



Image Upscaling by code prediction (CodeFormer)

April 24, 2023



Agenda

- Team intro
- Problem description
- Approaches
- Evaluation metrics
- Experiments
- Results
- Lesson learned
- Future work

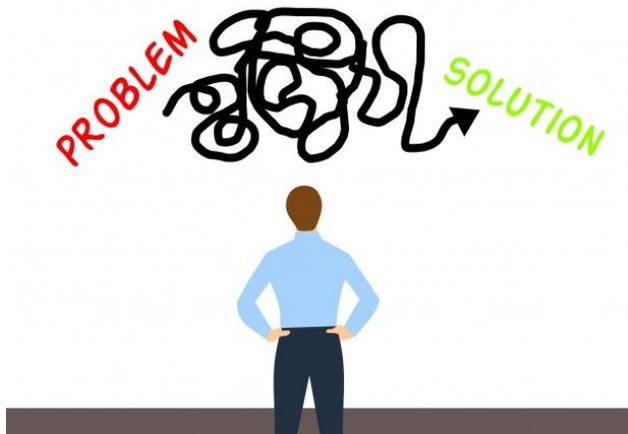


Team Intro

- Justin Wu, syuanyingwu@vt.edu, MEng CS @ NVC
- Yi-Han Chen, yihanchen@vt.edu MEng CS @ NVC
- Diego Romero, rdiego@vt.edu, MEng CS @ NVC

Problem description

1. Restoring face images often suffer from various degradation, such as compression, blur, and noise.
2. Details lost in the inputs (degraded image) needs to be complimented.
3. CodeFormer offers limited superiority to other methods. Sometimes cannot produce good results
⇒ *our experiment*





Approaches: CodeFormer Methodology

- Exploit **Discrete** codebook prior
- See blind face restoration as a **code prediction task**
- Proposed a **Transformer-based code** prediction network
- Proposed a **controllable feature transformation** module with an adjustable coefficient -> a trade-off between restoration quality and fidelity

Codebook Learning (Stage I)

What?

Pre-train the quantized autoencoder to learn a context-rich codebook

Objective

Reduce uncertainty of the LQ-HQ mapping and complement high-quality details for restoration

Codebook Lookup Transformer Learning (Stage II)

What?

Employ a Transformer to model global interrelations to make the prediction

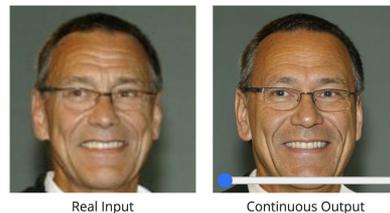
Objective

Improve the accuracy of code prediction for face restoration

Controllable Feature Transformation (Stage III)

What?

Create a flexible tradeoff between quality and fidelity of face restoration.





Evaluation metrics

- SSIM
- PSNR



SSIM (Structural Similarity Index Measure)

- Measure the similarity between two images
- It measures three factors: luminance, contrast, and structural similarity.
 - Luminance: the brightness of the images
 - Contrast: the difference between the images
 - Structure: how similar the patterns in the images are.

$$SSIM = l(x,y) + c(x,y) + s(x,y)$$



SSIM (Structural Similarity Index Measure)

$$l(x, y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1}$$

$$c(x, y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}$$

$$s(x, y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3}$$



SSIM (Structural Similarity Index Measure)

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

with:

- μ_x the **pixel sample mean** of x ;
- μ_y the **pixel sample mean** of y ;
- σ_x^2 the **variance** of x ;
- σ_y^2 the **variance** of y ;
- σ_{xy} the **covariance** of x and y ;
- $c_1 = (k_1 L)^2$, $c_2 = (k_2 L)^2$ two variables to stabilize the division with weak denominator;
- L the **dynamic range** of the pixel-values (typically this is $2^{\#bits \text{ per pixel}} - 1$);
- $k_1 = 0.01$ and $k_2 = 0.03$ by default.



SSIM (Structural Similarity Index Measure)

MAPPING SSIM TO MEAN OPINION SCORE SCALE

SSIM	MOS	Quality	Impairment
≥ 0.99	5	Excellent	Imperceptible
$[0.95, 0.99)$	4	Good	Perceptible but not annoying
$[0.88, 0.95)$	3	Fair	Slightly annoying
$[0.5, 0.88)$	2	Poor	Annoying
< 0.5	1	Bad	Very annoying



PSNR (Peak Signal-to-Noise Ratio)

- Evaluate the quality of compressed or reconstructed images or videos
- It measures the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation.
- PSNR is expressed in decibels (dB)

$$PSNR = 20 \cdot \log_{10} \left(\frac{MAX_I}{\sqrt{MSE}} \right)$$
$$MSE = \frac{1}{m n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i, j) - K(i, j)]^2$$



PSNR (Peak Signal-to-Noise Ratio)

PSNR Value	Quality	MOS
PSNR > 33 dB	Excellent Quality	5
33 dB > PSNR > 30 dB	Fair Quality	2
PSNR < 30 dB	Poor Quality	1



