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A study on rain streaks removal from an image in outdoor vision systems

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ABSTRACT

The quality of captured images will be highly affected by an abnormal weather like rain or snow. Such bad weather conditions can degrade and corrupt the performance of various outdoor vision systems like CCTVs, traffic cameras etc. Even if many bad weather conditions can affect the quality of captured images, rain affects the image in a more negative way because, it is observed as bright streaks. Because of the negative effect of rain on outdoor vision systems, rain removal is an important problem. Detecting rain streaks accurately is a difficult task since rain has no particular location in an image. Rain removal has been an active research topic over many years and several techniques has been proposed. From all these studies, rain removal from an image can be classified into four main categories. The first category is simply filtering based whereas the second category builds models for rain streaks. In the third category, a 2-step processing is performed for rain removal and in the fourth category, deep learning techniques are used. So, in this paper, we have done a detailed study on the effects of rain on images and various rain removal methods.

Keywords— *Rain Streaks, Rain Removal, Outdoor Vision Systems, Dynamic Components*

1. INTRODUCTION

The better performance of outdoor vision systems like surveillance cameras can be ensured by checking the quality of the captured images. In traffic surveillance, clarity of captured images is very important for the analysis of road user behaviour, accident causation, crime scene evaluation etc. Even if the camera is of good condition, the images will not be clear due to some unusual weather conditions. Based on the physical properties and visual effects caused in an image, weather conditions can be classified into two. Steady weather conditions and dynamic weather conditions. The individual particles of steady weather like fog, mist etc. are having very small size (1-10 μm) whereas the individual particles of dynamic weather like rain, snow etc. are having larger size (0.1–10 mm). So, dynamic weather particles can be easily caught by camera. Here, the effect of only rain is considered. The effect of rain streaks will change the information that an image is trying to convey.

Fig. 1: Ill effects of rain on an image: (a) rain image caught on camera, (b) ill effect of rain

Figure 1 shows the ill effects of rain on an image. Figure 1(a) shows a rainy image caught on camera. It is clear from Figure 1(b) that the image is not clear. Such unclear image can cause many problems in traffic surveillance and CCTVs. So, removing rain from an image is important. Rain belongs to the dynamic weather category where the constituent particles are of larger size and are easily caught by cameras. The effect of rain on images is studied by Garg and Nayar [1] whose observations and findings are the key to many rain removal algorithms. They said that rain contains rain drops that are distributed spatially and having high falling velocities. Sharp intensity changes are produced in an image when it is affected by rain.

Rain removal from an image has several techniques which can be classified into four categories. In the first category of rain removal, a simple filter is used to remove rain particles from the image. The second category tries to build models for rain streaks and these models can be used to separate rain streaks from the background. In the third category of rain removal, a 2-step processing is performed in which the image is first decomposed into a low-frequency and high-frequency part where the low-frequency part will be completely free of rain, but is usually blurred whereas the high-frequency part will contain more image's details. Then, these image's details will be extracted from the high-frequency part and are added back to the low-frequency part to get a clean rain removed output. The last category of rain removal uses deep learning techniques to obtain more accurate output. In figure 2, a rainy image and its ground truth are given. The aim of various rain removal algorithms is to produce an output which is most similar to the ground truth.


(a) (b)

Fig. 2: Rainy image and its ground truth: (a) rainy image, (b) ground truth

2. THE IMPACT OF RAIN ON IMAGES
The occurrence of rain severely affects the quality of vision systems. Rain, when captured by camera will possess certain characteristics other than the non-rain pixels. These characteristics of rain are utilized in different rain removal algorithms. Some of the effects of rain on image is given below.
- Linear edges are produced on images due to rain streaks.
- The observed scene will appear brighter in the corresponding pixel areas because of the high refraction and blending of light rays by rain streaks.
- The intensity value of a rain pixel is high compared to other non-rain pixels.
- Rain streaks have identical falling directions in an image in most cases.
- Rain is semi transparent and colourless so the three colour channels (Red, Green and Blue) of a rain pixel will have nearly the same value.

There are several challenges in the rain removal task. The primary aim is to remove rain particles without losing other image's details. The de-rained output will be of high clarity and not blurred. Rain detection is an important stage in image de-raining. But in rain detection, some of the rain pixels are missed which will affect the result badly. Another problem that can come in rain detection is if the input image contains more structures similar to rain, they will be mis-detected as rain and are removed. So, all such problems are to be considered seriously in image de-raining.

