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A Robust Visibility Restoration Framework for Rainy Weather Degraded Images

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***Abstract* – Visibility restoration of color rainy images is inevitable task for the researchers in many vision based applications. Rain produces a visual impact on image, so that the intensity and visibility of image is low. Therefore, there is a need to develop a robust visibility restoration algorithm for the rainy images. In this paper we proposed a robust visibility restoration framework for the images captured in rainy weather. The framework is the combined form of convolution neural network for rain removal and low light image enhancement for low contrast. The output results of the proposed framework and other latest de-rainy algorithms are estimated in terms of PSNR, SSIM and UIQI on rainy image from different databases. The quantitative and qualitative results of the proposed framework are better than other de-rainy algorithms. Finally, the obtained visualization result also shows the efficiency of the proposed framework.**

***Keywords* – De-rain, Convolution Neural network, Low light image enhancement, Visibility enhancement.**

1. Introduction

Image captured in outdoor rainy images shows low colour intensity and low visibility scenes. There are two types of weather condition, the first is static weather condition like fog, haze etc., and the other is dynamic weather condition like rain and snow. Rain or snow consists of 0.1 mm to 10 mm particles. These particles impact a motion blurred effect on the image, so rain degraded the visual quality and intensity of the image [1].

Different types of algorithms have been proposed during the last decades by many authors for the visibility enhancement of rainy images. In paper [1], Garg et al. presented an extensive research of how the camera sees the rain and snow. In this paper, the particles were modeled, where raindrop size, exposure time and background light was taken into account. These studies can be used in advanced graphics where rain should be rendered, detected or removed. Rain has another impact on the image than haze and the streaks from rain can be annoying for an observer or a processing algorithm might fail. As rain and snow particles move, the temporal variety was an important factor to identify and remove the particles. The visible particles have to be within the camera's depth of field and the ones that were too distant would appear static with similar appearance to haze. Rain and snow had different appearances when the particles were visible. Rain has a higher velocity than snow which has more air resistance.

In [2], Fu et al. proposed a deep convolution neural network based de-raining algorithm. In this paper, author trained a neural network for the detail layer of rainy image and clean image. Author doesn't consider real time rainy images but synthesizes the image with rain for training purpose. The author also analyzes the camera parameter and the rain properties for enhancing the visibility of image during acquisition. In [4], Bossu et al. proposed a Gaussian model to detect the orientation of uniform mixture noise like, rain streaks. After that, a histogram oriented streak is applied to identify the pixels of the rain streaks in the foreground of the images. This Gaussian model of mixture noise is also used in video refining algorithm for enhancement of videos shots in rainy weather.

In [5] Kang et al. suggested a morphological component analysis technique for rain removal in rainy images. In this technique, a bilateral filter is used to decompose the rain into high and low

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frequency component. The rain streaks component is removed from high frequency component through sparse coding with the help of dictionary learning. Finally, rain free image is achieved by adding low frequency component and non rain high frequency component. This model is fail for the images captured in heavy rain fall conditions.

In [6], Chen et al. proposed a tensor structure model for capturing the rain streaks correlations. By this technique the author removed the rain streaks from the video and the images. The author also compared the run time of the algorithm with other algorithms. In [7], Chen et al. proposed hybrid feature for removing rain streaks from non rain high frequency part and depth of field. Eigen color vector is applied for the enhancement of the rainy image. In [8], Huang et al. suggested a technique for de-noising of single image with influence by Gaussian noise and rain. It is dictionary based sparse representation framework to obtain high spatial frequency part of noisy image to reconstruct it and obtain a de-noisy and rain free image. In [9], Chen et al. proposed an algorithm based for dynamic scene like rainy weather. For rain detection, the author used motion segmentation, chromatic and photometric consideration are applied to remove the rain streaks from rainy images.

In [10], Manu et al. proposed L_0 gradient minimization for removing the rain pixels. It locates the edges globally and diminishes the low amplitude and insignificant detail of the rainy image. This algorithm provides the smooth image so some features of the image disappeared as compared to the original image. In [11], Luo et al. proposed a dictionary based learning algorithm used in screen blend model for rainy images. Mutually exclusive property of two layers through sparse approximation leads to separate the layers from nonlinear composition in rainy images. In [12] Li et al., the author proposed rain streaks removal algorithm for single rainy image. Patch based prior method is used for foreground rain layer in rainy images. These priors are based on Gaussian model to accommodate the mixture of scaling in the rain streaks and multiple orientations. Drawback of the algorithm is edge artifacts and contrast loss in some portion of the image.

