Global Journal of Engineering and Technology Advances

eISSN: 2582-5003

Cross Ref DOI: 10.30574/gjeta

Journal homepage: https://gjeta.com/

(Research Article)

Check for updates

A comprehensive analysis on single image-based deraining using generative adversarial network

Md. Ashik Iqbal *, Soumitra Bhowmik and Md. Fazla Rabbi Talukder

Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh.

Global Journal of Engineering and Technology Advances, 2022, 11(03), 001–008

Publication history: Received on 12 April 2022; revised on 31 May 2022; accepted on 02 June 2022

Article DOI: https://doi.org/10.30574/gjeta.2022.11.3.0072

Abstract

Deraining is a process by which we can get a transparent image by removing raindrops from a rainy image. In the rainy time visibility of any scene decreases as vision property is affected by the rain. Recently generative adversarial network (GAN) is getting popular in the visual enhancement of hazy, dusty, and noisy images. It is essential to know the effectiveness of the diverse GAN algorithms in the natural rainy situations of different intensities. From this perspective, the present paper describes a comprehensive study on four single-image state-of-the-art GAN models, such as attentive GAN, cGAN, DHSGAN, and Cycle GAN for deraining. The experiment is done using the standard dataset consisting of real-world rainy images and the results are evaluated both objectively and subjectively. We have found somehow mixed results based on quantitative metrics and comparatively satisfactory results by the cGAN based on visual analysis.

Keywords: Generative Adversarial Network (GAN); Cycle GAN; Attentive GAN; cGAN; De-Haze and Smoke GAN (DHSGAN)

1. Introduction

Computer vision-based object detection and recognition algorithms mainly depend on different atmospheric conditions such as rain, haze, dust, noise, and lighting. During heavy rainy situations, it is difficult to properly detect an object from the captured images. Raindrops make images blurry and reduce the resolution such as saturation and contrast. Most of the vision algorithms are not able to give a proper outcome with these blurry and low-resolution images. Image deraining is a preprocessing technique that provides a derained image from the cloudburst ones.

There are three categories of techniques for image deraining. The first one is used multiple images for deraining, the second one is used a polarizing filter-based draining mechanism, and the third one is used single image deraining. Among these three categories, the first two techniques are not suitable for real-life rainy situations. Moreover, it is difficult in getting more information regarding rainy scenes using a single image. For solving this problem, researchers have been trying different approaches for experimentation with a single image according to the complexity of the situations.

The single image deraining process could be a little bit difficult as it is tough to get sufficient information from a single image. In the past, most of the solutions were dependent on handcrafted priors containing lots of limitations. Recently, generative adversarial network (GAN), initiated by Ian Good fellow [1] provides great performance in image enhancement through generative strategy. GAN can simulate various rain scenarios. A GAN model can be modified to cope with these situations. However, it is important to know how the models are performed on a rainy image in real situations. So, the principal aim of this paper is to investigate the success as well as a comprehensive analysis of four popular GANs for rainy conditions.

* Corresponding author: Md. Ashik Iqbal

Department of Computer Science and Engineering Daffodil International University Dhaka, Bangladesh.

The dominant contributions of this paper are as follows:

- A literature survey is on the existing state-of-the-art image deraining techniques.
- Experimentation with the formation of different types of GAN models, like attentive GAN, cGAN, DHSGAN, and Cycle GAN.
- Investigation of the validity and usefulness of the methods by using bench-mark datasets comprising artificial and actual rainy images.

The remaining parts of the paper are structured as follows: the second section represents the literature review, and the third section describes four GAN-based methods for deraining. The fourth section explains the results based on the experimentation using bench-mark datasets and finally, the conclusion is drawn in the fifth section.

2. Related works

Raindrop extraction is a challenging task for the existence of multiform rain amounts from the images. Reference [2] describes a survey on a single image deraining process where the techniques are trained and evaluated by rainy images of three types, such as rain streak, raindrop, rain, and mist.

Cai et al. [3] applied an end-to-end process for mediocre dispatch enumeration and took a fuzzy image as an input and outputs as its mediocre dispatch sketch. The sketch is used to restore a fuzzy-less derained image through an atmospherically distraction diagram. It takes a convolutional neural network (CNN) and can boost the standard of restoring fuzzy-less derained images.

