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Transform Domain Rain Removal Methods using Dictionary Learning Approach: A Comparative Study

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***Abstract*—Rain removal from color images and videos is one of the challenging tasks in image processing. This paper proposes an efficient algorithm for the removal of rain from rainy images. This paper shows the comparison of different techniques that can be adopted to remove rain from color images. While several previous pieces of the research proposed different ways of obtaining a rain-free image by using a bilateral filter, guided filters along with the dictionary learning method, this paper proposes a different approach i.e., using hybrid l_1-l_0 decomposition for the separation of the image into low-frequency and high-frequency components. The non-rain image details are extracted from the high-frequency part based on the histogram of oriented gradient (HOG) features using dictionary learning. These non-rain details are then added to the low-frequency part to obtain the final rain-free image. This paper also shows the performance comparison of the proposed algorithm in the presence of different filters for obtaining low and high-frequency components.**

***Index Terms*— Bilateral filter, guided filter, dictionary learning, and hybrid l_1-l_0 decomposition.**

I. INTRODUCTION

The presence of undesired climatic conditions such as rain, snow, fog, mist degrades the quality of the images that are taken in those conditions. The images thus obtained will be unfit for many image processing techniques. But in the application like object tracking, surveillance the images of high quality are required. Fog and mist have a relatively smaller size compared to that of rain and snow [1]. So, they can hardly be filmed in an image. Removal of rain from images has become a great concern for researchers these days. In the process of finding a solution to this problem, researches started to study the properties of rain and started to develop different algorithms for removing rain from videos. This was followed by images much later, the reason for which lies in the ease of identification of rain pixels in videos by the observation of two consecutive frames which is absent in case of images.

The first work towards the detection and removal of rain from images and videos started from the work of Garg and Nayar [2]. They proposed a correlation model and physics-based motion blur model for rain and then they detected and removed rain from videos using this model. Recently in [3], the author proposed a fast rain removal algorithm based on a rain map. The rain map is obtained by analyzing the position of the raindrops by obtaining the difference between the two adjacent frames of a video.

Apart from the above two articles, many papers proposed algorithms to remove rain and snow from the

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videos [4]-[6]. But in the case of a single image, the detection and removal become difficult and challenging. The first attempt towards the removal of rain from images was made by Halimeh and Roser [7]. They designed an algorithm that utilizes the geometrical shape and photometric properties of raindrops. Later researchers started using some filtering methods for rain removal. A multi-guided filter-based method for rain removal from a single-color image was proposed by Belagali et al [8]. The implementation of these filtering-based methods is quite easy. But the results obtained by these approaches are not satisfactory. Either they are blurred because of excess low pass filtering or some of the image details are lost. In recent days learning-based methods are being used for the removal of rain and snow from the images. A rain removal algorithm for grayscale images using dictionary learning and Morphological Component Analysis (MCA) [9] was proposed in [10] by Mhetre and Patil. Such an approach is a two-step approach. In the first step, a well-designed filter is used to obtain low and high-frequency components of the rainy image. The low-frequency image becomes free from the raindrops but at the same time, some of the image details are also lost because of blurring. However, the high-frequency part consists of all the edge jumps due to the raindrops along with many other image details. In the second step, the image details are extracted from the high-frequency part and are added to the low-frequency image.

This paper proposes a new method for rain removal from color images which follows the same two-step approach using hybrid l_1-l_0 decomposition for obtaining low and high-frequency components. This paper also compares the performance of the proposed algorithm in the presence of three different filters for obtaining low and high-frequency components.

II. Methodology

Improving the visual appearance of an image can be done by removing the rain streaks present in the image. The paper proposes a technique for the removal of rain from a single image. Fig.1 shows the proposed framework. Here the rainy image is first decomposed into low-frequency and high-frequency images represented by IL and IH respectively. Then, with the concept of Morphological Component Analysis (MCA) the high-frequency image is decomposed based on the various types of features present in the image from which the rain and non-rain features are separated. Then, with the help of sparse coding, the non-rain image is reconstructed which is added to the low-frequency image to obtain the final image which is free from rain.

This method consists of 4 sub modules

A. Decomposition of the rainy image into low-frequency and high-frequency components.
B. Dictionary Learning.
C. Dictionary decomposition.
D. Final rain-free image extraction.

