Bringing Old Photos Back To Life

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Introduction

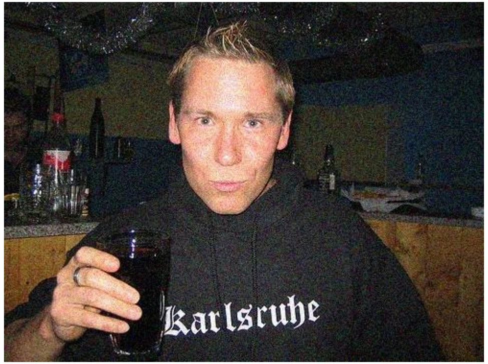
- Old photo prints deteriorate when kept in poor environmental condition, which causes the valuable photo content permanently damaged.
- Manual retouching is usually laborious and time-consuming, which leaves piles of old photos impossible to get restored.
- Most deep learning models perform poorly on photo restoration tasks, because degradation process of old photos is rather complex, and there exists no degradation model that can realistically render the old photo artefact. Therefore, the model learned from those synthetic data generalises poorly on real photos.
- Restore severely degraded photos through a deep learning approach using a triplet domain translation network consisting of two auto encoders photos into two latent spaces. This is to generalise the gap with real photos as the domain space is compact. Design two branches to address structured defects like scratches and dust spots, and unstructured defects like noise and blur.

DataSet

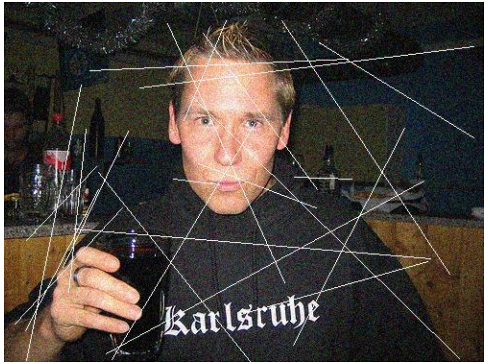
- Data was synthesised from the PASCAL VOC dataset. We added blur, noise and scratch to replicate the deterioration of 500 photos from the dataset.

