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Super Resolution for Compressed Screen Content Video

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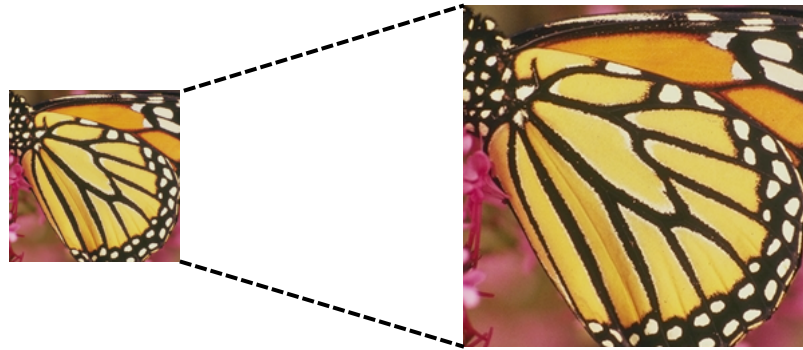
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Outline

- Introduction
- Compressed Screen Content Video SR Dataset
- Architecture of the proposed SR framework
- Compression and Perception Inspired Loss Function
- Experimental Results
- Conclusion

Introduction

- Super Resolution (SR)



Low Resolution (LR)

High Resolution (HR)

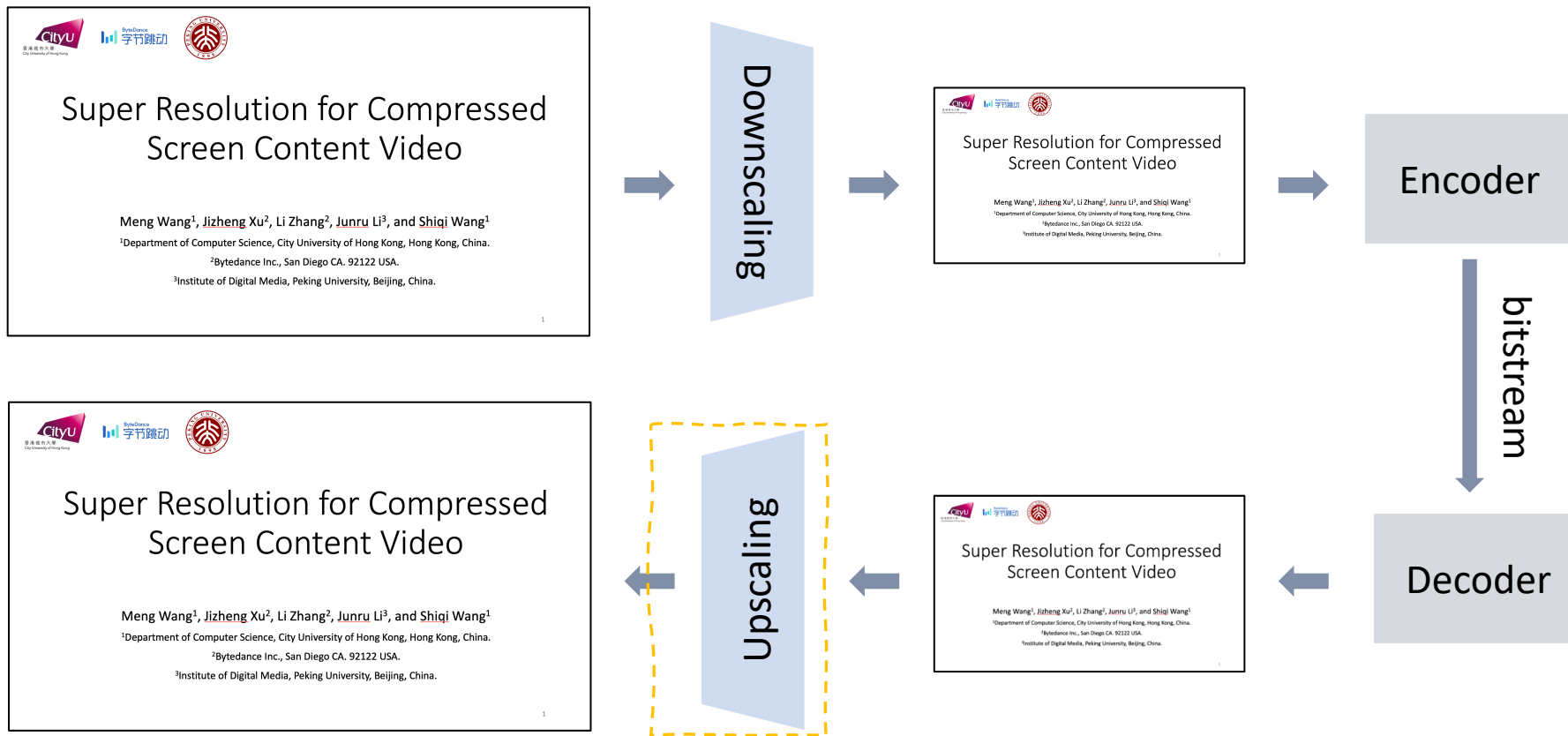
Recovering high-resolution image/video from the low-resolution one