In [13], Wang et al. proposed anisotropic filtering for suppress scratch noise like rain or snow that is very difficult to distinguish from the background of noisy image. In [14], Yang et al. proposed a model for the visibility of traffic signal labels during rainy weather conditions. In this method, the author improves the visibility enhancement by adding the visual noise feature with the already present texture noise feature. In [15] and [16] Son et al. described a rain removal sparse code algorithm. It is beneficial to the previous algorithm for removing the edge artifacts and detail loss in non-rain region. But the drawback of this algorithm is its dependency on the learned dictionary. If the rain structure is not included in training image, the algorithm fails to remove the rain structure. Hence, to improve the visibility restoration of rainy images, we proposed the algorithm for rainy color images.

In [17], the authors proposed a technique to recover the rain component and snow in frequency component rather than image space. Through analyzing of particle size, velocity and direction, a robust model is used to predict, how the rain or snow will appear in frequency components. After detection, rain streaks can be reduced depending on the applications. These rain models analyze a very simple approximation, the appearance of rain in image space in the form of the Gaussian model. In this method, the linear motion of the rain and snow appears as a Gaussian blurred. The results of this method provide better results as compared to a median filter or patch based methods. The main drawback of this method was that the image may be falsely classified and removed randomly.

In [18], Zheng et al. described the de-rainy algorithm for a single image. The noisy image first decomposed into high frequency component and low frequency component separately. The low component of the image treated as the guided image and the high frequency component is applied in the guided filter as input. Guided filter removed the rain component with the help of guided image in rainy image. Mostly, rain streaks reveal similar and repeated patterns in an image. The rain free image can be obtained by addition of low frequency component and guided filter output. This algorithm is used in most of the rainy images. In [19], Chen et al. established a correlation between spatial and temporally rain streaks with appearance of low-rank model. Through this model, the rain streaks are removed from single color rainy image in defined manner. In [20], Chen et al. also described a framework for single color rainy image. This rain removal technique is based on the sparse coding representation by formulating the image. Authors used guided bilateral filtering to separate the high frequency component and low frequency component of rainy images. Rain component presented in high frequency part of image is eliminated through dictionary learning based sparse coding technique. Various feature set like edges in non –rain texture, orientation gradient through histogram, depth through eign fields were also employed in high-frequency component of the rainy images. The output results of this algorithm not only remove the rain components completely, but the visual qualities of the rainy images were also improved. In [21], Garg et al. developed a correlated physics model for rain dynamics motion blur analysis and photometry of rain. Based on this model, the author creates a technique for rain removal from rainy videos and rainy images. Properties of the camera are also included in this algorithm.

In [22] Zhau et al. analyzed the chromatic and spatiotemporal properties in the rain images comprehensively. On the basis of these properties, the author proposed the rain removal algorithm for sequential images. Algorithm is useful for light and heavy rain fall condition in steady scenes, not the dynamic scene. In [23], Sun et al. described a de-rainy algorithm, which is based on structural similarity of the normal and rainy image. Rain removal is achieved by image matrix reconstruction by the similarity index associated with learning formulation.

In [24] Utaminingrun et al. described a composite technique, which is mixed form of blurring method, image quantization, image enhancement and rank ordered mean filter. Quantization of image obtained from the original rainy image and a standard blurred image. The rain component of the image is achieved from this quantization. These rainy pixels are replaced by the pixel of image enhancement pixels based on three frame methods. In [25], Wang et al. described de-rainy algorithm for heavy rain images. Firstly, the author used a guided bilateral filter to separate the image component in high and low frequency part. To obtain a rain free image, the author used the dictionary learning method on high frequency component of rainy images. The author also applied the sensitivity variance of principal direction in image color channels of given patch, to extract more non rain detail for enhancement of color rainy images. In [26] Fu et al. also describe the deep convolution neural network to clean the rainy images. Authors minimized the objective function between clear ground truth image and high frequency component of rainy image. They applied this objective function on real and synthetic rainy images to clean rain streaks from rainy images. In [27] Pu et al. used a deep convolution network based on the cycle generative adversarial network to solve the rainy problem in rainy images. In [28] Shi et al. applied a weighted medial filter convolved with the detail rain part of the image to achieve unclear rain free image, then they used appropriate enhancement filter to achieve the clear de-rainy image.

