Image Inpainting

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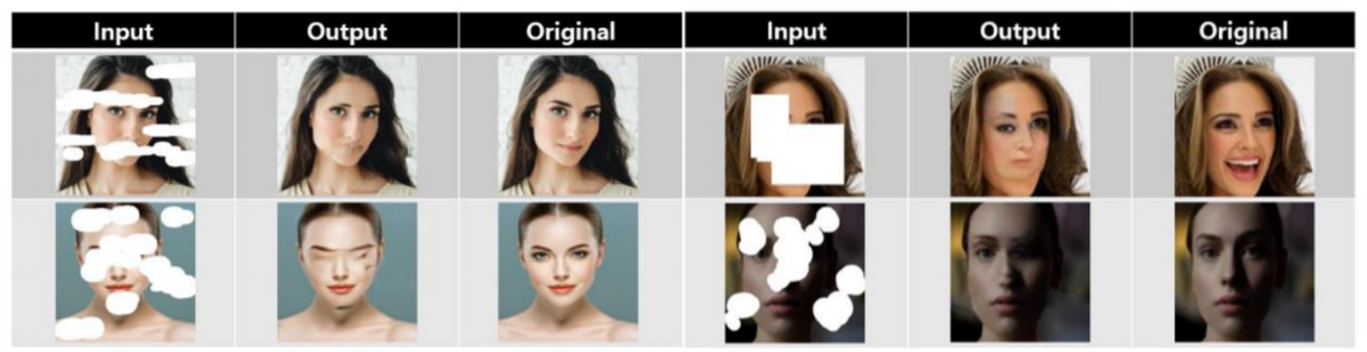
Introduction & Problem

- Image Inpainting

- A task which fills missing pixels with semantically and perceptually plausible contents.

- Problem



- Many inpainting methods gives blurry or awkward images. From this project, I will generate clear and plausible outputs to improve image quality.

Methods

- Recurrent Convolution

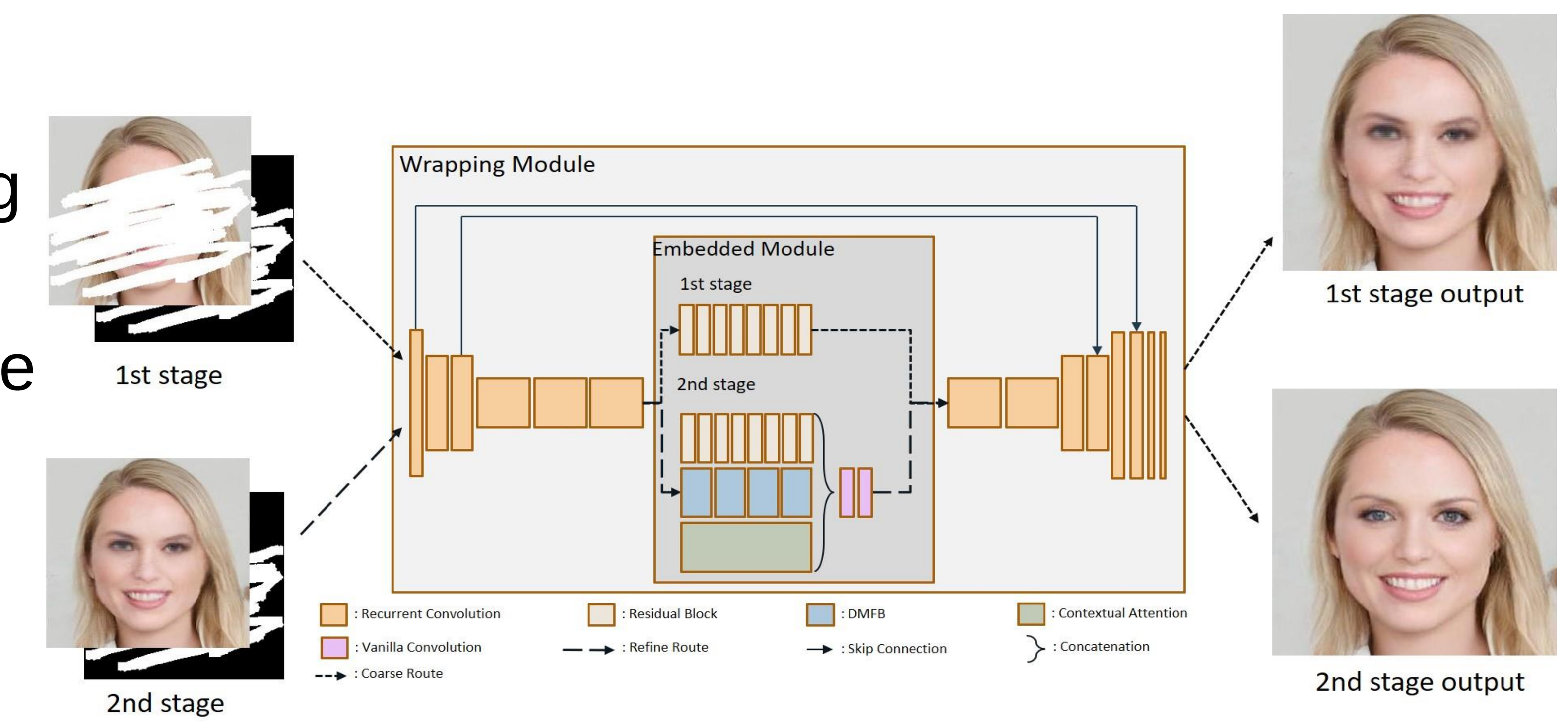
- Implement RNN structure by using buffer
- Reduce the network size & solve gradient vanishing

