

# Rain Streaks Removal in digital images by Dictionary based sparsity process with MCA Estimation

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## Abstract

During the rainy season, many public outdoor crimes have been caught through video surveillance, and they do not have complete feature information to identify the image features. Rain streak removal techniques are ideal for indexing and obtaining additional information from such images. Furthermore, the rain substantially changes the intensity of images and videos, lowering the overall image quality of vision systems in outdoor recording situations. To be successful, the elimination of rain streaks in the film will require an advanced trial and error method. Different methods have been utilized to identify and eliminate the rainy effects by using the data on photon numbers, chromaticity, and probability of rain streaks present in digital images. This research work includes sparse coding process for removing rain streak by incorporating morphological component analyses (MCA) based algorithm. Based on the MCA algorithm, the coarse estimation becomes very simple to handle the rain streak or impulsive noisy images. The sparse decomposition of coarse is possible by estimating and eliminating all redundancies from the sources. This novel MCA approach is combined with sparsity coding process to provide better PSNR and less MSE



results from the reconstructed images. This method is compared with of the existing research works on rain streak removal process. Besides, the obtained the results are illustrated and tabulated.

**Keywords:** Rain streak removal, sparse representation process

## 1. Introduction

Most computer vision and image processing algorithms make assumptions about scene clarity and visibility in digital images. Regardless, bad weather should always be considered while photographing outside. Rain produces various types of vision reduction [1-3]. A raindrop that falls and flows on a camera lens or a windshield may cause several issues with the background: it can obscure, distort, and/or blur the picture. Rain streaks caused by distant thundershowers accumulate across the landscape, distorting vision in the same way as fog does, that is, by scattering light and scattering light, reducing perceptibility. Specular highlights, scattering, and blurring may occur in the vicinity of nearby rain streaks, leading to lower visibility owing to the rain streaks' specular highlights, scattering, and blurring effects [4-6]. In figure 1, we see that rain streaks result in a diminished vision.



**Figure 1.** Rain Streaks Image

Images are used in film production and criminal convictions, where both benefit from image processing methods. Image enhancement uses rainfall streak removal, which is a key technique for that process [7, 8]. A number of the inventions have established a connection to the dynamics-correlation of rain droplets detection and removal in movies [9]. Digital edge artifacts such as noise, blur, and haze are the primary target of image smoothing process. For sharpness and clarity, the image smoothing method maintains the features at the edges while enhancing the visual resolution. Unwanted signals (such as noise) are the signals that interfere with the picture, and this happens mainly due to mistakes in the image capturing process [10]. A random fluctuation in image signal levels may produce noise in images.



**Figure 2.** Example of Removing of Rain Streak from the Image

The picture becomes blurred when the edges are blurred by lowering the contrast and this gives a very smooth transition from one hue to the next. When we can see all the items and their

forms clearly in a picture, the image appears more detailed [11-13]. An excellent example is when a facial image has sharpness to the eyes, nose, ears, etc. Since then, we can recognize the eyes, nose, ears, etc. extremely well. The edge of the item becomes more responsible. Dust and smoke tend to accumulate from relatively dry air, leading to haze [14].

The air can become dangerously polluted when the atmosphere is saturated with smoke and other pollutants. Because of this, when weather conditions prevent the spread of smoke and other pollutants, they concentrate and form a low-hanging shroud that impairs visibility and could pose a respiratory health risk. Air pollution from industrial activities may produce a thick cloud known as smog. Haze is usually defined as a natural meteorological phenomenon caused by dry particles in the air, including dust, smoke, fog, sand, snow, and other dry particles. To capture a picture, the purity of the sky cannot be seen, owing to the hazy nature of the atmosphere [15].

## **2. Organization of the Research**

The rest of the research paper is organized as follows: Section 3 provides existing research works on rain streak removal from digital images. Section 4 discusses about the proposed work for developing an efficient streak removal algorithm. Section 5 gives a discussion about the results obtained from the proposed work. The final section concludes and provides future possible enhancements to the research paper.