SR has been widely employed in various fields and computer tasks

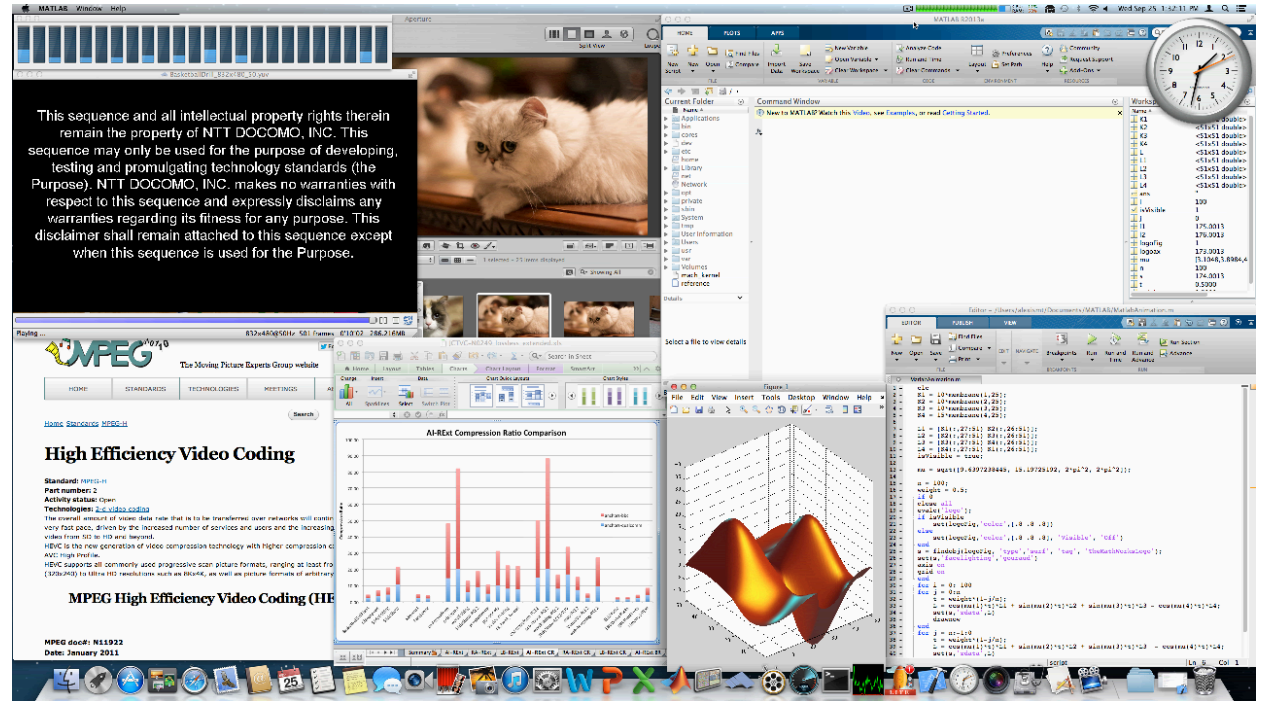
Introduction

- Super Resolution (SR)



Introduction

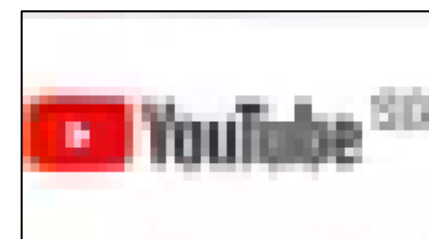
- Natural Scene Videos
 - With sensor Noise
 - Smooth Content
- Screen Content Videos
 - Noise Free
 - Sharp Edges
 - High Contrast



A typical mixed content frame

Introduction

- Screen content video with down-scaling coding and compression distortions
 - Block artifacts
 - Ringing artifacts
 - Blurring
 - ...