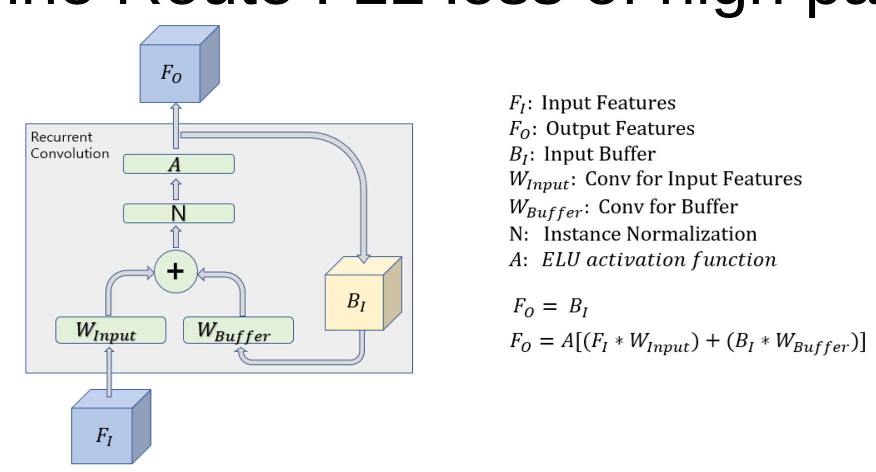
- Sobel Edge Discriminator

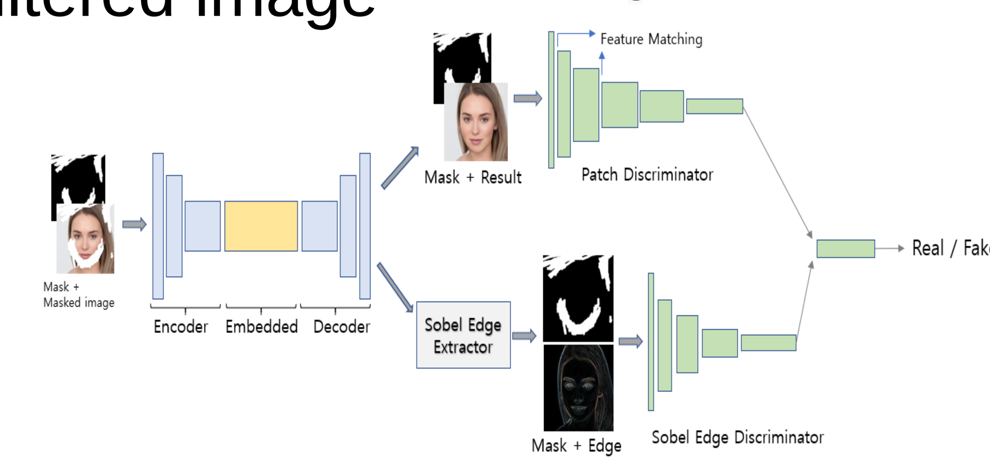
- Sobel edge discriminator distinguishes real and fake edge map of generated image and the ground truth