Wang et al. [4] proposed an end-to-end network which is known as a 'dual-task de-raining network' (DTDN). In this approach, there are two networks: the first one is the GAN and the second one is the CNN which is used to vanish raindrops by attaching two reciprocally obstructive objectives. DTDN is principally dispelled structural raindrops and used to restore all the details from the main images.

Garg and Nayar [5] presented an outlook design approach using photometric properties to determine raindrops and finally to derains the images.

Ancuti and Ancuti [6] proposed a fusion-based method where white balance and a contrast-enhancing process are used. They filtered the shapes by calculating three measures (weight maps): the first one is the 'luminance', the second one is the 'chromaticity', and the third one is the 'saliency'. To reduce internal objects initiated by the weight sketch or map, they used a Laplacian pyramid representation designed in a multiscale fashion.

Bossu et al. [7] described a method that used the histogram orientation of rain streaks to find raindrops.

Zhang et al. [8] attempted to lift the powerful generative model where the input image was indistinguishable from its resembling ground truth clear image. There is some adversarial loss from the GAN and it gives an excessive regularization which helped to earn upper outputs. They initiate a new loss operation within the generator and the discriminator for achieving acceptable outputs.

Li et al. [9] introduced a method that is known as 'simple patch-based priors' and applied in both background and rain layers. By the Gaussian mixture models [10] and the number of rain streaks this method successfully removes raindrops or streaks better than the other methods.

Luo et al. [11] proposed a dictionary learning-based algorithm to remove the rain layer and finally produces a derained layer.

Bao et al. [12] presented a proximal method that is based on dictionary learning problems. This learning method applies successfully in image recovery fields.

Kang et al. [13] introduced a framework based on morphological component analysis. The conventional image decomposition technique is not used directly here. In this method, they divide an image into low- and high-frequency parts as bilateral filters and decomposed the rain component into high frequency by dictionary learning and sparse coding that produced 'non-rain component'.

He et al. [14] applied an image prior called the dark channel prior process. Using the rainy imaging model and prior, the thickness of rain can be measured and retrieve a good quality rain-free image.

Narasimhan and Nayar [15] proposed a geometric framework and used it to analyze the chromatic effects by atmospheric scattering. Besides, they applied it by using three interactive algorithms and removed the weather effects. Later, Suarez et al. [17] introduced an approach that uses stacked conditional GAN to remove the rain.

3. Methodology

3.1. GAN-Based Deraining

For the image deraining process, SEVERAL METHODS ARE INTRODUCED, still, researchers are searching for a better approach. Utilizing rain-relevant methods, one or more fundamental systems are checked but few times they show good results. Recently, Ian Good fellow et al. [1] developed a new computational model – the generative adversarial network (GAN) which is found promising in solving environmental degradations for clear vision like denoising, dehazing, and, deraining, etc.

3.2. Generative Adversarial Network

Figure 1 shows a generic flow diagram of a GAN. Two CNNs are used in this architecture. One is a discriminator (D) which makes a difference between the actual picture and the generated picture, the other one is a generator (G) which generates the picture to ignoramus the difference [1, 17].

G (z) is the distribution of the samples. A probability distribution $\boldsymbol{p_g}$ defines by G. To get proper knowledge about the generator's distribution $\boldsymbol{p_g}$ we used a generative adversarial network. $\boldsymbol{p_r}$ Represents the real data distribution.

$$\min_G \max_D E_{z\sim p_z} log[D(x)] + E_{z\sim p_z} log[1 - D(G(z))) \qquad (1)$$

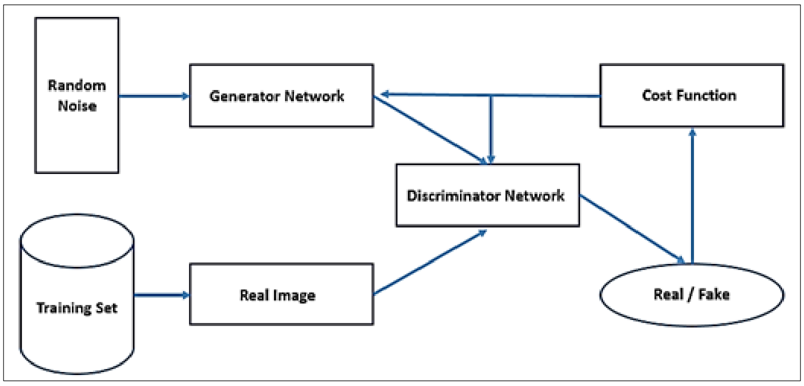

Figure 1 Generic architecture of GAN. Discriminator (D) and generator (G) are 2 deep neural networks (CNNs). D makes a difference between the actual picture and generated picture and G is generates the picture to ignoramus the difference

