Rain Streak Removal Using Sparse Coding

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Abstract: Rain removal from a single image and a video is a challenging task of image processing which has numerous applications in the area of out-door surveillance. In addition to applications point of view, deraining is a challenging task in image processing point of view as well. Deraining involves removing rain drop marks or rain streaks from the image. While the removal of these marks taking place, the leftover region need to be filled with that of true image which is not available. The second and important operation is not to distract the remaining region in the image. In this paper, a model of deraining was developed using sparse coding. Suitable regularization terms of required components were defined and iterated to get the approximation of clear image. A brief survey on deraining is presented. The simulation results shows superior performance of the proposed scheme. The simulation results also suggest that the proposed scheme is applicable only if the volume of rain drop size is below a certain level.

Index Terms: Deraining, rain streak removal, remote sensing, sparse coding, stripe removal, traffic control.

1. INTRODUCTION

Removal of rain imprints from either image or video is an interesting and a challenging task. Rain drops results in a local intensity variations and as a consequence, causes difficulty in visual aspects. When autonomous activities need to be performed, the images or video captured and processed will lead to wrong identification and recognition results. The rain drops in an image or video is a case with outdoor recording like a CCTV capturing. When the capturing of CCTV is autonomously processed using an application software, wrong decisions will be taken. The removal of rain drops from the image need to take the density, size of the drops and background scope of the image into consideration. Literally speaking, Derain means to fill the region which is covered by the rain drops with an approximated original background. In spatial domain, the background of rain drops is completely lost and filled by the pixel values of rain drops. The pixel values of rain drops is not exclusively that of rain drops but it is a result of both rain drop and background.

In addition to rain drops, there are other bad weather conditions which modifies the scene behind the objects of bad weather. These include snow, hail, smoke, haze and fog. Of these, smoke, haze and fog are of microscopic size. The remaining can be larger depending on the weather condition. The task of removing these additional objects from the image is always difficult irrespective of whether these effects are smaller or bigger. For instance, consider the effect of snow. Snow particles are minute and highly dense. The case of snow may be approximated by blurring to some extent. The perspective of rain removal is completely different from that of deblurring. Blurring is treated as overlapping of adjacent pixels and rain or bad weather condition is treated as, somehow, the addition of these effects to the original image, something like an additive noise. If the effect is the case of rain drops, then the size of these drops is bigger than snow, but irregular and random in position and size. Hence, the treatment of this effect is quite different from that of snow removal. For instance, if the size can be increased to even bigger than small objects, then more applications may be served. Derain is a quite recent research problem which was considered by very few researchers. It is mainly implemented on video. Single image deraining can be easily extended to video deraining, hence, in the literature, single image deraining schemes can also be found. In video deraining, in addition to special information, temporal analysis need to be done. In 2012, L. Kang, C. Lin and Y. Fu proposed a single image deraining scheme based on image decomposition [1]. The presence of rain drops on an image is treated as high frequency components in the image. Hence, before applying deraining, the image is divided into low and high frequency parts using bilinear filters. Then, dictionary learning and sparse representations are utilized to separate 'rain component' and 'non-rain component' of the high frequency part of the image. Now, from the original image, the rain component may be removed. This process retains most of the remaining part of the image. In 2012, A.K. Tripathi and S. Mukhopadhyay presented an efficient rain drop removal scheme on a video [2]. Spatiotemporal properties of image were exploited to identify and separate rain and non-rain pixels. In 2014, D. Chen, C. Chen and L. Kang proposed a single color image deraining scheme based on guided image filter and sparse coding [3]. This is an extension of work presented in [1]. In [3], guided image filters are utilized to decompose the image into low frequency and high frequency parts. Then, sparse coding and dictionary learning were used to decompose the high frequency part into rain and non-rain components. A hybrid feature set is used not only to remove rain component but also to enhance the non-rain component. In 2016, S. You, R. T. Tan, R. Kawakami, Y. Mukaigawa and K. Ikeuchi presented a video deain scheme based on spatiotemporal derivatives of raindrops [4]. In 2017, B. Chen, S. Huang and S. Kuo proposed a derain scheme on single image based on error-optimized sparse representation [5]. This method represents each patch of the image based on improved patch error restraints. In 2017, X. Fu, J. Huang, X. Ding, Y. Liao and J. Paisley presented a deep neural network for deraining from a single image [6]. In this work, mapping relations between rainy and clear images are learned. Images with rain and clear images are used in training phase and mapping relations are learning during testing. In 2017, Y. Wang, S. Liu, C. Chen and B. Zeng presented a hierarchical scheme for removal of rain and snow from a single image [7]. First, guided filters are used to separate low and high frequency parts of the image. Then, an over-complete

