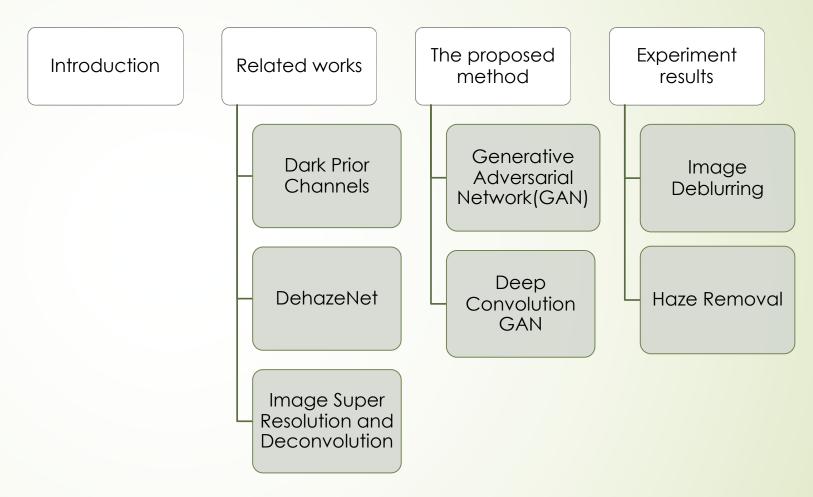
Applying Generative Adversarial Networks on Image Haze Removal

Dec 18th 2017





Introduction

Degradation of outdoor image: Lighting condition and atmosphere.

Images lose contrast and fidelity mostly due to the effect of haze and fog.

Required multiple images or additional information to perform haze removal algorithms.

Single image haze removal is a challenging problem.

Related works: Dark Channel Prior

K. He, J. Sun and X. Tang, "Singe Image Haze Removal Using Dark Channel Prior," IEEE Transactions on Pattern Analysis and Machine Intelligence, pp. 2341-2636, 2011.

The empirical statistic of experiments on haze-free images.

At least one color channel has some pixel with very intensities in most of non-haze patch. The algorithm consists of 4 steps:

- 1: Estimate transmission
- 2: Soft matting and refine transmission map.
- 3: Recover the Scene Radiance.



(1)





(2)



(4)

Related works: Dark Channel Prior

K. He, J. Sun and X. Tang, "Singe Image Haze Removal Using Dark Channel Prior," IEEE Transactions on Pattern Analysis and Machine Intelligence, pp. 2341-2636, 2011.

Problems:

1. It may not work for some particular images.

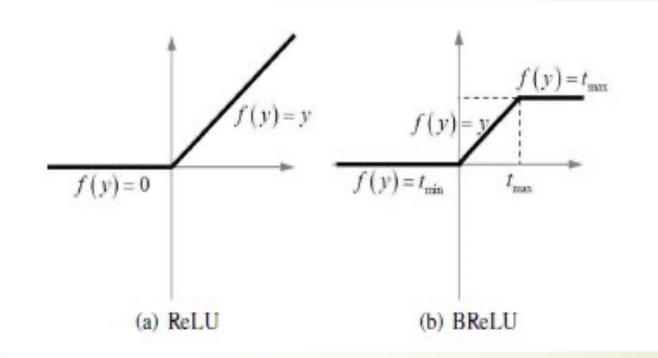
2. The algorithm cannot produce good results on sky regions and suffer distortion in objects when there is no shadow cast on them.





