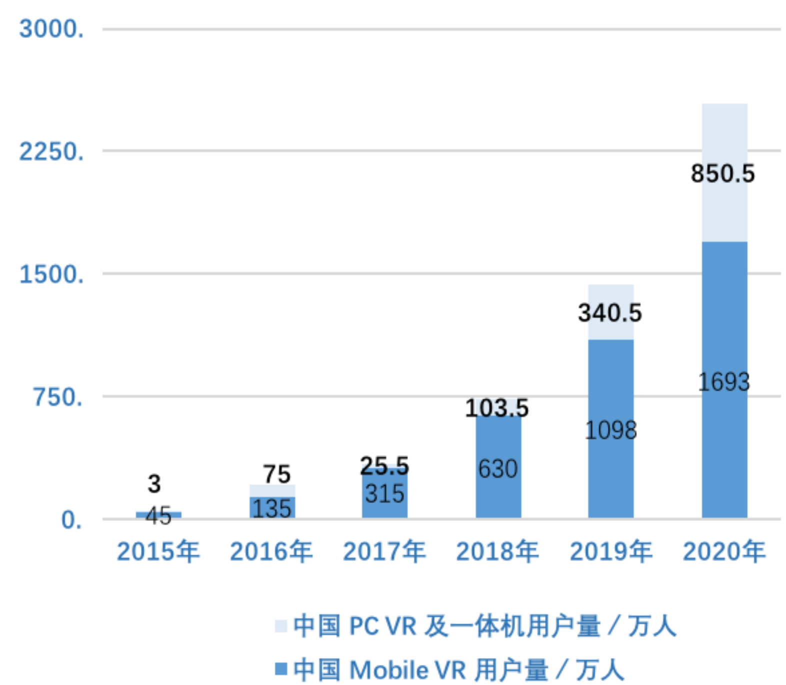
全球视频监控数据预测



VR/AR

带宽不足是制约AR/VR 普及的主要因素之一；整体市场潜力巨大

2015～2020年中国VR用户规模预计



图像压缩 VS. JPEG

测试网址：http://www.tucodec.com/picture/index

效果对比：http://www.tucodec.com/picture/comparison

注明：对比数据集采用 kodak24 数据集

原图：
Pixel: 2448*3264
Size: 1.77M

JPEG 压缩：Size: 332 KB
PSNR: 33.3

JPEG 压缩：Size: 78 KB
PSNR: 22.4

我们压缩：

Size: 73 KB

PSNR: 33.3

项 目 展 示-图片压缩高码率-25倍压缩率，网络图像使用码点

振铃失真

BPG: PSNR:37.92 ssim: 0.986 rate:0.923

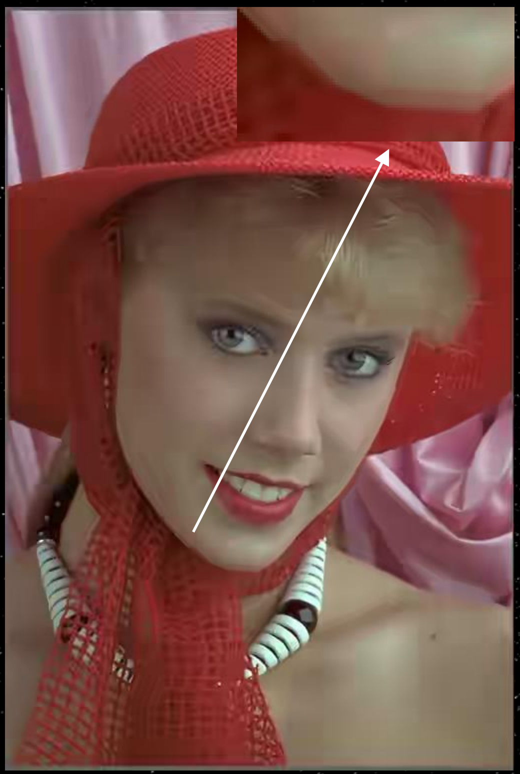
测试：tucodec.com/compare

方块效应

JPEG: PSNR:35.12 ssim: 0.982 rate:0.898

OUR: PSNR:37.99 ssim: 0.989 rate:0.903

项 目 展 示-图片压缩低码率-200倍压缩率-网络视频使用码点



BPG: PSNR:30.14 ssim: 0.921 rate:0.116

JPEG: PSNR:15.24 ssim: 0.527 rate:0.145

OUR: PSNR:29.28 ssim: 0.905 rate:0.107

音视频通信

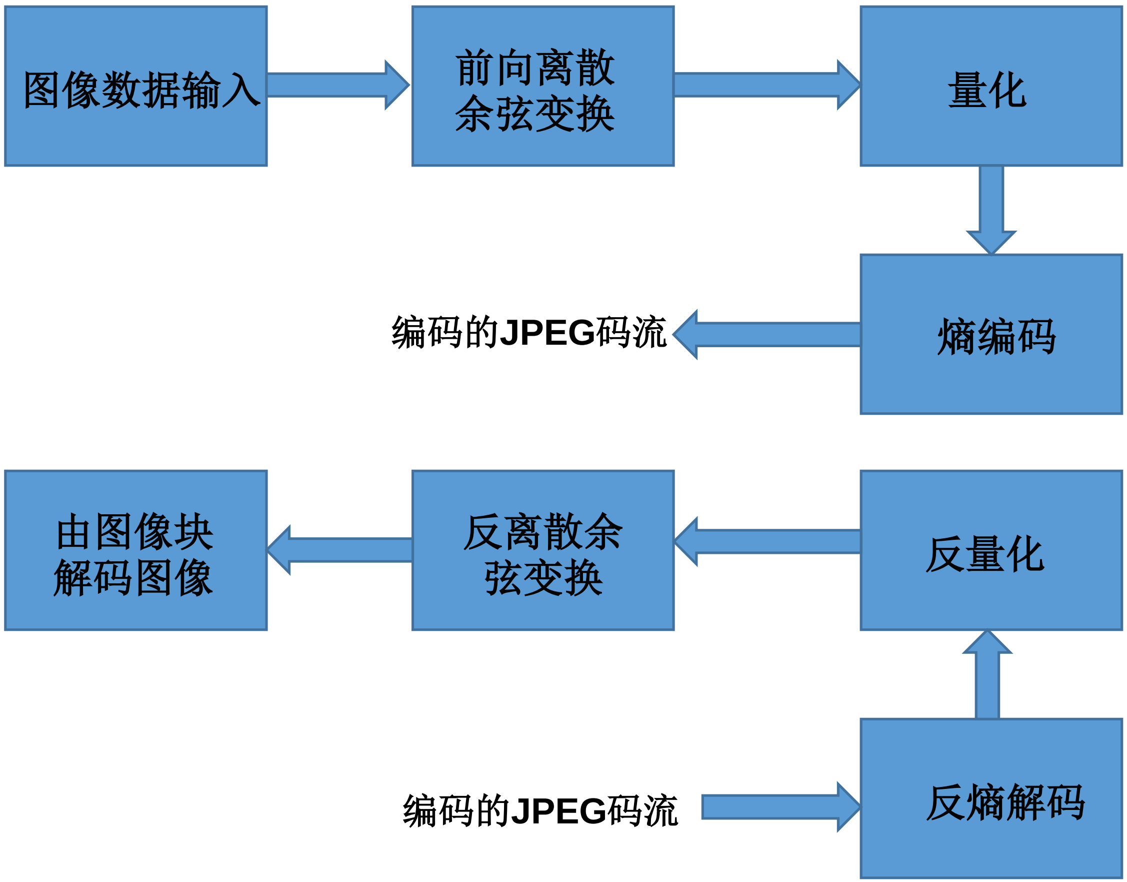
图鸭 VS 微信

测试：app store “AI 米听” “图鸭工具箱”

视频通信（VoIP）

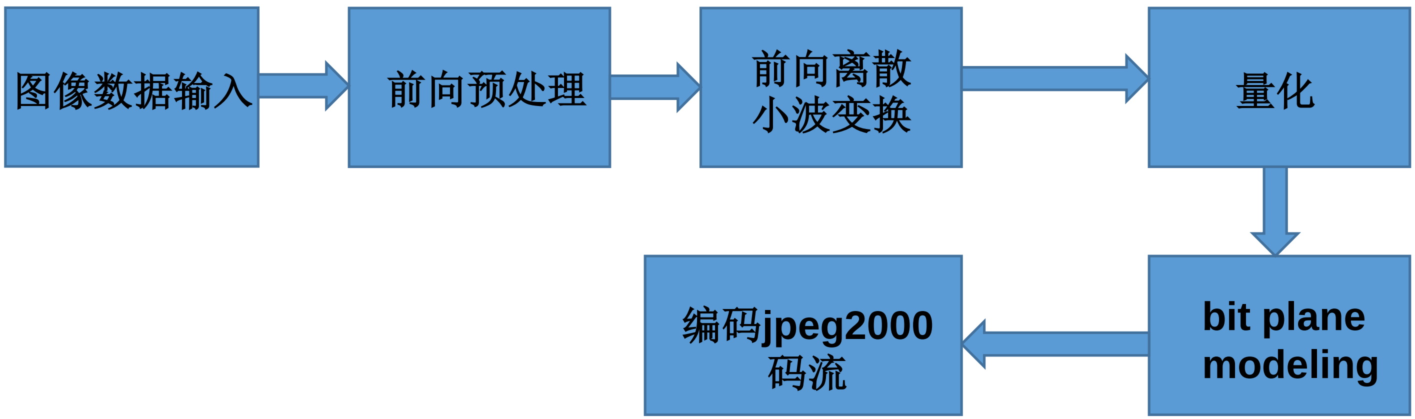
- 丢包 30% 视频流畅，支持 8人 实时通信
- 端到端延迟 50 ~ 100ms
- P2P 穿透70%