Real image & ground truth

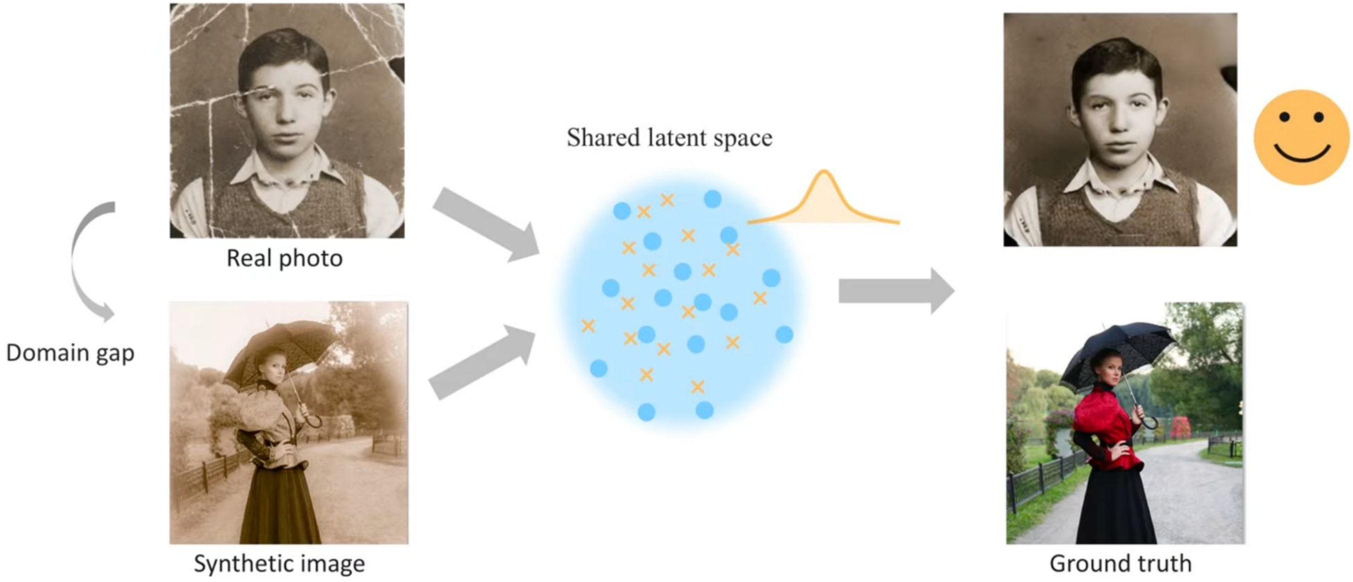
Unstructured defects



Structured defects



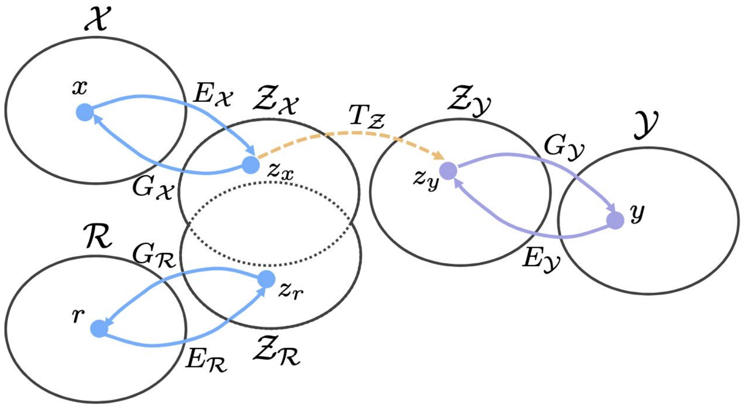
Baseline Model



Baseline Model

- Restoration via latent space translation
- Domain alignment in VAE latent space
- Restoration through latent mapping

https://openaccess.thecvf.com/content_CVPR_2020/papers/Wan_Bringing_Old_Photos_Back_to_Life_CVPR_2020_paper.pdf



The real photo domain R, the synthetic domain X where images suffer from artificial degradation, and the corresponding ground truth domain Y

Experiments

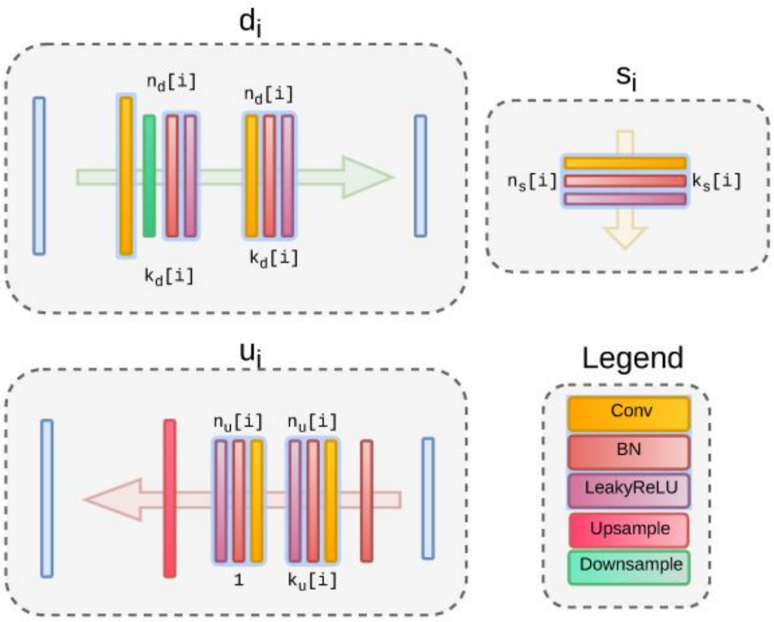
Deep image Prior

- Corrupted images are seen as combination of plain image and noise represented as X = r+y where X is synthetic input, r is the ground truth and y is the noise.

Experiments

Deep image Prior

- Network affects the prior distribution in parameter space.
- Plain image can be recovered if optimization is restricted.



Experiments

Conditional GAN (Pix2Pix)