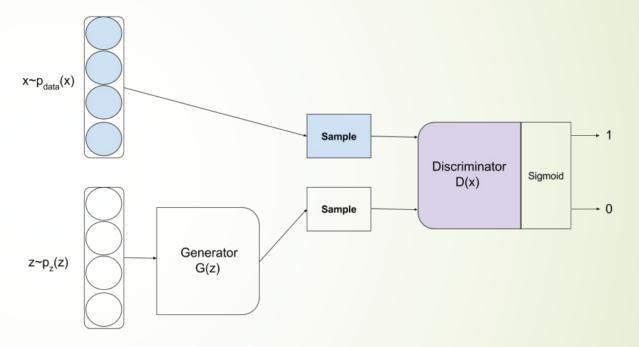
Related works: DehazeNet

- B. Cai, X. Xu, K. Jia, C. Qing, "DehazeNet: An End-to-End System for Single Image Haze Removal", IEEE transactions on Image Processing, v25, Nov, 2016
- A novel Convolutional Neural Network based, which is called DehazeNet is specialized for haze removal task.
- $f_{BReLU} = min(t_{max}, max(t_{min}, W^TX_{input} + bias))$
 - Where t_{max} = 1. t_{min} = 0
- Problem:
 - gradient vanishing,
 - hard to adjust the architecture.



Generative Adversarial Networks(GAN)

- GAN consists of two neural networks, generator and discriminator
- The generator and discriminator are adversarial and they are trained together.



Generative Adversarial Networks(GAN)

- Training GAN: trying to minimize the adversarial loss function of discriminator:
 - $l_D = \frac{1}{N} \sum_{n=1}^{N} \left(\log \left(D \left(G \left(x^{noise} \right) \right) + \log \left(1 D \left(x^{original} \right) \right) \right) \right)$
- While the backward propagation from discriminator will be used to update the hyperparameter of generator as follow:

•
$$l_G = \frac{1}{N} \sum_{n=1}^{N} \left(-\log\left(D\left(G\left(x^{noise}\right)\right)\right) \right)$$

Deep Convolutional GAN with depth information

- Activation of DCGAN generator for haze removal consists 2 part:
- $l_{gen} = (\alpha + \delta) * l_{gen_mse} + \beta * l_{G,adv}$

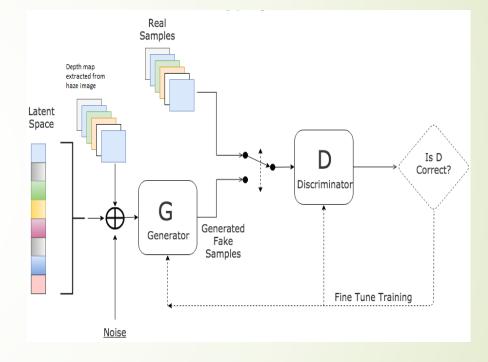
Adversarial loss:

$$l_{G,adv} = \frac{1}{N} \sum_{n=1}^{N} \left(-\log\left(D\left(G\left(x^{noise} \right) \right) \right) \right)$$

Content loss with depth information δ $l_{mse} = \frac{1}{r^2 w h} \sum_{x=1}^{rw} \sum_{y=1}^{rh} (I_{x,y}^{original} - G(I^{noise})_{x,y})^2$

$$l_{gen_mse} = l_{mse} + \frac{1}{r^2wh} \sum_{x=1}^{rw} \sum_{y=1}^{rh} \delta_{x,y} (I_{x,y}^{original} - G(I^{noise})_{x,y})^2$$

And δ is a matrix of depth representation of each image. $\delta_{x,y} \in [0, 1]$