3.3. Conditional GAN

The conditional generative adversarial network (cGAN) [17] works in a conditional framework, where both generator and the discriminator modules are conditioned with some additional data such as knowledge or category labels. Optimizing adversarial and perceptual losses can generate a clean image or picture from an input image. cGAN also reduces random noise from the image. The loss function equation is,

$$\min_G \max_D E_{I,z}[log\left(1 - D(I, G(I,z))\right) + E_{I,J}[logD(I,J] \qquad (2)$$

In the above equation, 'J' represents a clean image, 'z' is random noise, and the input hazy image is represented by 'I'.

3.4. Cycle GAN

Cycle GAN [18] is an automatic training process of the image-to-image translation model. In cycle GAN, two generators and two discriminators are used to learn mapping without pairing two domain images. Cycle GAN makes a better image translation by focusing on high frequency and the discriminator. In the loss function, a penalty term is added to assure that image is not changed so much after being translated. The process equation can be written as

$$G^* = \min_{G,F} \max_{D_X,D_Y} L(G,F,D_X,D_Y) \qquad (3)$$

In the above equation, G*is the well-trained generator G.

3.5. Attentive GAN

In the attentive GAN [19, 20] generative network makes an attempt to provide a picture as equal as potential and clean from raindrops. The discriminative network can affirm whether or not the picture made by the generative network appearance is actual. The generative adversarial loss equation is written as

$$\min_{G} \max_{D} \mathrm{E}_{\mathrm{R}\sim\mathrm{Pclean}}\left[\log\left(\mathrm{D(R)}\right)\right] + \mathrm{E}_{\mathrm{I}\sim\mathrm{Praindrop}}\left[\log\left(1 - \mathrm{D(G(I))}\right)\right] \ (4)$$

Where D is the discriminative network, G is the generative network, I is the sample that is retrieved from images from raindrops. R is known as a sample of a natural image.

3.6. De-Haze and Smoke GAN

De-Haze and Smoke GAN (DHSGAN) [21] provide a de-hazing architecture. In this architecture, there is no need for any type of post-processing or reversion of an atmospheric model. Using a convolutional network the final layer of DHSGAN can directly produce a clean image. For realistic clean images, this model is trained by the generative adversarial network. DHSGAN model has 2 sub-modules. The first one is the transmission module and the second one is the GAN module. The working process equation is,

$$J(X) = G\ [T\ \{I(X)\},\ I(X)] \qquad (5)$$

In the 1st sub-module, a fully convolutional recurrent architecture is pre-trained using ImageNet [22] dataset and initialized with VGG19 [23]. The 2nd sub-module (i.e. the GAN module) works with 2 CNN architectures.

Table 1 A brief architecture of these GANs

	cGAN	**Cycle GAN**	**Attentive GAN**	**DHSGAN**
Input Size	512×512×3	256×256	224×224×64	256×256
Conv. Layers	-	-	7	-
Filter Size	1,3	3	-	1,3
Stride	2	-	1.2	1.2
Parameter	-	-	-	-
FC Layer	2	1	-	1
Size	-	-	-	-
Depth	150	24	-	87

4. Results and discussion

4.1. Dataset

Here we have used the standard UCID (uncompressed color image database) dataset [24] for deraining. This dataset contains 1338 uncompressed rainy images along with their corresponding ground truth and a series of query images.

We have divided the image set into two categories: training (80% images) and testing (20% images). Among these, three sample rainy images and their corresponding ground truths are shown in Figure 2.

4.2. Experimentation

For evaluation purposes we have used two quantitative metrics – PSNR (peak signal to noise ratio) and SSIM (structured similarity indexing method). The average PSNR and SSIM values of the derained images for the four GAN-based techniques: Attentive GAN, cGAN, Cycle GAN, and DHSGAN are shown in Table 2. This table shows that cGAN gives the highest average PSNR value (22.06 dB) and cycle GAN gives the highest SSIM value (0.92). So, based on quantitative results, a single method does not satisfy both metrics. Obtained derained images by the four GAN-based techniques of the three sample images are shown in Figure 3, Figure 4, and Figure 5. From these visual results, it is confirmed that the cGAN shows superior results to the other methods.

