



AI视频插帧在实时互动场景中的应用

周世付

agora.io







- 1. AI视频插帧应用背景
- 2. AI视频插帧原理、研究现状、挑战
- 3. AI视频插帧的落地应用





○ 实时互动场景用户体验

- 低延时 声音、视频流畅
- 高质量 声音保真、画面清晰

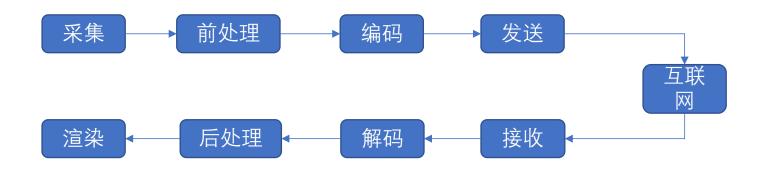




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实时互动视频传输

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- 前处理 检测、分割、美颜、ROI
- 编解码 pvc、roi
- 后处理 去噪、锐化、超分、插帧





○ 视频插帧与低延时

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■ 低帧率生成高帧率

低帧率视频传输,减轻网络带宽压力,降低传输时延,接收端 插帧恢复高帧率视频

■ 恢复丢失帧率

传输过程中, 出现丢包, 整帧数据丢弃, 再重传, 传输时延 大; 利用前后帧,恢复中间帧,无需重传







视频插帧方法

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在连续的两帧图像之间,生成1帧或多帧图像































































视频插帧的原理



$$I_t = \alpha * I_0 + (1 - \alpha) * I_1$$

$$I_t = \alpha * I_0 + (1 - \alpha) * I_1 \qquad I_t = \alpha * g(I_0, M_{0 \to t}) + (1 - \alpha) * g(I_1, M_{1 \to t})$$









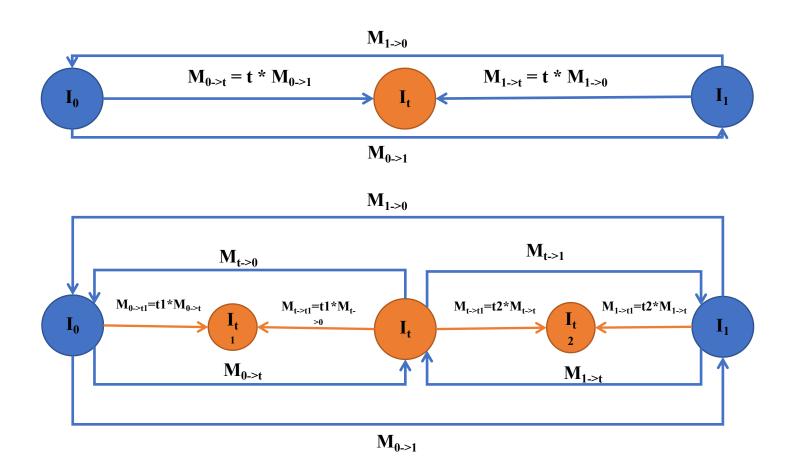








单帧与多帧插值









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• 传统方法

- I(x, y, t) = I(x + dx, y + dy, t + dt)
- $I(x, y, t) = I(x, y, t) + \frac{\partial I}{\partial x} dx + \frac{\partial I}{\partial y} dy + \frac{\partial I}{\partial t} dt + \epsilon$
- $I_{x}u + I_{y}v + I_{t} = 0$

• 深度学习方法

- FlowNet
- PWC-Net





Forward warp vs Backward warp

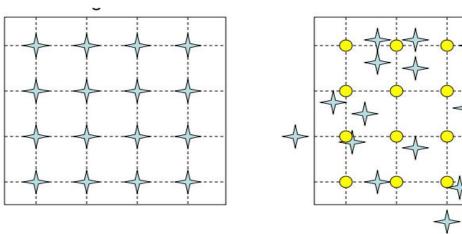


s(x', y'), d(x, y), f(u, v)