Depth Map extracted from image

$\delta(x) = \min_{c \in \{r,g,b\}}(\min_{y \in \Omega(x)}(J^c(y)))$











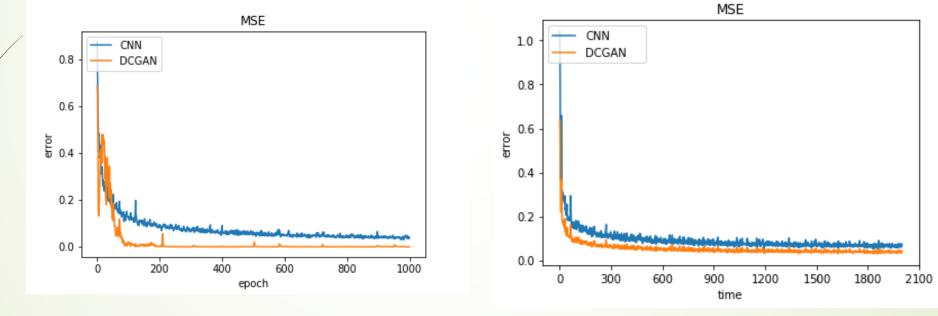


- Image deblurring on MNIST, Fashion MNIST dataset.
- MNIST, Fashion MNIST consist of 60,000 28x28 grayscale labeled images grouped into 10 categories along with a test set of 10,000 images within each dataset.
- Images are separated in two set: 5 classes for training and 5 classes of test

- The weights of the generator of each architecture are saved and tested with images which are not presented in training set.
- The performance of CNN and DCGAN are measured using PSNR scores

Dataset	ataset Epoch 100		Epoch 500		Epoch 1000		Epoch 2000	
	CNN	DCGAN	CNN	DCGAN	CNN	DCGAN	CNN	DCGAN
MNIST	55.54	58.13	59.09	70.92	68.13	70.99	68.14	71.20
Fashion- MNIST	54.91	55.34	56.37	57.71	58.12	60.09	61.70	66.41

The convergence of MSE of CNN and DCGAN on MNIST data and Fashion-MNIST data.



MSE convergence on MNIST

MSE convergence on fashion-MNIST

Valid and masked on the classes that do not present during training phase

Valid image

Blurred image

CNN generated image

DCGAN generated







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Valid and masked on the classes that do not present during training phase

Valid image	1	副	1	Ŵ
Blurred image				
CNN generated image	ſ			
DCGAN generated				

Experiment results on image dehazing

- Dataset:150 pairs of 4000x6000 outdoor images
- For every image, we sampled 10 images of size 256x256 randomly.
- Program is implemented in python3.0
- Hardware system: chip Xeon E5-2620, 2.10Ghz, GPU GFORCE TitianX.

The weights of the generator of each architecture are saved and tested with images which are not presented in training set.

Architecture	Epoch 100k	Epoch 300k	Epoch 500k	Epoch 700k
CNN	36.33	43.13	48.34	49.31
DCGAN	36.21	44.73	48.68	50.17
DCGAN with depth	36.48	46.21	50.01	51.35