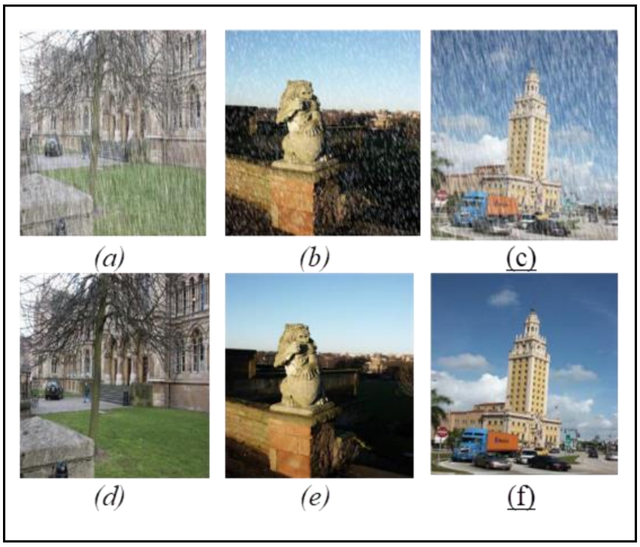

Figure 2 Sample test images (a) - (c) and their corresponding ground truth images (d) – (f) from the UCID dataset

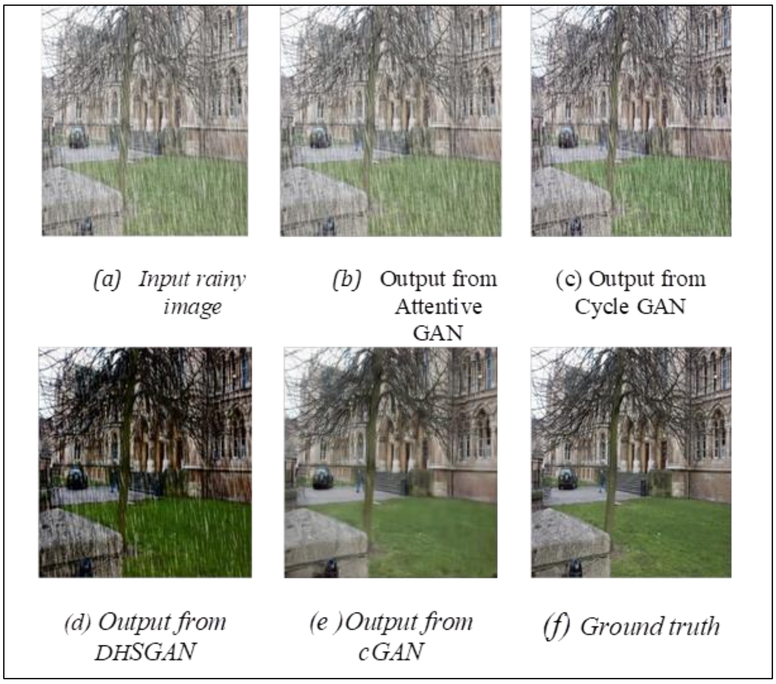

Figure 3 Visual results of different GAN methods using Figure 2(a) image as input

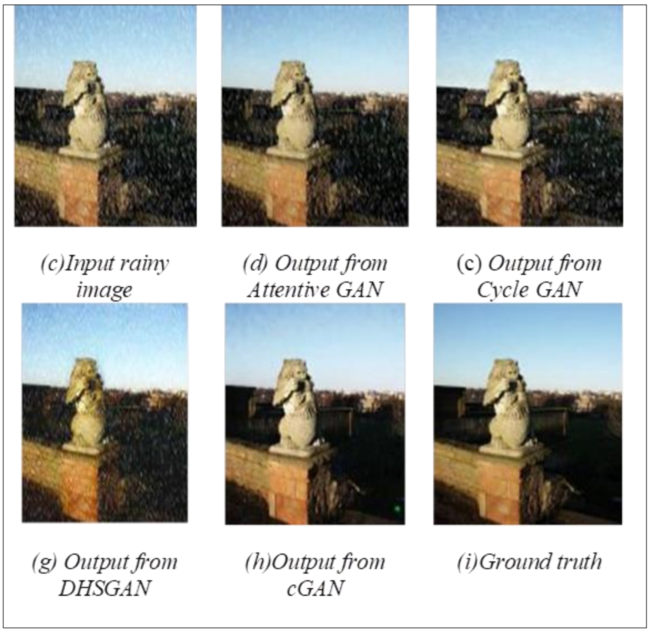

Figure 4 Visual results of different GAN methods using Figure 2(b) image as input