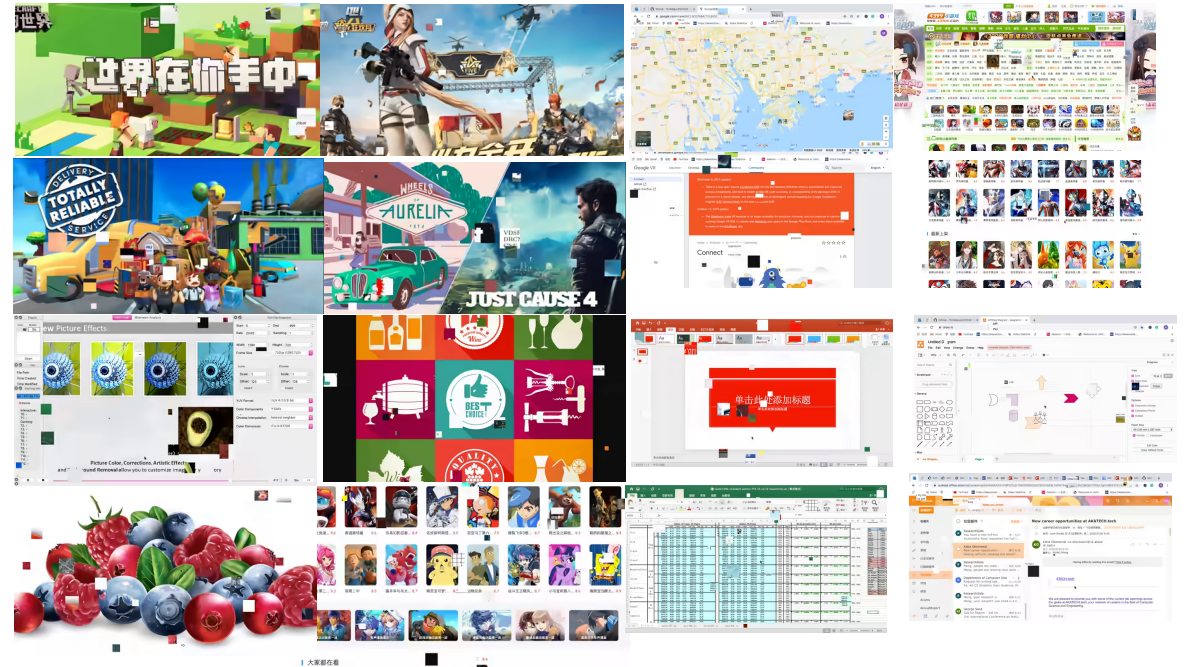


Original

Compressed

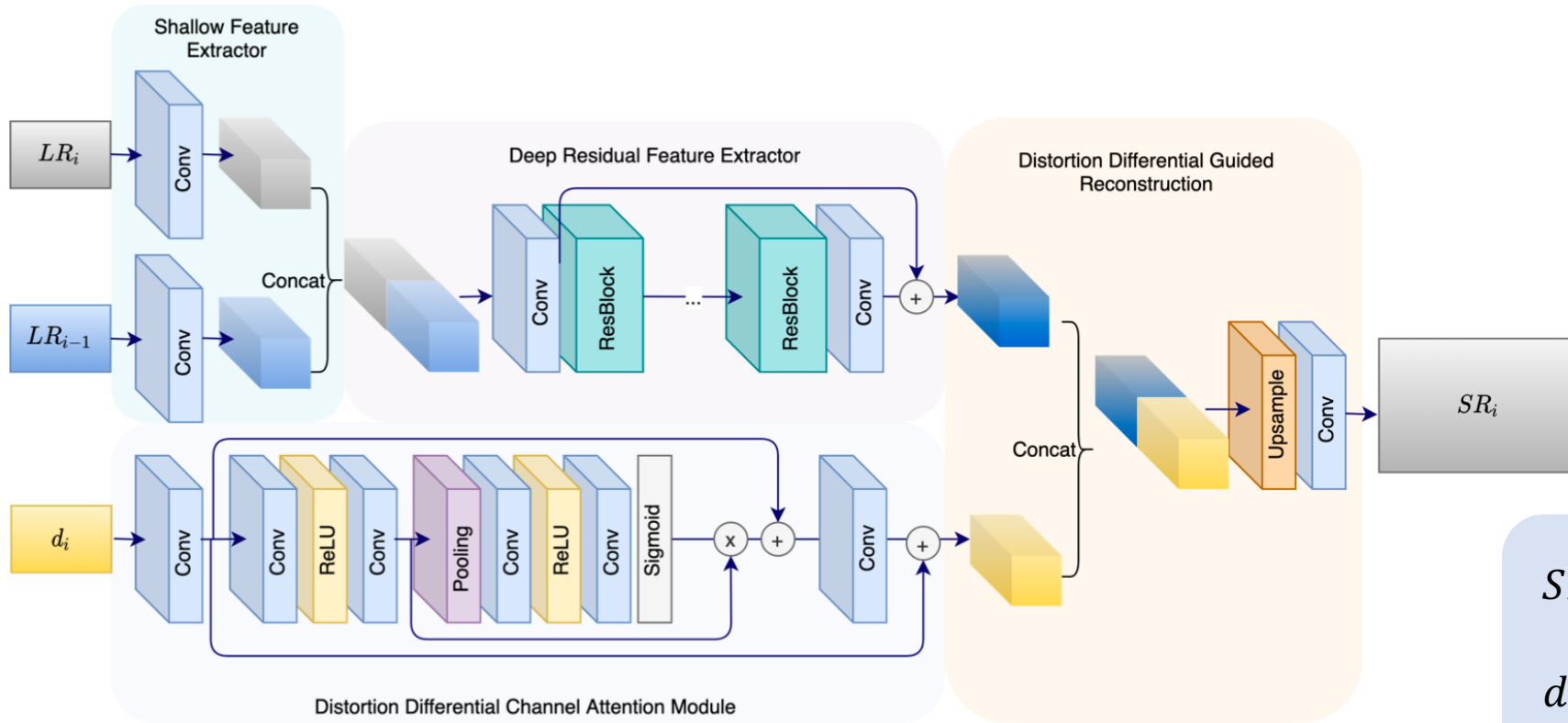
Compressed Screen Content Video SR Dataset