In order to enhance the visibility restoration and contrast of rainy images, there is a robust framework proposed for improving the visibility of color rainy images. The proposed framework is designed by combining the concept of convolution neural network [2] and low light image enhancement technique [3] for enhancing the visibility of color rainy images. The quantitative and visualization results of the proposed method are compared and analyzed to other recent existing de-raining algorithms in terms of image evaluation metrics such as peak signal to noise ratio (PSNR), universal image quality index (UIQI) and structure similarity index measurement (SSIM). We have obtained the rain free enhanced image through the proposed robust visibility restoration framework. The main features of this research paper are pointed as follows:

- A robust visibility restoration framework is proposed for enhancement of color rainy images.
- Proposed visibility restoration framework is developed by incorporating convolution neural network and low light image contrast enhancement technique.
- Contribution to state-of-the-art de-raining algorithm for visibility restoration of rainy images.
- Quantitative and visualization results of proposed framework are compared to other recent de-raining algorithms.

Outline of the research paper is in the following manner: we describe the method and materials in section 2, in this section, we have described robust framework for the improvement of visibility restoration and contrast enhancement of color rainy images. In section 3, the results and discussion are described. Finally, a conclusion is written in the last section.

2. Methods and Materials

A proposed visibility restoration framework is described in this section for quality improvement of rainy images. This proposed framework is described in two consecutive steps: in the first step, a convolution neural network algorithm is applied for removing the rain streaks and in the second step a low light image enhancement method is applied for contrast improvements of rain free images. The proposed framework is developed by incorporating convolution neural network [2] and low light image enhancement technique [3] and abbreviated as CNN-LIME algorithm. The proposed diagram of CNN-LIME framework is given in Figure 1.

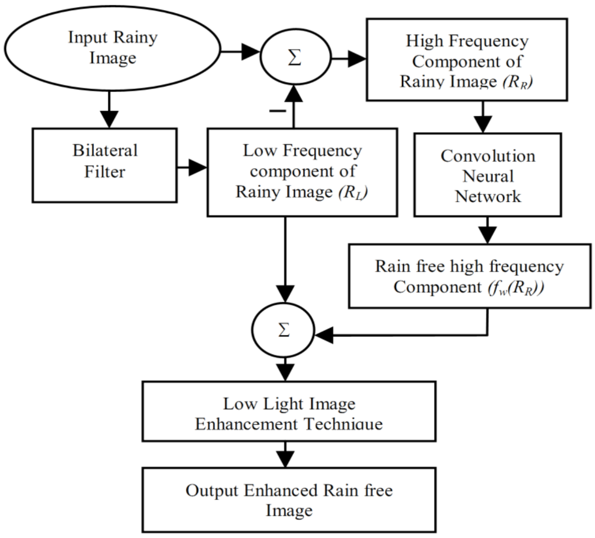


Figure 1.Block diagram of proposed visibility framework

A. Step 1: Convolution Neural Network

The architecture of convolution neural network is proposed by Fu et al. in 2016 [2]. In this architecture, the rainy image first decomposes into high frequency and low frequency component by using suitable bilateral filtering technique, which is given in Equation (1):

$$R_I = R_L + R_R \quad (1)$$

Where R_I is input rainy image, R_L is low frequency component and R_R is high frequency component with rain streaks.

In neural network, we process only the high frequency component of rainy image and high frequency component of ground truth image [2][29]. The objective function is defined in Equation (2).

$$\| f_w(R_R) - G_{IH} \|_F^2 \quad (2)$$

Where G_{IH} is high frequency component of ground truth image, w are weights of the network $f_w(.)$ and F is the Frobenius norm.

The objective function for mean square error is given in Equation (3).

$$E = \frac{1}{M} \sum_{m=1}^{M} \left\| f_w(R_R^m) - (G_{IH}^m) \right\|_F^2 \quad (3)$$

Where, M represents the training image, R_R^m is high frequency component of rainy image and G_{IH}^m is the high frequency component of ground truth layer.

Network Architecture:

The network architecture is used in the convolution neural network shown in Figure 2.