Table 2 Average PSNR and SSIM results for the investigated three GAN-Based methods for UCID dataset images

Metrics	Attentive GAN	Cycle GAN	DHSGAN	cGAN
PSNR (dB)	21.93	20.13	21.84	22.06
SSIM	0.85	0.92	0.90	0.89

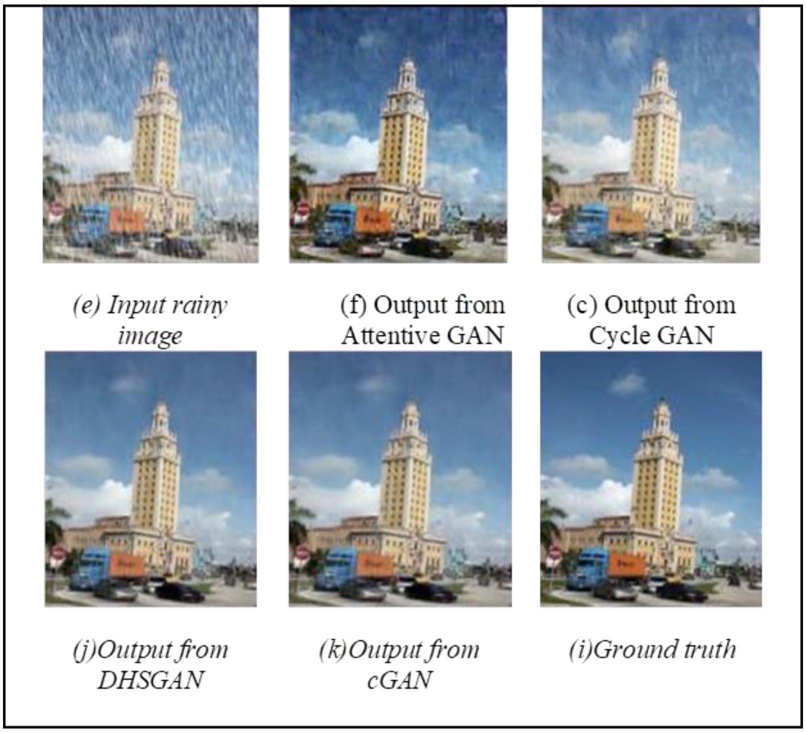

Figure 5 Visual results of different GAN methods using Figure 2(c) image as input

5. Conclusion

Due to random variations and intensities of rains, deraining is a challenging issue for ensuing clear visibility, which is very important for navigational purposes. We have presented a comprehensive analysis on four standard GAN models (Attentive GAN, cGAN, DHSGAN, and Cycle GAN) for image deraining. We did experimentation using the standard UCID dataset to investigate the effectiveness of the GAN-based deraining methods through quantitative (using PSNR and SSIM) and qualitative (using visual feeling) metrics. Evaluation results confirm that there is not any single best deraining algorithm that gives satisfactory performance under all metrics. However, on the basis of visual evaluation, it is found that cGAN gives a comparatively satisfactory result. To deal with the complicated, varying rains, one might need to consider a mixture model of experts. This finding will encourage researchers in developing robust algorithms to overcome real-life visibility problems caused by rainy situations.

Compliance with ethical standards

Acknowledgments

The authors wish to acknowledge themselves for all their efforts and resources inputted to ensure the success of the research manuscript. Also, thanks to their family for the support during this research.

Disclosure of conflict of interest

There is no conflict of interest at this manuscript.

References

[1] Goodfellow I, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley D, Ozair S, Courville A, Bengio Y. Generative adversarial nets. Advances in neural information processing systems. 2014;27.

[2] Li S, Araujo IB, Ren W, Wang Z, Tokuda EK, Junior RH, Cesar-Junior R, Zhang J, Guo X, Cao X. Single image deraining: A comprehensive benchmark analysis. InProceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition 2019 (pp. 3838-3847).

[3] Bolun Cai, Xiangmin Xu, Kui Jia, Chunmei Qing, Dacheng Tao, “An End-to-End System for Single Image Haze Removal,” IEEE Trans. Image Processing. Nov 2016; 25(11): 5187-5198.

