# How should I take pictures on a rainy day?

**Kateryna Starovoit**

**kateryna.starovoit@mail.utoronto.ca**

**Abstract**

Rain removal is an important challenge in the field of computational imaging as rain streaks can cause serious image degradation. Rain causes streaks of different size, shape and direction. Some images can be hard to derain, especially in case of heavy and accumulated rain.

There are many hurdles in both video and single image deraining. Even obtaining a verified dataset of rainy and clear images can be challenging because of light shift, camera motions and motion artifacts.

There have been advances in single image deraining methods. However, as a novice photographer, there remains an open question: Given the state of the art deraining model, how should I be taking my pictures on a rainy day for the best derained result?

## 1. Introduction

Single image deraining is a well-known problem in computational imaging. There are many ways to denoise a rainy scene and there have been major improvements in deblurring very noisy scenes with introduction of GT-rain and tackling additional noise.

However, the state of art methods still experience difficulties with reconstructing images in highly textured areas such as bricks and leaves. The deep learning based deraining methods can be also sensitive to adversarial attacks – perturbations near the rain or object areas.

So what kind of images would be the best for the model to work with? We propose to explore different options, taking GT-rain as state of art derainer.

1. Injecting more noise, which can be especially important in low-light settings. How would the model respond to images with perturbations next to rain or some objects?
2. What if we take a video of a rainy scene and derain each frame with our model. Would the results be still constistent?
3. Images with different exposures: what is the optimal exposure time to take your images under?
4. Would HDR do better for highly textured images?

## 2. Related work

There are various single image deraining techniques and approaches from matrix decomposition to probabilistic approach.

The state of art methods use convolutional neural networks to tackle data loss and artifacts caused by rain streaks.

It is usually hard to obtain a training dataset of real noisy and denoised images for deraining problems, so most of the networks were trained on synthetic data. The authors of [5] proposed a dataset of real rainy and clear images and a deraining model which outperforms state of art methods.

Most of deraining methods are vulnerable to adversarial attacks – noise and perturbations next to rain streaks and objects.  Another challenge is a cumulative noise, which occurs during long exposures. [4] provides an effective way to handle additional noise in rainy images.

### 3. Proposed method

We used GT-rain as an example of state of art model and tested it on both real and synthetic data. To work with different types of images we used the datasets from [4] and [5], simulated multiple sets of noisy images and videos.

For initial model training we used the 2.7 GB dataset from [5], both with real and synthetic data. Then we retrained it with more noisy images to ameliorate the performance for additional perturbations. To simulate noise we used a set of rain masks and different types of blur.

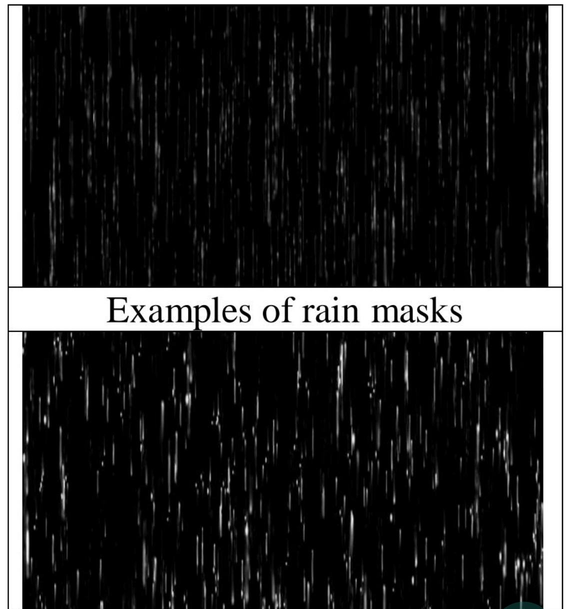


Figure 4.1

[4] shows that additional noise deteriorates the performance of most of the models. We tested our model on synthetic dataset from [4] and also simulated some additional noise next to the objects and rain streaks.

We had an assumption that the model should perform well for hdr images. Fir the tested set of images, each image was blurred with a rain frame and then derained by model.

