An Optimum Deraining Scheme using Sparse Coding

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Abstract—Rain streak removal is a challenging and interesting task of image processing where the rain streaks will be removed from an image with rain streaks. In the literature, a large number of proposals are made where rain streak removal is considered as image enhancement or denoising. In this paper, a model of rain streak removal was proposed using sparse coding. First the regularization terms of the rain streak removal are defined. Then, a suitable dictionary of sub- dictionary with respect to specific patch of input rainy image are prepared. Finally, the Sparse code is applied on the patches of input image individually. The simulation results prove that the proposed technique performs very well even if the raindrop size is above a certain threshold.

Index Terms— deraining, rain streak removal, remote sensing, sparse coding, stripe removal.

1 INTRODUCTION

The objective of this research work is to propose a deraining model where the rainy drops will be removed from the scene. It is quite natural that in rainy season most of the images captured from CCTV footages will contain raindrops. And the capturing of any scenes from regular cameras will also contain rainy drops when rain is falling [1]-[4]. To the image captured in the rainy situation is a really image in most cases it is required to remove the rain drops so that the original objects behind the rain will appear. Moreover, when this CCTV footages are the images captured used in driving some autonomous process, these rainy drops will create lots of difficulty for the system to take decisions. All face recognition systems will fail if the density of rain is higher. In outstation, if the number plate direction is being done automatically it will be very difficult for the autonomous system to identify the number plates and corresponding communication to either transport or police department will be difficult. In industry applications also, if a camera is placed outdoor and if the activities being done inside of some industry, if the rain falls between the camera and operations and if the contents of the camera are being used for taking some decisions, it will create difficulty for the system when the rain is falling [5]-[8].

An example case can be detecting filled bottles in a pipeline. If a camera is placed in front of a pipeline where few bottles are being filled with some liquid and if the level of filling is being processed and controlled by the rear of the camera it will be very difficult if the rain is falling in between the camera and the inside operations. This particular case may not be a practical scenario but there exist many industrial applications where outdoor operations are being captured by CCTV footage. In the scenario, if the rain is falling the raindrops in the captured image will create uncertainty in decision making [9]-[14].

2 BACKGROUND

The rain image model can be described by the following.

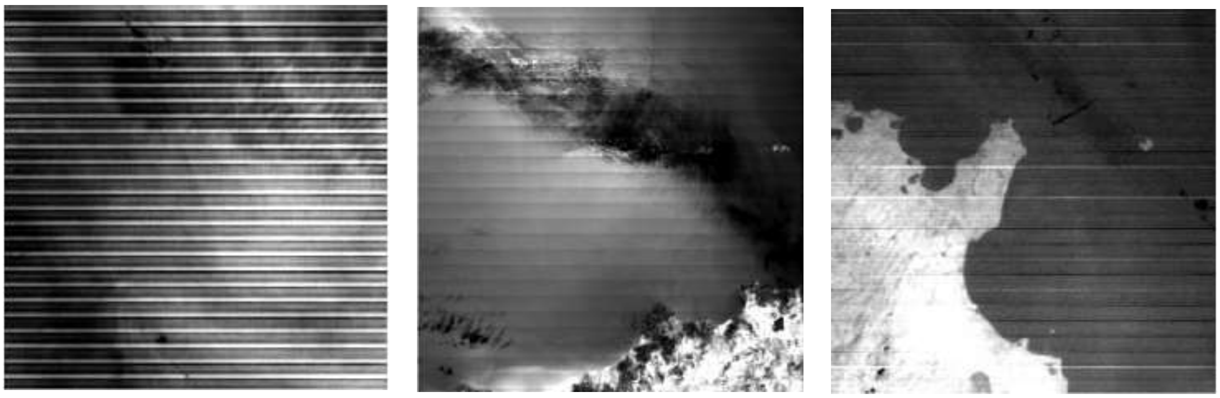
$$\mathbf{T} = \mathbf{C} + \mathbf{R} \tag{1}$$

where $\mathbf{T} \in \mathbb{R}^{M\times N}$ is the true image which is observed by the observer, $\mathbf{C} \in \mathbb{R}^{M\times N}$ is the clear image with no rain drops and $\mathbf{R} \in \mathbb{R}^{M\times N}$ 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 ways to deal the images with rain drops.

