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Rain Streaks Removal from Rainy Images Using Convolutional Neural Networks

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Abstract:

Image processing is very important thing to improve the contrast and enhance the degraded images of real world. The rainy images are blurred and contain unclear structure of the objects for that apply deep learning based method to recover the rainy image objects. In this paper, remove the rainy streaks from rainy image and improve the contrast of the rainy image for that apply deep learning method of RainyNet is based on the Convolutional Neural Network. The RainyNet is made up of the encoder-decoder structure is constitute the detail rectify the network to find out the final clear structure. Here, DarkRain trained synthesised dataset is take over to testify the proposed method to produce good results than state-of-art methods. The proposed RainyNet is achieved better results than existing methods in terms of PSNR and SSIM.

Keywords: Rainy Image, Image Enhancement, Convolutional Neural Network, Poor Illumination, Rainy Streaks Removal.

1. INTRODUCTION

Rain is a boom to our earth but sometimes it was give sweet memories and bad memories. The bad weather always give foggy images and its details are blurred especially in the rainy time took images are always blurred. The rainy streaks and bad weather hide the image details. The traditional methods are used to remove the rainy streaks from the image and enhance the degraded image but it's failed. The rainy weather image is totally different from normal weather image [6].

On the other hand, the model-based methods and data-driven like end-to-end architecture is used to enhance the degraded image. The trained synthesised dataset and real world dataset is used to test the performance of derainy image methods [1-3]. Traditional rainy removal methods are performing well but which is fails to update the clear rainy image background. [7]. Whenever the night time images are not clear especially the rainy night time images are look so bad from that we cannot get clear details. The night time rainy images contain low light and foggy environment conditions while the rainy streaks are hidden the image clear details. The light scattering is one of the problems in rainy image streaks removal [5, 8].

The CNN based rainy streaks removal methods are produced better results than existing methods in terms of qualification and quantification metrics. Moreover, some CNN based methods are fails to update the background details when improve the brightness and removes the rainy streaks from the image. First of all improve the illumination at the same time removes the rainy streaks from the image [3].

This work is formatted as follows: Section I introduce the importance of the Image Enhancement. Section II describes related research works of the Rainy image streaks removal techniques. In the section III represent the proposed methodology. Section IV shows the experimental results and discussion of proposed work. Finally, Section V describes about the conclusion and future work.

II RELATED RESEARCH WORKS

Kui Jiang et al.,[1] proposed the method of Multiscale progressive fusion network for single image deraining. In this paper CNN based multi-scale progressive fusion network is used to removes the rainy streaks from the rainy image successfully and here take over the different deraining synthesized datasets and real-world scenarios for test the performance of this proposed method to produce better results but this method is highly cost effective.

Yifan Jiang et al., [2] presented the research work of Deep light enhancement without paired supervision for improve the contrast of lowlight illumination images. In this paper, address the issues of low-light illumination images with unsupervised network. The enlighten GAN is used to improve the low vision images and this method is applied on different low vision dataset to produce better results that state-of-art methods. This method is complicated to apply some levels of light illuminations images.

Chongyi Li et al., [3] represented the method of learning to enhance low-light image via zero-reference deep curve estimation for low-vision images. Redesigning the network structures and redevelops the curve estimation according to different types of low vision images. The method is successfully applied on low vision rainy images to get better results on performance metrics. This method is very cost effective and does not apply on high vision images.

Ruoteng Li et al., [4] proposed the method of Integrating Physics Model and Conditional
Adversarial Learning is based on novel2 stage CNN method for removing the rainy streaks from rainy image. In first stage, the guided filter is used for decompose the image front image into front details and background derails. The physics based back bone structure is made by depth-guided GAN network structure is used in second stage to recover the background details. The experimental results outperforms on both synthetic and real rain images. This method is applicable only for rainy images and cost effective.

Ruijie Quan et al., [6] described the method of deep learning based cascaded network architecture for rainy streaks removal from rainy images. This method is effectively identified the difference between raindrops and rain streaks and remove those things from rainy image successfully. This method is produce better results on RainDS real-world data. This method is comparatively applied on low vision real rainy images and synthetic rain images to produce effective performance than state-of-art methods. Moreover, this method is applicable only particular type of applications not for all.

III PROPOSED METHODOLOGY

The proposed RainyNet is based on Convolutional Neural Network end-to-end architecture and which is constructed by three levels. The first two levels are constituted by encoder and decoder network architectures that grasp the more textual information through the large receptive fields. The final level employs a network architecture that consider the original input image (in this step didn't apply any sampling operations), due to that updating the target neat texture in the enhanced output image. Figure 3.1 shows the three levels of proposed method RainyNet architecture.

