

Bitstream-Corrupted JPEG Images are Restorable: Two-stage Compensation and Alignment Framework for Image Restoration

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Presented by:

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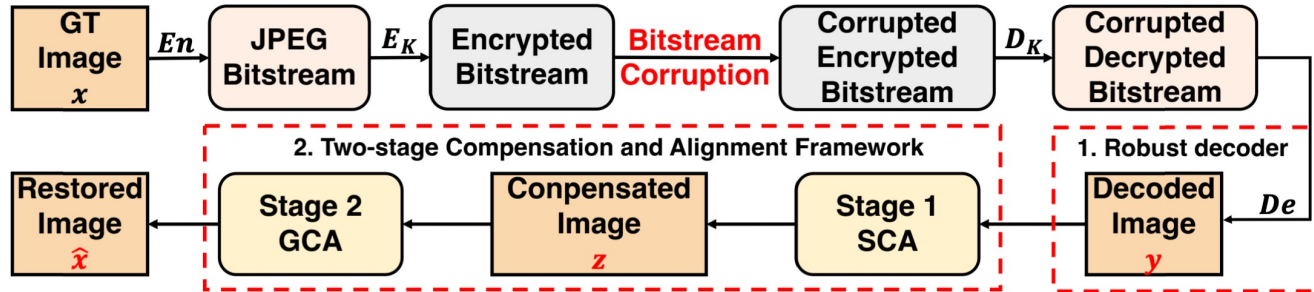
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Summary of the highlight

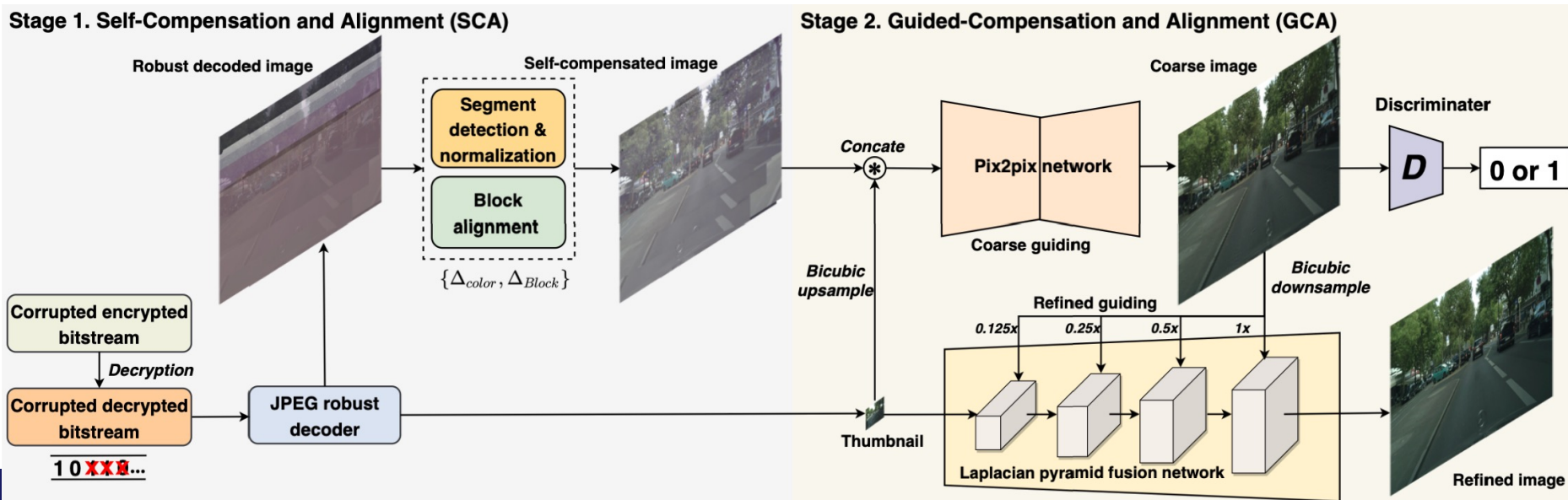
- To the best of our knowledge, this is the first work to restore corrupted JPEG images which contain severe bit errors in their encrypted bitstream
- We propose a robust JPEG decoder, followed by a two-stage compensation and alignment framework to achieve the restoration



- E_n/D_e – JPEG encoding/decoding
- E_K/D_K – encryption/decryption
- SCA – Self-compensation & alignment
- GCA – Guided-compensation & alignment

Summary of the highlight

- The proposed robust JPEG decoder adopts an error-resilient mechanism to decode the corrupted JPEG bitstream without error abort.
- The proposed two-stage compensation and alignment framework performs block-level and pixel-wise image restoration by leveraging the extracted low-resolution thumbnail from the JPEG header.