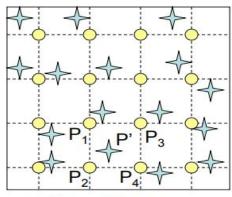
$$x = x' + u$$
$$y = y' + v$$

$$x' = x - u$$
$$y' = y - v$$

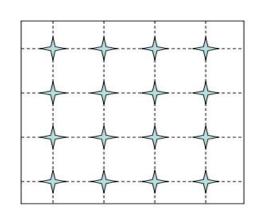
Forward warp



backward warp

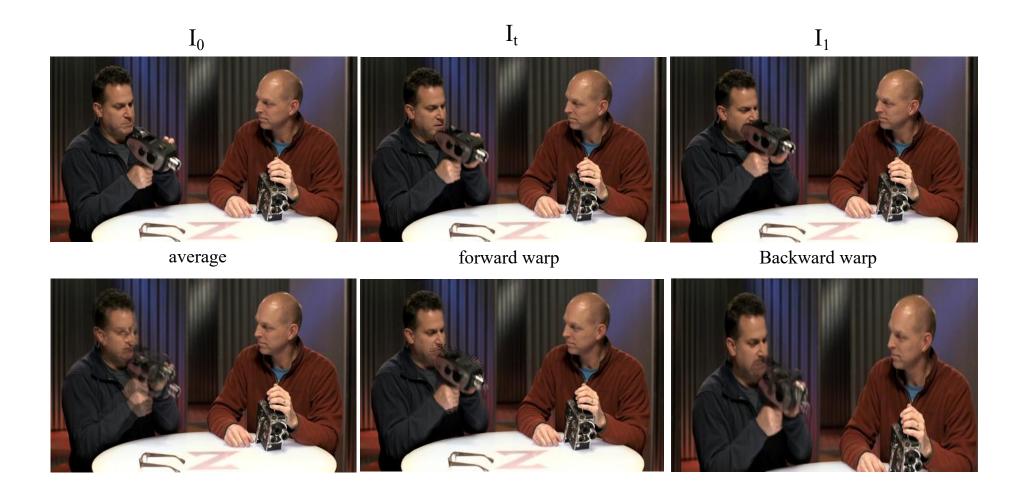


P' will be interpolated from P₁, P₂, P₃, and P₄





方法对比







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视频插帧研究现状

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基于光流+backwarp

- super slomo
- RIFE

基于kernel+deformable convolution

• AdaCof

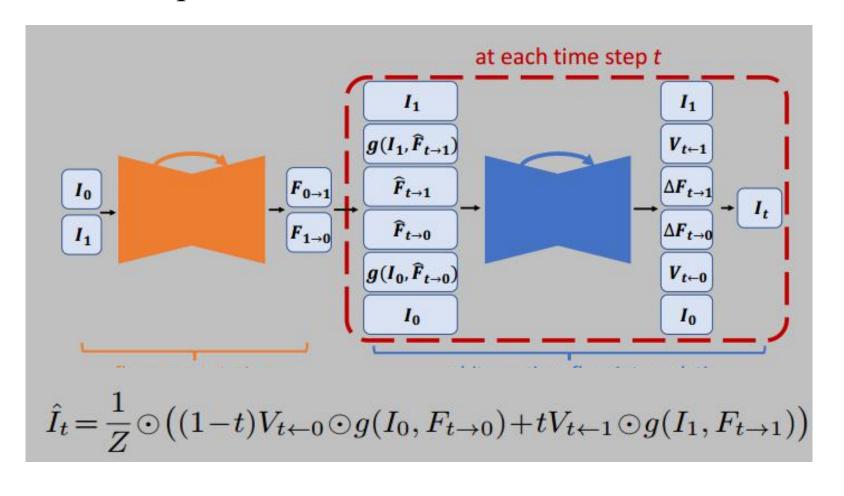






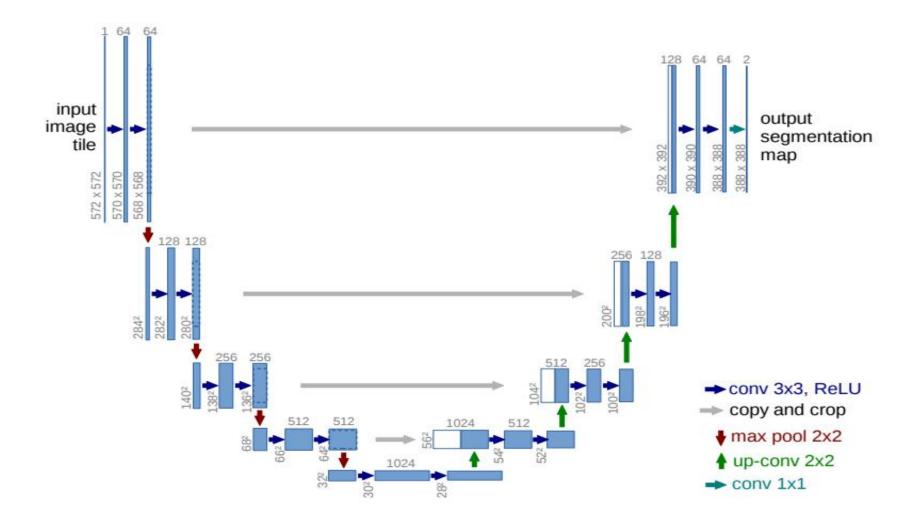
Super slomo: High quality estimation of multiple intermediate frames for video interpolation