A. Decomposition of the rainy image into low-frequency and high-frequency components

Many methods can be employed to obtain different frequency components of an image. Here in this paper, a comparison is presented between three different techniques that can be employed to obtain low and high-frequency components and their impact on the results obtained. The three different techniques that are used here are

a. Bilateral Filter
b. Guided Filter
c. Hybrid l_1-l_0 decomposition.

a. Bilateral Filter:

Bilateral filter [11] [12] is used for the preservation of edges, decreasing the noise quantity present in the images and is also used for smoothening of the images. Due to these aspects, it is used in various fields. The uniqueness of bilateral filter lies in its property of filtering the image in the given range whereas other filters use the whole spatial domain for performing the same. Bilateral Filter performs the filtering operation by calculating the Gaussian weighted average of the intensity values from the surrounding pixels and replacing the obtained value for each pixel intensity.

b. Guided Filter:

Guided filter [13] performs the filtering operation on an image by preserving the edges and smoothing by taking the weights from a guidance image. The processing time taken by a guided filter is very low. The working of a guided filter can be explained as below:

$$Y(i) = ai * I(i) + bi , \quad i \in wk$$

Where, I and Y are input and output images respectively, (ai, bi) are the constants taken from the window w_i which is taken from reference image I_{ref}. For any input image I and a reference image I_{ref}, the guided filter takes the weights from the reference image and computes the output by a linear combination of the constant coefficients in the weight matrix with the input image.

c. Hybrid l_1-l_0 Decomposition:

The advantage of using a hybrid layer decomposition model [14] is the use of l_1-l_0 regularization. One of the major pros arises with the usage of the l_1 term that due to the property of irregularity rejection of l_1 term, the large gradient details of the low-frequency term are conserved. Another major merit resides in the usage of l_0 term where l_0 term is used for flattening of small insignificant variations and conserves important edges. Thus, the use of this hybrid l_1-l_0 layer decomposition method suppresses the problem of over-enhancement and the visual appearance of the image is enhanced.

B. Dictionary Learning

For any given image both the rain pixels and non-rain pixels are all present together and separation of them is a difficult task just by observing the pixel value. The dictionary learning method is the best approach for such image decompositions. All rain pixels that are present in the input image now prevail in the high-frequency component in addition to some image details which are lost in the low-frequency component. Thus, to extract non-rain details from the high-frequency component, dictionary learning is performed. Fig. 2(a) shows the representation of a dictionary of an image.

To perform dictionary learning on the high-frequency image, 16*16 patches are extracted from it and the corresponding dictionary atoms are obtained using K-SVD [15] dictionary learning algorithm. All the obtained dictionary atoms are added to the final dictionary D.

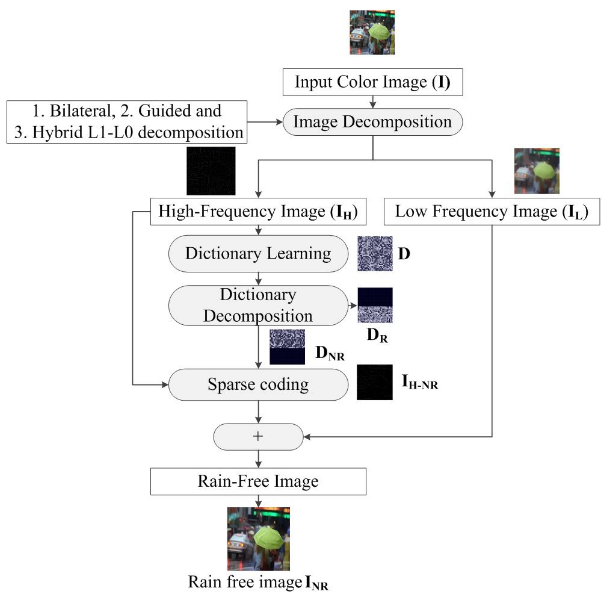

Figure 1. Proposed rain removal algorithm (where IH, IL represents high frequency and low-frequency components respectively. D, DR, DNR represents dictionary, rain sub-dictionary, and non-rain sub-dictionary respectively. IH-NR represents a non-rain high-frequency image and INR represents the final non-rain image)

C. Dictionary Decomposition

The obtained dictionary contains both rain and non-rain atoms in it. All the raindrops fall in the same direction, therefore, the gradients of the raindrops are oriented in one direction. So, HOG feature descriptors are used for the partition of rain and rain-free components. Moreover, the rain streaks and the other objects in an image are separated by an edge jump. So, the atoms with rain pixels are associated with a high average horizontal gradient. For each atom, a 1-D histogram of gradient or the edge orientations is obtained. The HOG features of all the rain atoms will be closely separated and they are largely separated from those of non-rain atoms. The joint entries of the HOG features of all the atoms represent the HOG feature of the dictionary.