- 200 screen content video clips
- Local Mutations, rotations, cut-in, cut-off
- 1280x720, 960x480
- Plenteous types of scene
 - Webpages
 - Game scene
 - Documents
 - Cartoons
- Low resolution frames are generated with bicubic down-sampling and compressed with VTM-8.0
 - With QP 22, 27,32,37 and 42
 - All intra configuration



Examples of the Compressed Screen Content

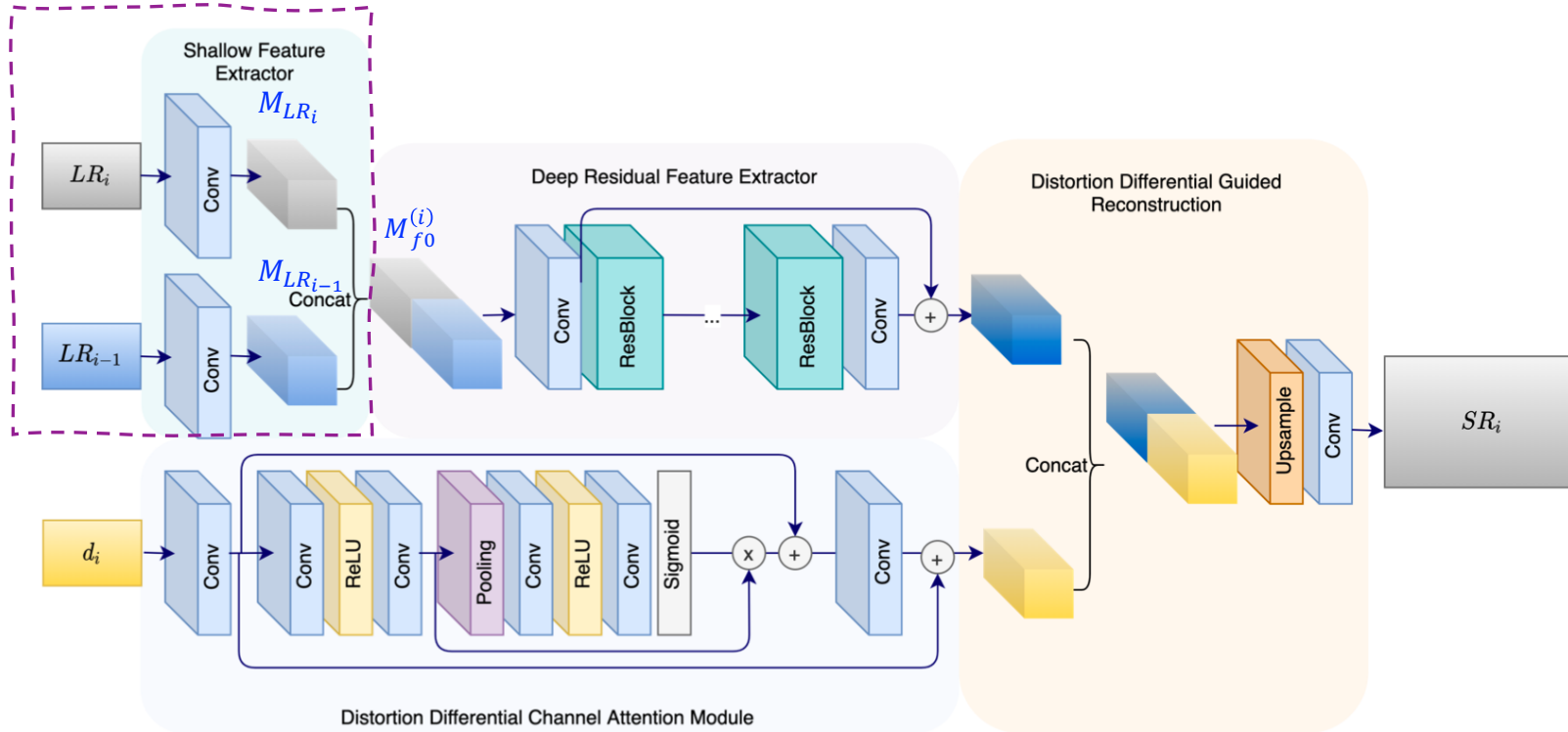
Architecture of the proposed SR framework