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$$l = \lambda_r l_r + \lambda_p l_p + \lambda_w l_w + \lambda_s l_s. \tag{7}$$

$$l_r = \frac{1}{N} \sum_{i=1}^{N} ||\hat{I}_{t_i} - I_{t_i}||_1.$$
 (8)

$$l_p = \frac{1}{N} \sum_{i=1}^{N} \|\phi(\hat{I}_t) - \phi(I_t)\|_2, \tag{9}$$

$$l_w = ||I_0 - g(I_1, F_{0 \to 1})||_1 + ||I_1 - g(I_0, F_{1 \to 0})||_1 +$$
 (10)

$$\frac{1}{N} \sum_{i=1}^{N} \|I_{t_i} - g(I_0, \hat{F}_{t_i \to 0})\|_1 + \frac{1}{N} \sum_{i=1}^{N} \|I_{t_i} - g(I_1, \hat{F}_{t_i \to 1})\|_1.$$

$$l_s = \|\nabla F_{0\to 1}\|_1 + \|\nabla F_{1\to 0}\|_1.$$





○实验结果

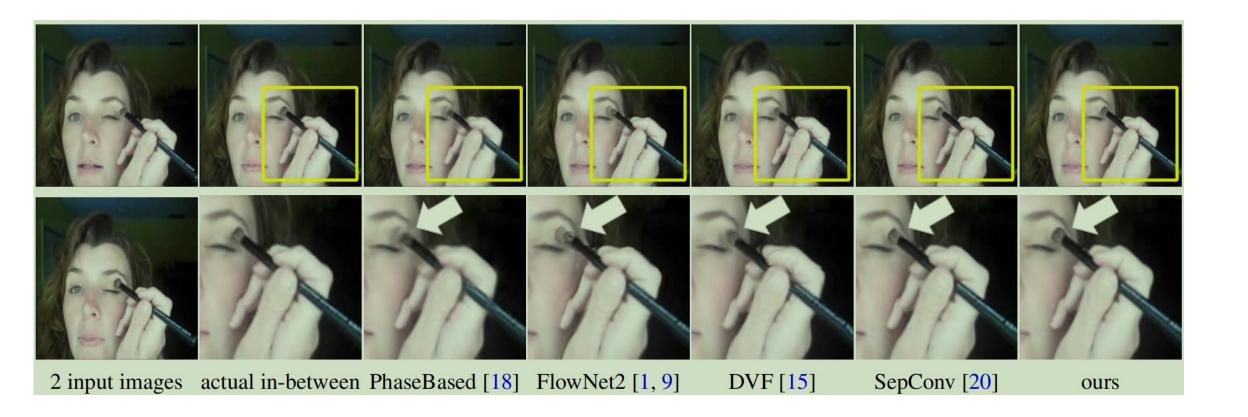
	PSNR	SSIM	ΙE
Phase-Based [18]	32.35	0.924	8.84
FlowNet2 [1, 9]	32.30	0.930	8.40
DVF [15]	32.46	0.930	8.27
SepConv [20]	33.02	0.935	8.03
Ours (Adobe240-fps)	32.84	0.935	8.04
Ours	33.14	0.938	7.80

	PSNR	SSIM	IE
Phase-Based [18]	31.05	0.858	8.21
FlowNet2 [1, 9]	34.06	0.924	5.35
SepConv [20]	32.69	0.893	6.79
Ours	34.19	0.924	6.14

	PSNR	SSIM	IE
Phase-Based [18]	28.67	0.840	10.24
FlowNet2 [1, 9]	30.79	0.922	5.78
SepConv [20]	31.51	0.911	6.61
Ours	32.38	0.927	5.42