3. DIFFERENT CATEGORIES OF RAIN REMOVAL
Several studies have been made on removing rain particles from images. Based on these studies, a single image rain removal can be classified into four main categories.

3.1 Filtering Based Rain Removal
This is the simplest way of removing rain streaks from an image. Here, a non-local mean filter or guided filter can be used to remove rain particles from an image. Since it uses only a simple filter, the implementation is very fast. But the output obtained will not be of better quality. Some of the image's details are smoothed out and blurring is also present.

In [2], a guidance image method is put forward to remove rain from an image. A guidance image is obtained from the imaging model of a rain drop when it is moved through the CCD of the camera. But, some of the meticulous information will be lost by the use of a guidance image. In order to overcome that, a refined guidance method is used. The refined guidance image has identical contour with the un-degraded image and also maintains the detailed information which may be lost at the guidance image and at the same time removes the linear edges happened by rain thereby providing a better result. After calculating the refined guidance image, use a guided filter two times to get the rain removed output. This method is also suitable for snow removal. The results show that this method could reduce the degradation caused by dynamic weather and also could maintain some detailed information of local regions.

In [3], an adaptive nonlocal means filter is used for image de-raining. Based on kernel regression method, detect the regions where rain streaks are present. Peculiarly, the covariance matrix of gradients is computed within a local block centered at each pixel, extract the rotation angle and the aspect ratio of the rain kernel via the singular value decomposition (SVD), and then find out the locations of rainy pixels by assuming that rain streaks have elongated elliptical shapes. Next, restore the rain streak regions using the nonlocal means filter, in which the weights for nonlocal neighbour pixels are adaptively determined to quench the impacts of rainy pixels on the restoration. Here, the adaptive non-local means filter selectively applies to rain pixels only thereby retaining image texture more faithfully and produces a better result.

3.2 Removing Rain by Building Model For Rain Streaks
This is the second category of rain removal where models for rain streaks are created and these models are further used to separate rain particles from the background. In [4], a novel low-rank appearance model is proposed for image de-raining. Here, the shape

and chromaticity of rain particles are also taken into account. First, build a low-rank appearance model for rain streaks based on two observations.

a) The falling direction of rain streaks will be same in an image.
b) The falling velocity of raindrops is constant which shows similar rain streaks for a certain period of time.

Using this low-rank appearance model, rain removal is performed. The run time of this method is about 3.2 seconds.
In [5], the rain layer and the de-rained image layer is separated from a rain image. Here, a non-linear composite model called screen blend model is used for modeling rain images. In screen blend model, a rain image is formed by two layers, a de-rained image layer and a rain layer. By performing dictionary learning, the de-rained image layer and the rain layer can be accurately separated using sparse coding. But the results obtained are not perfect. This method might not produce good result when the input image has many structures matching with rain drops. Here the running time is about 75.7 seconds.

In [6], rain removal is expressed as a layer decomposition problem. First, separate the rain free background layer and the rain streak layer from the input rainy image. Based on Gaussian mixture model (GMM), simple patch based priors are created for both background and rain layers. Here, an assumption is made that the two layers are independent of each other. This method provides good results by retaining the image's details. When the rain is heavy, the density of rain streaks is so high that individual streaks cannot be seen and the output obtained will not be satisfactory. The time is calculated to be 370 seconds for 20 iterations.

3.3 Rain Removal Using 2-Step Processing

This method produces more reasonable results. In most of the 2-step processing techniques, the first step is to subdivide the input image into a low-frequency part and a high-frequency part. The low-frequency part will be free of rain almost completely, but is blurred. The high-frequency part will contain more image's details. So, in the second step, the image's details are extracted from the high-frequency part and these are added back to the low-frequency part to get an accurate output.

In [7], The image is break down into low-frequency and high-frequency part using a bilateral filter and the MCA-based image decomposition scheme. The high-frequency part is then subdivided into rain component and non-rain component by applying dictionary learning and sparse coding. The main idea of MCA is to use the morphological diversity of various features in the image to be decomposed and then associate each of the morphological components to a dictionary of atoms. Sparse coding is used to find the sparse representation of a signal with a few numbers of nonzero coefficients corresponding to atoms in a dictionary. This method can effectively remove rain streaks without blurring the original image's details.