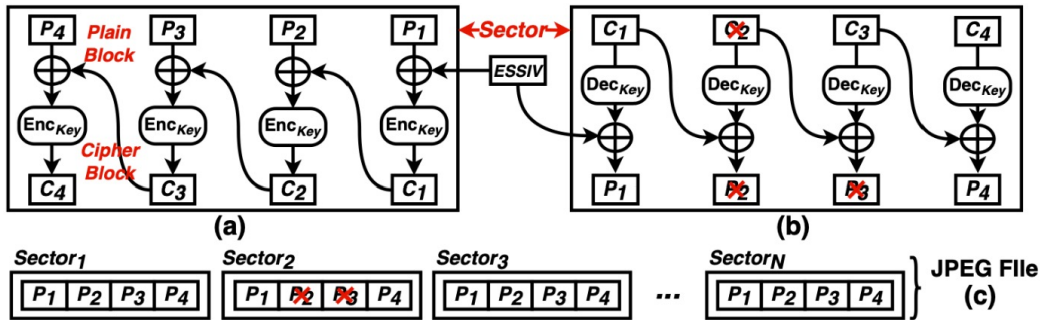
Outline

- Background
- Challenges
- Our method
 - Robust decoder
 - SCA stage
 - GCA stage
- Experiment setting
- Experiment results



Background

- Full-disk encryption is widely used in smartphones that allows each memory sector to be encrypted independently to protect users' data privacy
- Bit errors occur naturally in storage devices as memory cells wear out
- What happens when full-disk encrypted JPEG images have bit errors in memory sectors?

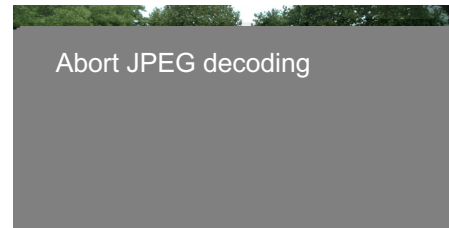


Full-disk encryption/decryption of a sector is sector-independent. (a) Encryption. (b) Decryption with bit errors in c_2 . (c) The decrypted JPEG bitstream with the bit errors shown in (b) would not cause bit errors in other sectors



Initial intact GT image

Bit errors



Bitstream corrupted image decoded by standard decoder

Challenges

- The standard JPEG decoder may abort image decoding for the corrupted bitstream
- Bit errors bring unpredictable color cast and block shifts on the decoded image even in our proposed robust decoder outputs.



