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Rain removal in single image system using CNN with guided and L0-smoothing filters

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Abstract

In this work a robust rain removal algorithm is proposed for removing rain from still images. The algorithm uses a deep network architecture called DerainNet for effective rain removal. The proposed network directly learns the mapping relationship between rainy and clean image detail layers from the given set of data. In order to modify the objective function and also to improve deraining process, other Deep CNN based architecture increases the width or depth of the neurons, which in turn increases the complexity of the network. But this work makes use of the Image Processing domain knowledge which reduces the complexity of the network. Instead of training the entire image, only the detail layer of the image is trained. The detailed layer of the image is obtained using two low-pass filters one after the other. They are guided filter and L0-Smoothing filter. The results obtained proves that, the proposed network performs better deraining on images in comparison to paper [2] with light rain streaks. Python version 3.8 is used for this work.

Keywords: CNN, Guided filter, L0-Smoothing filter, Detail layer.

1. Introduction

Rain removal in single image is currently in research in image processing domain. Bad weather conditions like haze and rain generally reduce the quality of the image when it being captured by a camera. When these images are then used for surveillance purpose or any other computer vision algorithms like object detection or object recognition then it becomes very difficult to identify the accurate information in the image. The main reason behind reduction in the information of the rainy image is due to the fact that rain leads to pixel variations in the images and makes the image

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look blurry. Removal of snow in the image ie. Dehazing algorithms also works on removing pixel variations in the images. But they have excellent methods devised. Because unlike rain snow doesn't provide any variations due to directions or orientations. Even in rain removal, rain removal in videos have better algorithms when compared to rain removal in single image. This is due to the fact that, videos contain several frames so the temporal information can be easily obtained while moving from one frame to another. But this is not possible in case of images. There will only be one image and any algorithm devised has to act only based on the information that is present in that single image.

There are various applications for rain removal task. They are object detection, object recognition, surveillance etc., but the crucial task in any rain removal algorithm is separation of rainy regions from non-rain regions. In order to achieve this a low pass filter is often used. But the low-frequency part produced after filtering would not completely enclose the image information, some part of the image information would be present in the high frequency part. And more over the low frequency part may also contain some rain streaks which are undesirable. This usually happens when the low pass filter is not strong enough. But, by making the filter strong enough, some image information is also removed. This concludes that the high frequency part not only contains the rain streak information but also the image information. After the classification of the images into high and low frequency part, some learning-based methods or convolution algorithms are generally designed that retrieves the image information from the high frequency part. Finally, the low frequency part and the restored high frequency part are summed up together to produce a derained image.

Initially a simple CNN without any image processing knowledge was used to was used to remove rain droplets from an image. But this method did not succeed in producing a clear image due to dense raindrops thus producing blurry image.

Xu et al [13] used chromatic property of rain streaks and introduced rain removal algorithm using guided filter. Initially a coarse rain free image which is a guidance image is obtained and then the rain removed image is obtained by filtering the rainy image. in this method no pixel-based information is required, but rain removal is done only using a reference image. In order to enhance the filtered image, image enhancement algorithms were implemented. Then resultant image is more blurred and the rain streaks are removed completely.

Followed by this Zheng et al [15] proposed a new rain removal method using low frequency part of a single image. since the low frequency part is the non-rain part they have modified it as a guidance image and high frequency part serves as the input of the guided filter which has to remove the rain streaks. This method too suffers from blurring but is quite effective when compared with the previous method.

Kim et al [7] considered the rain streaks as elongated elliptical shape with vertical orientation. The rain streaks are identified by analysing the rotation angle and aspect ratio of the elliptical kernel at each pixel location. Then non-local filtering is applied by selecting the non-local neighbour pixels and their weights.

Fu et al [4] proposed a novel rain removal model as an image decomposition problem based on Morphological Component Analysis (MCA). Instead of conventional decomposition technique, they have decomposed the image into low frequency and high frequency part using bilateral filter. This work is further to be enhanced by improving the sparse coding and dictionary learning steps to make it automatic.

Kang et al [5] performed single image rain removal by image decomposition using morphological component analysis. This method faces limitation in detecting and removing dense rain circumstances.

Kang et al [6] performed rain removal in single images as a image decomposition problem. He also used MCA as a base and used dictionary learning and sparse coding as a model. The dictionary learning method that he proposed is fully automatic and there is no need for any human intervention.

