Convolution Neural Network based Rain Noise Removal for Real Time Application

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Abstract:

Image quality is affected by rain streaks that have an adverse effect on the applications which involves the ideas of surveillance, automatic path navigation. Hence it is important to process the information present in the images affected by water droplets caused by the rain or the mist. So this forms the basic need to identify the problem which does not have any mathematical correlation about the same. This research tries to work on the methodology which will denoise the criteria based on Convolutional neural network (CNN). CNN modelling helps in finding out the connections between the noise input image and rain streak. The proposed method uses synthetic database available publicly.

Keywords: Rain streaks, Convolutional neural network, Denoising.

1. INTRODUCTION

Bad weather distortion in still images conditions can negatively affect the eye performance of several pictorial structures. Rain belongs to one of inclusion situations that caused substantial distinctions in pictures [1-3]. A study by Garg [4] shows this inclusion situations, drizzle or mist subject to variable climate. A variable climate incorporates components of generally huge dimensions gathered of cameras. Consistent climate like haze elements, are lighter parts and can be minimally recorded. Thus, these atmospheric conditions contributes to difficult variable intensities and tarnishes them evidence that is carried in the image or series of images [5-6]. The existing methods denoise the images using background and foreground images. Notwithstanding, these strategies may neglect to manage certifiable downpour inferable from the unpredictability of rain for example, the overlapping between downpour streaks and complex surface [7-10]. As of late, because of the amazing elemental analysis of convolutional neural network (CNN), deep learning based deraining strategies [11-12] have
been proposed to eliminate downpour streaks in a solitary picture and accomplished promising execution [13-15]. They put forth an attempt to learn portrayals of various rain layers and afterward deduct these layers from the input picture.

Rest of the paper summarized as: section II represents the literature work of existing algorithms. Section III represents the proposed methodology. Section IV presents the result of the proposed methodology. Finally Section V represents the conclusion of overall framework

2. LITERATURE SURVEY

This section describes the related work on raindrop removal on still images. In the past few years, significant enhancement was observed in raindrop removal. Our work mainly focuses on raindrop removal on still images as it is very challenging using deep learning technique.

| Year   | Method                                         | Pros/Cons                                  | Dataset            | Parameters Calculated   |
|--------|-----------------------------------------------|--------------------------------------------|--------------------|-------------------------|
| 2018 [5]| 1. Attempt to separate rain streaks from background using wavelet Transform.  
2. Removal of haze veil using dark channel. | 1. Better results are obtained. 
2. Achieves better rain and haze veil removal. | NYU Depth V2 | PSNR, SSIM, NIQE |
| 2017 [6]| Rain removal is performed using deep learning networks. | Removes rain streaks even in extreme cases. | Rain12, Rain100H, Rain100L | PSNR, SSIM |
| 2019 [7]| Supervised and Unsupervised Learning | Doesn’t remove rain streaks in extreme conditions | Google images | PSNR |
| 2019 [8]| Attempt to separate rain streaks from background | Better results obtained. | Own dataset | SSIM |
| 2018 [1]| Convolutional Neural Network | It is effective and robust. | Rain12, BSD300 | SSIM |
| 2019 [2]| De-raining unit and dense connections are used | Better results obtained. | Rain100H, Rain100L, Rain1200 | PSNR |
A wide range of research has been carried out to denoise the images affected by the rain drops or mist. Most of the previous research was carried out using supervised learning and deep learning techniques, coarse fusion model etc. All the work carried out has minimal results under extremes conditions and hence we propose the CNN modelling to obtain the better results.

3. PROPOSED METHODOLOGY

A novel CNN algorithm is proposed for rain drop removal which also improves the performance. The input image is captured from the standard database as an RGB image, the basic stages for rain removal using image processing are as shown in Fig. 1.
Algorithm: ADM

1. Initially check if intensity of the pixel is equal to the max of min values.
2. Find the distance of the pixel from the origin if it is a valid pixel and if it lies between the noise probabilities.
3. Let the distance be r and window size is now assumed as 2r+1.
4. The median is computed after the window size is found.

The main aim of Adaptive mean filter is to remove noise from the image using standard mean filter. The main difference between these filters lies in variable dimensions of the mask. Based on the average pixels in the current mask this distinction depends. The adaptive mean filter deals the corrupted image filtering process with a potential noise impulse higher than 0.2.

3.1 Pre-processing:

To enhance or remove noise from the input image different pre-processing methods are used. Adaptive median filtering is a non-linear digital filtering technique employed to eliminate noise. It is very effective method as it preserves the edges and smoothen non-impulsive noise.

Fig. 2 (a) Input Image (b) Segmented Image

3.2 CNN Modelling:

CNN is a deep learning model which assigns importance to objects in input image and distinguishes it from other. CNN performs image identification and image recognition. CNN contains four layers: convolutional layer, pooling layer, fully connected layer and activation layer.