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dictionary is trained and three layers of network are designed to classify high frequency component into rain and non-rain components. In 2017, Y. Li, R. T. Tan, X. Guo, J. Lu and M. S. Brown presented single image derain scheme using layer priors [8]. In this scheme, respective image priors are superimposed on background true image component and rain component. Gaussian models are learned using almost atomic patches which can annotate a diverse background and rainy patches. These models are used to prepare image priors which will be superimposed to abstract unnecessary details from respective regions of the image. In 2018, Y. Luo, J. Zhu, J. Ling and E. Wu presented a simple shape prior from derain on a single image [9]. These shape priors will be correlated with rain drops of the image. In each iteration, by optimizing the characteristics of shape prior all the drops are identified and the layer of rain drops will then be removed from the image. In 2018, H. Xia, R. Zhuge, H. Li, S. Song, F. Jiang and M. Xu presented a residual dense network for deraining of single image [10]. A simplified dense network was implemented which exploit more useful information of the layers of detail and base. In 2019, C. H. Bahnsen and T. B. Moeslund presented a review of derain methods and propose a new dataset of varied weather conditions for traffic surveillance [11]. New assessment tools were devised to assess the derain algorithms based on the performance of segmentation, tracking, detection and recognition of objects on processed videos [12]-[19].

2 BACKGROUND

The rain image model can be described by the following.

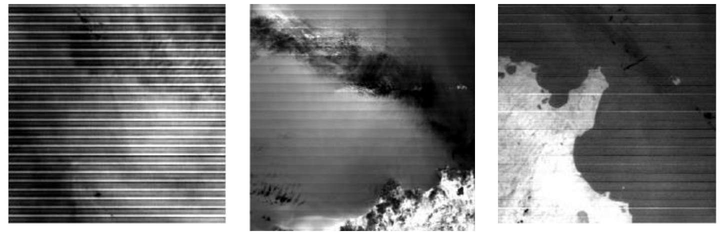
$$T = C + R \tag{1}$$

where $T \in \mathbb{R}^{M\times N}$ is the true image which is observed by the observer, $C \in \mathbb{R}^{M\times N}$ is the clear image with no rain drops and $R \in \mathbb{R}^{M\times N}$ is the rain image with rain drops. When compared with noise model, the rain image may be treated as noise. In the noise model, clear image C becomes the true image which need to be found. When the rain image model is compared with that of noise model, techniques like total variation, sparse coding, dictionary learning and neural networks may be thought of as a possible way to deal the images with rain drops.

It is argued that least-squares estimation is far better than an entire ensemble of all possible pictures[20]. Further, it is stated that, for images total variation norm is more opt than L2 norm and total variation norm is an L1 norm of derivatives [21]. Images acquired by MODIS sensor were denoised by handling striping problem using variational approach [22]. Striping can be modeled as follows.

$$I_s(x,y) = u(x,y) + s(x,y) \tag{2}$$

where $I_s(x,y)$ is sensor output, $u(x,y)$ is the true image and $s(x,y)$ is stripe noise. Samples of stripes are given in Fig. 1.