Chen et al [1] they have considered image decomposition problem based on sparse representation. In this too, the input image is decomposed into low frequency and high frequency part and the high frequency part containing the rain streaks is further decomposed into rain and non-rain components through dictionary learning. In order to separate the rain steaks from the high frequency part, a hybrid feature set, including histogram of oriented gradients, depth of field and eigen colour is used to further decompose the high frequency part.

Sun et al [9] performed rain removal by using structural similarity of high frequency basis and considered as an optimization problem. This helps in preserving the details that are present in the high frequency components and can be used well during reconstruction.

Wang et al [12] performed rain removal using image decomposition and dictionary learning using 3-layer hierarchical scheme. Decomposition is performed as mentioned in the previous procedures. New techniques are implemented in dictionary learning procedure. In the first layer, an overcomplete dictionary is trained and three classifications are carried out to classify the high frequency part into rain and non-rain components, in which some common characteristics of rain and snow is used.

Qian et all [10] designed an attentive generative adversial network for single image rain removal. In this work, there are two networks termed as generative and discriminative respectively. Generative network mainly focuses on the rain drop regions on the rainy image and the discriminative network accesses whether the image is completely free of rain drops or not. Generative network further consists of two subnetworks, they are attentive recurrent network and a contextual encoder. The former subnetwork focusses on the rain drop regions and the surrounding structures, to determine which region has to get maximum attention.

Meihua et all [11] inspired by deep residual network (ResNet), designed a deep convolutional neural network. This network takes entire image as input and can easily reuse the original image while removing the rain streaks from the rainy image. In this method, the original image is concatenated along with the feature maps generated by the previous layers before entering into the next layer.

Fu et al [3] being inspired by ResNet, proposed a deep detail network to directly reduce the mapping range from input to output. This makes the learning process much easier. This mapping is generally reducing by using negative residual mapping.

fu et al [2] proposed a deep neural network architecture called Derain Net which directly learns the mapping between rainy and clean images. This network easily learns the nonlinear mapping function between the clean and the rainy image automatically by initially dividing the image into base and detail layer by guided filter. Li et al [8] designed a channel attention U-DenseNet for rain detection and a residual dense block for rain removal. In this model a rainy image is decomposed into nonlinear combination of clean background image and a rain map. Here the rainy image is equal to rain map plus a clean background image multiplied by an inverted rain map. A new dataset is generated in accordance with the nonlinear model. this dataset synthesis more realistic images than all the other methods. The major advantage is the type of the network used and generation of the rainy images so close to the real images.

Yang et al [14] proposed a novel method in removing the rain streaks even in heavy rain images. In this work they have introduced a new region dependent rain model. In that model 1 indicates the presence of visible rain streaks and 0 if not. By considering heavy rain regions, they have also taken into account various shapes and directions of the overlapping rain streaks in the model. Followed by this they have created a deep network that automatically detects and removes the rains.

Li et al [8] proposed a recurrent squeeze and excitation-based context aggregation network for single image rain removal. They have a proposed a unified deep network for de-raining through which the rain is removed stage by stage. At each stage contextual dilated network is used to remove the rain. This method proves to be the best in removing complex rain streaks in heavy rain.

Wang et al [11] proposed a novel rain streak generation model which takes the motion blur kernel into account. In all the previous discussed papers a subnet is built to learn the contextual information but, in this work, a subnet is being built to learn the length and angle of the motion blur kernel. Distinguishing the rain streaks and line patterns are generally difficult. In this method it is solved by using the prior knowledge of the rain streaks that is the angle and length that is used to train the network.

Li et al [8] inspired by non-local means filter for efficient single image rain streak removal, proposed a non-locally enhanced encoder decoder network. The non-local operation stated in this work calculates the feature response at any particular position as the sum of feature responses in a specific range of positions in a given area. This model not only exploits the hierarchical features from all the convolutional layers by also captures all the long-distance dependencies for spatial context modelling.

Wang et al [12] proposed a novel method that introduces a semi-automatic method that includes temporal priors and human supervision to generate high quality clean image from rainy images. Through this method, a total of 30k rain/rain free images are generated covering different natural scenarios. Next, they have also introduced a novel Spatial Attentive Network (SPANet) to remove the rain streaks. This model detects and removes the rain streaks in a local to global manner. The spatial attentive module is generally built based on the identity matrix initialisation model. This model is most useful in natural processing and are easy to train and are used at long distance modelling. Then detection and removal is done through learned negative residuals. This method suffers minor limitations on processing haze like images.