Initial GT Image

By standard JPEG decoder



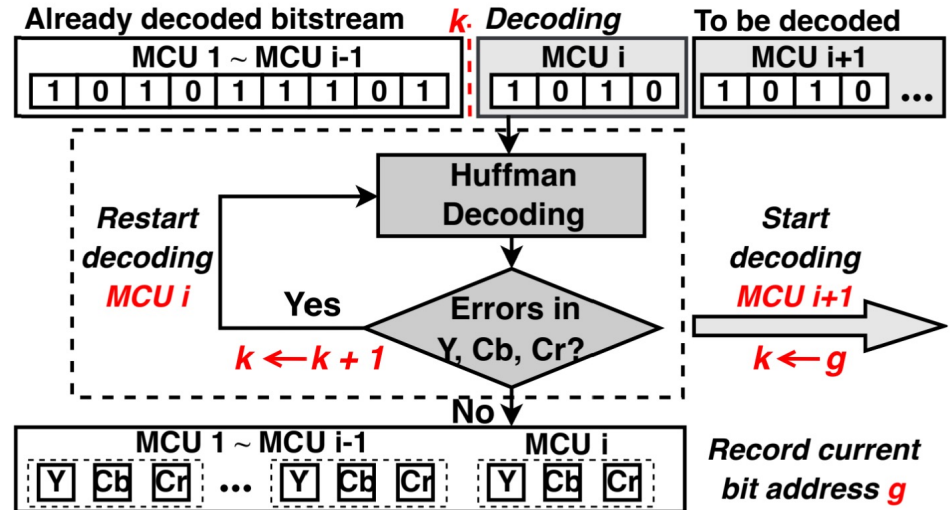
Bitstream Corrupted Image Outputs

By our robust JPEG decoder



Our method – robust decoder

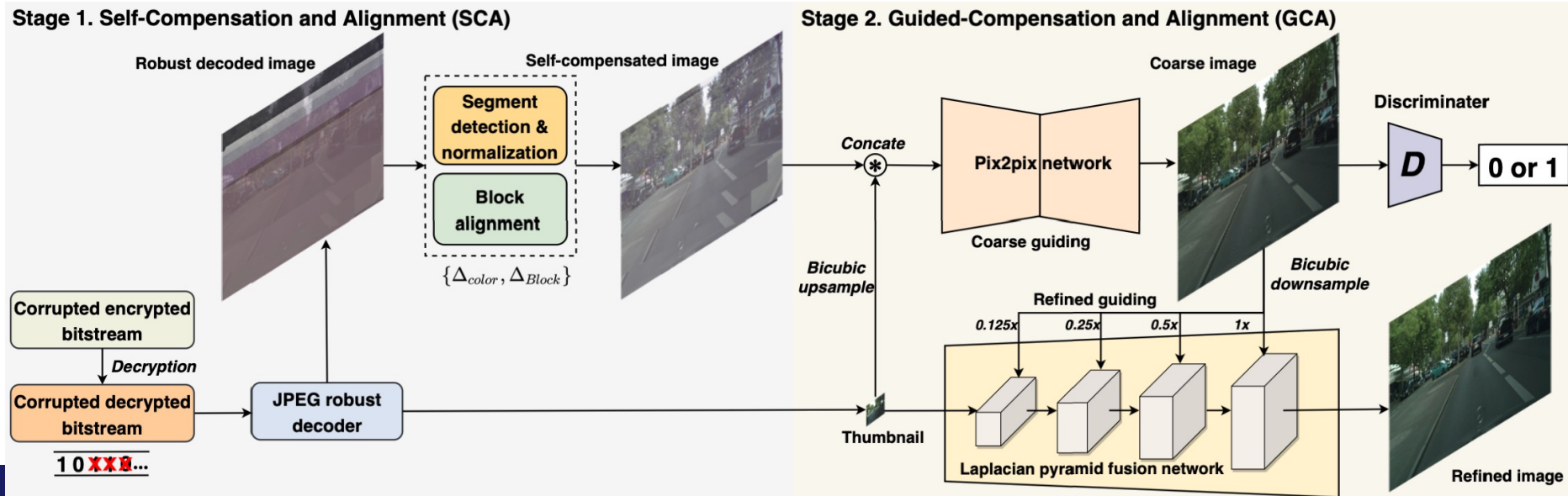
- We found two potential decoding errors that cause the decoding abort
 - Invalid codeword in Huffman table
 - Decoded coefficients overflow
- Based on the decoding errors, we propose an error resilient mechanism in our robust JPEG decoder



Error resilient mechanism in our robust JPEG decoder

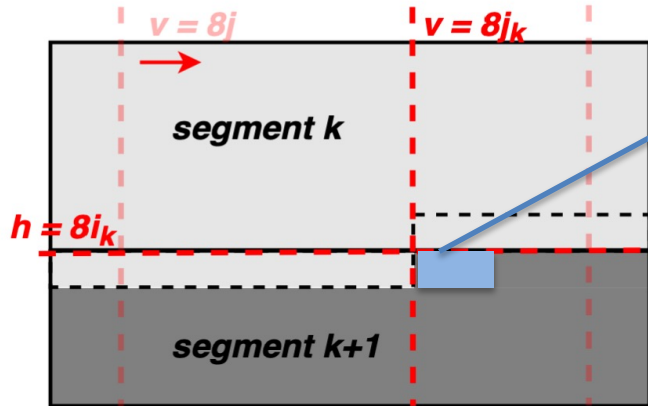
Our method – two stage structure

- SCA can adaptively perform block-wise image color compensation and alignment based on the estimated color and block offsets $\{\Delta\text{Color}, \Delta\text{Block}\}$.
- GCA leverages the extracted low-resolution thumbnail both in a coarse-guided pix2pix network and a refine-guided Laplacian pyramid fusion network to guide full-resolution pixel-wise image restoration.