三主观结果



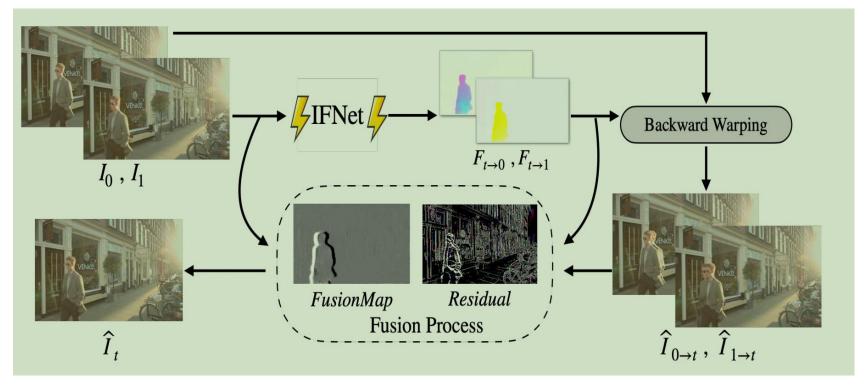




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RIFE: Real-Time Intermediate Flow Estimation for Video Frame Interpolation

- 多尺度光流
- 多尺度特征融合
- 残差信息融合



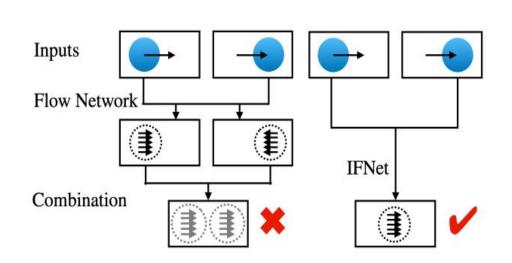


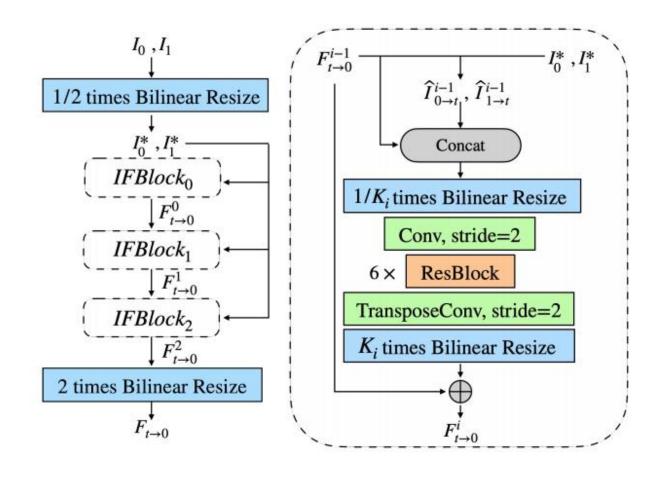




IFNet光流估计











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实验结果

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Mathad	# Parameters	Runtime	UCF10)1 [28]	Vimeo9	0K [35]	Middlebury [1]	HD [3]
Method	(Million)	(ms)	PSNR	SSIM	PSNR	SSIM	IE	PSNR
TOFlow [35]	1.1	430	34.58	0.967	33.73	0.968	2.15	29.37
SepConv- $\mathcal{L}_1[24]$	21.6	200	34.78	0.967	33.79	0.970	2.27	30.87
MEMC-Net [3]	70.3	121	35.01	0.968	34.40	0.970	2.12	31.60
DAIN [2]	24.0	125	35.00	0.968	34.71	0.976	2.04	31.64
CAIN [8]	42.8	<u>32</u> *	34.91	0.969	34.65	0.973	2.28	30.70*
SoftSplat [23]	7.7	135	35.39	0.970	36.10	0.980	-	-
BMBC [26]	11.0	770	35.15	0.969	35.01	0.976	=	-
RIFE (Ours)	10.4	21	35.14	0.969	35.69	0.978	2.05	32.04
RIFE-Large (Ours)	22.9	90	35.33	0.970	36.24	0.981	1.98	32.18

