IMVFX Term Project Report

Topic: Image Inpainting with External-Internal Learning and Monochromic Bottleneck

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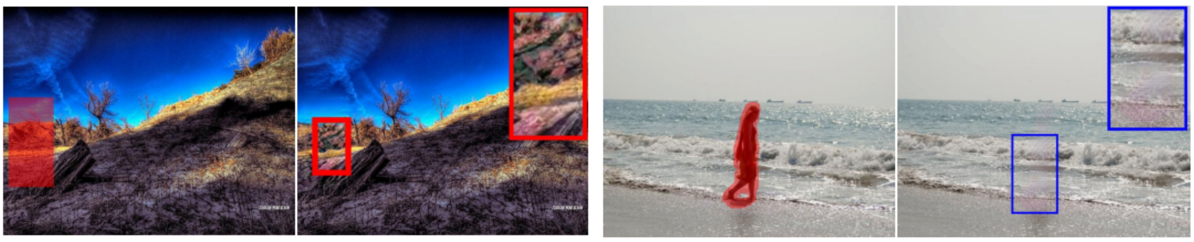
I. Goal

Since training image inpainting models takes a lot of time and resources, we look forward to trying some lightweight but effective methods. Due to our research, there is an interesting work called "Image Inpainting with External-Internal Learning and Monochromic Bottleneck", which is an algorithm that can address a common coloring problem in image inpainting, color bleeding, with a lightweight model.



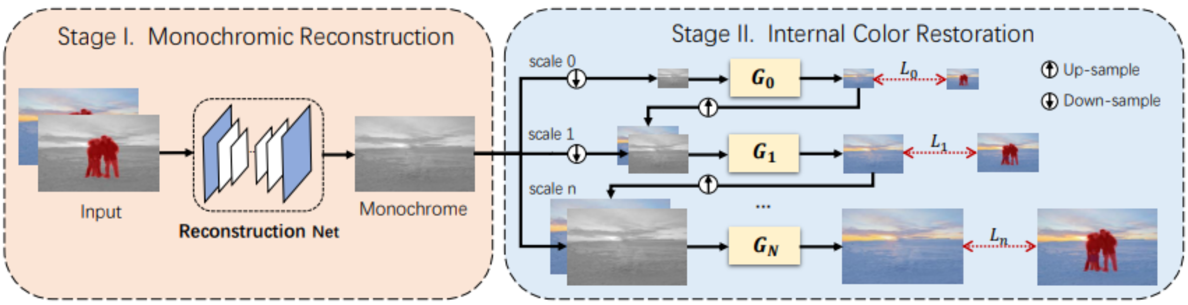
Methods trained on a large-scale dataset tend to introduce inconsistent colors that do not conform to the color distribution of the test image. We can see that for inpainted image on the right, there are unnatural pink color in the inpainting area. This is mainly caused by the color distribution gap between training and testing dataset. On the other hand, such color bleeding artifacts seldom appear in learning-free methods.

Our main goal is to implement this algorithm to address color bleeding. In addition, we conduct further research on the algorithm and manage to cope with some issues and future work mentioned in the article, that is, color restoration with guided color.

II. Method

A. External-Internal Learning

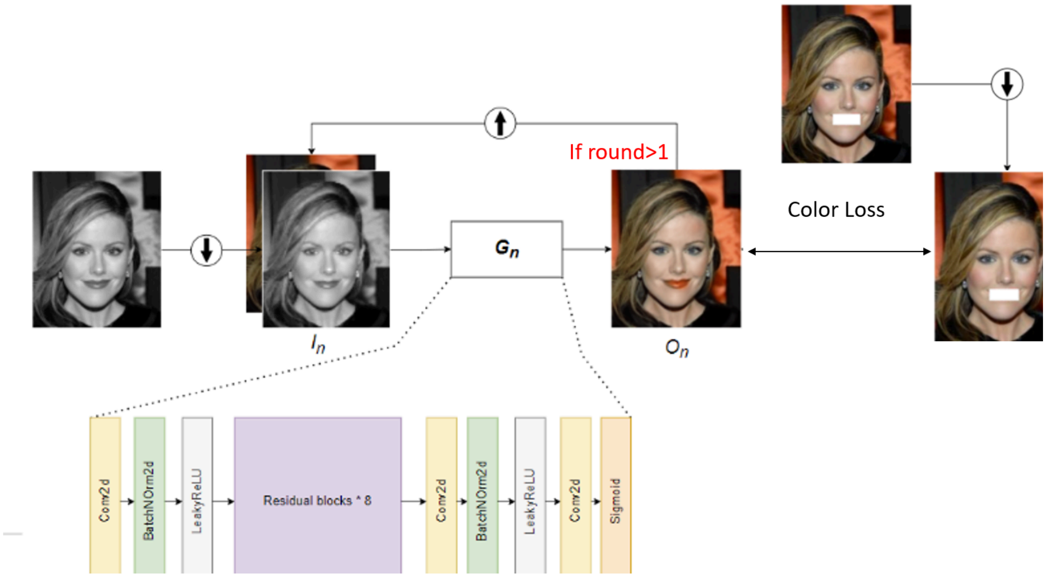
The method proposed by the paper we want to implement contains two stages.