$$SR_i = S(LR_i, LR_{i-1}, d_i, \theta)$$

$$d_i(x, y) = e^{-(LR_i(x, y) - LR_{i-1}(x, y))^2}$$

Shallow Feature Extractor

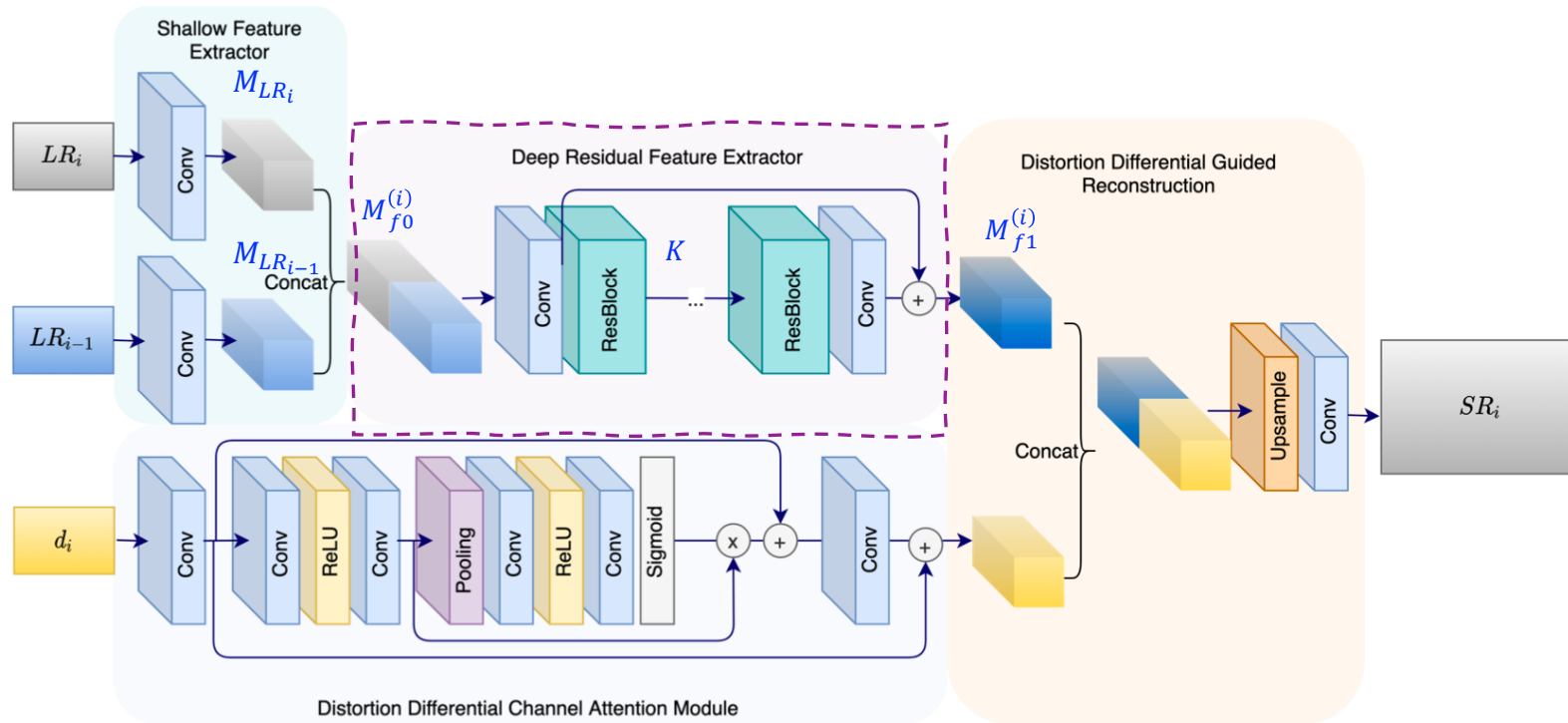


$$M_{LR_i} = S_{cov}^{(0)}(LR_i)$$

$$M_{LR_{i-1}} = S_{cov}^{(1)}(LR_{i-1})$$