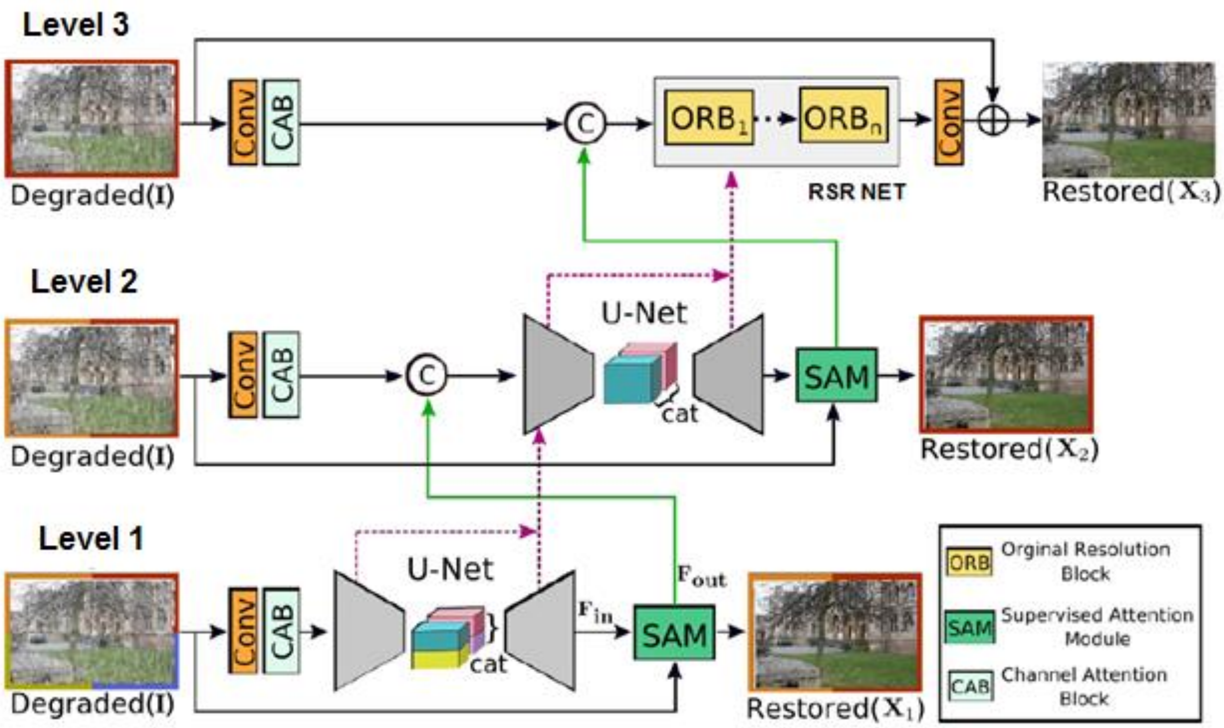

Figure 3.1: Proposed RainyNet architecture.

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The supervised attention module (SAM) is inserted into middle each and every two levels that grasps to recreate features before passing them to one level to the next level. Dotted pink arrows denotes about the cross stage feature fusion recognition mechanism. At any given Level L, it's directly predicts the residual image R_L instead of directly predicting a restored image X_L, and an input image I is added to obtain: $X_L = I + R_L$.

3.1. Rain and Illumination

RAIN: The rainy image D can be made up by the addition of a clean background scene B and accumulated rain layer R can be expressed as,

$$D = B + R \qquad (3.1)$$

Here based on this expression, updates the clean background image B through subtracting the rain layer R from the degraded rain image D.

ILLUMINATION: The classic Retinex theory approximately that the input degraded image D can be decomposed into reflectance and illumination can be expressed by,

$$D = F \odot \mathrm{I} \qquad (3.2)$$

Here F represents the captured image observation, I represent the lightness condition and ⊙ denotes as element wise multiplication then adjusting I to enhance the lighting condition.

RAIN AND ILLUMINATION: In this real world rainy weather is different from normal weather so when capture the rainy image with low illumination or low light leads to captured degraded image. Then the low illumination with rainy image can be expressed by,

$$D = F \odot I + R \qquad (3.3)$$

Here, through this expression, updates the enhanced rain streaks removal image C by $C=(D - R) \odot M$, then M represents the illumination map.