The convolution neural network architecture is expressed in three operations which are given in Equation (4) and Equation (5):

$$f^n(R_R) = \rho(w^n * f^{n-1}(R_R) + d^n) \text{ ,where } n=1,2 \quad (4)$$

$$f_w(R_R) = w^n * f^{n-1}(R_R) + d^n \text{ ,where } n=3 \quad (5)$$

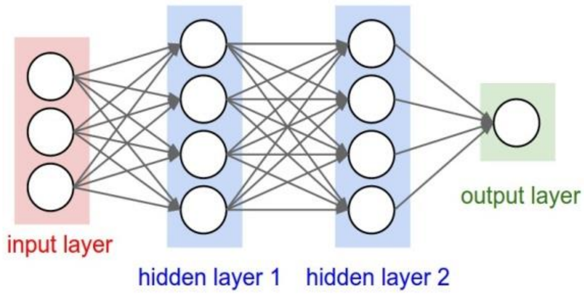


Figure 2.Neural Network Architecture

where n is the index layer number, $*$ means convolution operation d^n is the layer bias, $\rho(.)$ hyperbolic tangent function, $f^0(R_R)$ is basically high frequency component of rainy image itself, there are two hidden layer existing in network architecture. In the first hidden layer $(n=1)$, $f^1(R_R)$ extracts image patches and maps. 512 feature map of $f^1(R_R)$ is obtained by applying 512 different kernels with size (16x16) to the input $f^0(R_R)$ in RGB color channel. So, the size of w^1 in equation (4) is (3x16x16x512).The second hidden layer $(n=2\ )$,$f^2(R_R)$ generates 512 feature maps by applying 512 different kernels with the size of 1x1 to $f^1(R_R)$. The size of w^2 is (512x1x1x512). The third layer $f_w(R_R)$ in equation (5) is rain-free high frequency component layer or clean layer. This layer is obtained by applying 512 kernels with the size 8x8 to $f^2(R_R)$,the size of w^3 is (512x8x8x3).

Further, the objective function in equation (3) is minimized by the gradient process. By using synthesized rainy component with ground truth image for minimizing the objective function in equation (3) is given as:

$$w_{l+1} = w_l - \alpha(f_w(R_R) - G_{IH})^T \frac{\partial f_w(R_R)}{\partial w} \quad (6)$$

$$d_{l+1} = d_l - \alpha(f_w(R_R) - G_{IH})^T \quad (7)$$

In each iteration l, convolution neural weight w and bias d are updated by using back propagation [29], where, α (=0.01) is a learning rate.

The output rain free image is obtained by adding low frequency of rainy component with high frequency rain free layer as given in Equation (5).

$$R_o = R_L + f_w(R_R) \quad (8)$$

Output rain free image R_o obtained by convolution neural network has low visibility and low contrast present in the image captured under heavy rain conditions, therefore, we have used a low light image enhancement technique for contrast enhancement of the processed images from step 1.

B. Step 2: Low light image enhancement method

Low light image enhancement (LIME) technique is proposed by Guo in 2016. The main reason for selecting low light enhancement technique is because it is computational efficient technique for contrast enhancement of rainy images [3]. The low light rain free image (R_o) is given in Equation (9).

$$R_o = I \otimes L \tag{9}$$

Where I is the desired enhanced image and L is the illumination map of the image, $\otimes$ means element wise multiplication. The main objective is to estimate the illumination map L for recovery of the image I. The inverse of low visible rain free image can be express as.

$$1 - R_o = (1 - I) \otimes \tilde{L} + A(1 - \tilde{L}) \tag{10}$$

where A is atmospheric light.
Illumination map for each color channel c (R,G,B) for each pixel t is given below:

$$\tilde{L}(t) \Leftarrow \max_c R_o^c(t) \tag{11}$$

$$I(t) = \frac{R_o(t)}{\max_c (R_o^c(t) + \phi)} \tag{12}$$

Where constant ϕ is used to avoid zero denominator. By using dark channel prior [3], we can estimate the transmission map on *(1-R_o):*

$$\tilde{L}(t) \Leftarrow 1 - \min_c \frac{1 - R_o^c(t)}{A} = 1 - \frac{1}{A} + \max_c \frac{R_o^c(t)}{A} \tag{13}$$

Substituting Equation (13) into Equation (10), yields desired image

$$I(t) = \frac{R_o(t) - 1 + A}{1 - \frac{1}{A} + \max_c \frac{R_o^c(t)}{A} + \phi} + (1 - A) \tag{14}$$

If $A=1$, Equation (14) becomes same as Equation (12). Refining the illumination map by solving the optimization problem based on initial illumination map $\tilde{L}$ which is given below:

$$\min_L \left\| \tilde{L} - L \right\|_F^2 + \mu \left\| w \otimes \nabla L \right\|_1 \tag{15}$$

Where μ is a coefficient of balance, $\|\cdot\|_F$ Frobenious and $\|\cdot\|_1$ is l_1 norms respectively, w is the weight matrix and ∇ contains the vertical and horizontal first order derivative filter. In Equation (15), the first term is refinement of illumination L and the second term is considered for smoothness, edges and texture. After refining the illumination map, Gamma (*γ)* transform is manipulated with the illumination map, $L \leftarrow L^{\gamma}$, here we have taken γ=0.8.