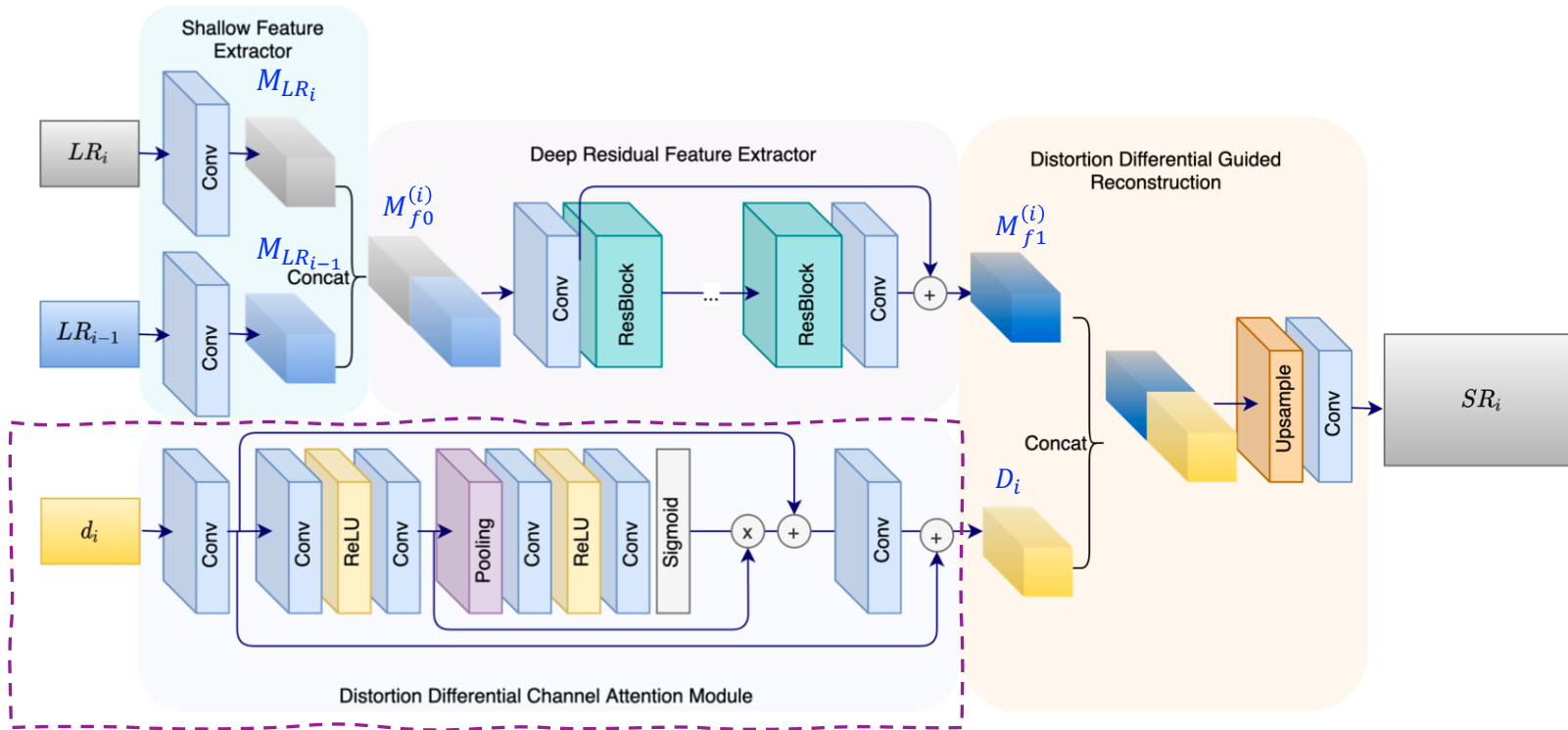
$$M_{f0}^{(i)} = S_{cat} \{M_{LR_i}, M_{LR_{i-1}}\}$$

Deep Residual Feature Extractor



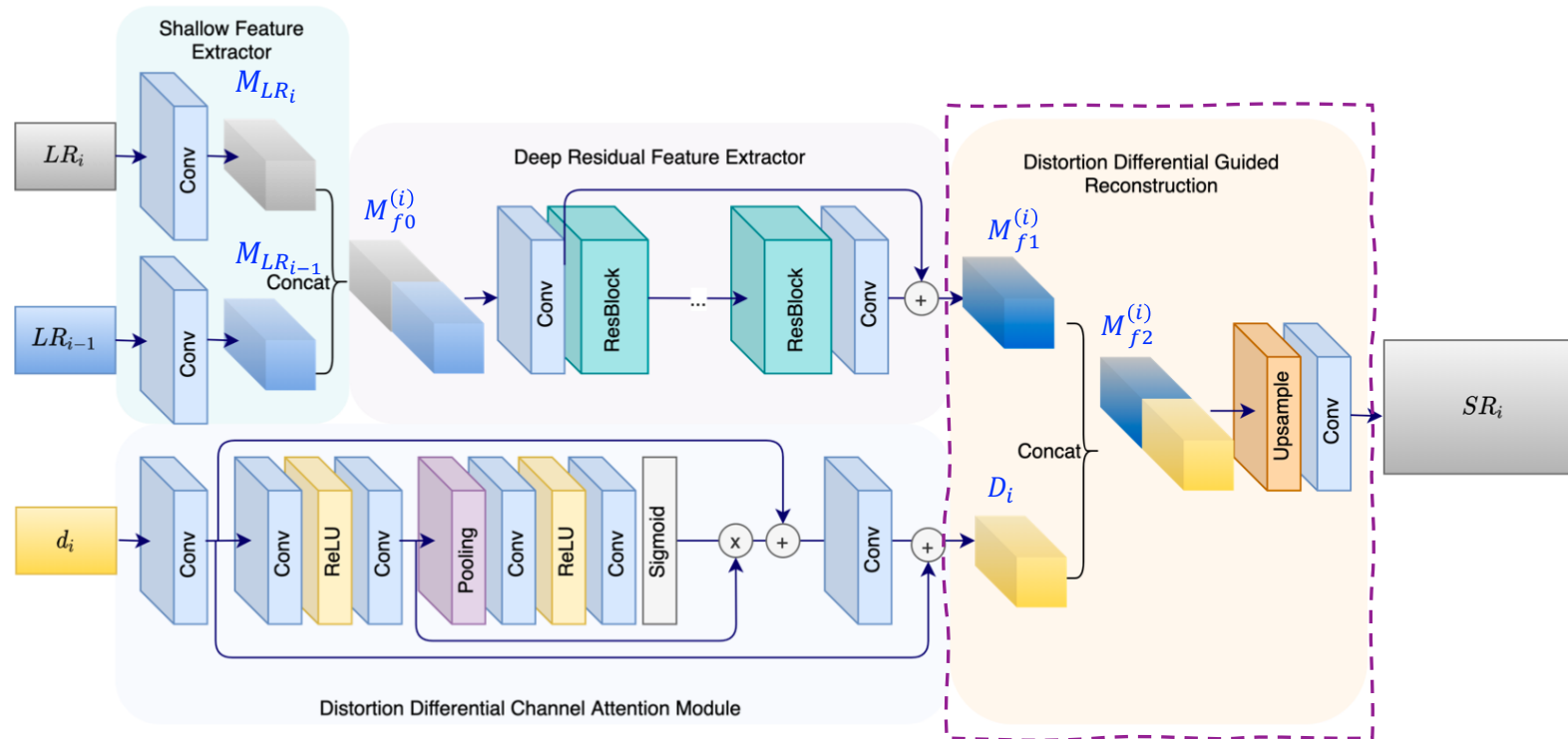
$$M_{f1}^{(i)} = S_{resi}(M_{f0}^{(i)})$$