In order to aid beginners in using neural networks for deraining, Ren et al [15] presented a very simple and effective progressive recurrent deraining network (PReNet). This model takes advantage of the recursive computation of ResNet. Instead of introduced a new method they have combined a few modules for a better result. This is better because the modules can be modified according to the results obtained. The network architecture that they have used is the shallow residual network (ResNet) with 5 residual blocks. Then PReNet is introduced by recursively unfolding ResNet into multiple stages without increasing the network parameters. They have used a very simple loss function (MSE). The resultant network is much simpler and proves to be effective in removing rain from images.

2. Proposed Work

Removing rain from a single image is much more difficult when compared to video. Most of the existing methods usually separate the rain streaks from images using low-level image features, which in turn hinder the deraining process. When the structure and orientation of the object is similar to that of the rain streaks, then the previously available algorithm suffers from over smoothening of the image. In order to address the above-mentioned problem of over smoothing, this work is focused on designing a robust rain removal algorithm based on CNN.

As a preliminary step, the image to be denoised is first decomposed into low frequency and high frequency part using a low pass filter. The low frequency part consists all the image information and the high frequency part contains the rain streaks and some image information. This high frequency layer is termed as the detail layer is given as the input to the CNN for rain removal.

Training the CNN directly in the image domain does not yield satisfactory results. Hence, there is a requirement to train a more complex network to achieve better results. The network complexity can we increased by two ways, one is to increase the depth of the network and the other is to increment the number of neurons ie., to increase the breadth of the network. In the former approach, increasing

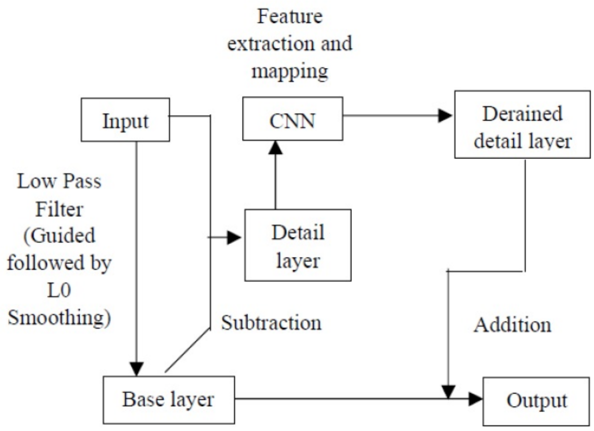

Figure 1: Pre-processing / input to the network

the count of hidden layers leads to a more complex network. In the later approach the number of neurons present in a layer are increased. In this case, when we do not have enough training samples, it would result in over-fitting problem.

So, in order to avoid such difficulties, some additional pre-processing operations are employed. we use a low pass filter to decompose the input image into rainy and rain free composition. This decomposition modifies the objective function without increasing the complexity of the network. Through the above-mentioned process, we get a base layer and a detail layer where the former refers to the low pass region and the later refers to high pass region. Hence, the entire image is now decomposed into a sum of base and detail layer.

This method of training base and detail layer has many advantages. First, we decompose the image into base layer using the low pass filter and subtract it from the image to get the detailed layer. Through the histogram representation in figure 2 of the original rainy and figure 3 of detail layer image, it can be easily be found that, most of the regions in the detail layer are close to zero and they are much sparser. Secondly, the mapping range has been decreased significantly. Since, the detail layer is much sparser, the mapping range reduces and the problem of regression is also easier to handle. The third advantage is that the convergence is achieved much faster while training the detail layer instead of training the entire image. Finally, when we decompose the input image into base and detail layer, image enhancement operation is performed in a much easier way.

In order to decompose the image into base and detail layer, we take the help of a suitable low pass filter. Guided filter, bilateral filter and rolling guidance filter are the predominantly used low pass filters as their computational complexity is low. But they suffer from a drawback in which some image information is present in the detail layer which reduces the efficiency of the deraining algorithm. Two or more low pass filters can be integrated to produce a better result, which in turn results in high pass region having a smaller number of image information. One such combination which proves to be fruitful is the guided filter followed by L0 smoothing filter.