(a) (b) (c)

Fig. 1. *(a) Detector stripes. (b) Mirror stripes. (c) Random stripes [23]*

Many destriping schemes assume that the stripe noise s is constant over the required scan duration. Hence, it can be removed easily by additional calibration. The usage of additional calibration can remove only significant stripes, but the previous existence of these stripes will be clearly evident even after calibrating the sensor. The removal of these stripes may create additional blurry effect. The stripes are horizontal line variations, hence the appearance and presence is clear when the images are viewed on y-axis. In contrast, the rain drops falls from the top to bottom, hence these rain stripes will be vertical and the variational information can be observed through x-axis. But, additional complexity with rain drop removal is that the stripes are completely random, hence the constant stripe condition does not hold with rain drops. The stripes of MODIS image will have a structured noise that satisfy the following condition. Here, the stripes are viewed as structured noise.

$$\left|\frac{\partial s(x,y)}{\partial x}\right| << \left|\frac{\partial s(x,y)}{\partial y}\right| \tag{3}$$

Many ill-posed problems of image processing applications like, denoising, restoration need a regularizing constraint on the final solution [23]-[25]. The solution will be used to update the energy functional and the algorithm will generally be iterated till the energy functional reaches an allowed level. A regularization term corresponds to the smoothness of the solution given by the algorithm. M. Bouali[26] presented a de-striping scheme using gradient based method. The method is to minimize the following energy functional.

$$E_k(u) = \int_\Omega \sum_{i+j=k,\, j\neq k} \left(\frac{k!}{i!(k-i)!} \left\| \frac{\partial^k (u-I_s)}{\partial^i x \partial^j y} \right\|^2 + \left\| \frac{\partial^k H_L \otimes (u-I_s)}{\partial^k y} \right\|^2 \right) dxdy \tag{4}$$

The destriping and deraining problems share common issues in finding a clear image from the captured image. Fig. 2 shows two images, one a remote sensing image with stripes and another with rain streaks.

From Fig. 2, it may be thought that these marks are tilt by 900. Though, this is true in many cases, in practice situations will arise where the rain drops may be of higher dense or lesser dense, slant by different angles throughout the image or partially within the image.

(a) (b)

***Fig. 2**. (a) Remote sensing image with striping effect (b) Rain Image*

3 PROPOSED METHOD

Stripe noise removal methods are based on standard denoising schemes that are based sparse coding. In this paper, rain removal method is proposed based on one of the de-striping method proposed by Liu, X., Lu, X., Shen, H., Yuan, Q., Jiao, Y. and Zhang, L [27]. The rain strikes' properties will be exploited and these need to be described in apposite terms. These terms will optimize the derain constraint and result in a better approximation to C of equation (1). The following components of rain image need to be considered while designing the energy functional.

1. Rain drops
2. Continuity and discontinuity in and across rainfall direction.

The component representing rain drops can be treated as a type of sparse matrix. But, the elements can be zeros or non-zeros that can be known only after getting the information of density of rain drops in the image. If the drops are more, then the number of zero elements will be more, otherwise number of non-zero elements will be high. If the density of rain drops is less, then there will be more number of zero elements in sparse matrix and correspondingly ℓ_0-norm need to be used, otherwise ℓ_1-norm. Hence, if the detection of density of rain drops is known, then the regularization term can be defined as follows.

$$R_1(R) = \begin{cases} \|R\|_0, & less\,dense \\ \|R\|_1, & high\,dense \end{cases} \tag{5}$$

This term is useful in rain drop removal. This also ensures that no additional information is lost, other than the rain drop region.

In the direction of rainfall, there can be few stripe-like patterns where the rain drops flow in an almost continuous manner. There comes the issue of local continuity through the line of rain fall. Hence the neighboring pixels differs in value, resulting in derivative to be minimum. This gives raise to another regularization term given below.

$$R_2(R) = \|\nabla_{rfd} R\|_1 \tag{6}$$

Here ∇_{rfd} refers to partial differentiation along rainfall direction.