Finally, we have obtained the visibility enhanced image from color rainy images after applying a deep convolution neural network and low light image enhancement technique. Therefore, I is the output enhanced rain free image that preserves the overall structure, smoothness and texture details.

3. Results and Discussions

The quantitative and visualization results of the proposed CNN-LIME framework and other existing de-raining algorithms on different color rainy image databases are presented in this section. In order to compute the results of the proposed CNN-LIME framework and other recent de-rainy algorithms are simulating on MATLAB 2015a software with 4 GB RAM and Core i3 processor.

A. Image Database

The proposed CNN-LIME framework and other recent existing de-raining algorithms are obtained on standard synthetic color rainy images and real color rainy images, which are taken from the Chang Hawn son's rain image database [15][16] (@https://sites.google.com/site/changhwan76son/home/rain-removal) and other database Manu [10].

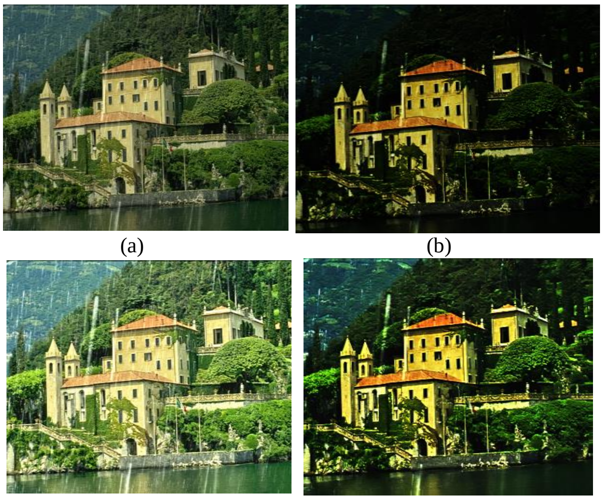
B. Image quality performances metrics

In order to evaluate the qualitative and quantitative results of the proposed CNN-LIME framework, first we have tested the proposed algorithm and the recent existing de-raining algorithms on synthetic rainy images [i.e. 001_in.png, 002_in.png, 003_in.png, 004_in.png [15]. After that, quantitative and qualitative results of the proposed CNN-LIME framework and the recent other de-raining algorithms are evaluated on different real world color rainy images from color rainy image databases [10][15][16]. The first image quality parameter peak signal to noise ratio (PSNR) is calculated in rain free image with corresponding rainy image for the proposed CNN-LIME framework and other existing de-raining algorithms The PSNR is described as:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (x_i - y_i)^2 \tag{16}$$

$$PSNR = 10 \log_{10} \frac{L_{\max}^2}{MSE} \tag{17}$$

Where, MSE is the mean square error, N is the number of samples or pixels. x_i and y_i are the corresponding pixel values, L_{max} is the maximum image pixel intensity (For a 8-bit image the value of $L_{max} = 2^8 - 1 = 255$). Higher value of PSNR indicates the quality of the algorithm. The second and third image quality parameters are structural similarity index measurement (SSIM) and Universal image quality index (UIQI) [30]. These image quality parameters are the good choice for the researcher to estimate the quality of the image. Better significant value of SSIM and UIQI indicate the quality of the algorithm.



