Image Enhancement Techniques

Denoising, Dehazing and Deraining

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Image Enhancement

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- Deraining

Example

Some sample representative images are shown below

Figure: Denoising, Dehazing and Deraining

Highlights

NTIRE CVPR Competition 2020

The work culminating out of this project has been accepted at **CVPR Workshop 2020**. The publication is available at CVPR Proceedings Website. We participated in the NTIRE 2020 Denoising Challenge and secured **16th** position among **250+** registrants.

- Our results are comparable to the NTIRE 2019 Image Dehazing Challenge. Our scores position among the Top-16 participants of the challenge.
- Results of Image Deraining Model is among state of the art methods available.

Mathematical Framework

$$M = C \oplus N$$

We have to find C from M. However, the inversion problem is not unique. In other words, $\oplus$ is not invertible. Mathematically it is impossible to solve the inverse problem in general.

Evaluation Metric

PSNR

It is an expression for the ratio between maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. It is usually expressed in terms of logarithmic decibel scale, due to its wide dynamic range. **Higher the better**.

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SSIM

SSIM is used for measuring the similarity between two images. The SSIM Index is a method for predicting the perceived quality of digital television and cinematic pictures, as well as other kinds of digital images and videos. It is a full reference metric, which means that the measurement or prediction of image quality is based on an initial uncompressed or distortion-free image as reference. **Closer to one is better**.

Image Denoising

Dataset

(Smartphone Image Denoising Dataset) SIDD Dataset
320 image pairs (noisy and ground-truth, in sRGB space) representing 160 scene instances, two images from each scene instance, gamma corrected.

Data Preprocesing

The original images are extremely high-quality images of dimensions 5328px $\times$ 3000px. However, due to lack of computational resources, the images have been resized to 256 $\times$ 256 pixels using OpenCV library.

Model Specifications

	Encoder	**Decoder**
Total parameters	582,496	582,241
Trainable Parameter	582,496	582,241
Non-trainable Parameter	0	0

Table: Number of Parameters

Results – I

The results for the model trained on 1000 epochs on training set are shown below.

Epochs	Mean PSNR	Mean SSIM
200	22.814	0.6773
400	23.408	0.6955
600	25.966	0.7705
800	**26.952**	**0.7796**
1000	26.466	0.7541

Table: Model Performance

Results – II (removing noise from images)

Image Dehazing

Dataset

We first preprocessed the Dense-Haze dataset, Trained and implemented **Denoising AutoEncoder** and evaluate the model through PSNR and SSIM Index

Description	Mean PSNR	Mean SSIM
Train	23.546	0.738
Test	10.244	0.537

Table: Dehazing results for the model trained on 500 epochs

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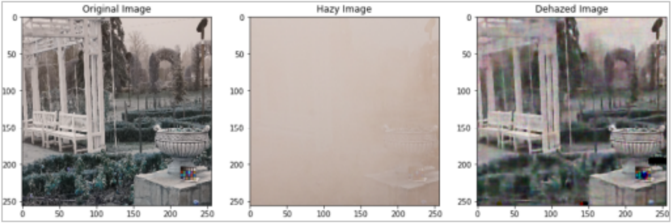

Improved Technique – Cycle GAN

Image Dehazing can also be looked as an Image Translation task where the objective is to transform an image in one style to another. This transformation is also commonly known as a Style Transfer effect.

Improved Technique – Cycle GAN

Image Dehazing can also be looked as an Image Translation task where the objective is to transform an image in one style to another. This transformation is also commonly known as a Style Transfer effect.
A random collection of images in style A and another random collection of images in style B is all what is required to perform the image translation in CycleGANs

Methodology

The dataset has been splitted with 45 images (80%) in training set and 10 images (20%) in test set.

Hyperparameters	Value
Epochs	1000
GAN-mode/objective	Least Square GAN
Learning Rate	0.0002
Batch Size	1
Image Size	256

CycleGAN–Results

Description	Mean PSNR	Mean SSIM
Training	15.6	0.503
Testing	13.44	0.438

Table: results for CycleGAN

Pix2Pix

Methodology

The dataset has been splitted with 45 images in training set (80%), 5 images in validation set (10%) and 5 images in test set (10%). Combined images from both styles (occluded/hazy and non-occluded/non-hazy) are needed to be created to be fed as input to the model for training. In Table 6 detailed information about the hyperparameters is reproduced.

Hyperparameters	Value
Epochs	1000
GAN-mode/objective	Cross Entropy
Learning Rate	0.0002
Batch Size	1
Image Size	256

Table: Hyperparameter for Pix2Pix

Pix2Pix–Results

Description	Mean PSNR	Mean SSIM
Training	22.434	0.722
Testing	15.963	0.602

Table: results for CycleGAN

Images that show the performance of Pix2Pix model on the test dataset/Holdout set is shown in below figure.

Image Deraining

Dataset

For our experiments we used two datasets 100H and 100L having heavy as well as light rain streaks respectively. Both datasets have been synthesized from BSD200. However, the size of dataset is 320px $\times$ 480px. We did a uniform downsizing of all images and converted the images to numpy pickle dump for faster processing

Set	type	category	number
Train	Heavy	Rain	1800
Train	Heavy	Norain	1800
Train	Light	Rain	1800
Train	Light	Norain	1800

Table: Dataset Size

Methodology & Model Specification

Parameters	Generator	Discriminator
Total	473,737	5,480,257
Trainable	472,201	5,476,545
Non-trainable	1,536	3,712

Table: Model Statistics & Parameter

Methodology & Model Specification

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Table: Model Statistics & Parameter

Hyper-parameters	Value
Epochs	100
GAN-mode/objective	Cross Entropy
Learning Rate	0.0001
Optimizer	Adam
Batch Size	1
Image Size	256px

Table: Hyperparameter for Derain Model

Deraining – Results

Description	Mean PSNR	Mean SSIM
Training	35.605	0.7669
Testing	35.582	0.6817

Table: Deraining Results

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Description	Mean PSNR	Mean SSIM
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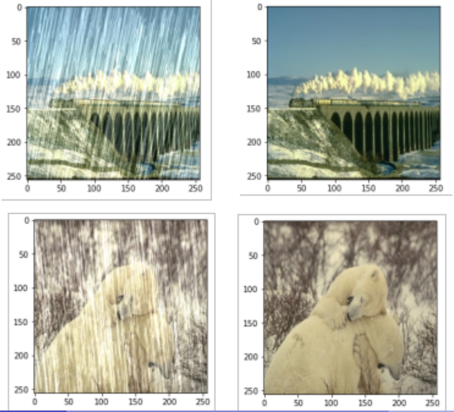
Table: Deraining Results



Summary of All Experiments

Technique	Model	Epochs	Mean PSNR	Mean SSIM
Denoising	Stacked Autoencoder	1000	26.952	0.7796
	Stacked Autoencoder	500	10.244	0.537
Dehazing	Pix2Pix	1000	15.963	0.602
	CycleGAN	1000	13.44	0.538
Deraining	GAN based Model	100	35.582	0.6817

Table: Result Summary

Possible Extensions

Future Directions

- **Denoising:** Residual Dense Network (RDN) and converting to high-resolution images (Super-Resolution)
- **Dehazing:** Generative Adversarial Networks (GANs) in general, are quite slow in learning and extremely hectic to train
- **Deraining:** Model is not suitable where computational cost is limited (on device ML) given the model volume (almost 58 million parameters) – reduce size of model

References

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Thankyou!