We took multiple rainy videos (both synthetic and real) and split each video into 100-500 frames to see if the model outputs the consistent results (we compared the results visually and to ground truth where avaliable).

The noise could affect the performance of the model for different exposure time, so we derained static scenes with different exposure time and same rain density for each scene.

## 4. Experimental results

### 4.1 Noisy images

We tested the model on multiple sets of images with heavy noise and highly
9 textured data.


*Figure 4.1 Results for noisy and*
14 *highly textured images*

10

| PSNR Input | PSNR Output | SSIM Input | SSIM Output |
|---|---|---|---|
| 23.6095 | 25.9785 | 0.8380 | 0.8765 |

*Table 4.1 PSNR and SSIM results for noisy images*

The performance of the model was quite
11 satisfying, even though there were a few underained rain streaks and minor quality deterioration for highly textured images.

### 4.2 Additional noise

Adversarial attacks aim to deteriorate the output of the deraining methods by adding a small amount of visually unperceivable perturbations to the input rainy images. The additional noise next to the objects and rain streaks can drastically deteriorate the performance of the model.

We tested the model on two sets of
images with different amounts of noise 12
next to objects or rain streaks. Even small perturbations significantly affect the deraining results. Larger noise also caused degradation of the image quality.

| PSNR Input | PSNR Output | SSIM Input | SSIM Output | |
|---|---|---|---|---|
| 12.1255 | 17.7954 | 0.4333 | 0.6569 | |

*Table 4.2 PSNR and SSIM results for images with additional noise*

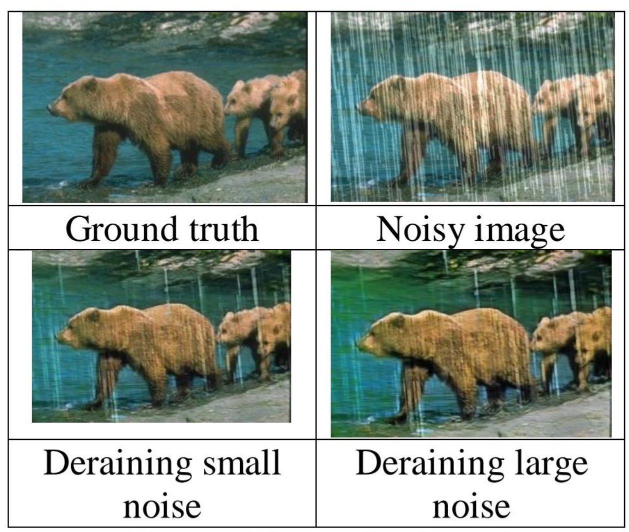


*Figure 4.2 Results for noisy and highly textured images*

After additional training the quality of derailing significantly improved, even though it`s still sensitive to large amounts of noise.