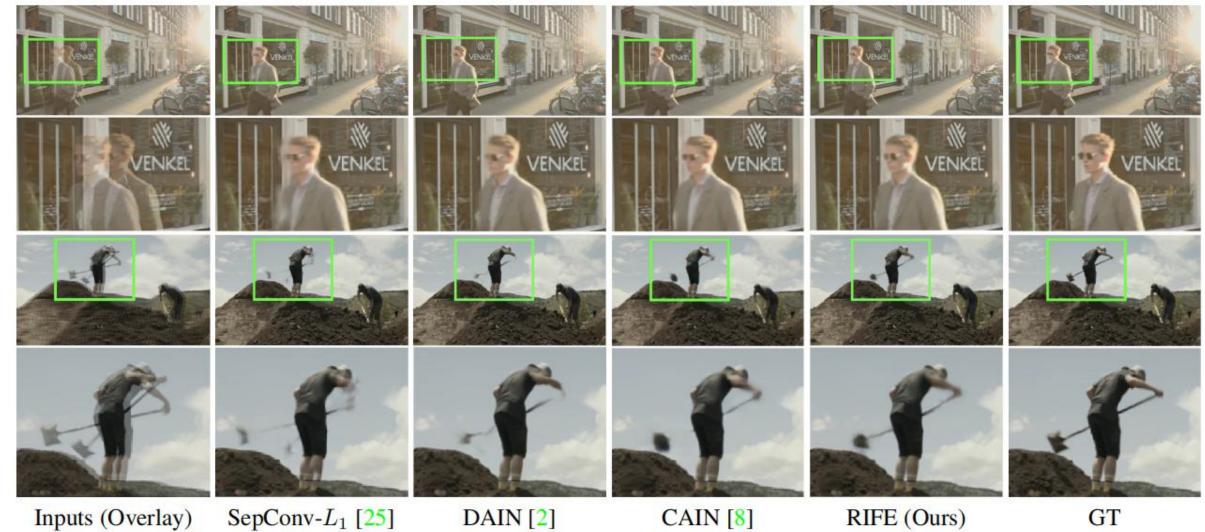
*: use officially released models to produce results





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实验结果







复杂度与收益



Scale Setting	RIFE	1.5C	2F	RIFE-Large
UCF101 PSNR	35.14	35.26	35.32	35.33
Vimeo90K PSNR	35.69	35.88	36.08	36.24
Middlebury IE	2.03	2.03	1.99	1.98
HD PSNR	32.04	32.13	31.96	32.18
# Parameters*	10.4M	22.9M	10.4M	22.9M
Runtime*	36ms	65ms	126ms	196ms
Complexity*	83G	185G	322G	724G

*: measure the whole algorithm on 720p videos







多帧插值







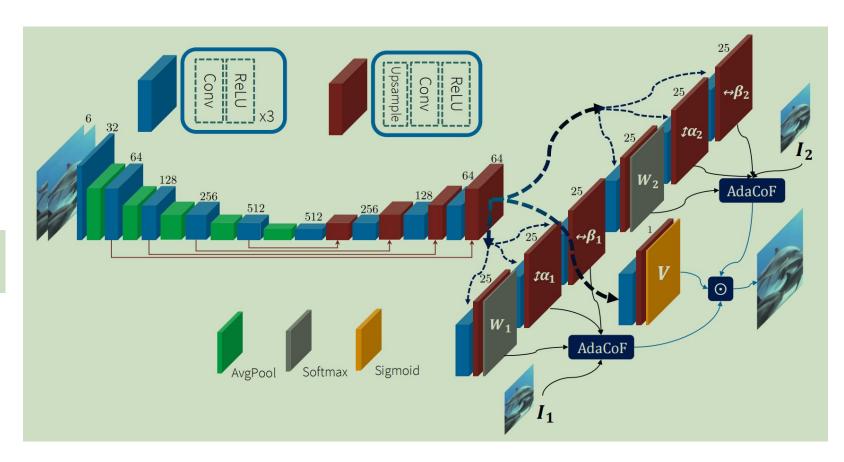
AdaCoF: Adaptive Collaboration of Flows for Video Frame Interpolation



Deformable-convolution

权重学习

$$\hat{I}(i,j) = \sum_{k=0}^{F-1} \sum_{l=0}^{F-1} W_{k,l} I(i+k+\alpha_{k,l},j+l+\beta_{k,l})$$