◆ 图像压缩-JPEG



图像数据输入
前向离散余弦变换
量化
熵编码
编码的JPEG码流
由图像块解码图像
反离散余弦变换
反量化
反熵解码
编码的JPEG码流

◆ 图像压缩-JPEG2000

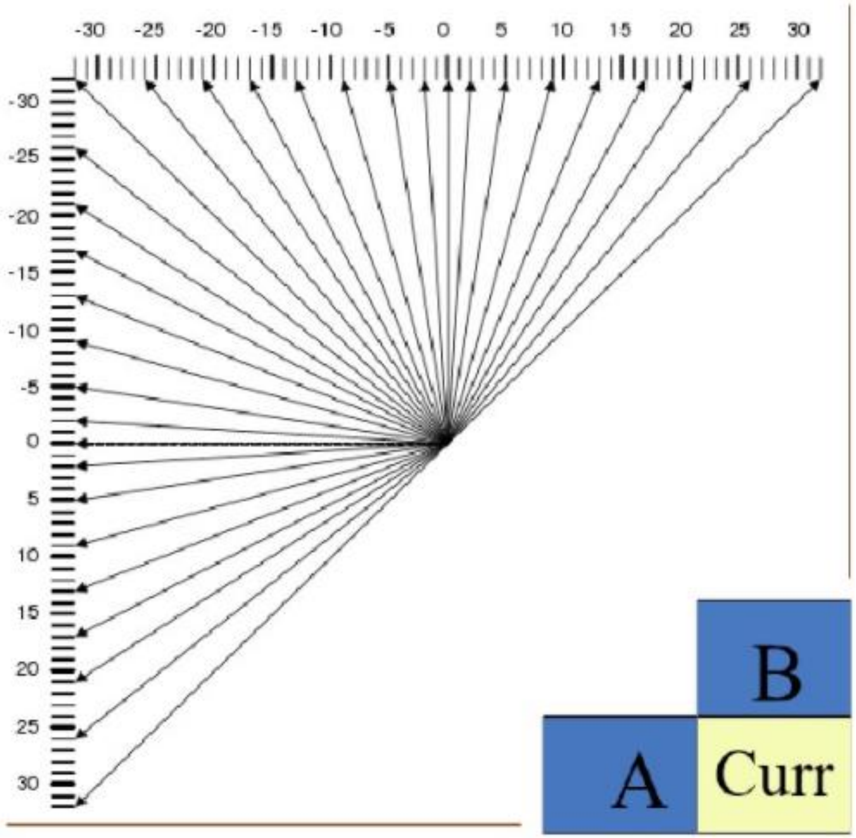


◆ 图像压缩-BPG

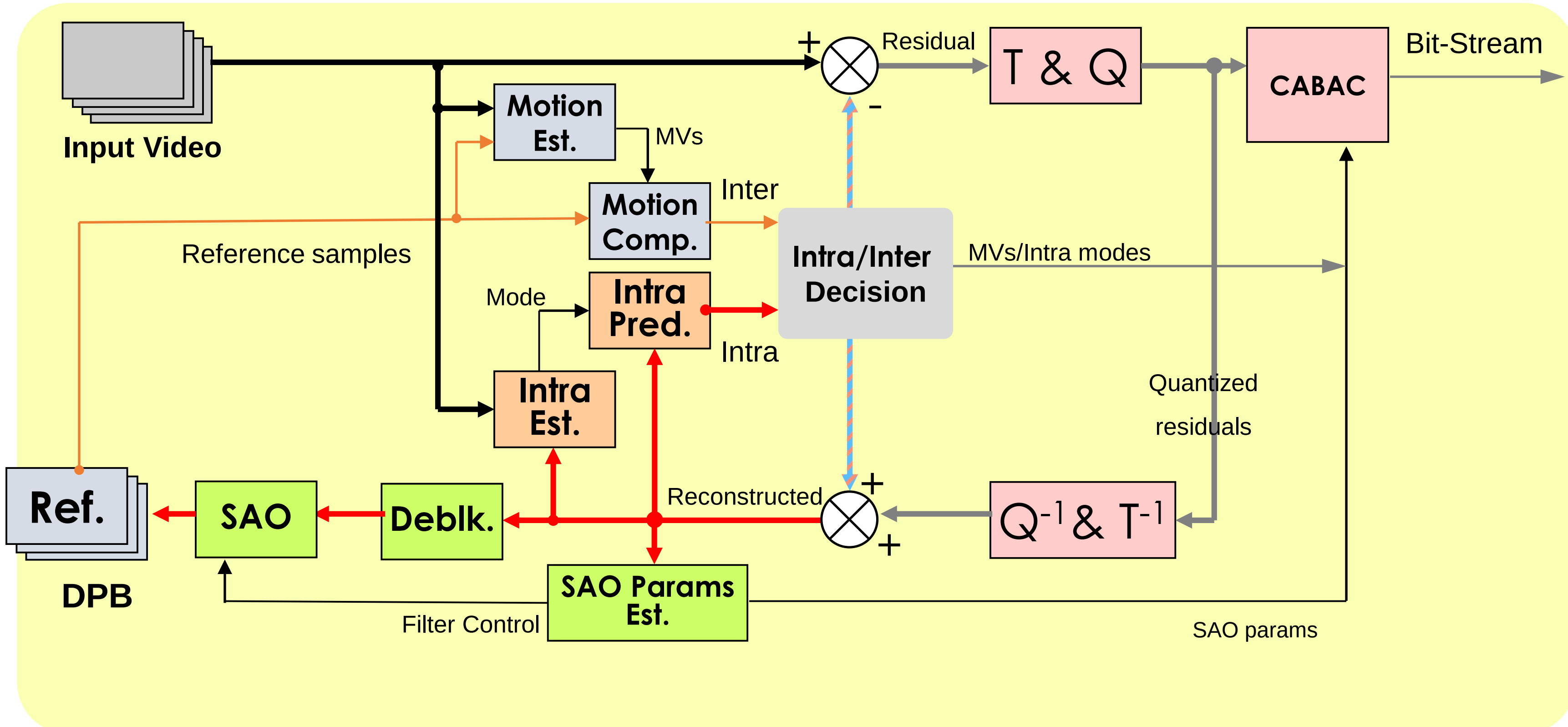
利用像素空间相关性消除空域冗余

多角度预测模式，进行图像内预测

对预测残差进行DCT编码



◆ 视频压缩-HEVC



Input Video
+
Residual
T & Q
CABAC
Bit-Stream
Motion Est.
MVs
Motion Comp.
Inter
-
Reference samples
Intra/Inter Decision
MVs/Intra modes
Mode
Intra Pred.
Intra
Intra Est.
Quantized residuals
Ref.
DPB
SAO
Deblk.
Reconstructed
+
+
Q^{-1} & T^{-1}
SAO Params Est.
Filter Control
SAO params

◆ 深度学习与图像视频压缩

如何用深度学习来设计图像或视频压缩算法？

深度学习在如人脸等视觉领域取得飞速发展，
能否对图像视频压缩领域进行更新？

深度学习做压缩有哪些独特的优势？

Full Resolution Image Compression with Recurrent Neural Networks , CVPR 2017，Google
LOSSY IMAGE COMPRESSION WITH COMPRESSIVE AUTOENCODERS，ICLR 2017, Twitter
Learning to Inpaint for Image Compression, NIPS 2017, Intel lab

OSC源创会 Opensource Innovation Meetup | IT大咖说 知识共享平台

典型的深度学习图像压缩框架介绍

$\mathbb{R}^{128\times128\times3}$

原始图片

CNN Encoder

编码

$c \in \Re^{8\times8\times256}$

Quanti

量化

y

Entropy Coding

熵编码

Bits

Dequant

反量化

$\hat{y} \in \Re^{8\times8\times256}$

CNN Decoder

解码

原图

重建误差

码字估计

率-失真优化

码字计算： $rate = \frac{\boxed{8\times8\times256}\times R}{128\times128} = R$ (bit/pixel)