3.2 Three Sub networks Framework Architecture

In this proposed method of RainyNet constituted by three sub networks and two networks RSRNet and ICNet are designed by U-Net-like [16] and both are the in same structure. The two networks are interconnected through Entwine Block (ENBlock) due to this achieve both better communication inbetween and rain removal with illumination enhancement.

In order to, the rain contain the higher frequency information so we first consider the input of high frequency details through the Laplace transform on RSRNet [12] together with the original image meanwhile low frequency information is obtained as global information through one minus Laplace transform on ICNet together with an input image. Moreover, in the downsampling process, here used instance normalization and leakyRelu[15] with a negative slope is equal to the value of 0.2. This is very useful to perform low-vision tasks. In upsampling process, here removed instance normalization and convolutional layers with pooling layers for reduce the unexpected errors and noise with artifacts from an output enhanced image.

3.3 The RainyNet Network Architecture

Consequently, RainyNet consists of three sub-networks such as Rain Streaks Removal Network (RSRNet), Illumination Compute Network (ICNet), and Detail Retrieval Network (DRNet) respectively and these three networks are made up to do to their works by specific constraints for separately. In order to, RainyNet changing the lightning conditions and remove rain to avoids the low illumination effect of bugs and obtains better quality of enhanced images. RSRNet and ICNet connect through well-structured Entwine Block (EMBlock) to detects rain streaks and enhance low illumination in simultaneously. These three sub networks such as EMBlock, RSRNet, and ICNet can fully grasp the low level and high level data transmission. Moreover, it's better under stands the rain and illumination effects via complementary features. However, DRNet is made up of multiple Detail Retrieve Blocks (DRBlocks) to find out the loss details to produce better enhancement image with retrieve loss details.

$$L = L_{rain} + L_{enhance} + L_{detail} \tag{3.4}$$

L_{rain} is the rain removal loss that contains a standard $\mathcal{L}_1$loss and a L_{SSIM} loss [15], calculated by,

$$\mathcal{L}_{rain} = \|X_r - Y_r\| + 1 - SSIM(X_r, Y_r) \tag{3.5}$$

Here Y_r is the corresponding rain-free image. $L_{enhance}$ is the illumination enhancement loss, similar to L_{rain}, $L_{enhance}$ is calculated by,

$$\mathcal{L}_{enhance} = \left\|X_e - Y_f\right\| + 1 - SSIM\left(X_e, Y_f\right) \tag{3.6}$$

Here Y_{rf} is the corresponding enhanced rain-free image. We further apply the detail recovery loss L_{detial} computed by,

$$\mathcal{L}_{detail} = \mathcal{L}_{Char}\left(X_f, Y_f\right) + \lambda \mathcal{L}_{edge}\left(X_f, Y_f\right) \tag{3.7}$$

Here L_{char} is the Charbonnier loss and then optimize proposed method RainyNet end-to end loss function is calculated by,

$$\mathcal{L} = \sum_{L=1}^{3}\left[\mathcal{L}_{char}\left(X_{L,}Y\right) + \lambda \mathcal{L}_{edge}\left(X_{L,}Y\right)\right] \tag{3.8}$$

$$\boldsymbol{\mathcal{L}}_{Char} = \|X_L - Y\|^2 + \epsilon^2 \tag{3.9}$$

Here ϵ denotes empirically fixed as 10^{-3} for throughout this experiments. Moreover, L_{edge} is the edge loss, calculated by,

$$\boldsymbol{\mathcal{L}}_{edge} = \sqrt{\|\Delta(X_L) - \Delta(Y)\|^2 + \epsilon^2} \tag{3.10}$$

Here Δ represents the Laplacian operator. The parameter $\boldsymbol{\lambda}$ in Eq. (3.8) controls the two loss terms and it is set to 0.05. The RainyNet algorithm is given below.

Algorithm

Input Image: *Degraded Rainy Image*
Output Image: *Restored Enhanced Image*
Step 1 : The input image is send to RSRNet to removes the rainy streaks from rainy image.
Step 2: The rainy image send to ICNet to remove low illumination artifacts and enhance the Low vision details.
Step 3: The Detail Retrieval Network DRNet is used to retrieval the information from the degraded input image.
step 4: Finally, Entwin Block is used to combine the three pictures to produce the restored enhanced image.
Step 5; The Enhnaced rainy streak removed rainy image is successfully updated.

4. RESULTS AND DISCUSSIONS

The proposed method of RainyNet is compared with state-of-art methods and tested its performance using evaluation metrics to provides better results than other methods then here conducted an experiments using DarkRain dataset to exhibit the performance of the proposed RainyNet. The proposed methods achieve better performance in terms of PSNR and SSIM metrics.