Across the direction of rainfall, there exists discontinuity. These discontinuities across the rainfall direction will result in large magnitude at rain drop locations and yield less magnitude at non-rain drop points. The following regularization term will serve the purpose.

$$R_3(R) = \|\nabla_{arfd} T - \nabla_{arfd} R\|_1 = \|\nabla_{arfd} C\|_1 \tag{7}$$

The final energy functional becomes

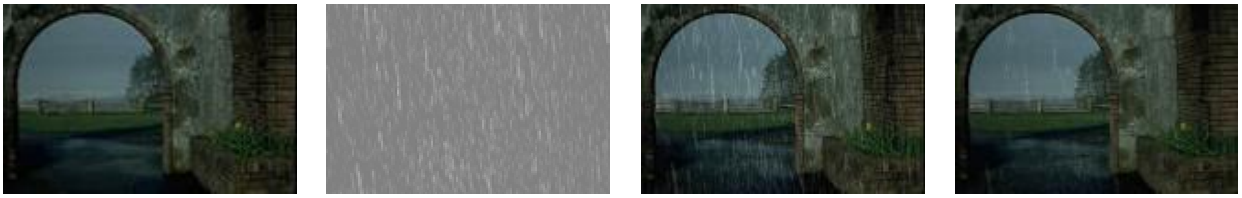
$$\hat{R} = \arg\min \left\{ \lambda_0 \|R\|_0 + \|\nabla_{rfd} R\|_1 + \lambda_1 \|\nabla_{arfd} T - \nabla_{arfd} R\|_1 \right\} \tag{8}$$

4 SIMULATION RESULTS

Real-time processing of rain images or video sequences are of greater importance as it can be used in traffic control, out-door surveillance, industrial applications where in addition to rain, a fog kind of weather difficulties can be handled effectively. To have quantitative analysis of the proposed deraining algorithm, in this work, clear image without rain drops was considered. A rain envelop is used to generate a rain image. Fig. 3 show all these images, along with the derain image with performance metrics. From Fig. 3, it is clear that the performance of the proposed algorithm is good if the size of rain streak is less. Also, if the size of the streak is less, then the effect of removal is less. The quality of the derain image may be less because of two reasons. One, rain component may not be removed completely. The second, tendency of blurring in non-rain component of image. From the simulation results, it is clear that the first difficulty is present in the proposed scheme. This is so when the rain drop area is prevalent. The second problem is clearly avoided.

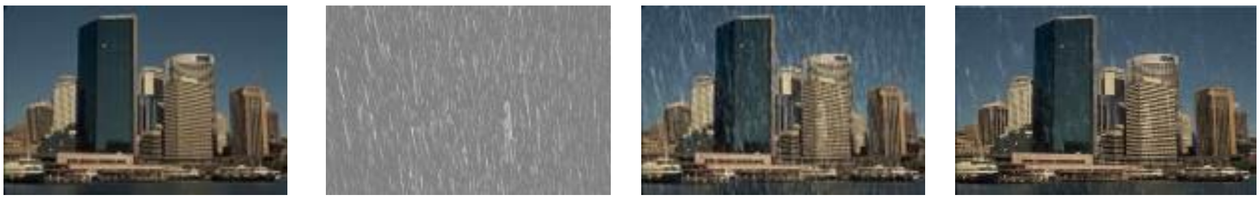
5 CONCLUSION

In this paper, a single image rain streak removal was done using sparse coding. Rain streak removal from a video is easier than that from a single image. In a video, temporal frames adds the information missed in another frame. Also, a spatial comparison of temporal frames gives an estimate of clear image as well as rain streaks. But, in single image case, only one temporal frame is available, hence structural analysis has to be conducted to find out shaded information covered by rain streaks. This can be done by decomposing the image into frequency components and inspecting the components to identify streak and for further processing. Suitable regularization terms were defined in this paper for different components and implemented to trace out the clear image. The simulation results show that the performance depends on the streak angle and volume. Best performance is observed when the angle of streak is exactly perpendicular to the earth and if the volume of rain drops is less. Further, when the volume of the rain drops increases to a level, the performance is degrading.