与网络相关参数

每个数据单元平均耗费的比特位数

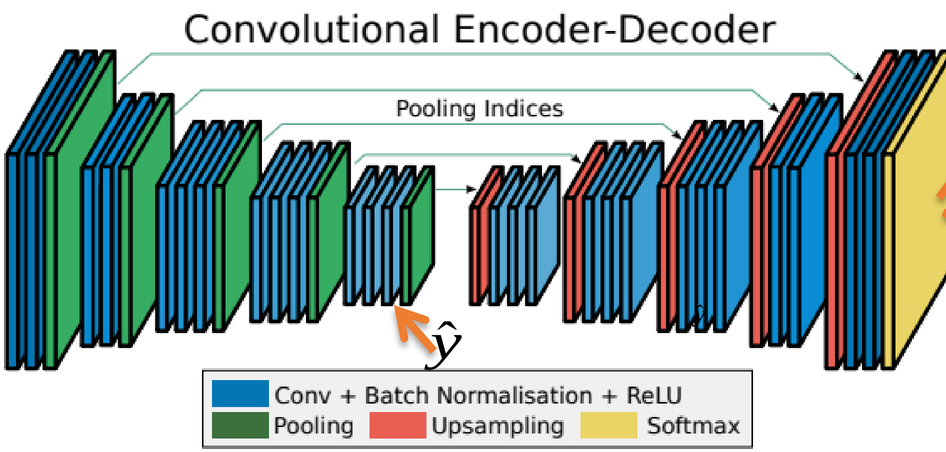
与码字分布和熵编码有关

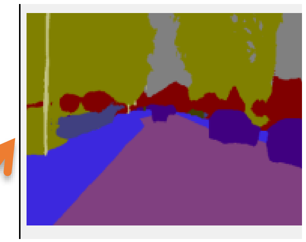
To generate a binary representation for an image by quantizing laten variable

完整的深度压缩网络所包括的模块

1 自编码网络
2 量化和反量化
3 重建误差
4 熵编码和码字估计
5 率-失真优化

自编码网络





场景分割

光流估计、视频帧预测等

- 编码网络结构可由卷积、池化等模块组成，如VGG，RESNET等
- 解码网络结构可由上采样，卷积，反卷积等模块组成

如果要应用到图像压缩，需要哪些新的设计？

量化

取整加随机噪声, (Lucas Theis, 2017)

$$\hat{y} \approx \lfloor y \rfloor + \varepsilon, \varepsilon \in \{0,1\}$$

训练时加随机噪声，测试直接取整 (Johannes Balle, 2016)

$$\hat{y} \approx y + u, u \in \{0,1\}$$

中心点分配, (Eirikur Agustsson, 2017)

$$\hat{y} \approx \sum_i c_i \varphi_i (\bar{y})$$

二值量化, (George Toderici, 2017)

$$\hat{y} \approx \begin{cases} 1, y > 0 \\ 0, y \leq 0 \end{cases}$$

LOSSY IMAGE COMPRESSION WITH COMPRESSIVE AUTOENCODERS, ICLR 2017

码字估计

$$R = E_{x\sim p_x}[-\log_2 p_{\hat{y}}(Q(g_a(x;\theta_g)))]$$

$\hat{y}$ 先验分布

现有的方法:

如果先验估计不准，不能引导模型良好训练

BinaryRNN for Entropy Coding--
Full Resolution Image Compression with Recurrent Neural networks.CVPR17

Bitplane Decomposition for Adaptive Arithmetic Coding--
Real-Time Adaptive Image Compression, ICML 2017

Gaussian Model for Entropy Rate Estimation--
Lossy Image Compression With Compressive Autoencoders, ICLR 2017

End to End Optimized Image Compression, ICLR 2017

利用重建图与原图误差构建损失函数

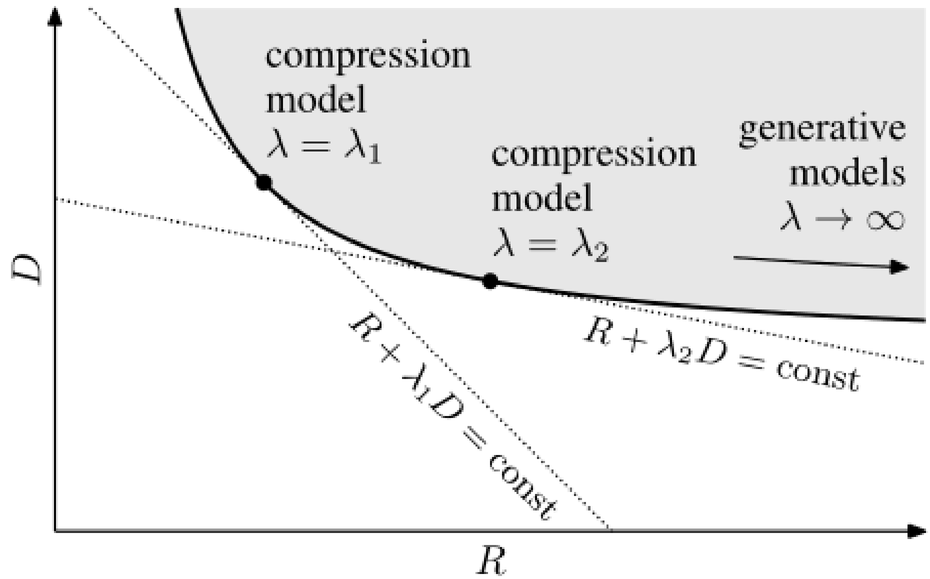
重建误差 - MSE.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2$$

描述型误差-MS-SSIM

Wang, Zhou, Eero P. Simoncelli, and Alan Conrad Bovik (2003). “Multi-Scale Structural Similarity for Image Quality Assessment”. In: Conf. Rec. of the 37th Asilomar Conf. on Signals, Systems and Computers. DOI: 10.1109/ACSSC.2003.1292216

率-失真优化



$$L[g_a, g_s, P_{\boldsymbol{q}}] = -\mathbb{E}\left[\log_2 P_{\boldsymbol{q}}\right] + \lambda\,\mathbb{E}\left[d(\boldsymbol{z}, \hat{\boldsymbol{z}})\right]$$

码字估计

重建误差

如何进行测评

数据库: Kodak Photo CD dataset

- 24 张768×512 PNG 图片

评价指标

- MS-SSIM （主观指标）
- PSNR （客观指标）

比较

- JPEG
- JPEG2K
- BPG
- 不同网络结构
  - LSTM, Associative LSTM, GRU
- 不同的重建框架
- One-shot, additive, residual scaling

典型方法介绍

两个主要的发展方向

- 端到端模式 (auto-encoders)
  - RNN (ICLR2016_Google, CVPR2017_Google, ICIP2017_Google)
  - CNN (ICLR2017_NYU, ICLR2017_Twitter, CSVT_HIT)
  - GAN (ICML2017_waveone, MIT_2017)
- 优化现在的视频编码器

  Intra CU mode decision

  Down-samping Coding

  in-loop filter & Post-processing

ICLR2016_Google

- RNN编码层
- 二进制量化层
- RNN解码层

$$b_t = B(E_t(r_{t-1})), \quad \hat{x}_t = D_t(b_t) + \gamma \hat{x}_{t-1}, \quad r_t = x - \hat{x}_t, \quad r_0 = x, \quad \hat{x}_0 = 0$$

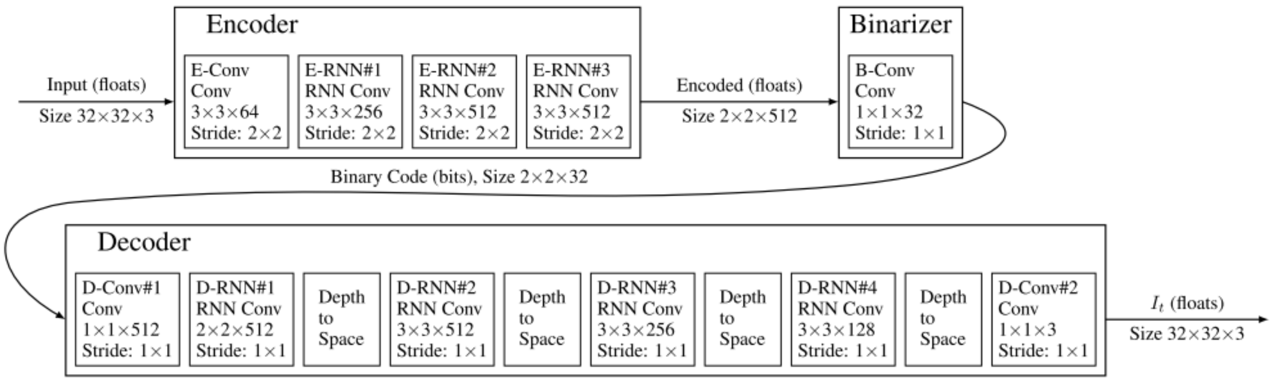
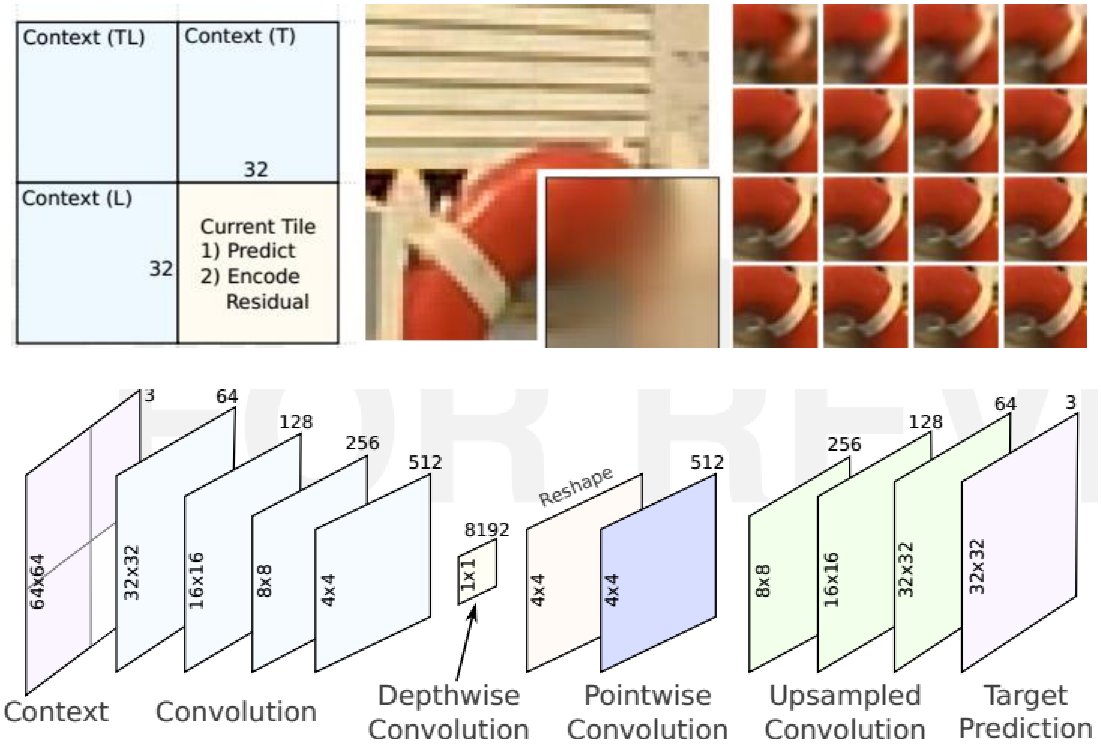