In this work, applying L0 Smoothing filter following the Guided Filter depicts better rain removed image than applying these filters separately. Comparison Metrics used here is the PSNR value. PSNR value of the combined filter is less when compared to guided filter, this is because, the combined filter produces smoothed image but lesser rain component when compared to the guided image. This is also an added advantage because most of the rain component will be present in the detail layer which will then be effectively removed by the de-raining algorithm.

As per the table 1, the PSNR value of the combined filter is less because the procedure successfully

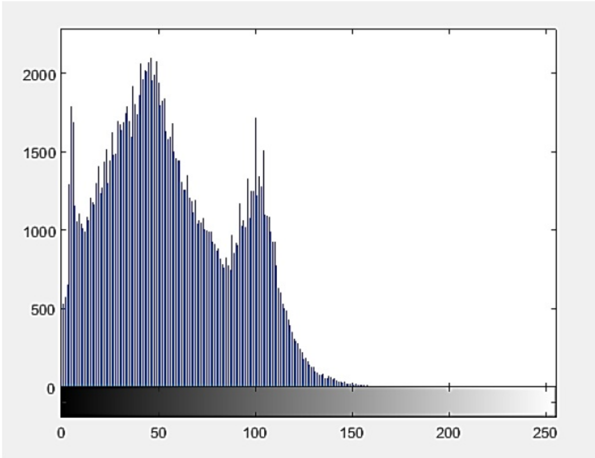

Figure 2: Histogram of original rainy image

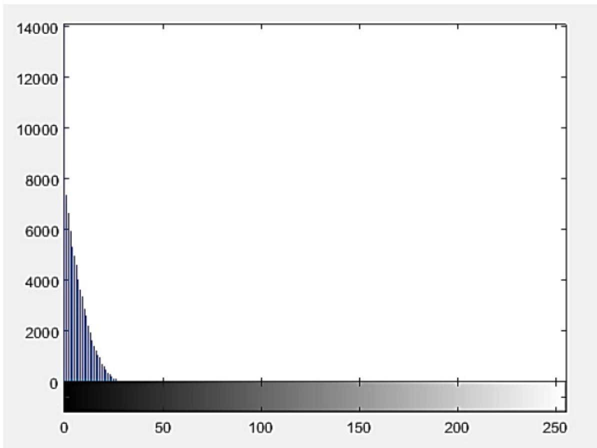

Figure 3: Histogram of detail layer of image

Table 1: PSNR values of the filters

Filter	**PSNR**
Guided filter	29.7822
L0 Smootthing Filter	22.4425
Guided filter followed by L0 Smoothing filter	29.6332

removes the rain drops but the smoothness of the image is quite large. This problem is resolved by applying edge-preserved smoothing followed by the application of the combined filter.

3. Derain Net

This work uses DerainNet, a CNN based structure for effectively removing rain from single images. The contribution of this network and the proposed work for rain removal is three-fold.

The structure learns the non-linear mapping function between the base and detailed layer of the input clean and rainy images respectively. Along with rain removal this work performs image enhancement in a much robust way as the images are decomposed into low and high frequency.
Decomposing the image into low and high frequency part generally uses guided filter as the low pass. Since, guided filter leaves much of the rain streak at the low frequency part of the image, hence a combination of filters is being used here. Here the combination filter that has been used is the guided filter followed by the L0 smoothing filter which results in fewer number of rain streaks in low pass region of the images.
The structure of the above-mentioned network is expressed as three operations in three layers. The first layer performs feature extraction, the second hidden layer performs rain streak removal and the final layer performs enhancement and reconstruction of the images.

The equation for the three layers can be given as,

$$f^l(A_{detail}) = \sigma(W^l * f^{l-1}(A_{detail}) + b^l), \quad l = 1, 2 \tag{3.1}$$

$$f_W(A_{detail}) = (W^l * f^{l-1}(A_{detail}) + b^l), \quad l = 3 \tag{3.2}$$

where,
l= layer number
$*$= convolution operation
b^l= bias
$\sigma(.)$= non-linear hyperbolic tangent function
$f^l(A_{detail}) = A_{detail}$
$f^2(A_{detail})$=is much smoother than $f^l(A_{detail})$
By closely examining the above-mentioned equations, the first hidden layer performs the operation of feature extraction on the input high frequency or the detail layer. The weight W^1 generally consists filters. These filters look like edge detectors which aligns themselves along the direction of the rain streaks and also the object edges. They collect the features of the edges of the rain streaks and the objects and filters them.