4.1 Performance Metrics

The following metrics are used to evaluate the proposed method using different Rainy Images from DarkRain dataset.

a) Peak Signal to Noise Ratio (PSNR)

The PSNR metric value is evaluated from the MSE metric. L is the dynamic range of input image pixel intensities. The PSNR and MSE have a some specific qualities to handle it’s such as, it’s a simple and elegant, it has correct distance metrics and it’s has clear physical structure to handle. Which has two signals one is normal and another one is distortion signal to produce the error signal.

$$PSNR = 10log_{10}\frac{L^2}{MSE} \quad (4.1)$$

b) Structural SIMilarity Index (SSIM)

The SSIM is used the x and y are the image patches of two different images where it's located at different location. Then it does consider the three constraints such as luminance $l(x, y)$, contrast $c(x, y)$ and structures $s(x, y)$. These are computed by using some statistics and combined to produce the SSIM.

$$\mathrm{SSIM} = l(x,y)\cdot c(x,y)\cdot s(x,y),$$
$$= \left(\frac{2\mu_x\mu_y + C_1}{\mu_x^2+\mu_y^2+C_1}\right)\left(\frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2+\sigma_y^2+C_2}\right)\left(\frac{\sigma_{xy}+C_3}{\sigma_x+\sigma_y+C_3}\right) \quad (4.2)$$

Here, μ_x and μ_y are the means of x and y image patches andσ_x, σ_y are the standard deviations of patches x and y. σ_{xy} is when remove the noise at that time this is the cross correlations of the patches of x and y. when c1, c2 and ce3 are constants to avoid near zero-divisions. Therefore, the Finally it's used to hardly handle the visual perception of image quality.

table 4.1 shows the performance evaluation of rainy imag1 and the table 4.2 shows the performance evaluation of rainy image2. In figure 4.1 shows the visual analysis of proposed method for single rainy images.

Table.4.1 Performance Evaluation of Proposed Method for Rainy Image1

Method	PSNR	SSIM
DerainNet	33.42	0.912
SEMI	32.24	0.845
DIDMDN	31.42	0.901
RainyNet	34.56	0.956

Table.4.2 Performance Evaluation of Proposed Method for Rainy Image2

Method	PSNR	SSIM
DerainNet	31.45	0.827
SEMI	34.30	0.845
DIDMDN	33.17	0.866
RainyNet	35.26	0.878

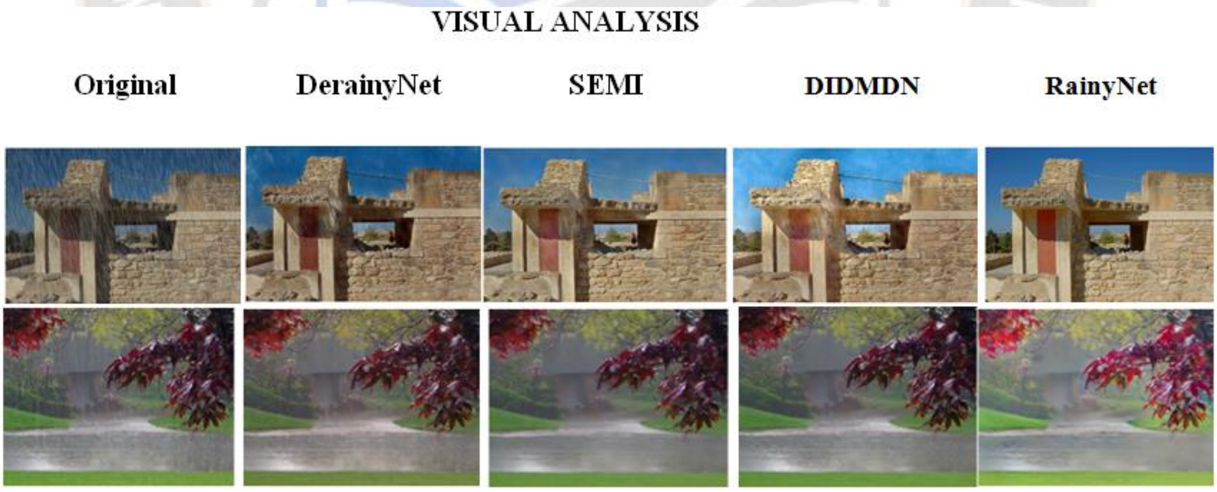

Figure 4.1 visual Analysis of Proposed Method for Rainy Images

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