Figure 1: A single iteration of our shared RNN architecture.

ICIP2017_Google

RNN with intra prediction



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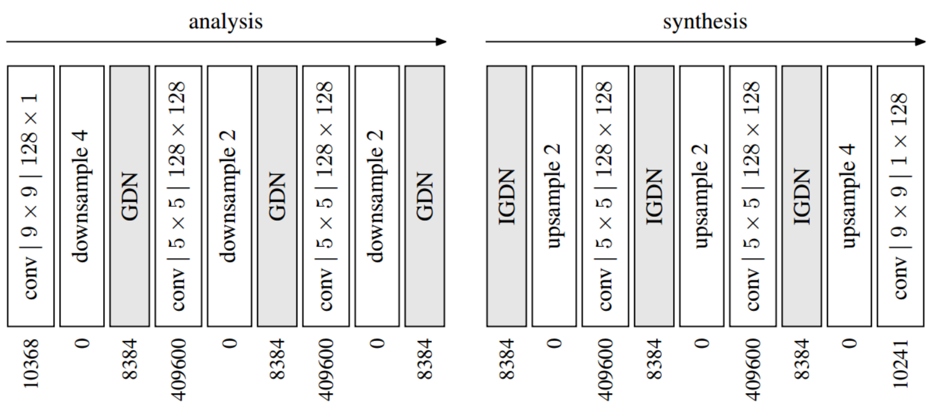
ICLR2017_NYU

- Generalized divisive normalization (GDN)

$$u_i^{(k+1)}(m,n) = \frac{w_i^{(k)}(m,n)}{\left(\beta_{k,i} + \sum_j \gamma_{k,ij}\left(w_j^{(k)}(m,n)\right)^2\right)^{\frac{1}{2}}}.$$

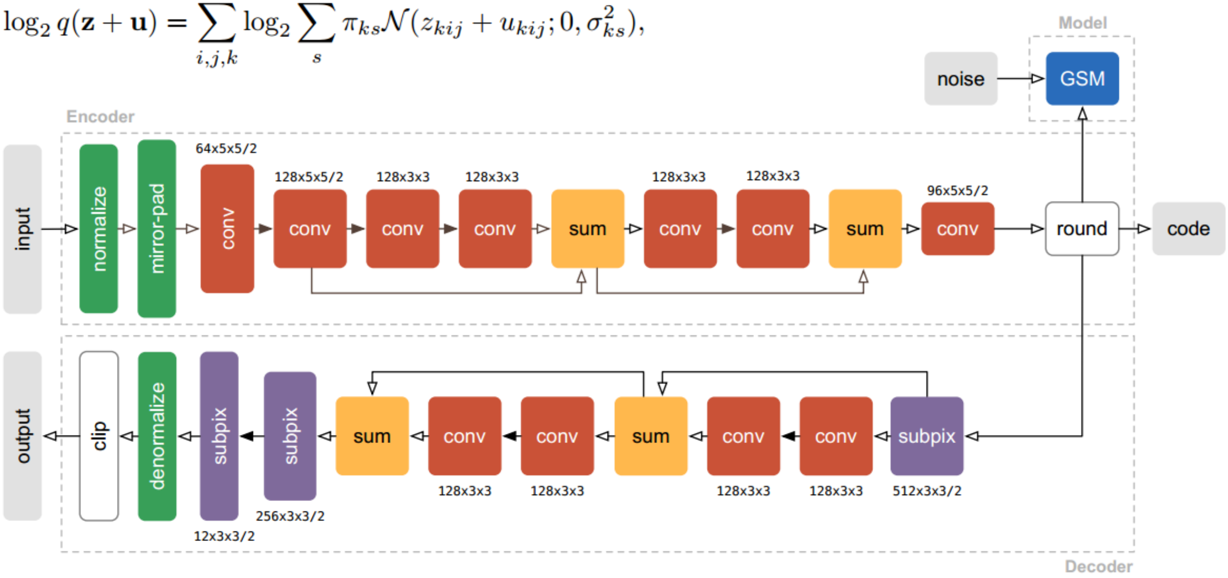
- 网络结构和码字估计



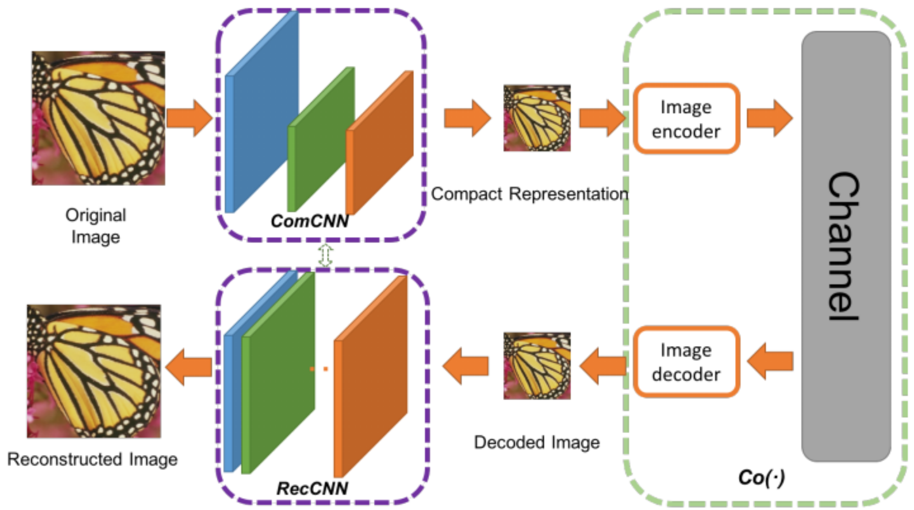
ICLR2017_Twitter

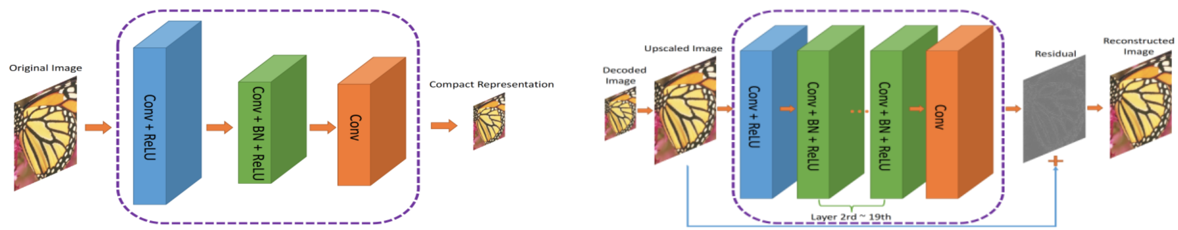
Rate estimation by Gaussian Scale Mixtures

$$\log_2 q(\mathbf{z}+\mathbf{u}) = \sum_{i,j,k} \log_2 \sum_s \pi_{ks} \mathcal{N}(z_{kij} + u_{kij}; 0, \sigma_{ks}^2),$$