The first stage is external monochromic reconstruction trained on large-scale datasets for generating semantically correct content. The reconstruction net here can be any image inpainting model that outputs a grayscale image. The second stage is the internal color restoration on the grayscale image for propagating the color from non-missing parts using a progressive structure. There are two main advantages of this architecture. First, it is easier to train an inpainting model for reconstructing grayscale images, because the dimension is lower, leading to a more structure-preserving result. Secondly, the progressive network in stage two can gradually learn the color distribution of the masked area from the coarsest scale and the finest scale.

B. Structure of Restoration network

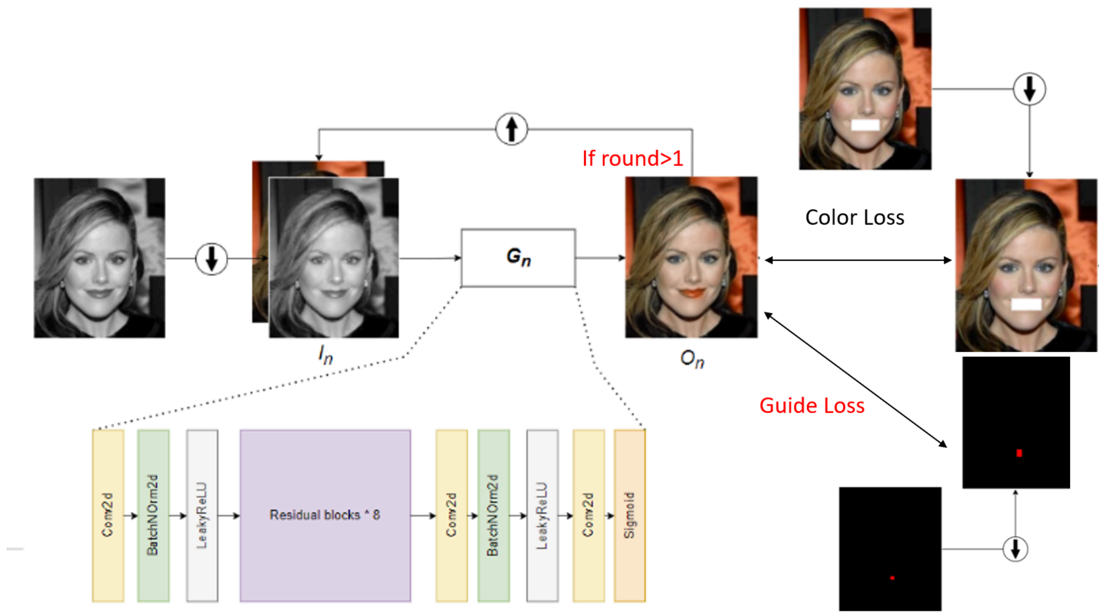
Our network for color restoration contains an input part, 8 residual blocks, and the output part.



In the first round(with the smallest scale) of training, the input only contains a gray image, which is obtained by downscaling the gray image that comes from the first part. In other rounds, the input includes gray scale image and upscaled color-restored image from the previous round.

C. User Guided color restoration

In addition to the basic part of the paper, we added an additional loss to the structure in order to implement user-guide color restoration.



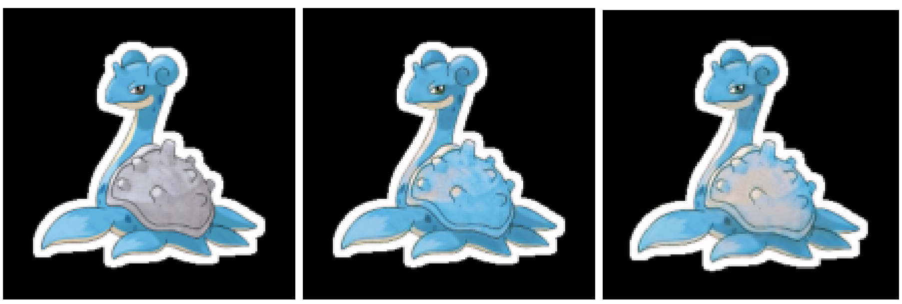
III. Results and Experiments

Original image / masked input / without user-guided color restoration

Original image / masked input / with user-guided color restoration

Original image/Inpainted image without user-guided color/with user-guided color (Eyes are masked)

Original image/Inpainted image without user-guided color/with user-guided color (Back of pokemon is masked)

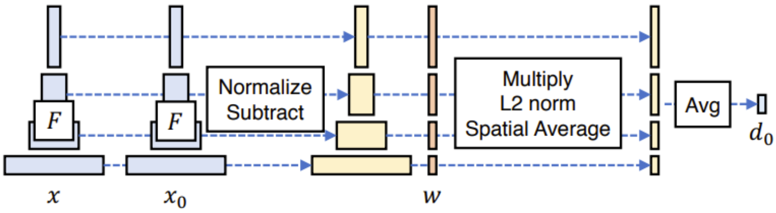


Metrics we've used for experiments:

- PSNR ⬆ : Peak signal-to-noise ratio

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

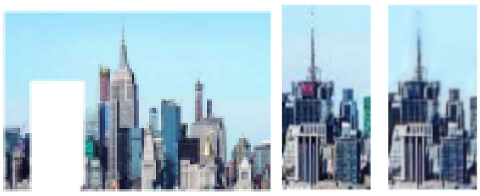
- LPIPS ⬇ : Learned Perceptual Image Patch Similarity



Experiments we've made:

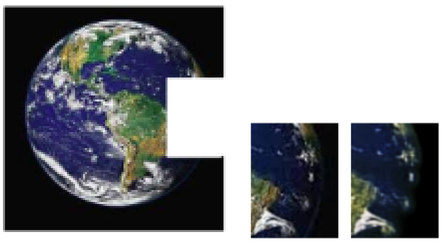
Images from different domains(Qualitization):

City:



Nature:

Satellite:



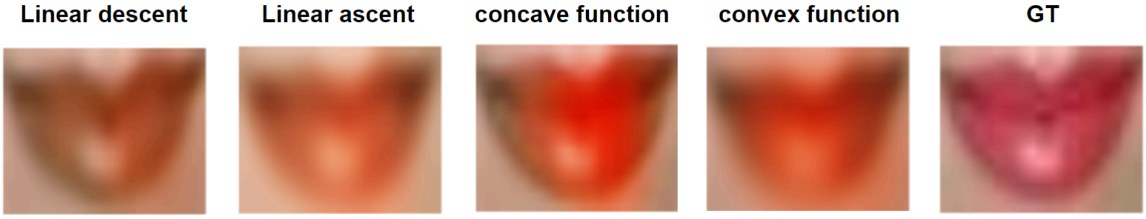
Painting:

X_ray

Images from different domains(Quantization):

Metric	City	Nature	Painting	Satellite	X_ray
PSNR	24.77	22.78	18.5	25.93	25.93
LPIPS	0.12	0.32	0.15	0.11	0.11

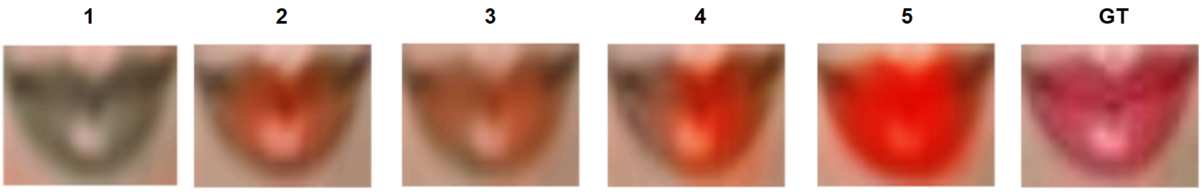
Different learning rate of each layers(Qualitization):



Different learning rate of each layers(Quantization):

Metric	Linear descent	Linear ascent	concave function	convex function
PSNR	22.24	20.26	21.53	24.11
LPIPS	0.23	0.32	0.17	0.07

Different number of layers(Qualitization):



Different number of layers(Quantization):

Metric	1	2	3	4	5
PSNR	19.06	21.25	22.24	17.37	15.99
LPIPS	0.34	0.25	0.23	0.19	0.2

IV. Difficulties and uniqueness

Undertaking a final project in image manipulation presents several challenges. One major hurdle is the struggle to find a model that is both lightweight and effective. This involves a lot of searching and experimenting, trying to strike a balance between a model's computational efficiency and its ability to fulfill image inpainting effectively. Another difficulty arises when considering the user-guided color restoration method. Trying to figure out a better way for users to interact with the system and incorporating it seamlessly into the chosen model.
In this project, our uniqueness is highlighted in the following aspects:

1. Extended the original work by introducing the color-guided loss to overcome its limitations.
2. Conducted thorough experiments across different image domains, numbers of layers, and learning rates.
3. Designed a user interface for drawing masks and guiding color.

V. Conclusion

In summary, we worked hard to reproduce Stage II of the original paper, making it better by adding color-guided loss. We also did many experiments with different kinds of images, layers of training, and learning rates of each layer to understand if the new approach works well in different situations. We showed both qualitative and quantitative results to prove that our method works. Last but not least, to make it easier for people to use, we made a simple interface where they can draw masks and choose guiding colors.

VI. References

Tengfei Wang*, Hao Ouyang*, Qifeng Chen. "Image Inpainting with External-internal Learning and Monochromic Bottleneck". CVPR (2021)[https://arxiv.org/abs/2104.09068]
Project Website, Original source code

VII. Contribution of each member

(45%) 109511097 江廷威:Discuss, make slides for proposal, implement the algorithm, make slides for presentation.
(20%) 109550093 黃得誠:Discuss, make slides for proposal, film the proposal video, try on diverse images for pursuable results, write for report.
(35%) 109550150 呂則諺:Discuss, make slides for proposal, conduct experiments and evaluate the results by evaluation metrics.