Distortion Differential Channel Attention Module



$$D_i = S_{ddca}(d_i)$$

Distortion Differential Guided Reconstruction



$$M_{f2}^{(i)} = S_{\text{cat}}\{M_{f1}^{(i)}, D_i\}$$

$$SR_i = S_{\text{cov}}^{(2)}(S_{\text{up}}(M_{f2}^{(i)}))$$

Compression and Perception Inspired Loss Function

$$F_l(HR_i, SR_i) = \frac{2 \cdot \mu_{HR_i} \cdot \mu_{SR_i} + c_1}{\mu_{HR_i}^2 + \mu_{SR_i}^2 + c_1}$$

$$s(I) = |I \cdot \phi_{k1}| + |I \cdot \phi_{k2}|$$

$$F_s(HR_i, SR_i) = \frac{2 \cdot s_{HR_i} \cdot s_{SR_i} + c_1}{s_{HR_i}^2 + s_{SR_i}^2 + c_1}$$

$$L_{LSSM} = \frac{1}{F_l(HR_i, SR_i) \cdot F_s(HR_i, SR_i)}$$

$$L = \omega_1 \cdot L_2 + \omega_2 \cdot L_{LSSM}$$

0	0	0	0	0
1	3	8	3	1
0	0	0	0	0
-1	-3	-8	-3	-1
0	0	0	0	0

(a) ϕ_1

0	0	1	0	0
0	8	3	0	0
1	3	0	-3	-1
0	0	-3	-8	0
0	0	-1	0	0

(b) ϕ_2

0	0	1	0	0
0	0	3	8	0
-1	-3	0	3	1
0	-8	-3	0	0
0	0	-1	0	0

(c) ϕ_3

0	1	0	-1	0
0	3	0	-3	0
0	8	0	-8	0
0	3	0	-3	0
0	1	0	-1	0

(d) ϕ_4

Experimental Results

- Network Settings and Training Configurations

Configurations	BL Model	EH Model	
Filter Size	3x3		
Filter number	64	128	
Residual block number	16	32	
scale	1	0.1	
Batch size	16	10	
LR input patch size	48x48		
Initial learning rate	0.0001		
Optimizer	ADAM	β_1	0.9
		β_2	0.999
		ϵ	10^{-8}
Training dataset	DIV2K & S_{22} /DIV2K & S_{37}	S_{22}/S_{37}	
Test dataset	$T_{ORG}, T_{QP22}, T_{QP27}, T_{QP32}, T_{QP37}, T_{QP42}$	$T_{ORG}, T_{QP22}, T_{QP27}, T_{QP32}, T_{QP37}, T_{QP42}$	

Experimental Results

- Quantitative Evaluation

Table 1: Quantitative results regarding the PSNR of the proposed SR method

Test Sets	Bicubic	EDSR-BL [3]	EDSR [3]	RCAN [5]	\mathcal{S}_{22} -BL	\mathcal{S}_{37} -BL	\mathcal{S}_{22} -EH	\mathcal{S}_{37} -EH
T_{ORG}	26.076	30.619	31.493	31.744	33.794	31.360	34.583	30.860
T_{QP22}	25.965	29.308	29.408	29.463	33.567	31.476	34.318	30.998
T_{QP27}	25.852	28.718	28.683	28.618	32.435	31.225	33.080	30.866
T_{QP32}	25.602	27.785	27.656	27.527	30.357	30.591	30.749	30.452
T_{QP37}	25.084	26.443	26.302	26.157	27.601	29.099	27.638	29.241
T_{QP42}	24.108	24.771	24.682	24.592	25.055	26.000	24.991	25.981
Average	25.448	27.941	28.037	28.017	30.468	29.959	30.893	29.733