CSVT2017_HIT





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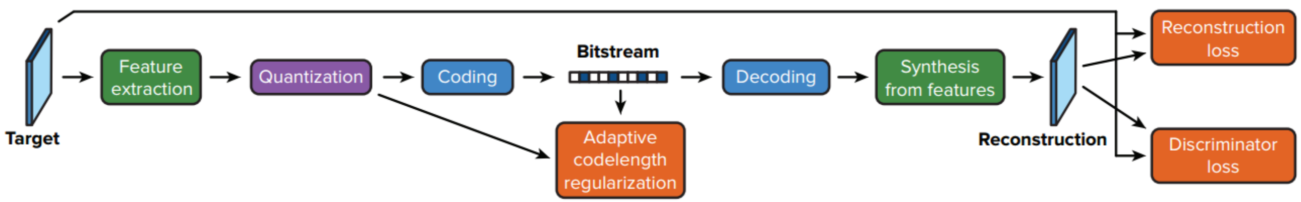
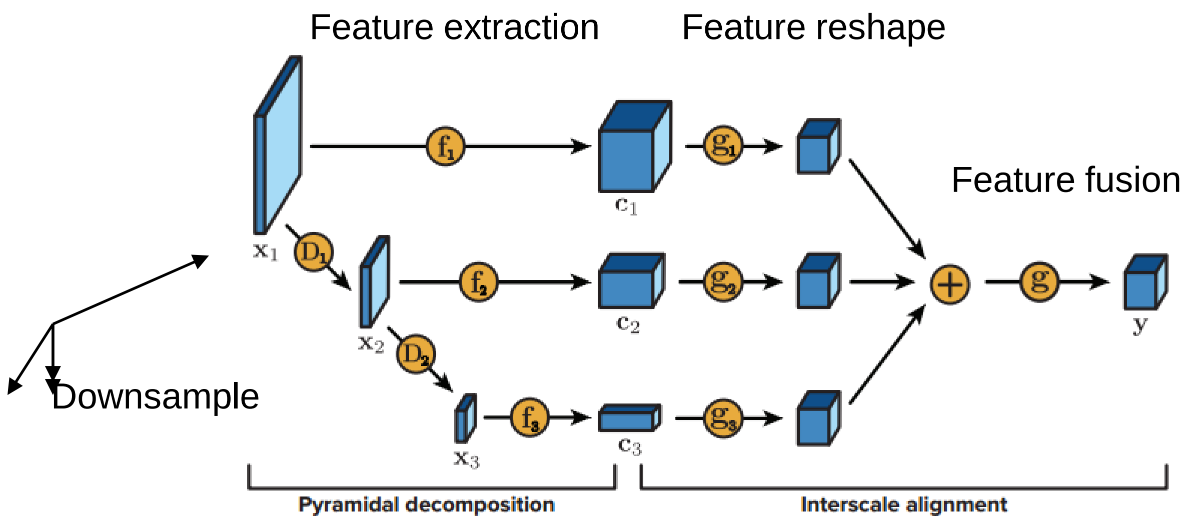
ICML2017_waveone



- 编码网络
  - Multiscale analysis
- 量化和熵编码
  - Adaptive arithmetic coding and adaptive codelength regularization
- 重建误差(Discriminator loss)

编码网络



Feature extraction
Feature reshape
Feature fusion
Downsample
x_1
D_1
x_2
D_2
x_3
f_1
f_2
f_3
c_1
c_2
c_3
g_1
g_2
g_3
g
y
Pyramidal decomposition
Interscale alignment

量化和熵编码

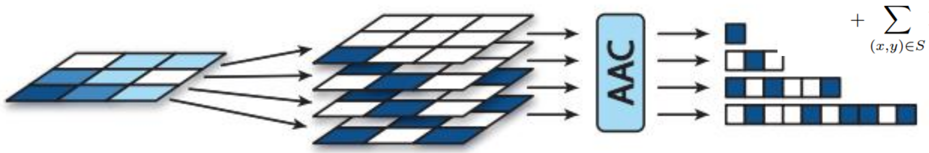
- 量化:

$$\hat{y}_{chw} := \textsc{Quantize}_B(y_{chw}) = \frac{1}{2^{B-1}}\left\lceil 2^{B-1} y_{chw} \right\rceil$$

- 适应性算术编码 (AAC)
  - Train context model to estimate probability of each bin

$$\mathscr{P}(\hat{\mathbf{y}}) = \frac{\alpha_t}{CHW}\sum_{chw}\Big\{\log_2|\hat{y}_{chw}| + \sum_{(x,y)\in S}\log_2\left|\hat{y}_{chw} - \hat{y}_{c(h-y)(w-x)}\right|\Big\},$$

- 适

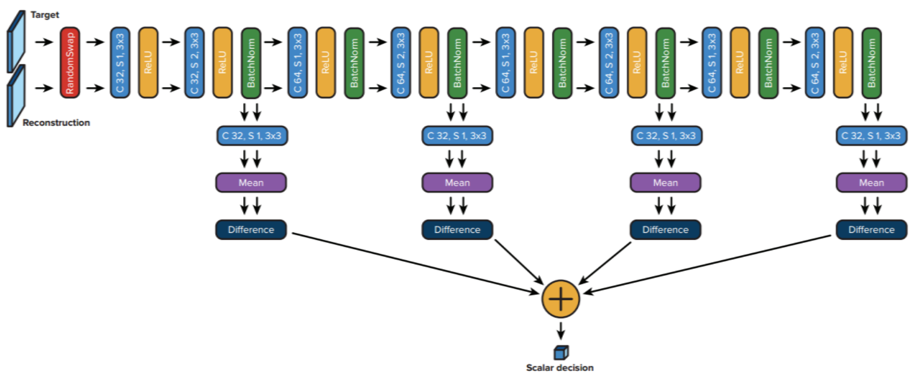


g

$\hat{\mathbf{y}}_c \in \mathbb{R}^{H\times W}$ Bitplane

重建误差(Discriminator loss)

- Discriminator:
  - Input: target and reconstruction
  - Multiscale discriminator
- Adversarial training
  - Alt
    dis



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  Intra CU mode decision

  Down-samping Coding

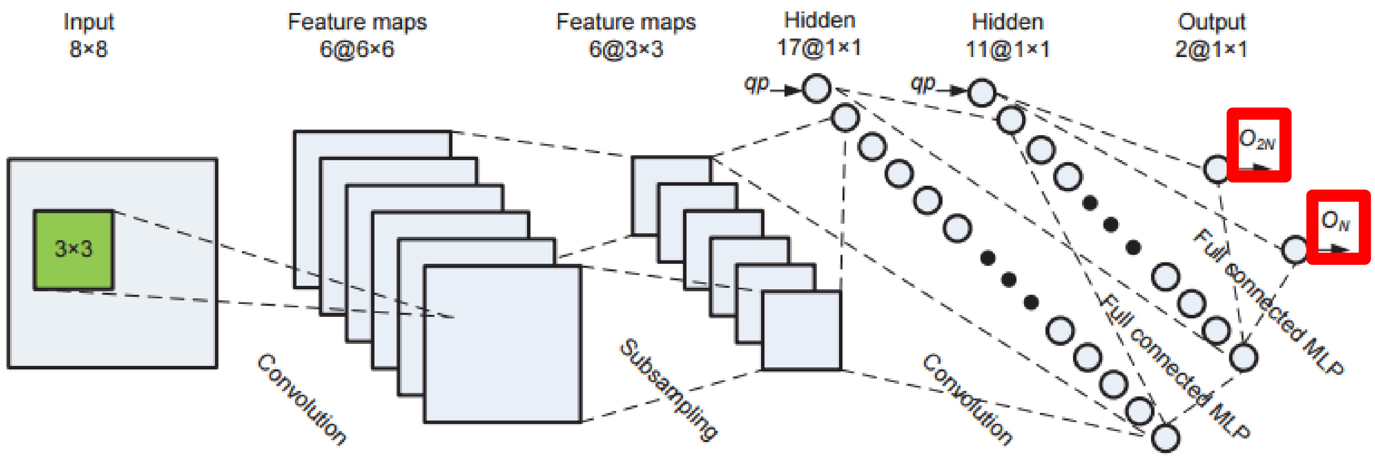
  in-loop filter & Post-processing

编码单元模式选择(Intra CU mode decision)

- CNN oriented fast HEVC intra CU mode decision
  - Contributions:
  - 1. Using CNN to analyze the textures of CU
  - 2. Reduce the maximum number of CU modes
  - 3. Introduce QP into CNN architecture design

Liu Z, Yu X, Chen S, et al. CNN oriented fast HEVC intra CU mode decision. ISCAS 2016: 2270-2273.

编码单元模式选择(Intra CU mode decision)



(b) Architecture of Convolutional Neural Network for CU Mode Decision

- Objective: learning to classify 2Nx2N or NxN
  - The output of two nodes are RD-Cost

编码单元模式选择(Intra CU mode decision)

- **时间和码字节省效果测评**
  - 63% time save with 2.7% loss in BDBR

Table III: Performance Comparison between Proposed Solution and Existing Algorithms

Algorithm	$\Delta T_{CMD}[\%]$	$\Delta T_{PMD}[\%]$	BDBR[%]	$\Delta T[\%]$	VLSI
[3]	50-α	α	0.7	50	No
[5]†	26	45	1.0	60	No
[6]	52	0	0.8	52	No
[7]†	52	5	5.1	57	Yes
[8]	62	0	4.5	62	Yes
Proposed	63	0	2.7	63	Yes

† indicates that class F sequences were not tested.