Experiment

1. Collect side face images
2. Generate LQ images
3. Upscale LQ images
4. Evaluate with ground truth
 - a. Visual Comparison
 - b. Evaluation Metrics

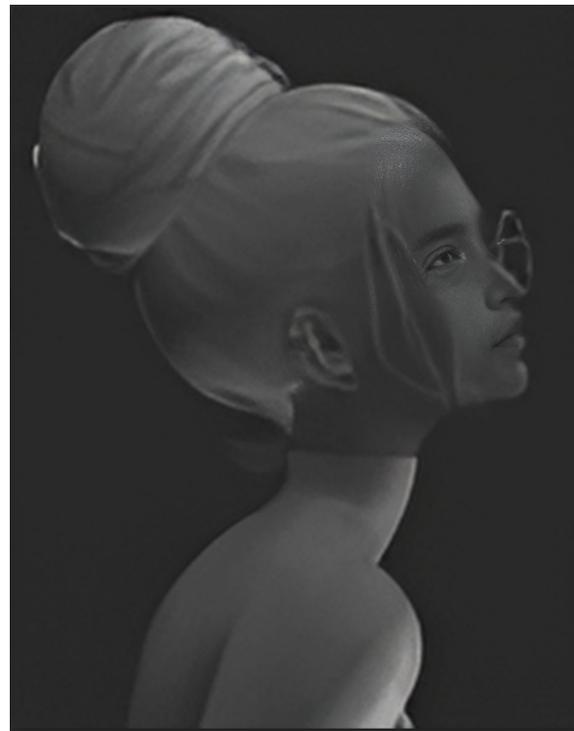
Collect side face images



Generate LQ images



Upscale LQ images





Evaluate with ground truth - Visual Comparison



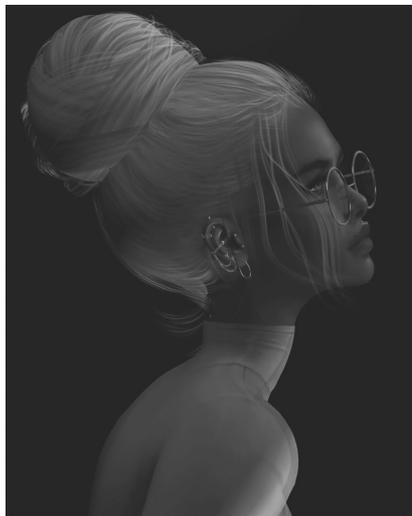
Ground Truth



Upscaled image



Evaluate with ground truth - Visual Comparison



Ground Truth



Upscaled image

Evaluate with ground truth - Evaluation Metrics

Methods	SSIM	PSNR
Score	0.66	23.52
Quality	Poor	Poor



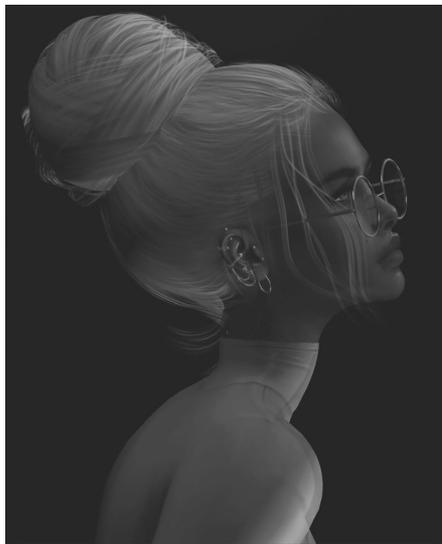
Ground Truth



Upscaled image

Evaluate with ground truth - Evaluation Metrics

Methods	SSIM	PSNR
Score	0.89	32.29
Quality	Poor	Fair



Ground Truth



Upscaled image



Evaluate with ground truth - Evaluation Metrics

Methods	Side Face (Our experiment)	CodeFormer
SSIM	0.75	0.61
PSNR	26.74	22.18



Results

- While the experiment yields better evaluation metrics than the paper, CodeFormer's output for the side face image still lacks naturalness, and has significantly lost detail such as accessories.
- The reason behind the better evaluation metrics could be the differences in the experimental setup, such as utilizing different degradation model parameters.



Future work

- Find side-face dataset to train the data for better code prediction.
- Same technique to restore old movies?





References

1. Shangchen Zhou Kelvin C.K. Chan Chongyi Li Chen Change Loy, “Towards Robust Blind Face Restoration with Codebook Lookup Transformer”, 2022
2. Chitwan Saharia, Jonathan Ho, William Chan, Tim Salimans, David J. Fleet, Mohammad Norouzi, “Image Super-Resolution via Iterative Refinement”, 2021
3. Yoanda Alim Syahbana; Herman; Azizah Abdul Rahman; Kamalrulnizam Abu Bakar, “Aligned-PSNR (APSNR) for Objective Video Quality Measurement (VQM) in video stream over wireless and mobile network”, 2011
4. Marco Zanforlin; Daniele Munaretto; Andrea Zanella; Michele Zorzi, “SSIM-based video admission control and resource allocation algorithms”, 2014