Learning Image Inpainting from Incomplete Images using Self-Supervision

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1. Introduction

Current state of the art for image inpainting employs DNN based methods that learn with full supervision i.e. using a training set having corrupted images with holes paired with corresponding uncorrupted images. Obtaining large datasets of uncorrupted images can sometimes be challenging. We propose a self-supervised image-inpainting DNN framework that can learn in completely unsupervised and semi-supervised modes, i.e. in the presence of incomplete images in dataset.

2. Method

Our method leverages the information available in the incomplete images within the given dataset to learn to inpaint. Given an incomplete image, we remove some known regions of the image and task our inpainting DNN framework to predict back the removed regions. A higher weight to the training loss in the removed regions puts the focus of DNN learning on inpainting holes.

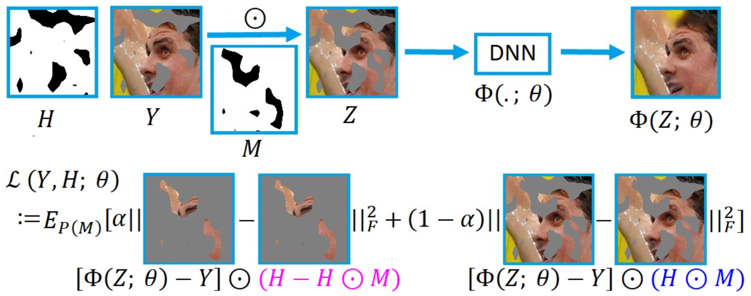


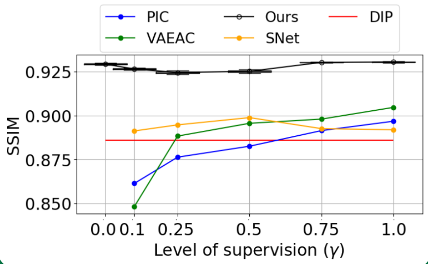
Figure: Given a training set image Y along with mask M that gives the pixels missing in Y, we introduce corruption H in Y and pass the resulting image through the DNN. $L(Y, H|\theta)$ gives the training loss. The value $\alpha = 0.75$ gave the best results.

3. Experiments

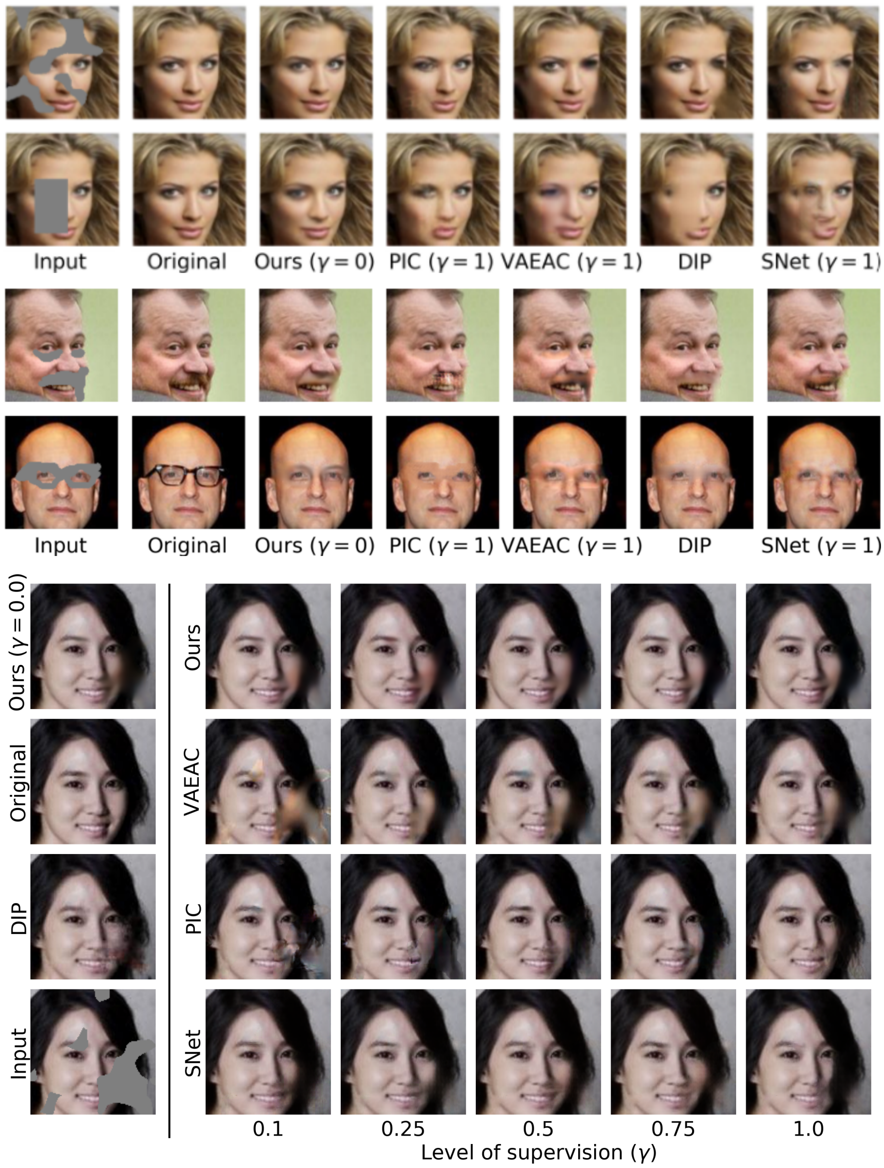
We generate incomplete images by corrupting images from CelebA face images dataset with random pattern masks. We vary the fraction of complete images in the training dataset (the level of supervision γ) and compare our method's performance to four recent methods: SNet[3], PIC [4], VAEAC [1], DIP [2].

4. Results - Quantitative

Method	Training Mode	SSIM
Ours	Fully **Supervised**	**0.938 (0.019)**
Ours	**Unsupervised**	**0.936 (0.019)**
VAEAC	Fully Supervised	0.913 (0.024)
PIC	Fully Supervised	0.907 (0.021)
SNet	Fully Supervised	0.891 (0.022)
DIP	Not Applicable	0.885 (0.021)



5. Results - Qualitative



6. Conclusion

Our self-supervised method can leverage incomplete images and produce high quality inpaintings. Our method's performance is not sensitive to drop in the level of supervision.

7. References

[1] Oleg Ivanov et al. "Variational Autoencoder with Arbitrary Conditioning". In: *ICLR*. 2019.

[2] Dmitry Ulyanov et al. "Deep Image Prior". In: *CVPR* (2017).

[3] Zhaoyi Yan et al. "Shift-Net: Image inpainting via deep feature rearrangement". In: *ECCV*. 2018.

[4] Chuanxia Zheng et al. "Pluralistic Image Completion". In: *CVPR* (2019).