[4] Wang Z, Li J, Song G. Dtdn: Dual-task de-raining network. InProceedings of the 27th ACM International Conference on Multimedia 2019 Oct 15 (pp. 1833-1841).

[5] Garg K, Nayar SK. Detection and removal of rain from videos. InProceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2004. CVPR 2004. 2004 Jun 27 (Vol. 1, pp. I-I). IEEE.

[6] Codruta Orniana Ancuti, Cosmin Ancuti. Single Image Dehazing by Multi-Scale Fusion, IEEE Trans. Image Processing. 2013; 22(8): 3271-3282.

[7] Jérémie Bossu, Nicolas Hautière, Jean-Philippe Tarel, “Rain or snow detection in image sequences through the use of a histogram of the orientation of streaks,” International Journal of Computer Vision. 2011; 93: 348–367.

[8] He Zhang, Vishwanath Sindagi; Vishal M. Patel “Image De-raining Using a Conditional Generative Adversarial Network,” IEEE Trans. Circuits and Systems for Video Technology. Nov. 2020; 30(11): 3943-3956.

[9] Y Li, RT Tan, X Guo, J Lu, MS Brown. Rain Streak Removal Using Layer Priors, IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA. 2016; 2736-2744.

[10] Zivkovic Z. Improved adaptive Gaussian mixture model for background subtraction. InProceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004. 2004 Aug 26 (Vol. 2, pp. 28-31). IEEE.

[11] Y Luo, Y Xu, H Ji. Removing Rain from a Single Image via Discriminative Sparse Coding, IEEE International Conference on Computer Vision (ICCV), Santiago, Chile. 2015; 3397-3405.

[12] C Bao, H Ji, Y Quan, Z Shen. L0 Norm Based Dictionary Learning by Proximal Methods with Global Convergence, 2014 IEEE Conference on Computer Vision and Pattern Recognition, Columbus, OH, USA. 2014; 3858-3865.

[13] L Kang, C Lin, Y Fu. Automatic Single-Image-Based Rain Streaks Removal via Image Decomposition, IEEE Transactions on Image Processing. April 2012; 21(4): 1742-1755.

[14] Kaiming He, Jian Sun, Xiaoou Tang. Single image haze removal using dark channel prior, IEEE Conference on Computer Vision and Pattern Recognition, Miami, FL, USA. 2009; 1956-1963.

[15] SG Narasimhan, SK Nayar. Chromatic framework for vision in bad weather, Proceedings IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Hilton Head, SC, USA. 2000; 1: 598-605.

[16] LC Valeriano, J Thomas, A Benoit. Deep Learning for Dehazing: Comparison and Analysis, Colour and Visual Computing Symposium (CVCS), Gjøvik. 2018; 1-6.

[17] PL Suarez, AD Sappa, BX Vintimilla. Cross-Spectral Image Dehaze through a Dense Stacked Conditional GAN Based Approach," International Conference on Signal-Image Technology & Internet-Based Systems (SITIS), Las Palmas de Gran Canaria, Spain. 2018; 358-364.

[18] Zhao W, Yang P, Ni R, Zhao Y, Li W. Cycle GAN-based attack on recaptured images to fool both human and machine. InInternational Workshop on Digital Watermarking 2018 Oct 22 (pp. 83-92). Springer, Cham.

[19] Rui Qian, Robby T. Tan, Wenhan Yang, Jiajun Su, Jiaying Liu. Attentive Generative Adversarial Network for Raindrop Removal from a Single Image.

[20] T Wang, X Yang, K Xu, S Chen, Q Zhang, RWH Lau. Spatial Attentive Single-Image Deraining With a High Quality Real Rain Dataset," IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Long Beach, CA, USA. 2019; 12262-12271.

[21] Malav R, Kim A, Sahoo SR, Pandey G. DHSGAN: An end to end dehazing network for fog and smoke. InAsian conference on computer vision 2018 Dec 2 (pp. 593-608). Springer, Cham.

[22] A Krizhevsky, I Sutskever, GE Hinton. Imagenet classification with deep convolutional neural networks, Proceedings of the 25th International Conference on Neural Information Processing Systems Lake Tahoe, NV. Dec 2012; 1097–1105.

[23] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556. 2014 Sep 4.

[24] Schaefer G, Stich M. UCID: An uncompressed color image database. InStorage and Retrieval Methods and Applications for Multimedia 2004 2003 Dec 18 (Vol. 5307, pp. 472-480). International Society for Optics and Photonics.