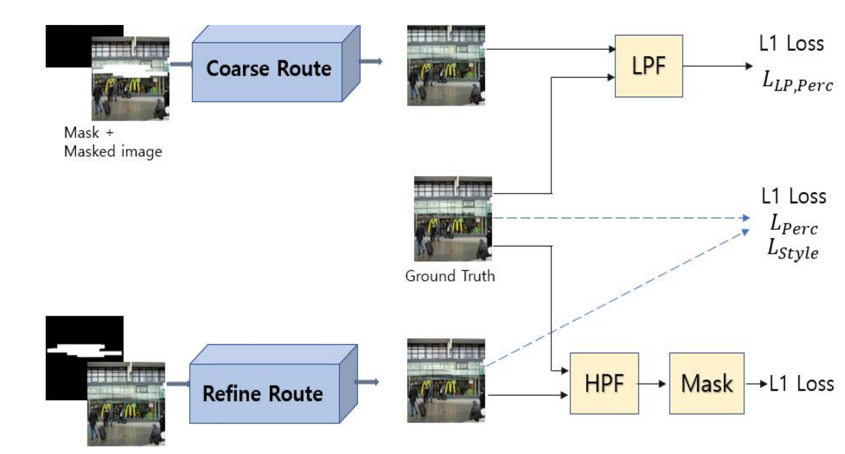
- Frequency Separation Loss

- Coarse Route : L1 loss of low pass filtered image
- Refine Route : L1 loss of high pass filtered image