In [8], the image is divided into low-frequency and high-frequency part using a guided image filter. A hybrid feature set including histogram of oriented gradients, depth of field (DoF), and Eigen color is used to extract image's details from the high-frequency part. By using the hybrid frequency set, most of the rain components can be removed and also the non-rain components can be intensified. This paper uses the property of photography where the DoF is calculated as a feature for rain image. The use of DoF helps to enhance the low frequency part of the image as well as the quality of dictionary atoms for the high-frequency part. It also helps to recover some non-rain information having nearly same orientation to the rain streaks. The time taken by this method to produce the output is about 465 seconds.

In [9], rain or snow detection is performed. Here, rain or snow is considered as dynamic components where the individual particles are of larger size and the other image's details are coming under non-dynamic category. In the first step, some low-pass filter is used to decompose the input image into high-frequency and low-frequency part. Then, a 3-layer hierarchy is developed to extract the other non-dynamic components from the high-frequency part. Online dictionary learning is used for extracting one set of non-dynamic components. Two characteristics of rain or snow is considered here which are Principal direction of an image patch (PDIP) and Sensitivity of variance across colour channels (SVCC). This method produces better results but for some relatively high images, it produces blurring. Also, the dictionary learning is time consuming. Total time taken by this method is about 82.6 seconds. In these, rain or snow detection takes 5.71 seconds, SVCC takes 1.85 seconds, dictionary learning takes 60.82 seconds and classification and sparse reconstruction takes 13.81 seconds. The user study result of the system is given as 65.5% for rain and 87.5% for snow.

In [10], the detection of rain pixels is done in the first step based on two characteristics of rain streaks. They are rain usually have higher reflection to light compared to its neighbours thereby leading to larger intensities, and rain is semi transparent. Here, the rain pixels are detected almost completely and also tried to avoid mis-detection of structures similar to rain. In the second step, construct a linear model for the detected rain pixels and using this model, removal is performed. Here, the output obtained will be much clear. The implementation time of this method is about 7.68 seconds and the user study result is 69.8%.

3.4 Rain Removal Based On Deep Learning

This is the last category of rain removal. Here, the rain removal is performed by designing appropriate deep learning networks.

In [11], the rain removal is performed based on deep Convolutional Neural Network (CNN). To improve the result, use a priori image domain knowledge which eliminates background interference and targets the model on the structure of rain in images. In this work, in order to learn the network, they have created synthetic dataset of 14000 rainy/clean image pairs. After training, the network can be used to produce de-rained output of a rainy image. This method produces a better output. But, due to the training needed on the large dataset, the method is time consuming. It takes about 14 hours to train the network. After training, only 10 seconds is needed for obtaining the result.

In [12], a model is created composed of a component representing rain streaks accumulation and another component representing different shapes and directions of rain streaks that overlaps, which usually happen in heavy rain. Then, a multitask deep learning architecture is build based on this model for rain removal. To retrieve more contextual information, a contextualized dilated network is advised to enlarge the receptive field. Finally, to restore the captured images with both rain accumulation and various rain streak directions, a recurrent rain detection and removal network is used that successively removes rain streaks. This method removes rain from an image even in the presence of rain streak accumulation and heavy rain.

In [13], Conditional Generative Adversarial Networks (CGAN) is introduced by enforcing an additional constraint that the de-rained image must be indistinguishable from its corresponding ground truth clean image. A new refined loss function is introduced for achieving improved results which is aimed at reducing the leftover introduced by GANs and ensure better visual quality. A novel single image de-raining method called Image De-raining Conditional Generative Adversarial Network (ID-CGAN) is proposed for obtaining better results. The accuracy of the system is about 78 % which is a much better result.

4. ANALYSIS OF DIFFERENT METHODS

Among the four categories of rain removal, 2-step processing and deep learning methods produces a high quality output. Compared to deep learning, 2-step processing takes lesser time because deep learning needs time consuming training. The first two categories take much lesser time but the result will not be sufficient. In Figure 3 the implementation time of various papers are given.