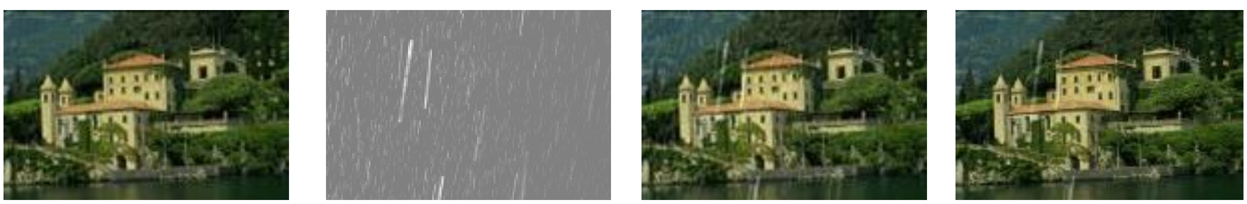
PSNR = 33.73
SSIM = 0.92

PSNR = 35.35
SSIM = 0.95

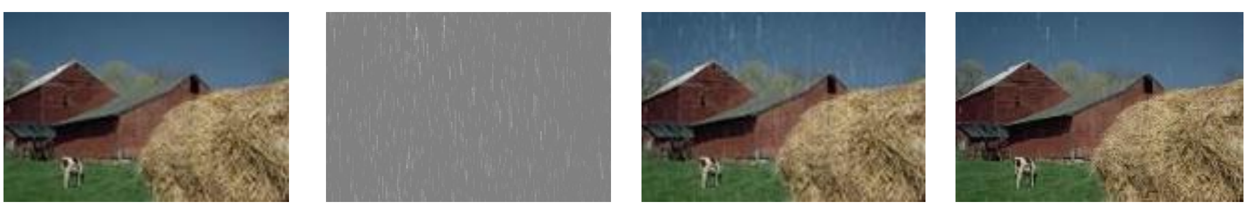


PSNR = 29.17
SSIM = 0.90

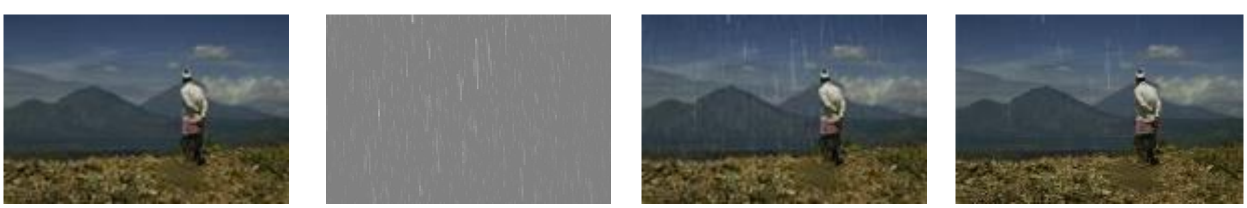
PSNR = 39.35
SSIM = 0.97



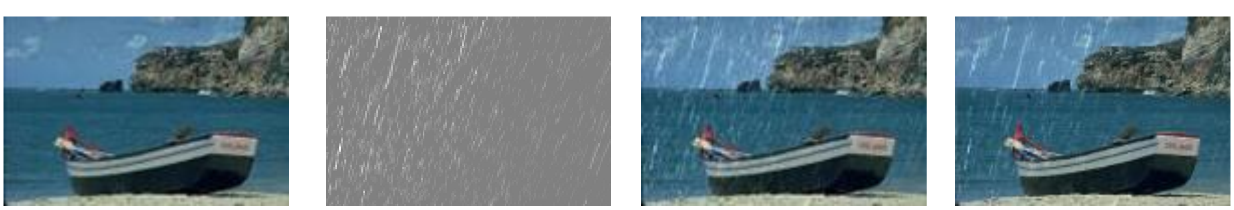
PSNR = 30.72
SSIM = 0.94



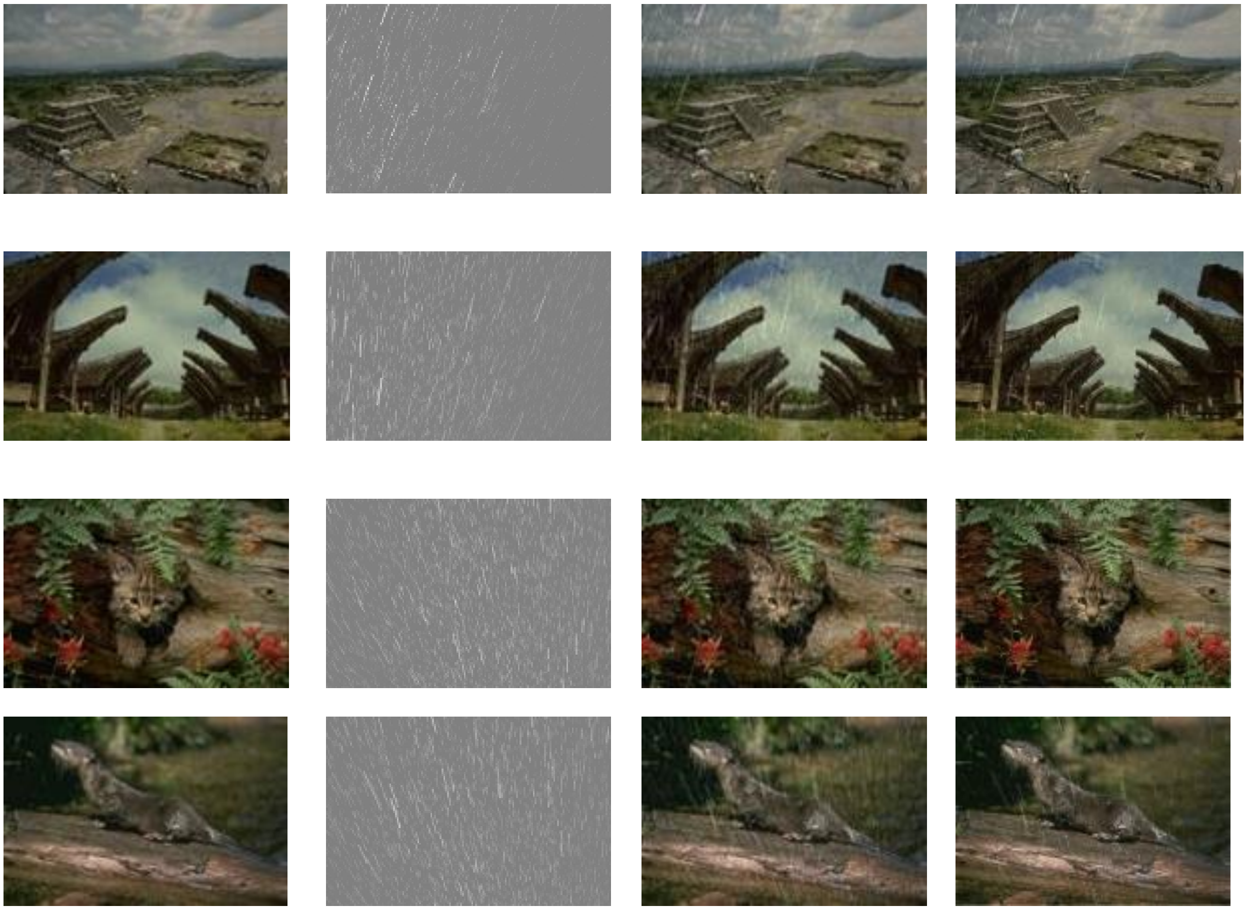
PSNR = 33.73
SSIM = 0.92



PSNR = 39.25
SSIM = 0.97



PSNR = 29.69
SSIM = 0.86



PSNR = 31.60
SSIM = 0.907

PSNR = 31.65
SSIM = 0.90

PSNR = 30.6
SSIM = 0.905

PSNR = 32.12
SSIM = 0.906

Fig. 3. *Derain results - Clean image, rain drop image, rain image and derain image.*

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