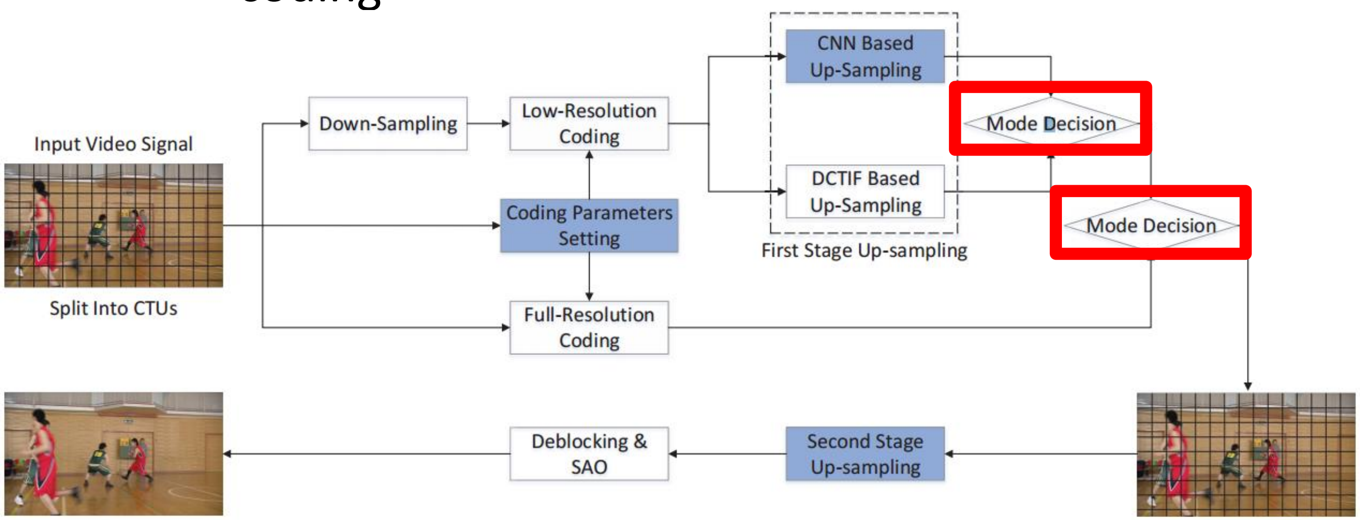
Downsampling-coding (下采样编码)

- 1. CTU (编码树单元)
- 2. Frame (视频帧)

1. Li Y, Liu D, Li H, Li L, Wu F. Convolutional Neural Network-Based Block Up-sampling for Intra Frame Coding.
2. Jia C, Zhang X, Zhang J, et al. Deep Convolutional Network based Image Quality Enhancement for Low Bit Rate Image Compression.

Downsampling-coding(下采样编码)

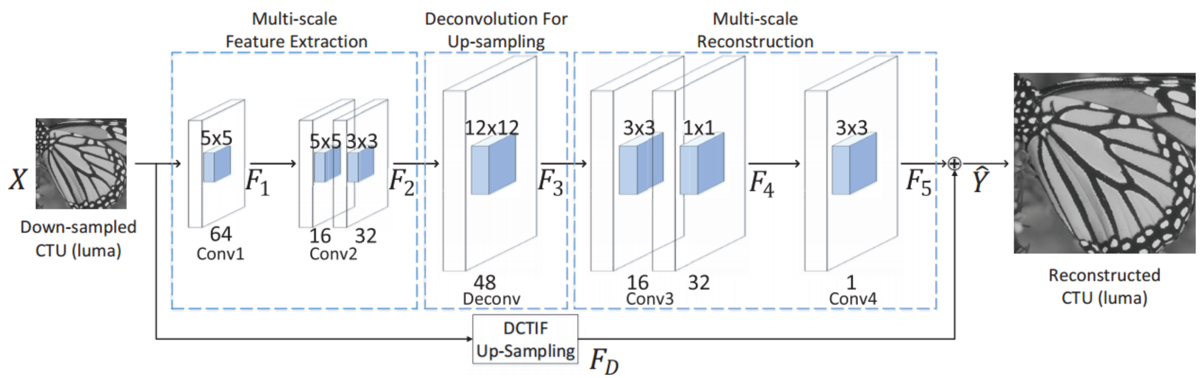
- CTU 层上的操作
  - Two steps RDO
    - 1. Down-sample coding / Full resolution coding



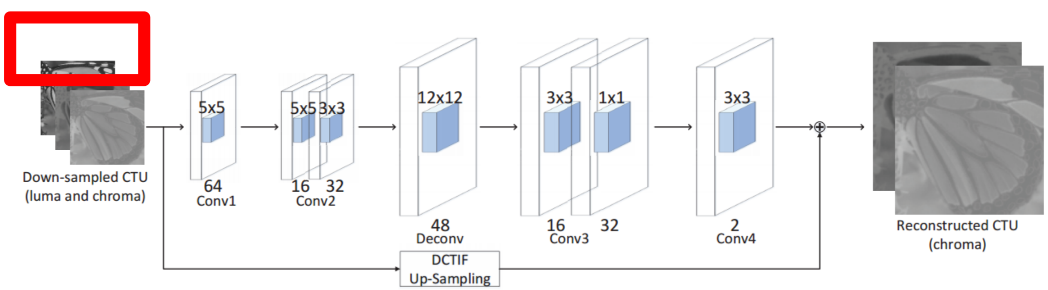
视频帧层上的操作

Downsampling-coding(下采样编码)

- 对亮度通道
  - Input: low resolution patch, output: high resolution



- 对色度通道: downsampled luma also input



Downsampling-coding (下采样编码)

- Test Condition
  - Qp: 32, 37, 42, 47

Class	Sequence	BD-Rate (Anchored on HEVC) Y	U	V	Y SSIM	BD-Rate (Anchored on HEVC+DCTIF) Y	U	V	Y SSIM
Class A	Traffic	–10.1%	–3.5%	6.0%	–12.9%	–8.0%	–13.2%	–2.6%	–7.9%
	PeopleOnStreet	–9.7%	–14.8%	–14.5%	–12.9%	–8.5%	–20.4%	–18.5%	–9.7%
	Nebuta	–2.0%	–22.0%	3.1%	–4.4%	–1.7%	–22.5%	1.6%	–3.6%
	SteamLocomotive	–1.7%	–27.7%	–25.4%	–6.1%	–1.2%	–34.2%	-25.6%	–2.8%
Class B	Kimono	–7.7%	–5.5%	18.8%	–9.6%	–3.4%	–25.9%	–4.3%	–3.4%
	ParkScene	–7.1%	–14.4%	–2.3%	–11.3%	–5.0%	–25.2%	–14.6%	–6.6%
	Cactus	–6.6%	–2.5%	8.3%	–10.0%	–5.0%	–6.5%	0.9%	–6.7%
	BQTerrace	–3.7%	–7.6%	–9.1%	–9.6%	–3.1%	–8.2%	–7.1%	–6.5%
	BasketballDrive	–6.1%	–1.2%	3.2%	–10.8%	–3.4%	–5.8%	–2.5%	–3.8%
Class C	BasketballDrill	–4.9%	4.5%	8.1%	–7.9%	–4.0%	4.9%	2.1%	–6.6%
	BQMall	–2.9%	–7.2%	–7.2%	–6.2%	–2.3%	–10.6%	–9.1%	–5.3%
	PartyScene	–1.0%	–5.1%	–1.6%	–4.0%	–1.0%	–5.5%	–3.2%	–3.6%
	RaceHorsesC	–6.7%	4.6%	7.5%	–10.7%	–6.0%	1.9%	3.9%	–8.6%
Class D	BasketballPass	–2.0%	–3.7%	9.2%	–4.3%	–2.3%	–7.5%	12.3%	–4.4%
	BQSquare	–0.9%	–0.6%	–21.1%	–1.4%	–0.5%	1.7%	-16.7%	–1.2%
	BlowingBubbles	–3.2%	3.1%	–8.0%	–5.3%	–1.7%	0.5%	-9.6%	–3.8%
	RaceHorses	–9.9%	7.5%	6.4%	–12.6%	–9.6%	5.0%	6.6%	–11.1%
Class E	FourPeople	–7.2%	–10.5%	–11.0%	–11.0%	–7.2%	–14.7%	–14.5%	–9.5%
	Johnny	–9.0%	–3.2%	–3.2%	–11.1%	–7.1%	–6.0%	–8.3%	–5.6%
	KristenAndSara	–6.8%	–11.2%	–11.1%	–13.0%	–5.3%	–8.4%	–10.6%	–8.2%
Class UHD	Fountains	–4.0%	–12.9%	–11.2%	–7.4%	–2.0%	–16.1%	–9.2%	–2.0%
	Runners	–11.2%	22.8%	–0.1%	–12.4%	–7.0%	0.9%	–13.7%	–6.0%
	Rushhour	–8.5%	4.4%	1.8%	–10.3%	–3.2%	–9.2%	–9.5%	–3.0%
	TrafficFlow	–12.7%	–11.7%	–5.8%	–12.7%	–6.9%	–17.3%	–11.9%	–5.6%
	CampfireParty	–8.4%	–10.8%	–0.8%	–9.5%	–6.5%	–10.8%	–5.0%	–6.4%
Average of Classes A-E		–5.5%	–6.0%	–2.2%	–8.8%	–4.3%	–10.0%	–6.0%	–5.9%
Average of Class UHD		–9.0%	–1.6%	–3.2%	–10.5%	–5.1%	–10.5%	–9.9%	–4.6%

In-loop filter & Post Processing

- 视频帧环路滤波和后处理

1. In-loop

Park W S, Kim M. CNN-based in-loop filtering for coding efficiency improvement. IEEE Image, Video, and Multidimensional Signal Processing Workshop (IVMSP) 2016: 1-5.