## **3. Preliminaries**

A technique for detecting rain combines both temporal and chromatic characteristics were developed by Zhang et al. [16]. Barnum et al. have used a blurred Gaussian model to predict how the rain or snow streaks would perform. In the frequency space of many frames, the amount of rain and snow may be determined by using statistical information [17].

It was suggested in a paper by Bossu et al. (2011) with cloud removal might be achieved by using foreground separation and selection criteria. By using these techniques, rain or snow may be completely removed from movies. However, these techniques are not applicable to a single image since there is no temporal information for reference. Thus, it is harder to complete the job with a single picture [18].

Rain streaks, as well as the borders of background objects, are seen in the high-frequency component. Sparse coding-based dictionary learning using HoG features is used to try to extract the rain streak frequencies from the high-frequency layer. Low-frequency and processed high-frequency layers combine to produce the output. Even while the process can remove the non-oriented snowflakes, it can't remove the non-orientation snowflakes [19]. Researchers Xu et al. have suggested a technique that uses a computerized filter to exclude rain or snow [20].

Garg and Nayar demonstrate a different technique that utilizes the ability to influence the operating settings of a video camera while shooting a wet scene. To this aim, they demonstrate that exposure duration and depth of focus in cameras affects the visibility of rain in photographs. Reducing the look of rain streaks will be achieved by changing these settings while keeping the video's perspective constant [21].

Rain detection that was suggested by Bossu et al. in the last several years uses a histogram to approximate streak orientations. The key concept is to transform histograms of rain into Gaussian distributions to isolate them from the noise created by other dynamic objects. To produce the histogram, the technique utilizes background subtraction [18].

To get rain streaks, Kim et al. first assume the elliptical form and the vertical direction of the rain then use nonlocal mean filtering to remove identified streaks. Individual rain streaks are detectable if their orientations, scales, and densities are consistent. However, in most situations,

identifying individual rain streaks is a challenge since the streaks may have widely varying characteristics [22].

### 3.1 Research Gap

Many techniques have been suggested to combat the rain streaks that form on the camera lens and the windshield as droplets. While the difficulties faced adhering to raindrops are very different from rain streaks, they do have some shared traits due to noises appearance. Notably, the aforementioned types of precipitation, namely static adherent droplets, are often thin than rain streaks. Currently, these issues are solved by many sparse and sparse representation processes in image processing techniques. Finally, this consideration could be a solution with good efficiency to the rain streaks issues in digital images.