Dataset preparation





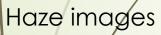
Training set

Test set

Experiment result on image dehazing

Haze-free images











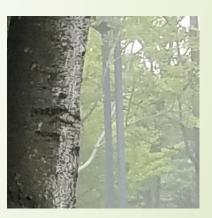


























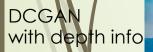








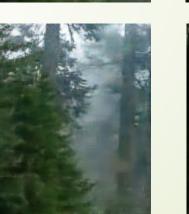














DehazeNet: PSNR = 36.15



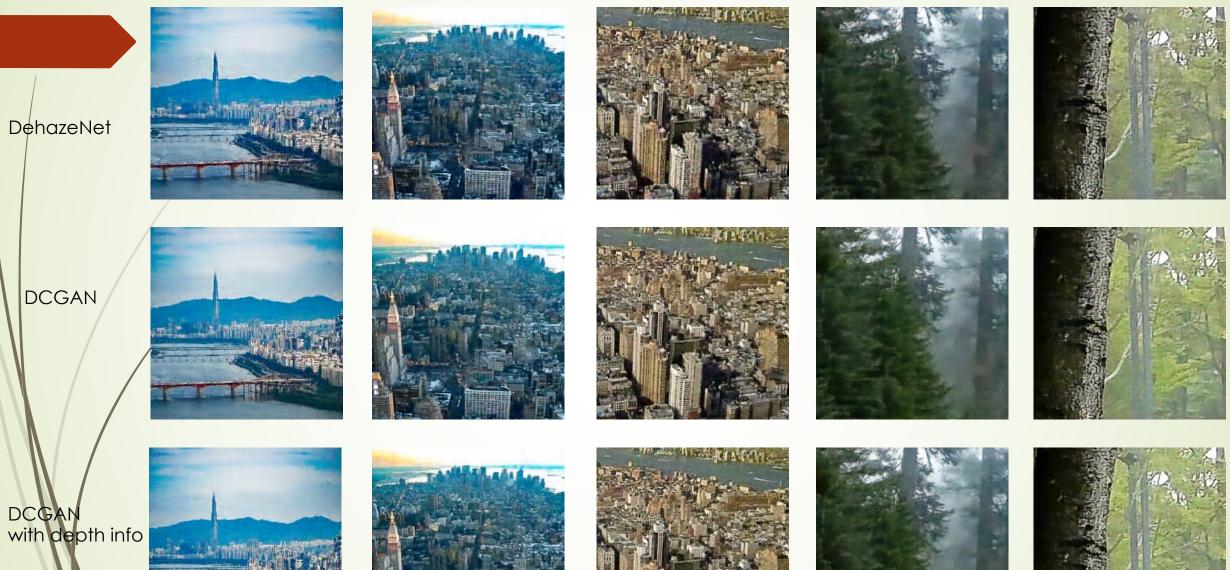


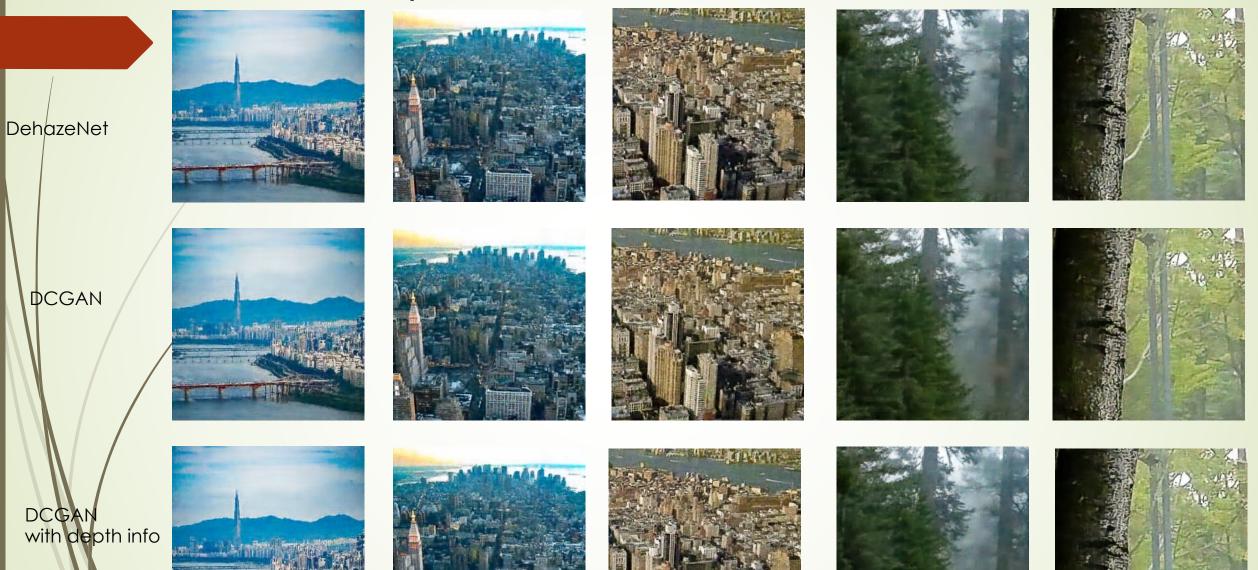
DCGAN with depth information : PSNR = 40.28



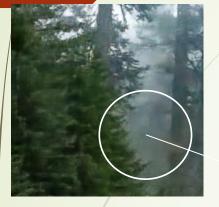
DCGAN : PSNR = 38.51







DehazeNet : PSNR = 48.70





DCGAN with depth information PSNR = 50.22



DCGAN : PSNR = 49.21



DehazeNet























DCGAN with depth info