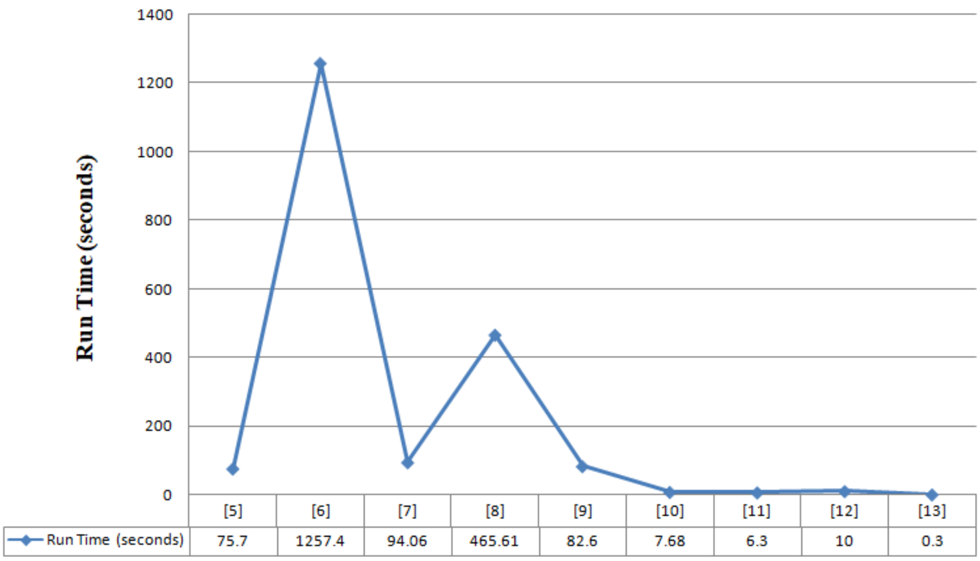

Fig. 3: Implementation time of various methods

In figure 4, the user study result of five methods is given. These values are taken from [10]. The authors said that they have conducted a visual evaluation by 20 viewers in terms of three aspects:

a) Less rain residual,
b) Maintenance of image details,
c) Overall perception.

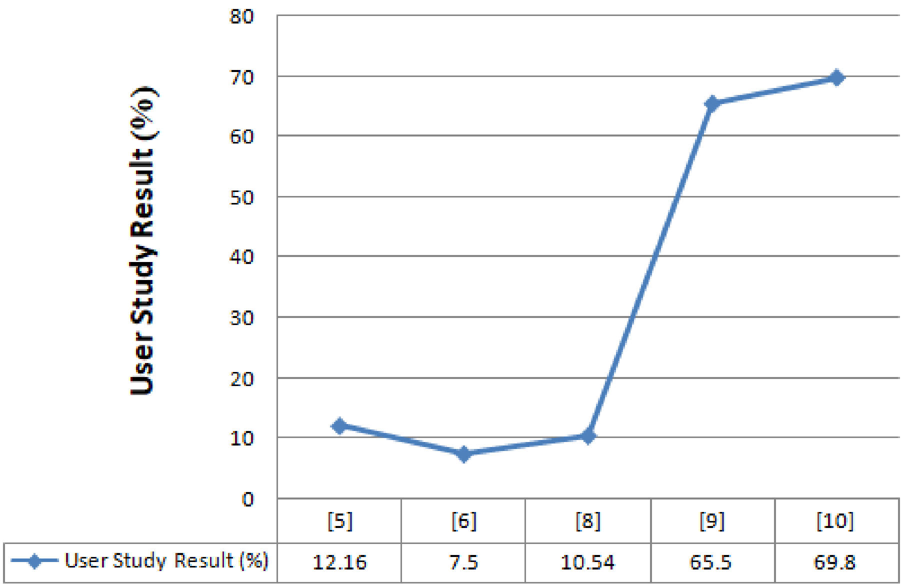

Fig. 4: User study result of various methods

Table 1 shows the qualitative comparison of four different methods. Here, the technique used in these methods is discussed in brief and also the advantages and disadvantages of each method are given. Table 2 shows the PSNR, SSIM and run time of various methods.

Table 1: Comparison of different rain removal methods - A qualitative approach

Method	Reference papers	Techniques used	Advantages	Disadvantages
Filtering Based Rain Removal	[2], [3]	A non-local mean filter or guided filter is used	• Easy to implement • Fast implementation	• Does not remove rain streaks completely • Output obtained is blurred
Removing rain by building a model for rain streaks	[4],[5],[6]	Attempt to discriminate rain streaks from the background	• Fast implementation	• Some details of the image will be mistreated as rain • Might not work when the input has many structures similar to rain
2-step processing	[7],[8],[9],[10]	• A low-pass filter is used to decompose the image into low-frequency and high-frequency part • Some processing is done on the high-frequency part to produce the output	• Produce better results • Removes rain streaks to a great extent	• Some non-rain details will be mis-detected as rain • A very small portion of the rain still remains in the image
Deep Learning	[11],[12],[13]	Rain removal is performed by designing appropriate deep networks	• Produce better results • Removes rain streaks almost completely	• High implementation time • Memory requirement is high