In [15], it is argued that least-squares estimation is far better than an entire ensemble of all possible pictures. In [15], it stated that, for images Total variation norm is more opt than L_2 norm. Total variation norm is an L_1 norm of derivatives. In [16], images acquired by MODIS sensor were denoised by handling striping problem using variational approach. Striping can be model 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 [17].



(a) (b) (c)

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

Fig. 2 shows two images, one a remote sensing image with stripes and another with rain streaks.

(a) (b)

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

3 Proposed Method

In this research work the sparse coding is extensively used to perform image restoration. Sparse coding is known for its application and effective performance in image Restoration in the areas of image denoising and image deblurring. In either case, in sparse coding, first the patches of high-quality images are being process to form a dictionary and consequently sub-dictionaries. The first step in Spark coding is to construct high quality natural images. These images will be divided into patches. If we have a 256x256 image, we may define 8x8 patches and extract as many patches as possible preferably without overlapping. And the cases with overlapping patches are also being explore in the literature. When 8x8 patches are extracted from 256x256 image there will be large number of patches generated. Out of this, patches which are dissimilar will be very less and similar patches will be very high in number.

So, out of these many patches, only meaningful patches will be included in further dictionary learning. This can be done this can be done by fixing some threshold and rejecting the patches which are having and average intensity level which is less than the threshold. Now we have only meaningful patches. The next step used to form clusters. Here cluster is a group of patches which are having some sort of similarity. Hence some criteria must be chosen to form clusters. This is done by calculating the equilibrium distance among the patches. By calculating the equal premium distance among the patches clusters of patches will be formed.

After having clusters of patches, the task is to choose the clusters but a specific patch of rain image. Hence it is the time to divide the input rainy image into patches. Each patch need to be processed starting from dictionary learning. Here dictionary learning refers to select the clusters of patches for a given patch of input image. This is clearly and input invariant method where dictionary will be built based on the input image. For a specific patch of the input image few clusters will be selected.

This is referred as sub-dictionary. Like this each patch of rainy image i.e., input image number of sub-dictionaries will be formed. The ensemble of all the sub dictionary is referred as dictionary. Using a dictionary which is formed using the method described just before, sparse code will be run for deraining. Energy function as mentioned earlier all the terms related to the raining or already embedded. Hence the deraining will be performed using the sparse code for individual patches.

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 raindrops 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 raindrops is less, then there will be a greater 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 raindrops is known, then the regularization term can be defined as follows.

$$R_1(R) = \begin{cases} \|R\|_0, & less\ dense \\ \|R\|_1, & high\ dense \end{cases} \tag{3}$$

This term is useful in rain drop removal. This also ensures that no additional information is lost, other than the rain drop region. This gives raise to another regularization term given below.

$$R_2(R) = \left\|\nabla_{rfd}R\right\|_1 \tag{4}$$

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.

$$R_3(R) = \left\|\nabla_{arfd}T - \nabla_{arfd}R\right\|_1 = \left\|\nabla_{arfd}C\right\|_1 \tag{5}$$

The final energy functional becomes

$$\hat{R} = argmin\left\{\lambda_0\|R\|_0 + \left\|\nabla_{rfd}R\right\|_1 + \lambda_1\left\|\nabla_{arfd}T - \nabla_{arfd}R\right\|_1\right\} \tag{6}$$

4 Simulation Results

In this section simulation results of the proposed method are presented. The first one is original image and the second one is the rainy drop image which is supposed to be over imposed on the original image to obtain a rainy image. Real time rainy image may also be taken but for performance comparison issues rainy image is simulated in MATLAB. And the last row shows the derained image using the proposed method. Simulation metrics like PSNR and structural similarity are evaluated for performance analysis. PSNR and structural similarity both are quality metrics and supposed to be high for better results. PSNR is a pixel-to-pixel comparison metric whereas structural similarity is defined in terms of statistical parameters of the overall structure.