(a) (b) (c) (d)

Figure 3. Visibility enhancement results of synthetic rainy image 003_in.png: (a) Original (b) CNN (c) LIME (d) Proposed CNN-LIME framework

The mathematical expression of SSIM and UIQI are defined in Equation (18) and Equation (19) respectively.

$$SSIM = \frac{(2\bar{x}\bar{y} + c_1)(2\sigma_{xy} + c_2)}{(\bar{x} + \bar{y} + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (18)$$

$$UIQI = \frac{4\sigma_{xy}\bar{x}\bar{y}}{(\sigma_x^2 + \sigma_y^2)[(\bar{x})^2 + (\bar{y})^2]} \quad (19)$$

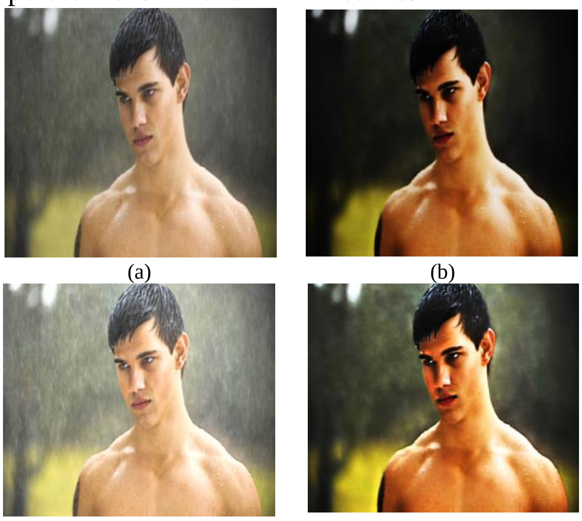
Where $\bar{x}$ and $\bar{y}$ are the average of x and y, σ_x and σ_y are the variance of x and y, σ_{xy} is the covariance of x and y, c_1 and c_2 are the variable to stabilize the division. $c_1=(k_1 L_{max})^2$, $c_2=(k_2 L_{max})^2$, whereas $k_1=0.01$ and $k_2=0.03$ by default, L_{max} is the dynamic range of pixel value as described in Equation (17).

Therefore, the performance of the proposed CNN-LIME framework and other existing recent de-raining algorithms such as Manu's [10], X. Fu's [2], and C.H. Son's [16] are compared in terms of PSNR, SSIM and UIQI. First, we presented comparison of the above mentioned image quality parameters on synthetic rainy images [i.e. 001_in.png, 002_in.png, 003_in.png, 004_in.png]. After satisfying the quantitative and qualitative results on synthetic rainy images, we have presented comparison of the proposed CNN-LIME framework and other existing recent de-raining algorithms on many real world rainy images but demonstrate here only five [i.e. 3_.tif, 5_.tif, 26_.tif, 38_.tif, Rain1.jpg].

C. Illustration of the proposed CNN-LIME framework

The effect of proposed visibility restoration algorithm in each stage for enhancing the rainy image is described in this subsection. It demonstrates the effectiveness of incorporating the concept of convolution neural network and low lightness enhancement technique together enhancing the minute details present in rainy images with lesser artifacts. Figure 3. and Figure 4. give a visual enhancement results comparison of the proposed CNN-LIME framework with convolution neural network (CNN) and low lightness enhancement technique (LIME).

We can notice from the Figure 3.(b) and 4.(b) that the visibility of the output image of convolution neural network is not clear. We can also notice from the Figure 3.(c) and 4.(c) that the output image of low light image enhancement technique contains rain components but the contrast of the image is good. Therefore, in order to achieve the clear visibility in image we have incorporated the concept of convolution neural network and low lightness enhancement technique together to provide good visibility of image. The main advantage of the proposed CNN-LIME framework is its robustness and very effectiveness because background scene and object are clearly visible but the main limitation of the proposed algorithm is to increase little computational complexity. Therefore, the qualitative results prove that the proposed CNN-LIME framework yields the better visualization incorporated to CNN and LIME results.



(a) (b) (c) (d)

Figure 4. Visibility enhancement results Real world Rainy Image, 38_.tif: (a) Original (b) CNN (c) LIME (d) Proposed CNN-LIME framework

Table 1. Performance comparison of various visibility enhancement algorithms for synthetic rainy images

Image	Image Quality metric	Manu's [10]	X. Fu's [2]	C.H. Son's [16]	CNN-LIME frame-work
001_in.png	PSNR	29.145	62.513	32.032	**69.102**
	SSIM	0.7110	0.994	0.830	**0.999**
	UIQI	0.254	0.239	0.295	**0.358**
002_in.png	PSNR	28.836	60.340	60.967	**64.923**
	SSIM	0.703	0.991	0.650	**0.998**
	UIQI	0.230	0.205	0.260	**0.308**
003_in.png	PSNR	29.645	61.946	50.129	**63.883**
	SSIM	0.723	0.994	0.350	**0.998**
	UIQI	0.253	0.152	0.268	**0.348**
004_in.png	PSNR	29.306	59.766	47.797	**62.669**
	SSIM	0.818	0.991	0.400	**0.997**
	UIQI	0.2508	0.1829	0.3429	**0.359**