The second layer performs the rain streak removal. The output from this layer is much smoother meaning a substantial amount of noise is removed when compared to layer 1.

The third and the final layer performs reconstruction and enhancement of the smoothed details obtained from the second hidden layer by comparing them with the input images.

3.1. Training of the Dataset

The objective function at (3.1) is minimised using Stochastic Gradient Descent (SGD) since simple gradient descent algorithm cannot be used for larger datasets as they are very slow. SGD is an iterative method for optimizing an objective function with suitable smoothness properties like differentiable properties. The learning rate is much smaller and learning is faster with SGD even when there is large dataset, it only requires fewer passes going through the dataset to get the accurate coefficient value.

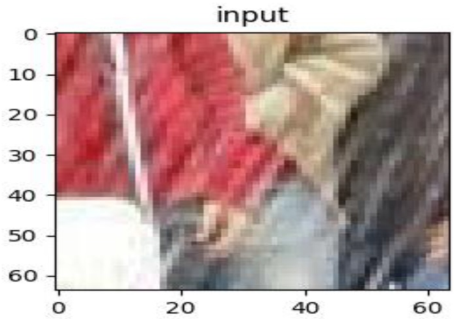

Figure 4: Learning through patches - Rainy

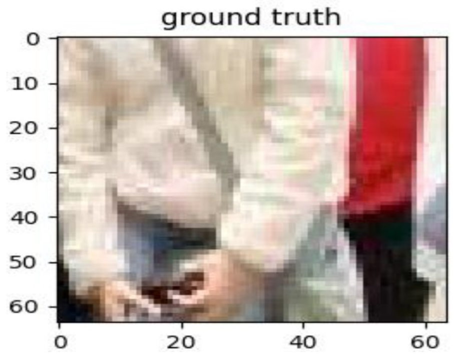

Figure 5: Learning through patches – Clean

As for the training samples are considered, 1 Million 64×64 samples are selected. To avoid border effects due to convolution, a 56×56 output is generated. For each iteration i, the CNN weights and biases are adjusted through back-propagation.

Fig 4 and Fig 5 depicts how the network learns the images as patches. The network takes 10Lakh 64×64 patches from the rainy image dataset and the clean image dataset and then use it for training. In the figure the left side indicates the input provided to the network and the right side is its corresponding ground truth.

4. Results

Evaluation of the proposed system is done on both synthetic and real-time images. All the testing procedures are performed on a PC with Intel Core i3, 8GB RAM and Radeon Graphics with Python idle version 3.8. The quantitative evaluation is done through PSNR and SSIM (Structural Similarity Index). Since the ground truth of the synthetic images are known, SSIM is also considered as a matrix. An increase in the value of SSIM ie. when the value of SSIM is closer to 1, then it means that, the de-rained image is much closer to the ground truth image This section discusses about the different parameters that are used to train the network and also how it affects the performance of the network. The parameters are chosen as per the base paper [2].

4.1. Size of the Kernel

The kernel size that is used in this network for 3 levels are 16-1-8 respectively. Two methods have been followed for fixing the kernel. First is fixing the kernel size of the first and third layer and changing the size of the second layer and the second is fixing the size of the kernels of second layer and changing the size of the first and third layer. The two possibilities are, 16-2-8,16-4-8 and

Table 2: SSIM values for various kernel sizes

Kernel Size	SSIM Values	From [2]
16-1-8	0.8932	0.89+ -0.06
16-2-8	0.8856	-
16-3-8	0.9021	0.89+ -0.06
4-1-2	0.7135	0.84+ -0.06
12-1-4	0.8321	-
16-5-8	0.8891	0.90+ -0.07

Table 3: SSIM values for various width of the Kernel

Width of the Kernel	SSIM	From [2]
512×512	0.8891	0.89+ -0.06
64×64	0.7456	0.8+ -0.05
128×128	0.7821	0.82+ -0.05

4-1-2,12-1-4 respectively. By using all the above kernel sizes, it can be seen that, the size of 16-1-8 achieves higher SSIM.

Larger kernel sizes provide a better SSIM value. When the size of the kernel is large, then a greater number of texture and structure can be modelled easily. Since, there are more mapping values, SSIM increases. On the other hand, by keeping the 1st and 3rd layer kernels constant and by increasing the size of the 2nd layer kernel does increase the SSIM value but the computational time also increases as it requires a greater number of convolutions. Thus, the optimum value which is 16-1-8 is selected as the size of the kernel.