Our method – SCA stage

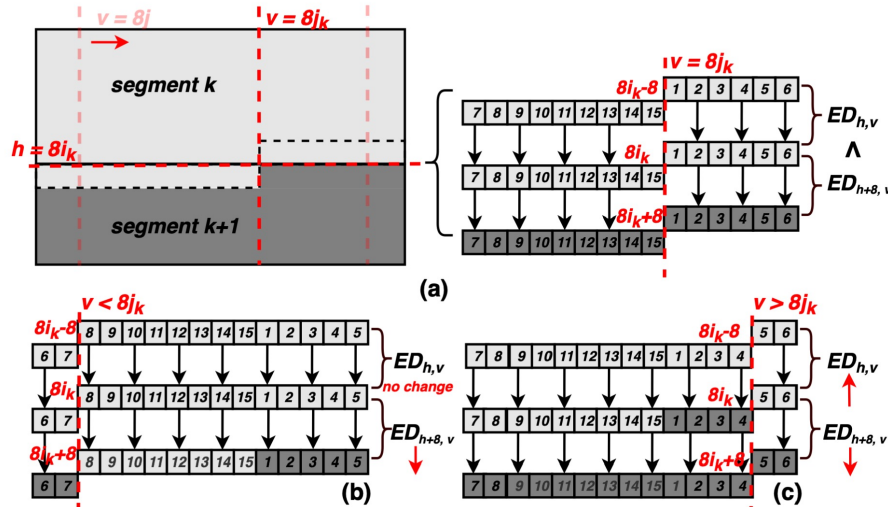
- To estimate the color and block offsets $\{\Delta\text{Color}, \Delta\text{Block}\}$, we intuitively cast this problem as an image segment detection problem
- Blocks inside a segment share the same DC shift and hence have smooth image contents after decoding, and blocks between two consecutive segments have a big difference in image contents after decoding



1. Self-synchronization area
2. DC error propagation will shift the same DC values of the rest blocks after the self-synchronization area
3. DC shifts will result in all 64 pixels of a block shifting by the same values in RGB channels.

Our method – SCA stage

- To estimate the color and block offsets $\{\Delta\text{Color}, \Delta\text{Block}\}$, we intuitively cast this problem as an image segment detection problem
- Blocks inside a segment share the same DC shift and hence have smooth image contents after decoding, and blocks between two consecutive segments have a big difference in image contents after decoding



For segment horizontal coordinate h detection

$$\operatorname{argmax} ED_h = \frac{1}{W} \left(\sum_{i=1}^W (p_{h+1,i} - p_{h,i})^2 \right)^{1/2},$$

For segment vertical coordinate v detection

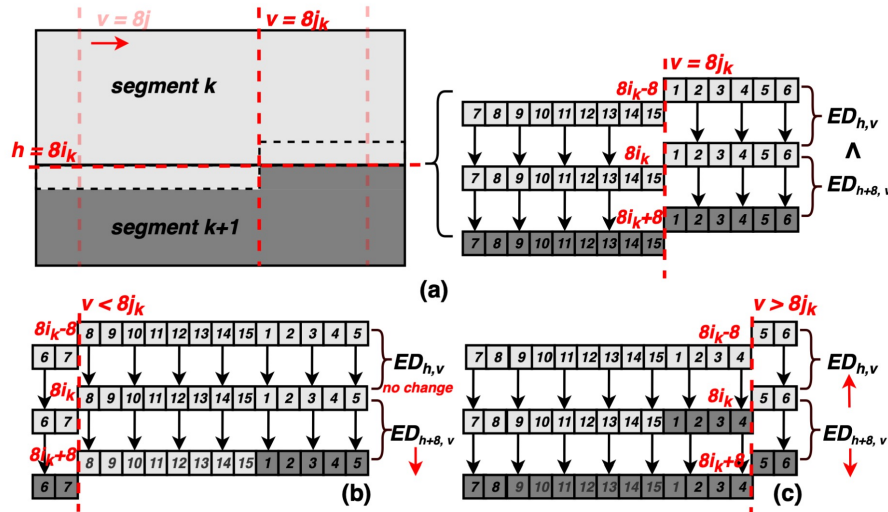
$$\operatorname{argmax} CED_{h,v} = |ED_{h+8,v} - ED_{h,v}|,$$