- Image to Image translation
  - Maps pixel to pixel
- New conditional loss

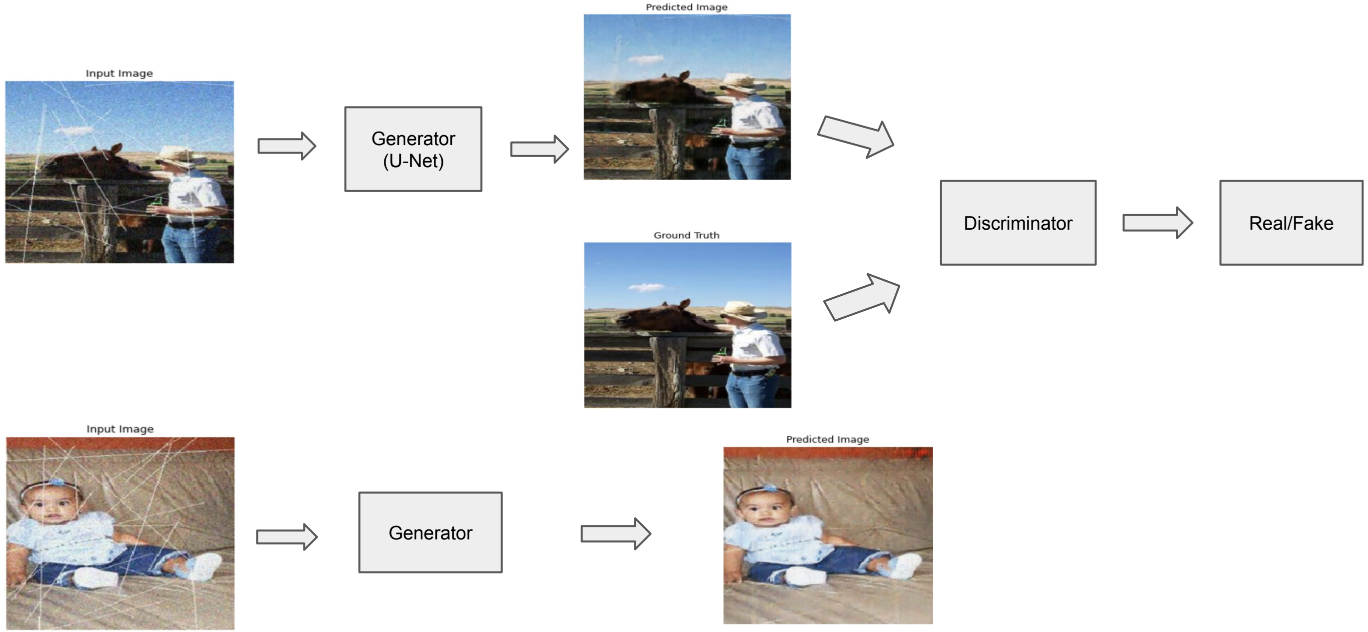
$$\mathcal{L}_{cGAN}(G, D) = \mathbb{E}_{x,y}[\log D(x, y)] + \mathbb{E}_{x,z}[\log(1 - D(x, G(x, z))],$$

$$\mathcal{L}_{GAN}(G, D) = \mathbb{E}_{y}[\log D(y)] + \mathbb{E}_{x,z}[\log(1 - D(G(x, z))].$$

- Generator
  - U-Net
- Discriminator
  - Patch GAN

Experiments

Conditional Cycle GaN (Pix2Pix)



Experiments

Cycle GAN

Input domain (X) - Noisy image

Output domain (Y) - Clean image

Generator function (G) - Maps noisy -> Clean image

Generator function (F) - Maps clean -> Noisy image

Training the model involves training the following functions - Generators G, F and Discriminators Dx,Dy

The loss functions used are :

- Adversarial loss

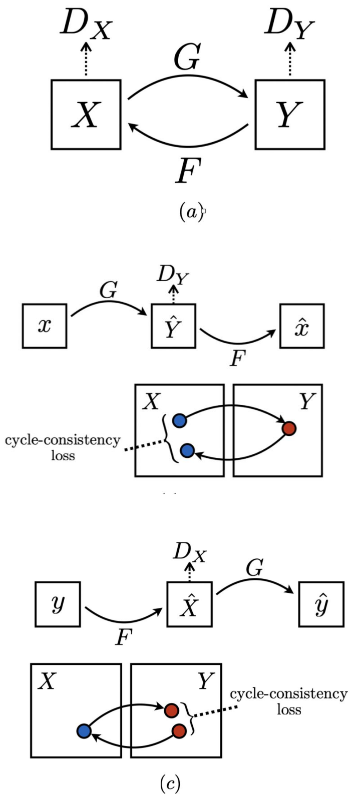
$$\mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) = \mathbb{E}_{y\sim p_{\text{data}}(y)}[\log D_Y(y)] + \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log(1 - D_Y(G(x))],$$

- Cyclic loss

$$\mathcal{L}_{\text{cyc}}(G, F) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\|F(G(x)) - x\|_1] + \mathbb{E}_{y\sim p_{\text{data}}(y)}[\|G(F(y)) - y\|_1].$$

- Total loss

$$\mathcal{L}(G, F, D_X, D_Y) = \mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) + \mathcal{L}_{\text{GAN}}(F, D_X, Y, X) + \lambda\mathcal{L}_{\text{cyc}}(G, F),$$



Results & Comparison

Input Image

Ground Truth

VAE

Pix2Pix

CycleGAN(R)

DIP

Conclusion

- All models were able to restore image close to ground truth.
- VAE model was capable of upscaling image resolution
- VAE outperforms Pix2Pix, CycleGAN, DIP in terms of scratch removal.
- VAE was better at detecting and removing unstructured defects from the input data.

References

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[2] Dimitry Ulyankov, Andrea Vedald, Victor Lempitsky, Deep Image Prior arXiv preprint arXiv:1711.10925, 2020

[3] Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, Alexei A. Efros et al. Image-to-Image Translation with Conditional Adversarial Networks arXiv:1611.07004

[4] Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. https://arxiv.org/pdf/1703.10593.pdf