By applying Fuzzy-C Means Clustering to the obtained HOG representation of the dictionary, the corresponding rain and non-rain sub-dictionaries are achieved as shown in Fig. 2(b) and Fig. 2(c) respectively, represented by D_R and D_{NR} respectively.

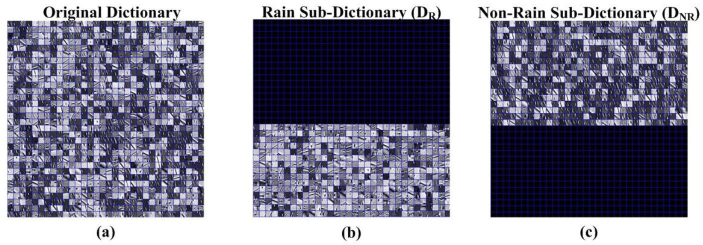

Figure 2. (a) Dictionary Representation of image, (b) Rain sub-dictionary, (c) Non-rain sub-dictionary

D. Final rain-free image extraction

The final rain-free high-frequency image $I_{H\text{-}NR}$ is obtained by sparse coding of the obtained rain-free sub-dictionary D_{NR} using the Orthogonal Matching Pursuit (OMP). This non-rain high-frequency image is added to the initial low-frequency component I_L to attain the final rain-free image I_{NR}.

III. Experimental Results and Discussion

All three decomposition techniques have been implemented on a set of 30 images and the resultant rain-free images are obtained. The results of a couple of images are shown below in Fig.3 and Fig.4 where rain removal is done by using all three techniques.

The Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Blind/Reference-less Image Spatial Quality Evaluator (BRISQUE), Perception-based Image Quality Evaluator (PIQE) and Naturalness Image Quality Evaluator (NIQE) of the obtained rain-free images are calculated and the results are tabulated. The following tables Table I, Table II, Table III show the results calculated for Bilateral filter, Guided filter, Hybrid l_1-l_0 layer decomposition techniques respectively.

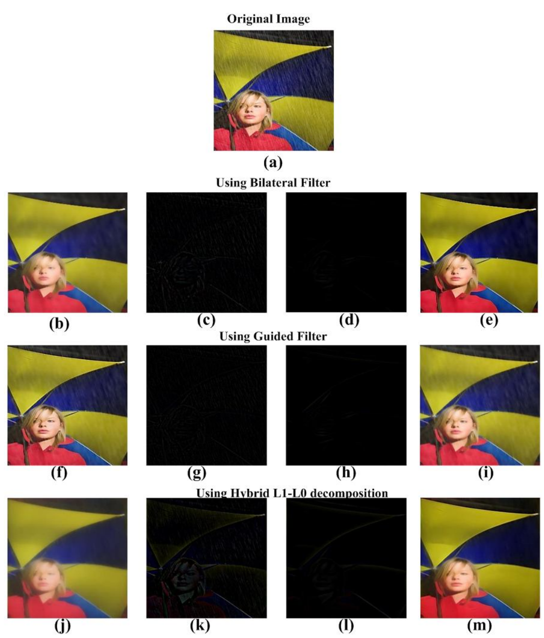

Figure 3. Results obtained for a given rain image. (a) original image, (b) low frequency using Bilateral filter, (c) high frequency using Bilateral filter, (d) non-rain high frequency using Bilateral filter, (e) rain-free image using Bilateral filter, (f) low frequency using Guided filter, (g) high frequency using Guided filter, (h) non-rain high frequency using Guided filter, (i) rain-free image using Guided filter, (j) low-frequency image using Hybrid l_1-l_0 decomposition, (k) high-frequency image using Hybrid l_1-l_0 decomposition, (l) non-rain high frequency using Hybrid l_1-l_0 decomposition, (m) rain-free image using Hybrid l_1-l_0 decomposition