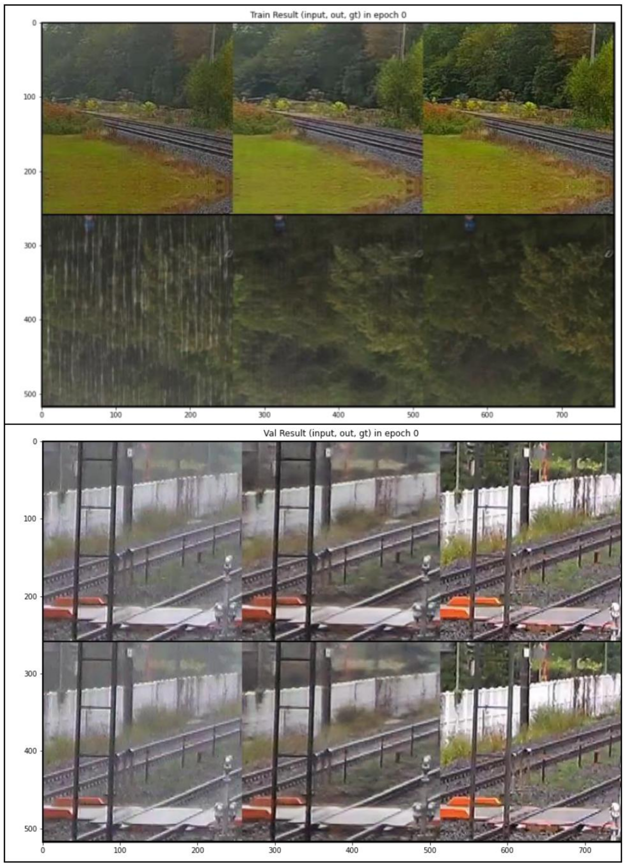


Figure 4.3 Additional training and validation results

| Ground truth | Noisy image | Derained image |
| --- | --- | --- |

*Figure 4.4 Results for noisy and highly textured images*

| PSNR Input | PSNR Output | SSIM Input | SSIM Output |
| --- | --- | --- | --- |
| 12.1255 | 20.2312 | 0.4333 | 0.6918 |

*Table 4.3 Results for images with extra noise after additional training*

## 4.3 HDR data

The model performed quite well for HDR images even with heavy noise.

| Ground truth | Noisy image | Derained image |
| --- | --- | --- |

*Figure 4.5 Results for HDR images*

| PSNR Input | PSNR Output | SSIM Input | SSIM Output |
| --- | --- | --- | --- |
| 28.0912 | 31.2409 | 0.7411 | 0.8220 |

*Table 4.4 PSNR for hdr images*

## 4.4 Exposure measurement

We disassembled multiple rainy videos into frames and derained each frame. The results were quite consistent.

Then we simulated different exposure time and could observe cumulative noise which was hard to derain. For tested rain density, the model performed best for exposure time 10-15s.

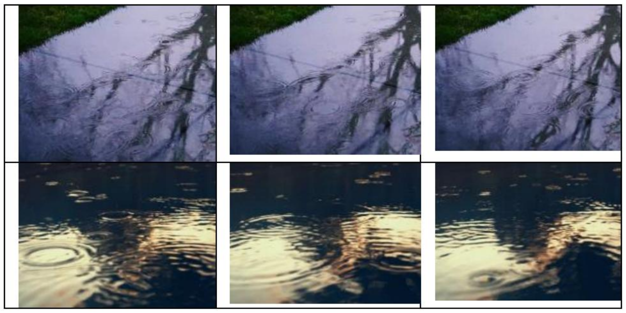

*Figure 4.6 Disassembled rainy videos*

## 5. Conclusions

So, what kind of images should I take on a rainy day? In general, state of art models work well even for very noisy images, but they might struggle with highly structured data such as leaves or bricks.

The deraining for hdr images is very effective even for heavy noise, but additional noise next to the objects or rain streaks deteriorates the model performance and requires additional training or changes to the model architecture.

Deraining results of a static scene video per frame are quite consistent and could be used to validate and calibrate the model or to find a ground truth for video deraiining.

It is also important to take into account exposure time. Longer exposure time can lead to cumulative noise and decrease deraining, especially for bigger rain density.

## 6. Acknowledgements

The author would like to thank Mian Wei supervising me during the project.

The author would also like to thank Yi Yu and Yunhao Ba for providing the starter code and the dataset images. The videos from 4.4 were uploaded from https://pixabay.com/videos/raining/.

## 7. References

1. Ping Xue et al.,"Research of Single Image Rain Removal Algorithm Based on LBP-CGAN Rain Generation Method", 2021
2. Weihong Ren et al, "Video Desnowing and Deraining Based on Matrix Decomposition", CVPR 2017
3. Wenhan Yang et al., "Joint Rain Detection and Removal via Iterative Region Dependent Multi-Task Learning", 2016
4. Yi Yu et al, "Towards Robust Rain Removal Against Adversarial Attacks: A Comprehensive Benchmark Analysis and Beyond", CVPR 2022
5. Yunhao Ba et al, "Not just Streaks: Towards Ground Truth for Single Image Deraining", CVPR 2022