Table 2: Quantitative results regarding the SSIM of the proposed SR method

Test Sets	Bicubic	EDSR-BL [3]	EDSR [3]	RCAN [5]	\mathcal{S}_{22} -BL	\mathcal{S}_{37} -BL	\mathcal{S}_{22} -EH	\mathcal{S}_{37} -EH
T_{ORG}	0.886	0.949	0.956	0.958	0.963	0.948	0.966	0.941
T_{QP22}	0.881	0.929	0.930	0.930	0.958	0.946	0.961	0.942
T_{QP27}	0.878	0.919	0.918	0.917	0.949	0.942	0.952	0.940
T_{QP32}	0.870	0.904	0.903	0.901	0.932	0.934	0.935	0.934
T_{QP37}	0.859	0.883	0.881	0.879	0.903	0.918	0.904	0.920
T_{QP42}	0.840	0.854	0.852	0.815	0.864	0.880	0.864	0.833
Average	0.869	0.906	0.907	0.900	0.928	0.928	0.930	0.918

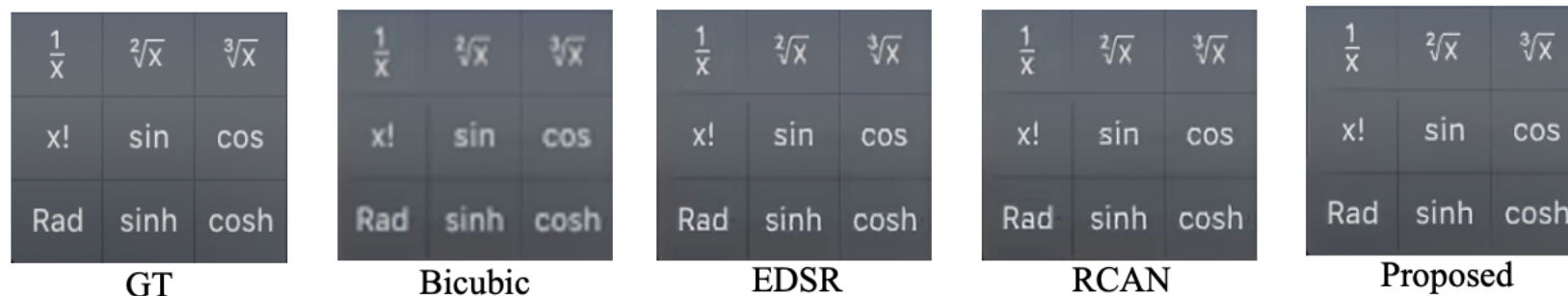
Experimental Results

- Qualitative Evaluation

- LR is compressed with QP22



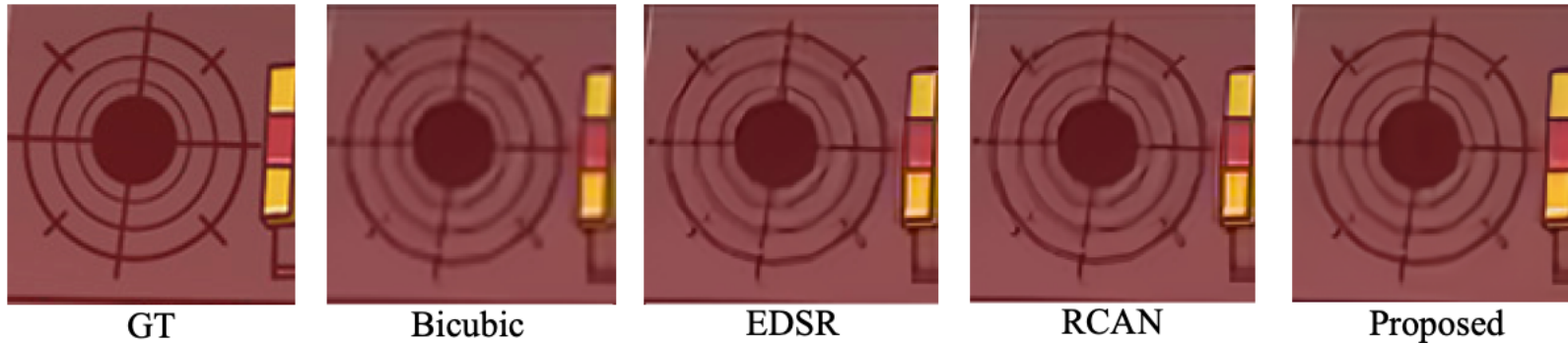
- LR is compressed with QP27



Experimental Results

- Qualitative Evaluation

- LR is compressed with QP32



- LR is compressed with QP37



Conclusion

- SR solutions for compressed screen content video
- Exploring the inner-properties and temporal inter-dependencies
- Design compression and perception inspired loss function
- A dataset for the SR of compressed screen content video



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Thank You !