2. Post Processing

Dai Y, Liu D, Wu F. A Convolutional Neural Network Approach for Post-Processing in HEVC Intra Coding. MMM 2017: 28-39.

In-loop filter

- 视频帧图像滤波
  - In-loop

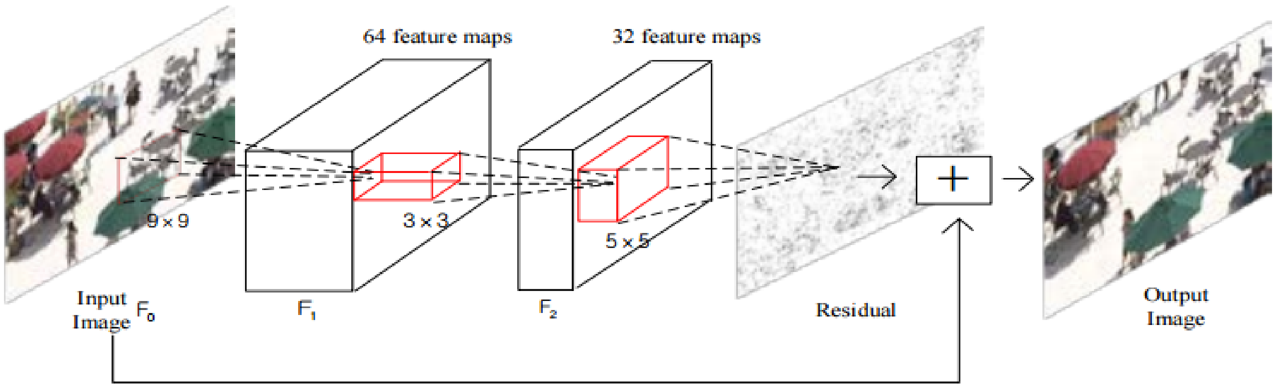
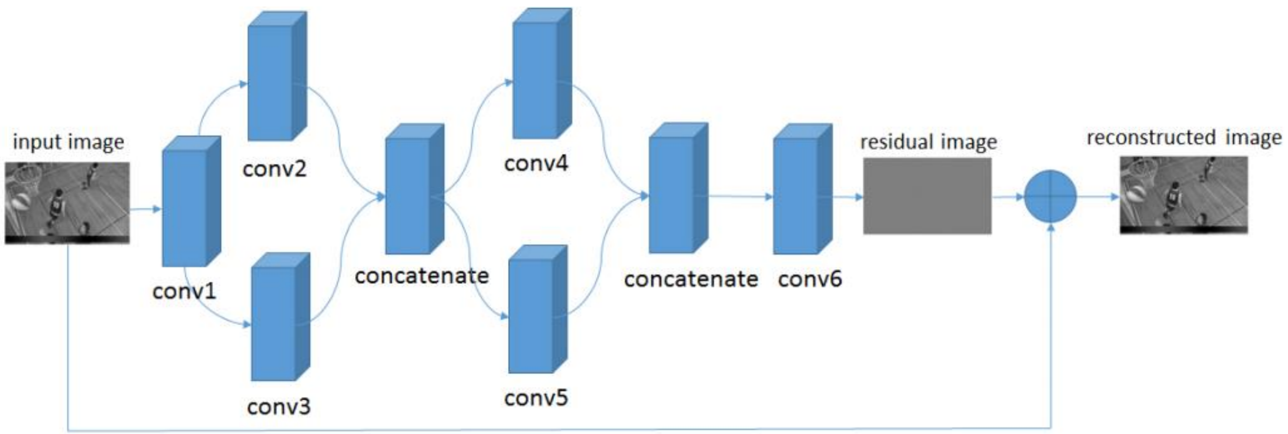


Table 1. Performance of our proposed IFCNN in comparison with SAO in terms of BD rates (BDBR).

Sizes	Seq.	All Intra	LDP-Case I	LDP-Case II	RA-Case I	RA-Case II
		BDBR (%)	BDBR (%)	BDBR (%)	BDBR (%)	BDBR (%)
832×480	BD	-10.1	-5.3	-3.0	-6.0	-6.7
	BQM	-3.7	-3.0	-2.4	-2.4	-2.9
	PS	-2.7	-2.0	-1.2	0.0	-1.1
	BDT	-7.6	-3.5	-2.4	-4.3	-4.9
416×240	BP	-3.3	-2.8	-1.5	-0.6	-1.1
	BQS	-2.4	-3.3	-2.9	1.4	-0.8
	B	-3.4	-2.3	-2.6	0.0	-1.4
	RH	-4.9	-0.4	0.6	-1.2	-1.6
	Avg.	-4.8	-2.8	-1.9	-1.6	-2.6

Post-processing

- 视频帧图像滤波
  - Post processing, All Intra
  - QP: 22, 27, 32, 37



VDSR	Class A	-2.8	-3.2	-3.1
	Class B	-2.7	-2.7	-3.3
	Class C	-4.1	-4.8	-5.7
	Class D	-4.4	-5.6	-7.3
	Class E	-5.7	-5.7	-6.1
	Overall	**-3.8**	**-4.3**	**-4.9**