$$ED_{h,v} = \frac{1}{W} \left(\sum_{i=v}^W (p_{h+1,i} - p_{h,i})^2 + \sum_{i=1}^v (p_{h+9,i} - p_{h+8,i})^2 \right)^{1/2}$$

- For each segment
1. Subtracting its mean value
 2. $\text{Clip}(x, -150, 150)$
 3. Min-max normalization

Our method – SCA stage

- To estimate the color and block offsets $\{\Delta\text{Color}, \Delta\text{Block}\}$, we intuitively cast this problem as an image segment detection problem
- Blocks inside a segment share the same DC shift and hence have smooth image contents after decoding, and blocks between two consecutive segments have a big difference in image contents after decoding



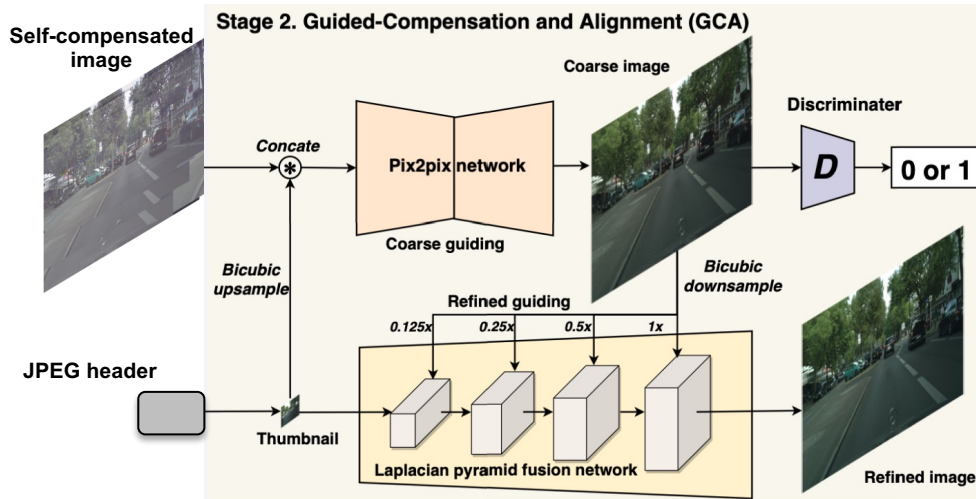
For block shifting of each segment, we try to directly compensate each block row rather than segment

Each time block row shift one block left or right, calculate ED

$$\operatorname{argmin} ED_h = \frac{1}{W} \left(\sum_{i=1}^W (p_{h+1,i} - p_{h,i})^2 \right)^{1/2},$$

Our method – GCA stage

- Self-compensated image still vary greatly from actual color and structure
- GCA leverage the extracted low-resolution thumbnail in both pix2pix and pyramid network to achieve coarse-to-fine image restoration
 - Pix2pix network is adopted from the previous work EPDN
 - Pyramid network is to refine the thumbnail gradually under the different scales of the coarse image guidance



We follow the same alternative iteration training scheme

During each training step

- Update Pix2pix network with L_A , L_{FM} , L_E
- Update Pix2pix network and pyramid network L_{VGG} , L_C , L_E
- Update discriminator L_A