Table-2: PSNR, SSIM values and Runtime of different methods

	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]
PSNR	28.74	36.84		34.9	42.78	39.34		36.11	24.34
SSIM	0.92	0.945	0.76	0.873	0.95	0.847	0.90	0.97	0.843
Run Time(s)	75.7	1257.4	94.06	465.61	82.60	7.68	6.3	<10	0.3

Peak Signal to Noise Ratio (PSNR) is used to compare the error between two images in decibels. Here, the output and ground truth are considered. This ratio can be used as a quality measurement which shows how the output is similar to the ground truth. A high value for PSNR means the output obtained is of high quality. To calculate PSNR, first calculate the mean-squared error (E_{msq}) using the following equation.

$$E_{msq} = \frac{\sum_{M,N}[I_1(m,n)-I_2(M,N)]^2}{MN} \tag{1}$$

Where M and N are the number of rows and columns of the input image. Now, the PSNR value can be calculated as follows:

$$PSNR = 10log_{10}\frac{R^2}{E_{msq}} \tag{2}$$

Where R is the maximum fluctuation in the data type of the input image. If the input image has a double-precision floating point data type, then R is 1. If it has an 8-bit unsigned integer data type, R is 255, etc.

The Structural Similarity Index (SSIM) is a metric that quantifies image quality degradation that are caused by various image processing techniques such as data compression or loss in data transmission. So, a higher value for SSIM indicates that the de-rained output obtained will be closer to ground truth in terms of structure properties. (SSIM = 1 for Ground Truth). SSIM can be calculated based on three comparison measurements between x and y samples. They are luminance (l), contrast(c) and structure(s). The comparison functions can be individually calculated as:

$$l(x,y) = \frac{2\mu_x\mu_y + c1}{\mu_x^2+\mu_y^2+c1} \tag{3}$$

$$c(x,y) = \frac{2\sigma_x\,\sigma_y+c2}{\sigma_x^2+\,\sigma_y^2+c2} \tag{4}$$

$$s(x,y) = \frac{\sigma_{xy}+c3}{\sigma_x\sigma_y+c3} \tag{5}$$

Where x and y are the two windows of size M×N

- μ_x is the average of x
- μ_y is the average of y
- σ_x^2 is the variance of x
- σ_y^2 is the variance of y
- σ_{xy} is the covariance of x and y
- $c1 = (k1x)^2$, $c2 = (k2x)^2$ where L is the dynamic range
- k1 = 0.01 and k2 = 0.03 by default
- c3 = c2/2

Now, we can calculate SSIM as a weighted combination of the comparative measures as follows:

$$SSIM(x,y) = \left[l(x,y)^{\alpha}.\,c(x,y)^{\beta}.\,s(x,y)^{\gamma}\right] \tag{6}$$

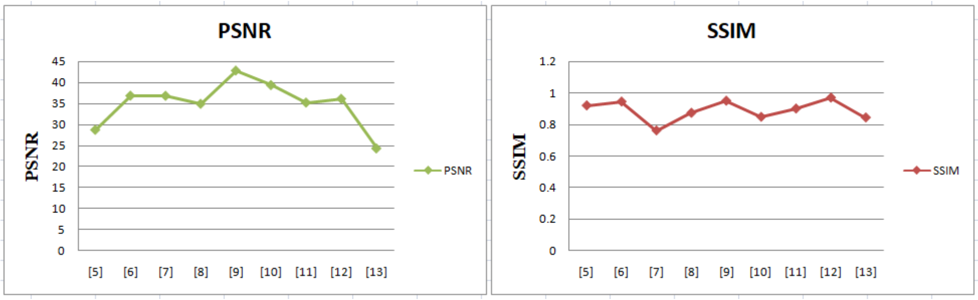

Fig. 5: PSNR and SSIM values of various methods

In figure 5, the graphs showing PSNR and SSIM values of various papers are given.

5. CONCLUSION

The quality of images captured by outdoor vision systems should be of great importance now days because they are used in detecting human behavior, accident causation, evaluating crime causation etc. An outdoor image in a rainy day will suffer from quality degradation because rain can affect the quality of captured images in a negative way. So, image de-raining is very important. In this paper, we have made a study on the effect of rain on an image and various image deraining techniques. There are four different methods for rain removal. Out of these four methods, deep learning produce better results. The first two category of rain removal does not produce good results. But, in the third category, [10] and [11] produce good results which are nearly similar to deep learning works [11] and [13].

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