At first each information picture will go through a progression of convolution layers with channels (Kernels), Pooling, Fully associated layers (FC). Finally, softmax work, which is an
activation function is applied to order an item with probabilistic qualities somewhere in the range of 0 and 1. The below figure Fig. 3 is a progression of CNN to handle a picture and arranges the articles dependent on values.

![Architecture of the Proposed Methodology](image)

**Fig. 3: Architecture of the Proposed Methodology**

- **Convolutional layer**: A “kernal” is rolled over the image, taking a few pixels at a time and creating a vector that identifies the set to which every property belongs.

- **Pooling layer (down sampling)**: It diminishes the amount of data in each component acquired in the convolutional layer and jam the most prominent data.

- **Fully connected input layer (flatten)**: It takes the yield of the past layers, "flattens" them and transforms them into a solitary vector that can be a contribution for the following stage.

- **The first fully connected layer**: It takes the contributions from the element investigation and applies loads to foresee the right mark.

- **Fully connected output layer**: gives the finishing probabilities for every label.

3.3 **Softmax function**: It is a normalized exponential function. It is used as an activation function to normalize the output of system to a probabilistic distribution over a predicted output division.

The softmax function for the input vector $x$ of $k$ real numbers is defined as:

$$
\sigma(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{k} e^{x_j}} \quad \text{for } i=\ldots,k \text{ and } x = (x_1,\ldots,x_k) \in \mathbb{R}^k
$$
4. RESULTS

4.1 Evaluation Parameters:

4.1.1 Peak signal to noise ratio (PSNR) is ratio between the maximum signal power to the power of noise signal. It is generally used to calculate the quality of reconstructed image that have been compressed. PSNR is most easily defined via the mean squared error (MSE). The MSE for a given image \( I \) with \( pxq \) rows and columns is defined mathematically as:

\[
MSE = \frac{1}{pq} \sum_{r=0}^{a-1} \sum_{s=0}^{b-1} [I(r,s) - K(r,s)]^2
\]

\[
PSNR = \log_{10} \frac{MAX_I}{\sqrt{MSE}}
\]

Where \( MAX_I \) is maximum possible pixel value of image.

Structural similarity index measure (SSIM) is a metric which has three components which are luminance\( l \), contrast\( c \), structure\( s \) which are defined mathematically as follows.

\[
l(a, b) = \frac{(2m_a m_b + d_1)}{(m_a^2 + m_b^2 + d_1)}
\]

\[
c(a, b) = \frac{(2v_a v_b + d_2)}{v_a^2 + v_b^2 + d_2}
\]

\[
s(a, b) = \frac{v_{ab} + d_3}{v_a v_b + d_3}
\]

\( m_a \) is mean value of \( a \)

\( m_b \) is mean value of \( b \)

\( v_a^2 \) is variance of \( a \)

\( v_b^2 \) is variance of \( b \)

\( v_{ab} \) is covariance of \( a \) & \( b \)

\( d_1 = (n1,T)^2 \)

\( d_2 = (n2, T)^2 \)

\( d_3 = d_2/2 \)

\( n1=0.01 \) and \( n2=0.03 \) by default

\( T \) is the dynamic range of pixel values

Now, SSIM is weighted combination of these measures:

\[
SSIM(a, b) = [l(a, b)\delta c(a, b)\theta s(a, b)\theta]
\]

Where\( \delta, \theta, \theta \) is 1.
4.2 Datasets:

In the proposed work synthetic dataset used which is publically available. This dataset contains more than 4k images. Sample images of synthetic datasets are shown in Fig. 4.

![Sample datasets of Rain (Synthetic Datasets)](image)

**Fig. 4:** Sample datasets of Rain (Synthetic Datasets)

4.3 Results:

The experimentation was carried in MATLAB 2015 software. The system specifications on which the images are processed includes 4 GB RAM with NVIDIA graphic card.

Table 2: Comparison of Proposed work with PSNR & SSIM parameters with existing methodologies

| S. No. | Author Name       | Parameters Evaluated | PSNR(db) | SSIM  |
|--------|-------------------|----------------------|----------|-------|
| 1.     | Chen et al. [1], 2018 | -                    | -        | 0.94  |
| 2.     | Liang et al. [5], 2018 | 30.19                | 0.95     |
| 3.     | Yupei et al. [10], 2019 | 28.3                 | 0.91     |
| 4.     | Yang et al. [6], 2017 | 36.05                | 0.96     |
| 5.     | Kui et al.[3], 2020 | 22.48                | 0.904    |
| 6.     | Wei et al. [7], 2019 | 26.98                | -        |
| 7.     | Proposed Work     | 21.81                | 0.971    |
**PSNR (db)**

| Chen et al. [1], 2018 | Liang et al. [5], 2018 | Yupei et al. [10], 2019 | Yang et al. [6], 2017 | Kui et al. [3], 2020 | Wei et al. [7], 2019 | Proposed Work |
|----------------------|------------------------|------------------------|----------------------|---------------------|---------------------|---------------|
|                      |                        |                        |                      |                     |                     |               |