More details can be seen in the paper

Experiment setting

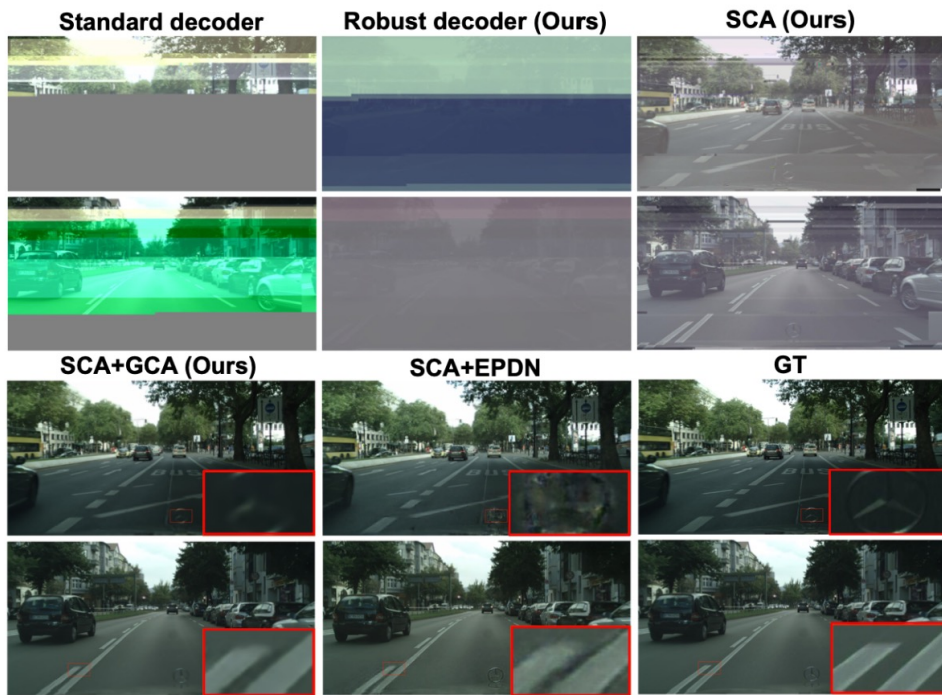
- BER = 10^{-5}
- Using AFHQ, CelebA-HQ and Cityscapes datasets, corresponding to the image resolution 512x512, 1024x1024 and 2048x1024
- Thumbnails are from bicubic downsampling with the maximum side fixed at 160 pixels
- Adam optimizer with a batch size of 4 and a learning rate of 0.0002
- Epochs = 200

Experiment results

- It shows our robust decoder + SCA + GCA can achieve the best image restoration performance
- We also compare our GCA network with a baseline image-to-image translation network EPDN, which adopts the same pix2pix network. GCA outperforms EPDN by a significant margin

Table 1. Quantitative comparison of different methods on different scales of Cityscapes [4] datasets in terms of PSNR/SSIM.

Method	Cityscapes [4]		
	512×256	1024×512	2048×1024
Robust decoder (Ours)	12.41/0.58	12.38/0.64	12.37/0.70
SCA (Ours)	14.34/0.72	14.32/0.75	14.31/0.78
SCA + EPDN	33.51/0.94	33.25/0.94	33.40/0.95
SCA + GCA (Ours)	42.05/0.98	40.09/0.97	38.92/0.97



Experiment results

- We ablate our proposed components in SCA and GCA stages, which demonstrates the effectiveness of the components.

Table 2. Ablation Study of the impact of our proposed components in SCA and GCA stages.

Method	Cityscapes [4]	
	512×256	1024×512
w/o SCA	33.88/0.92	33.52/0.91
w/o Block alignment in SCA	36.50/0.95	35.01/0.92
w/o Laplacian fusion in GCA	36.65/0.95	36.16/0.93
w/o Edge & Charbonnier loss	41.27/0.98	39.53/0.97
Ours	42.05/0.98	40.09/0.97

Experiment results

- Current image restoration methods fail to resolve bitstream-corrupted JPEG files to get the decoded images.
- Given the only extracted low-resolution thumbnails, we compare with existing SOTA super-resolution (SR) methods in bicubic degradation methods.