- 我们的技术

利用深度学习实现新的图片压缩方法

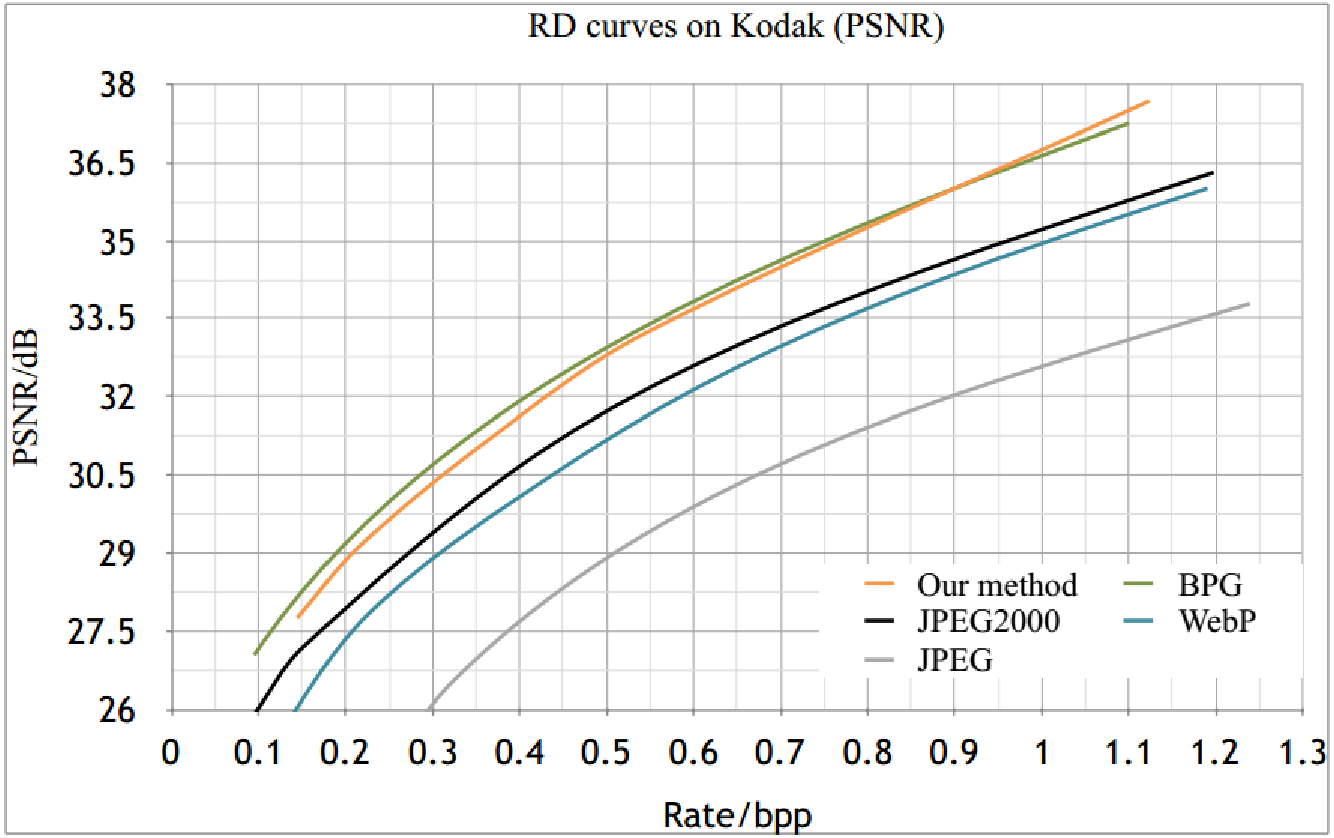
在线比较：

http://tucodec.com/compare/index

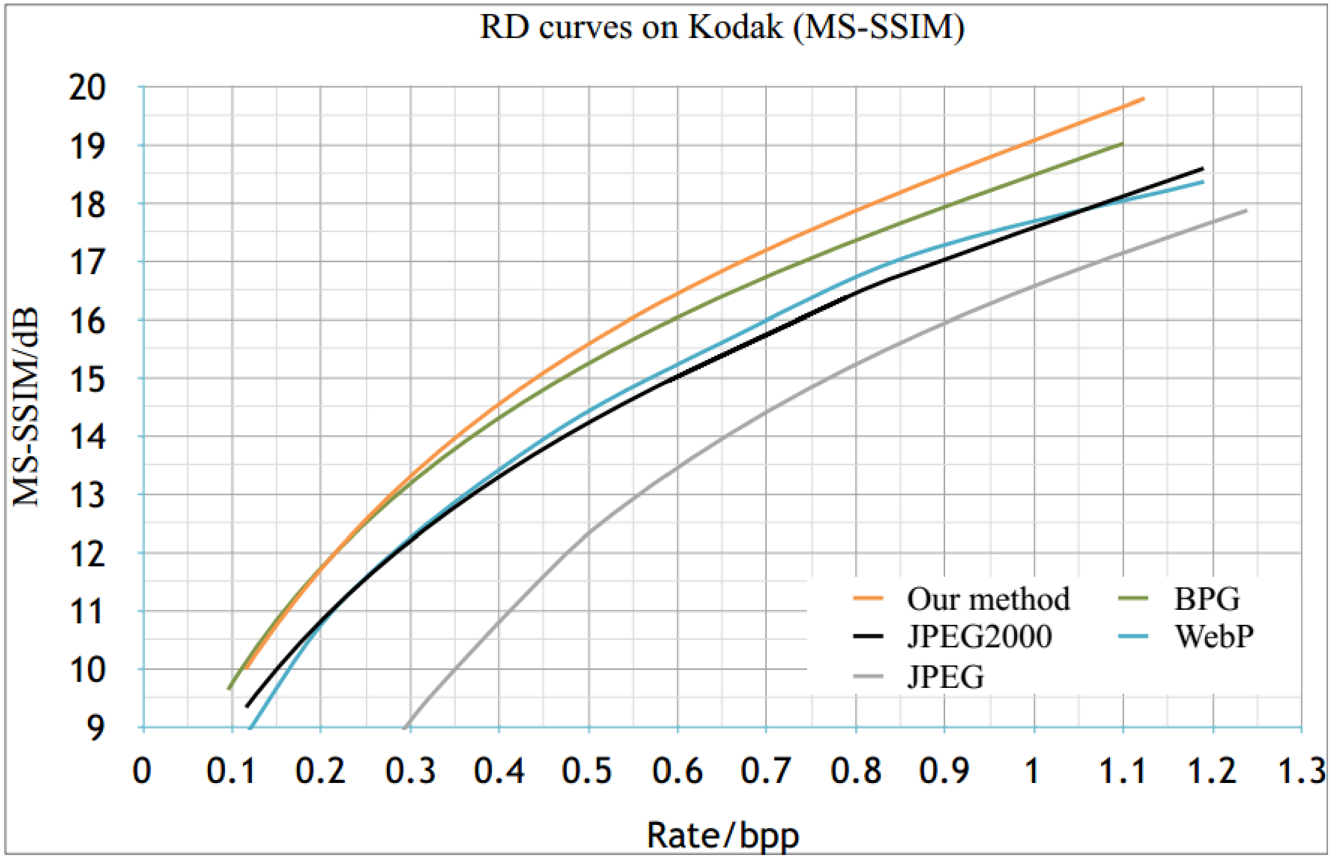
在线测试：

http://tucodec.com/picture/index

在KODAK数据集上的测评结果



◆ 在KODAK数据集上的测评结果

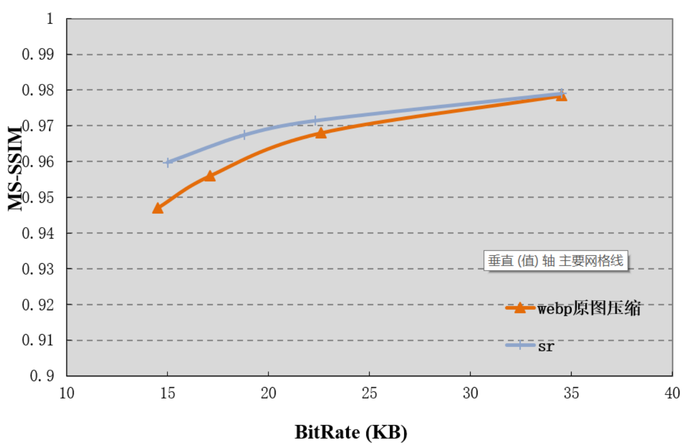


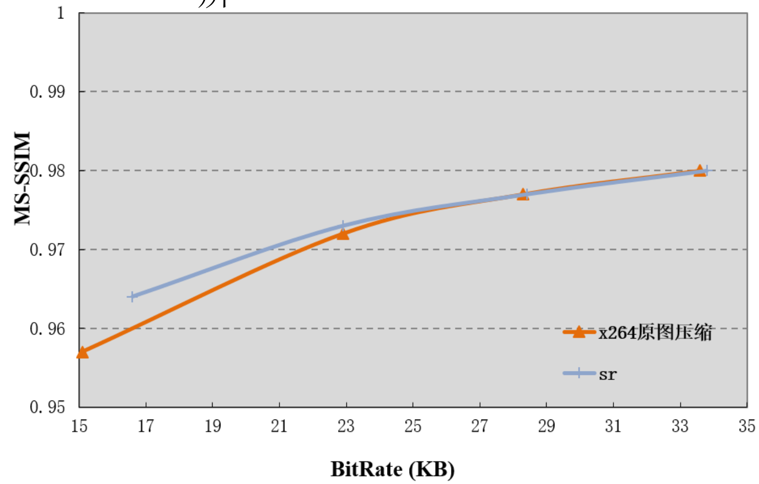
- 我们的技术

利用深度学习超分辨降低带宽

原图直接压缩

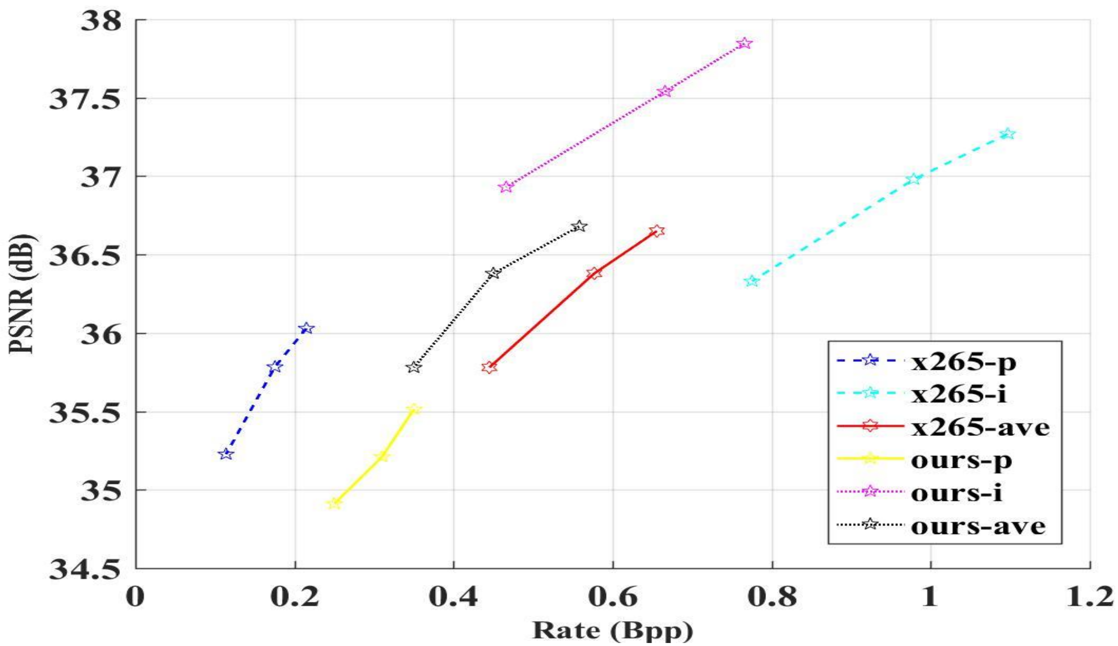
原图缩小压缩再超分辨





- 我们的技术

利用深度学习设计视频多帧压缩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37.5
37
36.5
36
35.5
35
34.5
PSNR (dB)
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0.2
0.4
0.6
0.8
1
1.2
Rate (Bpp)
x265-p
x265-i
x265-ave
ours-p
ours-i
ours-ave

◆ 发展趋势

1 提升性能、降低复杂度

2 为特定的应用场景定制高效的算法

3 设计端到端的视频编码结构

4 结构化存储，将编码与分割、分类、检索等多任务相结合