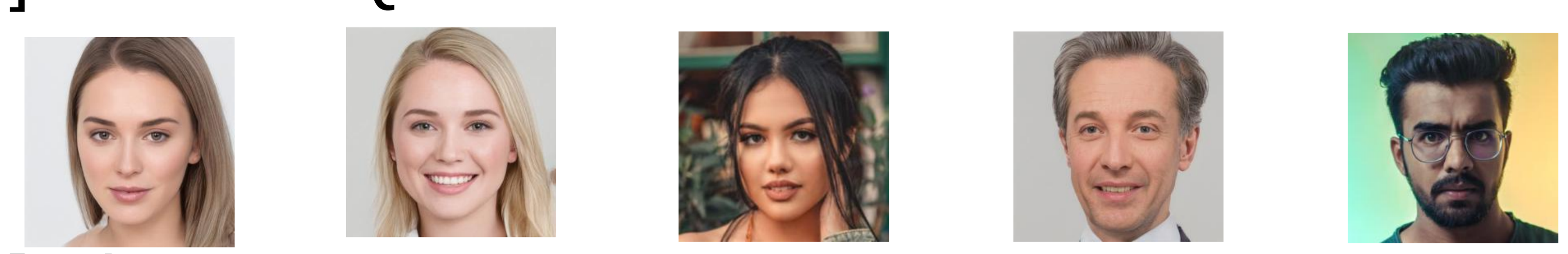




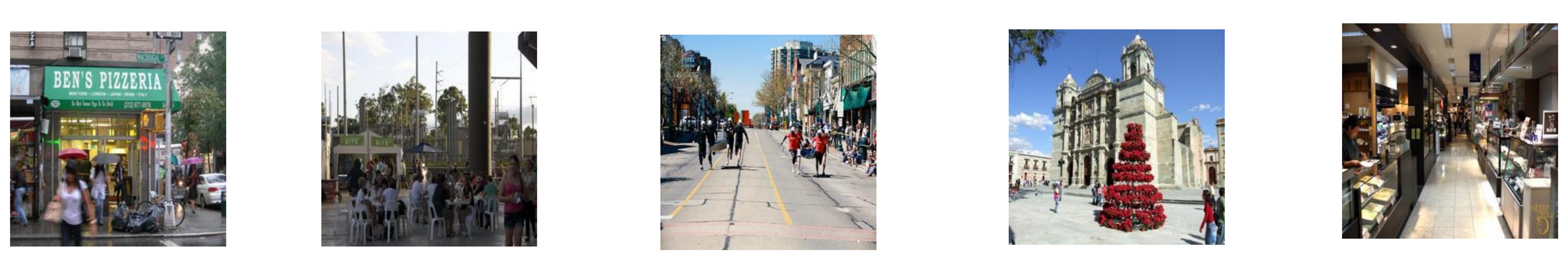


Dataset

[1] CelebAHQ

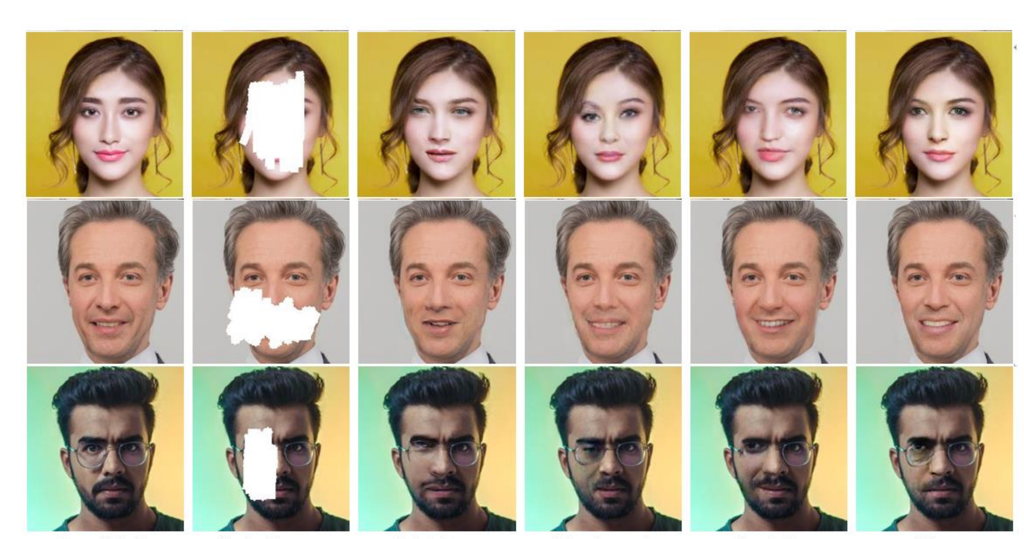


[2] Places365



Experimental Results

Face



Background

Mask rate (%)	10~20				20~30				30~40			
Type	Gated	Edge	Plural	Ours	Gated	Edge	Plural	Ours	Gated	Edge	Plural	Ours
L1 error (%) ▼	4.95	5.79	4.11	5.76	6.54	6.70	6.32	6.54	9.86	9.19	10.12	8.76
L2 error (%) ▼	1.47	1.32	1.47	1.28	2.03	1.54	2.72	1.43	4.38	2.79	4.81	2.58
Perceptual Loss▼	0.431	0.554	0.358	0.542	0.592	0.632	0.512	0.604	0.813	0.794	0.739	0.762
PSNR ▲	29.575	29.803	29.693	29.920	27.853	28.748	27.847	29.152	24.026	25.888	24.468	26.012
SSIM ▲	0.933	0.917	0.941	0.920	0.904	0.898	0.912	0.905	0.849	0.854	0.854	0.863

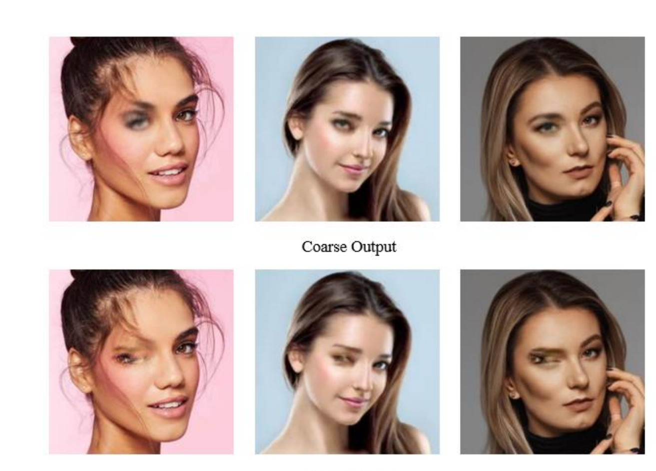
Mask rate (%)	10~20				20~30				30~40			
Type	Gated	Edge	Plural	Ours	Gated	Edge	Plural	Ours	Gated	Edge	Plural	Ours
L1 error (%) ▼	14.25	12.70	14.60	11.82	16.47	15.52	18.89	14. 02	28.24	27.55	32.087	24.840
L2 error (%) ▼	12.25	10.03	10.53	9.99	12.80	11.17	13.89	10.53	25.62	22.06	26.217	19.999
Perceptual Loss▼	0.682	0.592	0.718	0.546	0.927	0.847	1.001	0.775	1.311	1.205	1.413	1.118
PSNR ▲	23.311	24.112	22.835	24.237	21.617	22.270	21.313	22.572	19.114	20.104	18.890	20.308
SSIM ▲	0.899	0.898	0.880	0.907	0.858	0.856	0.832	0.871	0.769	0.768	0.729	0.789

Conclusion

- Analysis

My model produces better outputs than other methods for both face and place dataset. The outputs are more natural and give better PSNR, SSIM, and Loss

- Future Work



However, there are some cases which coarse outputs are better than refine outputs. There might be a problem with refine network. Hence, the refine module can be modified to solve this issue.

References

[1] Yuqing Ma, Xianglong Liu, Shihao Bai, Lei Wang, "Coarse-to-Fine-Image Inpainting via Region- wise Convolution and Non-Local Correlation" in Twenty-Eighth International Joint Conference on Artificial Intelligence, 2019
[2] Sherstinsky, Alex. "Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network." Physica D: Nonlinear Phenomena 404 (2020): 132306.
[3] K. Nazeri, E. Ng, T. Joseph, F. Qureshi, and M. Ebrahimi, "Edgeconnect: Generative image inpainting with adversarial edge learning. arxiv 2019," arXiv preprint arXiv:1901.00212.