Table 3. Quantitative comparison in PSNR/SSIM of bicubic, SOTA SR, and our method at different scale factors on Cityscapes [4] datasets

Method	Scale factors	
	$\times 3$	$\times 6$
Bicubic	30.94/0.88	29.79/0.82
SRMD [40]	33.37/0.92	31.66/0.87
USRNet [38]	32.78/0.92	31.18/0.86
Ours	42.05/0.98	40.09/0.97

Experiment results

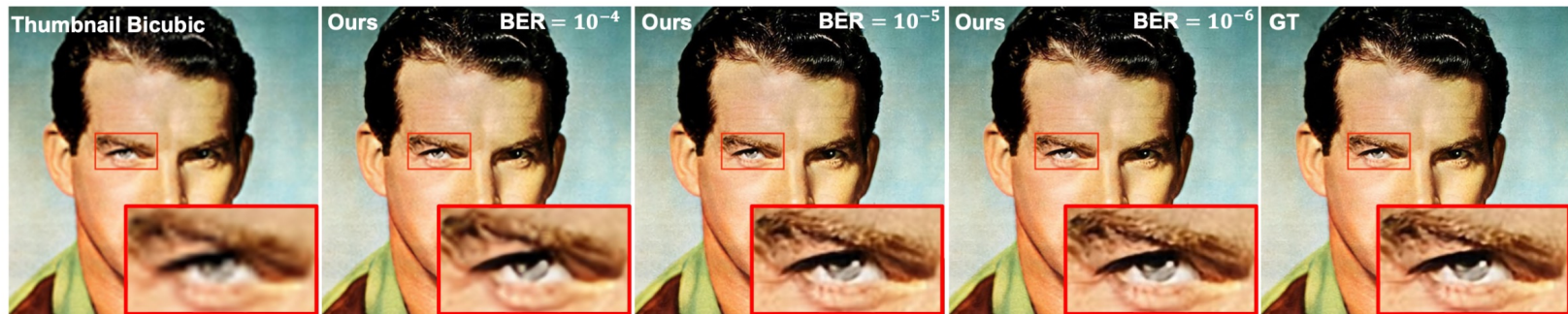
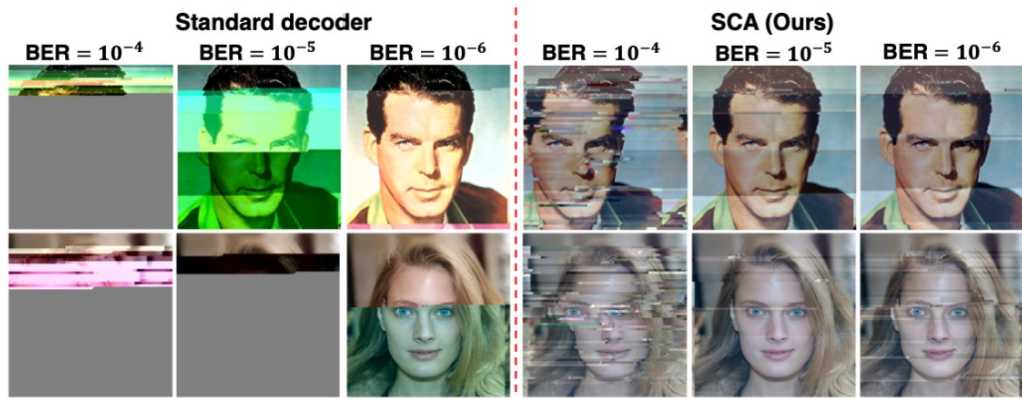
- We also test the generalization of our method in handling varying degrees of BERs in the JPEG file without retraining.

Table 4. Quantitative comparison on varying BERs in terms of PSNR/SSIM with the training under BER= 10^{-5}

Method	BER	AFHQ [3]	CelebA-HQ [17]
SCA (Ours)	10^{-4}	13.44/0.45	12.29/0.57
	10^{-5}	16.77/0.70	16.06/0.77
	10^{-6}	17.46/0.73	15.82/0.74
SCA+GCA (Ours)	10^{-4}	32.41/0.86	35.45/0.92
	10^{-5}	39.00/0.94	41.76/0.97
	10^{-6}	41.39/0.95	41.85/0.97

Experiment results

- We also test the generalization of our method in handling varying degrees of BERs in the JPEG file without retraining.



SCA+
GCA