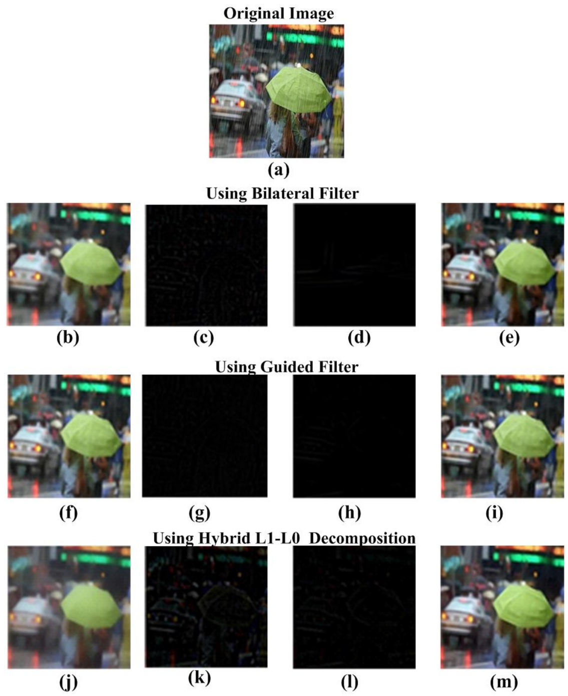

Figure 4. Results obtained for a given rain image. (a) original image, (b) low frequency using Bilateral filter, (c) high frequency using Bilateral filter, (d) non-rain high frequency using Bilateral filter, (e) rain-free image using Bilateral filter, (f) low frequency using Guided filter, (g) high frequency using Guided filter, (h) non-rain high frequency using Guided filter, (i) rain-free image using Guided filter, (j) low-frequency image using Hybrid l_1-l_0 decomposition, (k) high-frequency image using Hybrid l_1-l_0 decomposition, (l) non-rain high frequency using Hybrid l_1-l_0 decomposition, (m) rain-free image using Hybrid l_1-l_0 decomposition

TABLE I. PSNR, MSE, BRISQUE, PIQE, AND NIQE FOR RESULTANT IMAGES OBTAINED USING BILATERAL FILTER.

Image	PSNR (dB)	MSE (%)	BRISQUE	PIQE	NIQE
Fig. 3.	23.82	0.50	38.50	59.92	4.07
Fig. 4.	24.13	0.39	45.02	84.62	7.52

TABLE II. PSNR, MSE, BRISQUE, PIQE, AND NIQE FOR RESULTANT IMAGES OBTAINED USING GUIDED FILTER.

Image	PSNR (dB)	MSE (%)	BRISQUE	PIQE	NIQE
Fig. 3.	30.56	0.57	23.72	31.65	3.97
Fig. 4.	30.92	0.38	46.17	60.85	6.08

TABLE III. PSNR, MSE, BRISQUE, PIQE, AND NIQE FOR RESULTANT IMAGES OBTAINED USING HYBRID L_1-L_0 DECOMPOSITION.

Image	PSNR (dB)	MSE (%)	BRISQUE	PIQE	NIQE
Fig. 3.	24.16	0.56	31.51	54.68	6.65
Fig. 4.	24.86	0.36	42.12	73.69	6.92

By analysing the obtained resultant rain-free images from the three decomposition methods, one could say that the clarity of the rain-free image obtained as a result of usage of the bilateral filter is over enhanced, because of which small particles are also enhanced which are not necessary, so it still contains some of the rain left in it. While resultant rain-free images obtained by the usage of decomposition using hybrid l_1-l_0 decomposition is free from rain to a much greater extent.

IV. CONCLUSION

This paper thus presents a comparative analysis of the three techniques that can be employed to remove rain from color images and the corresponding results are shown. Dictionary learning based sparse coding is performed to obtain the non-rain component from the high-frequency image. The non-rain image obtained from the high-frequency component thus obtained is added to the low-frequency component to obtain the final rain-free image. The final rain-free image results are shown. It is observed that the results obtained by using hybrid l_1-l_0 decomposition are completely free from the rain pixels while those obtained from the other two techniques have some rain factor in it. However, the parametric values of the results namely PSNR, mean square error, BRISQUE, PIQE and NIQE values of the results obtained from all the three techniques are comparable.

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