Deformable Convolution

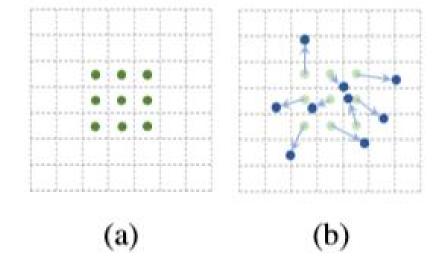


Convolution

$$\hat{I}(i,j) = \sum_{k=0}^{F-1} \sum_{l=0}^{F-1} W_{k,l} I(i+k,j+l)$$

Deformable Convolution

$$\hat{I}(i,j) = \sum_{k=0}^{F-1} \sum_{l=0}^{F-1} W_{k,l} I(i+k+\alpha_{k,l}, j+l+\beta_{k,l})$$







实验结果

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	Middlebury		UCF	101	DAVIS	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
F = 1	32.879	0.956	33.449	0.967	24.787	0.828
F = 3	35.212	0.975	34.728	0.973	26.535	0.867
F = 5	35.715	0.978	35.063	0.974	26.636	0.868
F = 7	35.927	0.979	34.974	0.974	26.987	0.873
F = 9	36.019	0.980	35.012	0.973	27.029	0.875
F = 11	36.094	0.981	35.024	0.974	26.941	0.873

Table 2: Experimental result on kernel size F.

	Middlebury		UCF101		DAV	VIS
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
d = 0	35.489	0.977	35.032	0.974	26.710	0.870
d = 1	35.715	0.978	35.063	0.974	26.636	0.868
d = 2	35.876	0.980	35.099	0.974	26.910	0.870

Table 3: Experimental result on dilation d.







实验结果

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	Middlebury		UCF	UCF101		VIS
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
Overlapping	27.968	0.879	30.445	0.935	21.922	0.740
Phase Based [32]	31.117	0.933	32.454	0.953	23.465	0.800
MIND [28]	31.346	0.943	32.437	0.963	25.570	0.852
SepConv [35]	35.521	0.977	34.735	0.973	26.258	0.861
DVF [27]	34.340	0.971	34.465	0.972	25.880	0.858
SuperSlomo [20]	34.234	0.972	34.055	0.970	25.699	0.858
Ours	35.715	0.978	35.063	0.974	26.636	0.868
Ours +	36.139	0.981	35.048	0.974	27.070	0.874

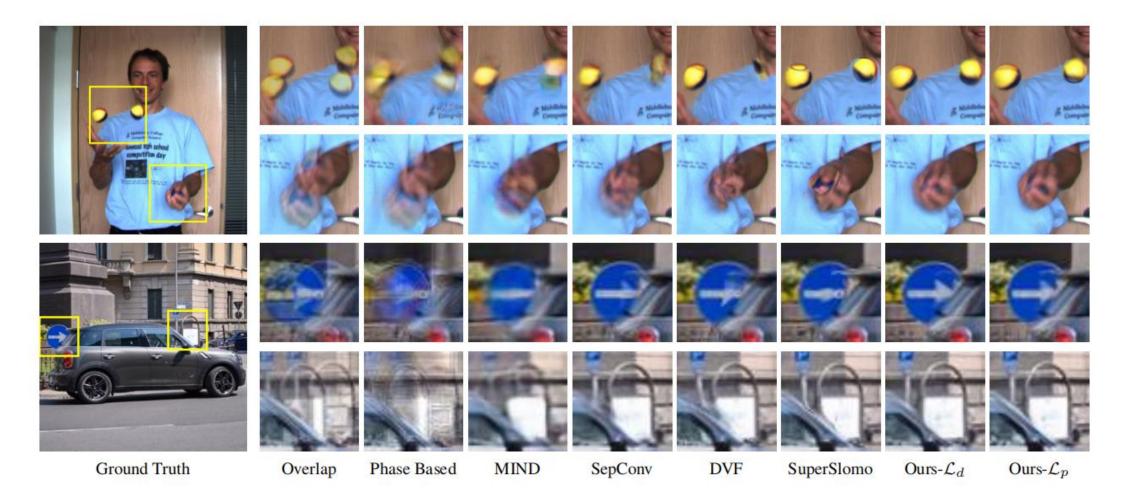






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主观效果









视频插帧存在的问题

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■ 插帧效果

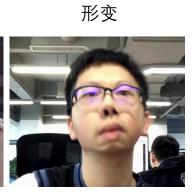
- 生成帧清晰度下降
- 低帧率插帧出现模糊、重影、形变

■可用性受限





重影



模型	大小	GFLOPs	推理速度 720p nvidia 1060
SuperSlomo	151MB	14G	200ms
RIFE	114MB	724G	190ms