Fig. 5: Comparison of Proposed work with PSNR parameters with existing methodologies

**SSIM**

| Chen et al. [1], 2018 | Liang et al. [5], 2018 | Yupei et al. [10], 2019 | Yang et al. [6], 2017 | Kui et al. [3], 2020 | Wei et al. [7], 2019 | Proposed Work |
|----------------------|------------------------|------------------------|----------------------|---------------------|---------------------|---------------|
|                      |                        |                        |                      |                     |                     |               |

Fig. 6: Comparison of Proposed work with SSIM parameters with existing methodologies
5. CONCLUSION

The paper mainly focused on the effective noise removal caused by the rain streaks in the still images using convolution neural networks. The results are vivid and conclusive that the proposed methodology has a very good yield. The similarity index has increased to 0.971 when compared to the previous work. The PSNR values obtained is 21.81dB which is in the acceptable range comparatively. The results can be more effectively used to improve the quality of the images using hybrid models.

References

[1] Chen, T., & Fu, C, “Single-image-based Rain Detection and Removal via CNN”, Journal of Physics: Conference Series, 1004, 012007, 2018.

[2] Cong Wang, Man Zhang, Jinshan Pan, Zhixun Su, “Single image rain removal via densely connected contextual and semantic correlation net”, Journal of Electronic Imaging 28 (3), 033018, 2019.

[3] Kui Jiang, Zhongyuan Wang, Peng Yi, Chen Chen, Baojin Huang, Yimin Luo, Jiayi Ma, Junjun Jiang, “Multi-Scale Progressive Fusion Network for Single Image Deraining”, 28 Mar 2020.

[4] K. Garg and S. K. Nayar, "Detection and removal of rain from videos," Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2004. CVPR 2004., Washington, DC, USA, 2004, pp. I-I.

[5] Liang Shen, Zihan Yue, Quan Chen, Fan Feng and Jie Ma "Deep joint rain and haze removal from a single image" IEEE 2018 24th International Conference on Pattern Recognition (ICPR) Beijing, China, August 20-24, 2018.

[6] W. Yang, R Tan, J. Feng, J. Liu, Z. Guo and S. Yan, “Deep joint rain detection and removal from a single image”, IEEE Conference on Computer Vision and Pattern Recognition (CVPR-2017), pp. 1685-1694, Honolulu, HI, USA, July 21-26, 2017.

[7] Wei Wei, Deyu Meng, Qian Zhao, Zongben Xu, Ying Wu, “Semi-supervised Transfer Learning for Image Rain Removal”, IEEE/CVF Conference on Computer
Vision and Pattern Recognition (CVPR-2019). Pp. 3872-3881, USA, June 15-20, 2019.

[8] Y. Himabindu, R. Manjusha, Latha Parameswaran, “Detection and Removal of Rain Drop from Images Using Deep Learning”, ICCVBIC 2019, pp. 1355-1362.

[9] Wenhan Yang, Robby T Tan, Jiashi Feng, Zongming Guo, Shuicheng Yan, Jiaying Liu, “Joint rain detection and removal from a single image with contextualized deep networks”, IEEE transactions on pattern analysis and machine intelligence 42 (6), 1377-1393, 2019.

[10] Yupei Zheng, Xin Yu, Miaomiao, Shunli Zhang, “Residual Multiscale Based Single Image Deraining”, bmvc2019.

[11] Xueyang Fu, Jiabin Huang, Xinghao Ding, Yinghao Liao, and John Paisley. Clearing the skies: A deep network architecture for single-image rain removal. IEEE Transactions on Image Processing, 26(6):2944–2956, 2017.

[12] Yu Li, Robby T Tan, Xiaojie Guo, Jiangbo Lu, and Michael S Brown. Rain streak removal using layer priors. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2736–2744, 2016.

[13] Ponnapalli, Venkata A. Sankar, VY Jayasree Pappu, and B. Srinivasulu. "Design of thinned rhombic fractal array antenna using GA and PSO optimization techniques for space and advanced wireless applications." In Microelectronics, Electromagnetics and Telecommunications, pp. 719-727. Springer, Singapore, 2018.

[14] Subbarao, D. "The Influence Of Electronic Communication On Machine Learning." International Journal of Advanced Research in Computer Science 2.3 (2011).

[15] Prasad, Kantipudi MVV, and H. N. Suresh. "Spectral Estimation Using Improved Recursive Least Square (RLS) Algorithm: An Investigational Study." Emerging Research in Computing, Information, Communication and Applications. Springer, New Delhi, 2015. 363-376.