Table 2: Performance comparison of various visibility enhancements algorithms For real world rainy Images

`Image	Image Quality Metric	Manu's [10]	X. Fu's [2]	C. H. Son's [16]	Proposed CNN-LIME
3_.tif	PSNR	37.681	62.288	37.681	**65.938**
	SSIM	0.392	0.995	0.392	**0.998**
	UIQI	0.200	0.452	0.300	**0.527**
5_.tif	PSNR	27.22	62.390	36.226	**66.170**
	SSIM	0.987	0.995	0.968	**0.998**
	UIQI	0.355	0.265	0. 411	**0.544**
26_.tif	PSNR	47.307	60.014	47.309	**65.072**
	SSIM	0.382	0.990	0.378	**0.997**
	UIQI	0.317	0.379	0.325	**0.575**
38_.tif	PSNR	36.710	60.832	26.710	**66.338**
	SSIM	0.672	0.991	0.663	**0.997**
	UIQI	0.213	0.296	0.246	**0.572**
Rain1.jpg	PSNR	48.503	60.398	48.5031	**62.1255**
	SSIM	0.414	0.993	0.5149	**0.9972**
	UIQI	0.341	0.443	0.3455	**0.4818**

D. Discussions

The quantitative and visulization results of the proposed CNN-LIME framework and other existing recent de-raining algorithms were tested on different synthetic color rainy images as well as on real world rainy images from the different color rainy image databases [10][15][16], but here we have described only the quantitative and the qualitative results of four synthetic rainy images and five real world rainy images from different color rainy image databases. The quantitative evaluation metrics of the proposed CNN-LIME framework and other existing recent de-raining algorithms such as Manu's [10], X. Fu's [2], and C. H. Son's [16] are computed and compared in terms of standard image quality parameters like PSNR, SSIM and UIQI.

The qualitative results of the proposed CNN-LIME framework and other existing recent de-raining algorithms on synthetic color rainy images and real world rainy images were given in Figure 5. and Figure 6. We have calculated PSNR, SSIM and UIQI values for the proposed CNN-LIME framework and other existing recent de-raining algorithms on synthetic color rainy images and real world color rainy images were given in Figure 5. and Figure 6. All numerical values of PSNR, SSIM and UIQI for these rainy images are furnished in Table 1. and Table 2. From Table 1. and Table 2., we can observe clearly that the proposed CNN-LIME framework has better value of PSNR, SSIM and UIQI in comparison to other existing recently visibility restoration rainy algorithms, it means the proposed CNN-LIME framework provided better visibility enhanced rain free images in comparison to the other existing recently de-raining algorithms such as Manu's [10], X. Fu's [2], and C.H. Son's [16] algorithms.

Second, we can also observe the visualization of the output rain free images from the proposed CNN-LIME framework and other existing recent de-raining algorithms. It can be noticed that from the synthetic images in Figure 5. and the real world rainy images in Figure 6. that our proposed CNN-LIME framework provided better visually pleasing rain free image as compared to other existing recent de-raining algorithms. Our proposed CNN-LIME framework also provides the clear visibility of the objects like road signs and background things of rainy images. The advantage of the proposed CNN-LIME framework is robust and very effective for visibility enhancement of images captured under rainy bad weather conditions. There is little computational complexity in this algorithm.
Therefore, on the basis of visualization results and quantitative results like PSNR, SSIM, UIQI ; our proposed CNN-LIME framework provided better visibility in comparison to other existing de-raining algorithms like Manu's [10], X. Fu et al. [2], and C.H. Son et al. [16].

4. Conclusion

This paper proposed a robust visibility restoration framework for visibility and contrast enhancement of the images captured under rainy weather conditions. In comparison to other existing de-raining algorithms, the proposed CNN-LIME framework provided visually pleasing rain free images. Proposed CNN-LIME framework was tested on different real world color rainy images and synthetic color rainy images from different rainy image databases. Quality wise visibility restoration performance of CNN-LIME framework was simulated and compared with other state-of-the-art existing de-raining algorithms. The performance of the proposed CNN-LIME framework was evaluated in terms of PSNR, SSIM and UIQI and compared with other existing recent de-raining algorithms. Simulation result also indicated that proposed CNN-LIME framework provided better values of PSNR, SSIM and UIQI in comparison to other existing recent de-raining algorithms. On the basis of simulation results, the proposed CNN-LIME framework provided better visualization results in comparison to other existing recent de-raining algorithms. Visibility of images obtained from the proposed CNN-LIME algorithm was visually better as compared to other existing de-raining algorithms. Therefore, the proposed CNN-LIME framework performed efficiently and effectively for visibility restoration for rainy images. The proposed algorithm will also use for the clear visibility in the rainy images captured under heavy rain fall conditions.