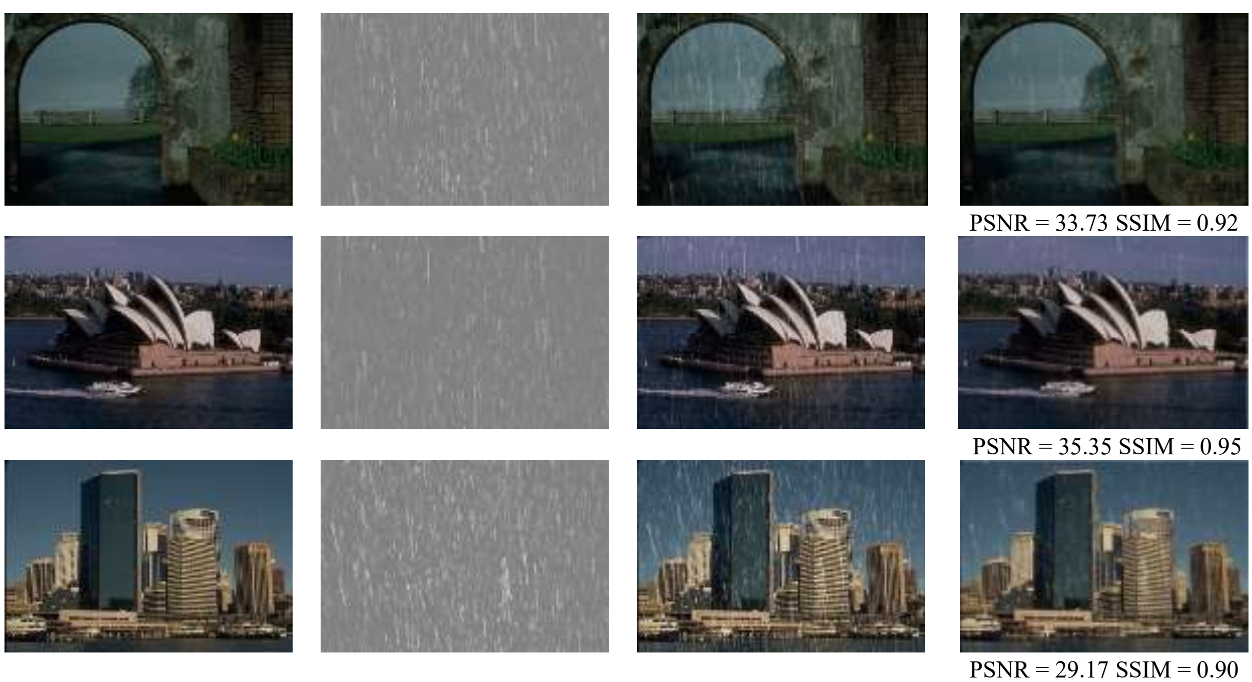


Fig. 3 Simulation Results

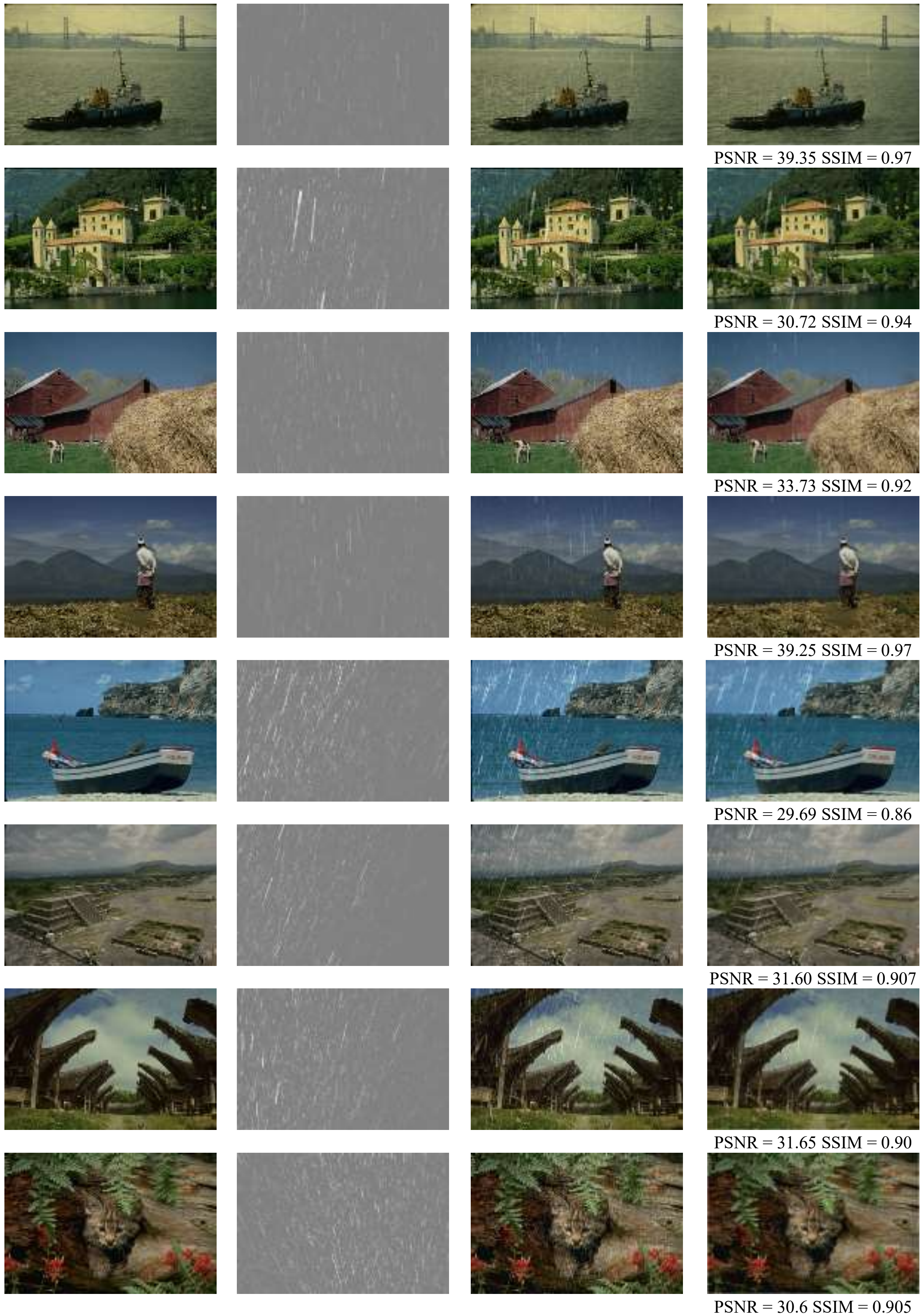


Fig. 4 Simulation Results (Continued)

5 CONCLUSIONS

In this paper single image deraining scheme is proposed using sparse code. The rain streaks on an image create difficulty of higher level for autonomous systems which takes decision. The rain streaks or normal in any CCTV footages which are placed outdoor. The video sequences out of the CCTV footages are also supposed to get derained when inspecting. In the present work the passcode was it by considering suitable regularization terms for both the raindrops and rainfall direction. Regular pass coding mechanism is used for the purpose of the raining but with different regularization terms.

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