4.2. Width of Kernel

The default width set for this work is 512×512. Two other options were considered like 64×64 and 128×128. But increase in the kernel size improves the performance of the network by extracting a greater number of features. But this increase in performance comes with the cost of increase in the running time.

4.3. Analysis

A total of 512×512 feature maps are selected for training. Training and testing of the image are performed on an RGB image and hence the number of channels is fixed at 3. Ten lakh 64×64 patches are randomly selected and are included as inputs and their corresponding ground truth image patches are considered as labels. The learning rate of the network is fixed at 1e-3. A total of 1e5 iterations are made while training the network and the network stops training when the specified maximum epochs count is reached. After training the network it is tested against synthetic and real-world data.

The parameters are considered by measuring only the light rain images. Hence by observing the SSIM values form the comparison of different combinations of both proposed work and from [2], it can be seen that, the work from [2] has a greater SSIM value. By applying these parameters to medium and light rain images, the proposed work achieves better efficiency which is shown below.

Figure 6 to Figure 14 represents the rainy and derained images of various samples that are affected differently from the rain streaks. Each of the three samples are introduced with light, medium and heavy rain streaks. The structure, orientation and intensity of these rain streaks are different in each of the light, heavy and medium samples. Table.4 represents the SSIM values for each of these

Figure 6: Sample-1 Light Rainy and derained image

Figure 7: Sample-1 Medium Rainy and derained image

Figure 8: Sample-1 Heavy Rainy and derained image

Figure 9: Sample-2 Light Rainy and derained image

Figure 10: Sample-2 Medium Rainy and derained image

Figure 11: Sample-2 Heavy Rainy and derained image

Figure 12: Sample-3 Light Rainy and derained image

Figure 13: Sample-3 Medium Rainy and derained image

Figure 14: Sample-3 Heavy Rainy and derained image

Table 4: SSIM values for various image samples

Sample	Light		Medium		Heavy	
	Proposed	From [2]	Proposed	From [2]	Proposed	From [2]
Sample 1	0.8443	0.8546	0.7755	0.7582	0.6984	0.6758
Sample 2	0.8932	0.9012	0.7291	0.7154	0.6889	0.6772
Sample 3	0.9298	0.9302	0.7402	0.7265	0.6733	0.662

samples. The proposed algorithm works well for removing light rain streaks in images, this can be verified with their SSIM values. Images with medium rain streaks, while deraining, retain some rain streaks. The work in [2] depicts that while removing rain from medium rain streaks, the image becomes blurry, but in this proposed algorithm, the derained image retains some rain streaks but do not appear blurry. The images with heavy rain streaks have the least SSIM. This is because, while removing heavy rains, the background image gets occluded and the content cannot be seen perfectly.

From table 4 it can be seen that the work from [2] exceeds the proposed work in case of light rain images. Medium and heavy rain images were not considered in paper [2]. By taking into account the medium and heavy rain images and by comparing the proposed work and the work from paper [2], it can be seen that, the proposed work removes medium and heavy rain streaks much efficiently when compared to the work done in [2].

5. Conclusion and Future Work

The proposed work performs rain removal from single images using the concept of CNN and the proposed work is known as DerainNet. This work removes rain within 15 sec. The proposed network works well for synthetic images. The SSIM values are higher when synthetic images affected by light rain streaks are given as input. On providing images with medium and heavy rain streaks, the SSIM values drop. As far as real-time images are concerned, it can be derained but it cannot be compared with the existing Metrix because, the ground truth of the image is not known. In real time images, the intensities of the rain drops vary differently at different locations which hinders the performance of the algorithm. At some places it would be light and at some places it would be dark and occlude the objects behind it, hence while removing rain the occluded region would be over smoothed. This work is carried out based on the paper [2]. The low pass filter in paper [2] is replaced with the combination filter. The proposed method uses guided filter followed by L0 Smoothing filter as the low pass filter. Since real time images faces some problem for deraining, ie some amount of rain streaks are present in the derained image, a higher pass filter can be introduced at the pre-processing stage to remove the rain streaks. The proposed work removes rain efficiently when compared to the work in [2]. As a future work a combination of DerainNet and ResNet can be introduced to remove rain during heavy rain conditions.

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