Figure 5. Rain free results of synthetic rainy color images for various visibility restoration de-raining algorithm

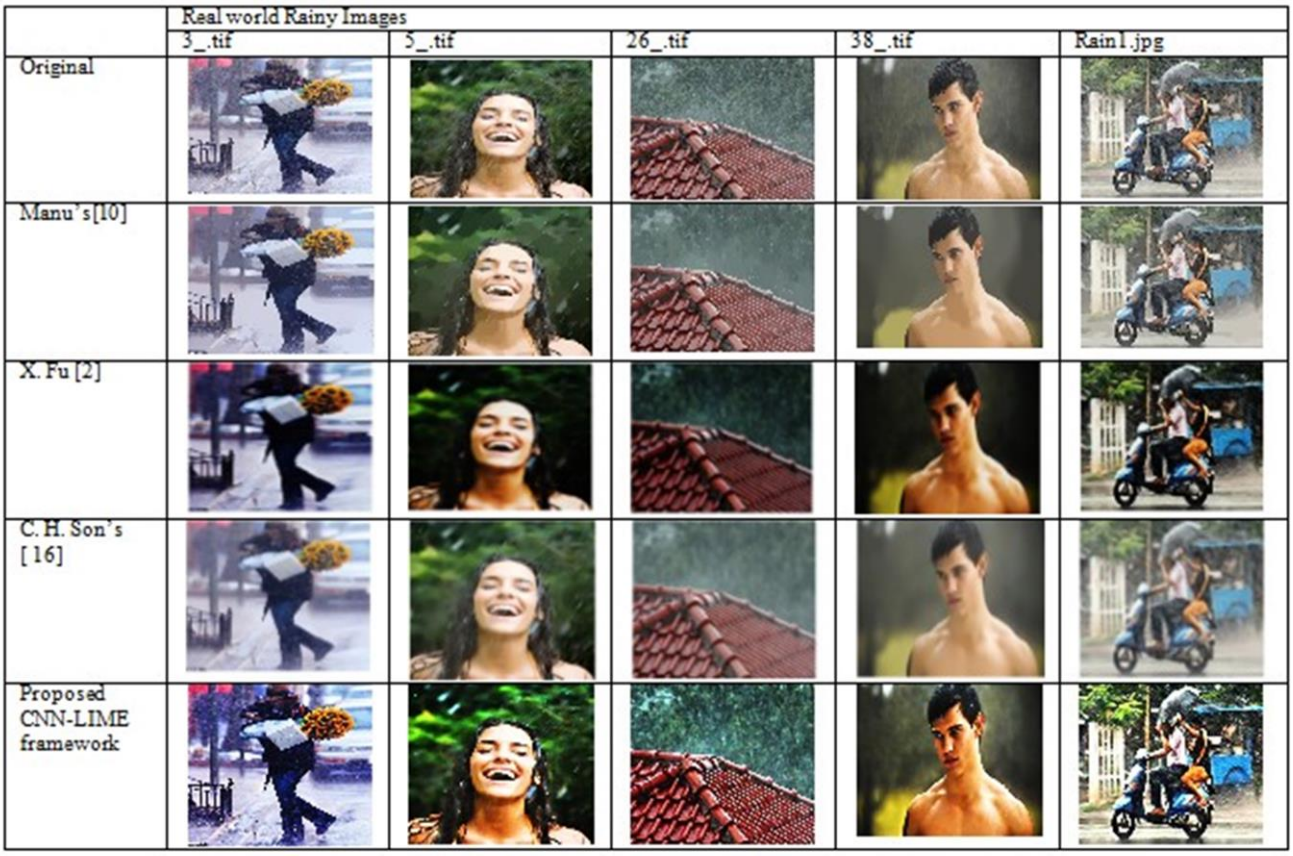


Figure 6. Rain free results of real world rainy images for various visibility restoration de-raining algorithms

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