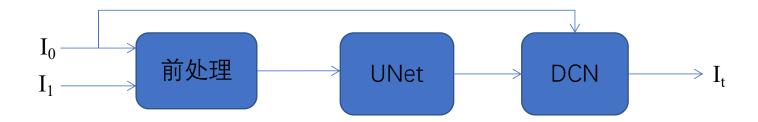




○ 视频插帧方案



- 前处理
- 单方向光流
- Kernel+Deformable convolution







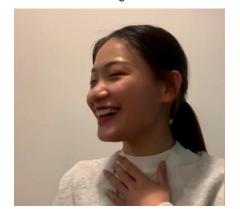


前处理

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规避大幅度运动 防止效果回退

 I_0



 I_{t}



 I_1







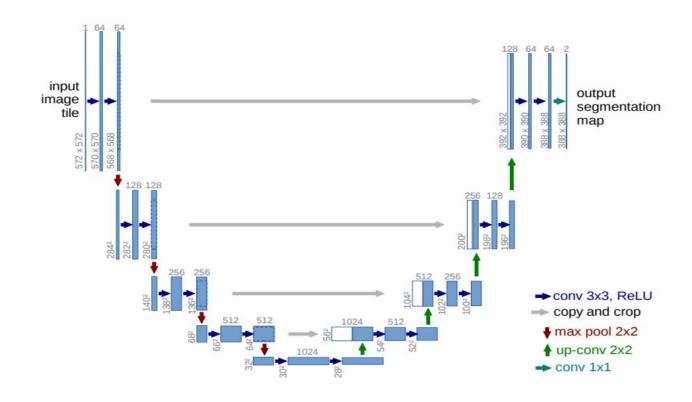


Unet

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多尺度 运算量集中头尾部 参数里集中中部

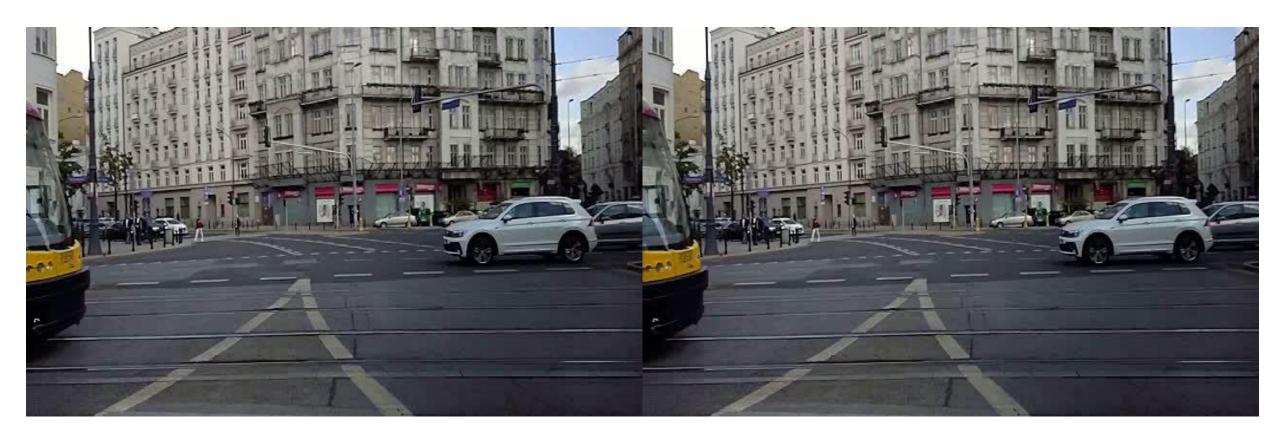
计算单向光流 add代替cat 常规conv2d 插值法代替decon

















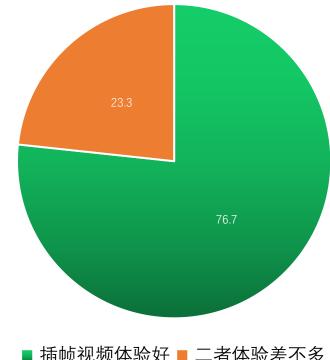
主观评估

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12人进行主观评估

30个视频片段, 帧率 6fps~15fps

A-B对比



■ 插帧视频体验好 ■ 二者体验差不多





○ 总结

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● 更低帧率视频的插帧

● 多帧插帧

● 处理高分辨率