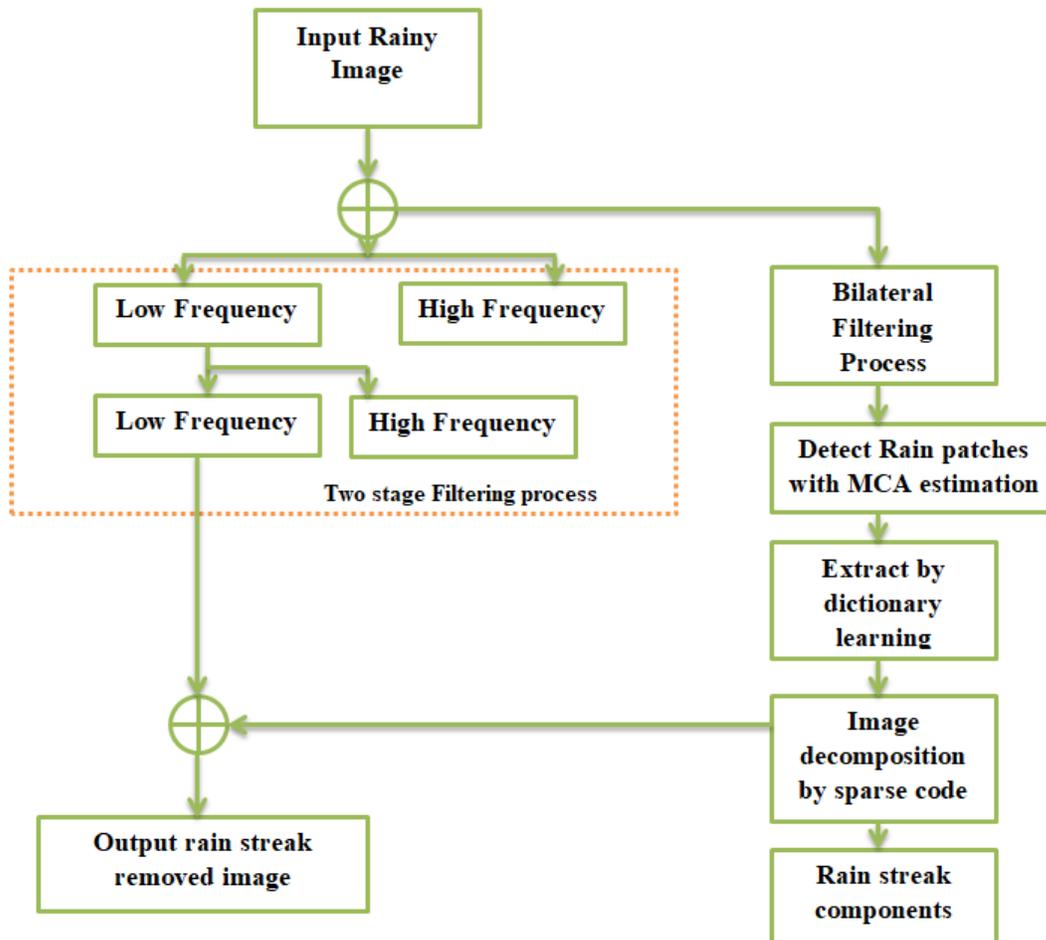
## 4. Methodologies

The research gap is fulfilled by following consideration in our proposed work;

1. It is a global dictionary to use when someone provides you with an image with either rain streaks or geometrical components that have been drawn into the picture.
2. In some of the locations of rain pictures, the geometric components are unusually combined with rain streaks and sounds. The extraction of rain streaks may be accomplished via the segmentation or decomposition method, which decomposes the picture into smaller pieces and uses those pieces to find the rain streaks.
3. The little, dispersed streaks of rain in the image reflect local area features mapped into a local patch characteristic dictionary.

#### 4.1 Sparsity Coding Process

Our sparseness in coding is a method for determining if a signal can be modelled with a sparse representation, such as with noise. For that purpose, we use a limited number of nonzero or significant coefficients, representing the dictionary's entries. Pioneering work done by Olshausen has shown that mammalian primary visual cortex cells have simple receptive fields that are spatial, orientated, and bandpass.



**Figure 3.** Overall Proposed Framework

The proposed research shows that a coding strategy that seeks to maximize sparsity is enough to account for these three properties, and it was also discovered that a learning algorithm [23] will come up with a family of localized, oriented, and bandpass receptive fields when tasked with the co-efficients of finding sparse linear codes for natural scenes. The rain removal architecture presented does not utilize any global dictionaries to separate a rain picture into its rain and non-rain components, instead of learning two local dictionaries based on training patches that extract components from a rain image [24].

## 4.2 Streak Removal Process

### Step 1:

After image registration, extract the low-frequency components from the image along with the rain streak. The high-frequency components are separated by bilateral filters.

### Step 2:

Image patches are extracted through online dictionary learning by sparse coding.

### Step 3:

This online dictionary feature is used for sparse representation.

### Step 4:

The residual features are classifying with the distinct clusters which can be applied through fixed formula.

### Step 5:

Detect the proper clusters in the online and geometric dictionary for high-frequency features through the MCA algorithm flows from input to output.

**Step 6:**

$$\theta_{HF}^k \in \min_{R^n} \|b_{HF}^k - D_{HF}\theta_{HF}^k\|_2^2$$

Where  $b_{HF}^k \in R^n$

**Remarks 1:**

This patch equation  $b_{HF}^k$  is used to reconstruct high frequency components from the input images through sparse co-efficient.

**Remarks 2:**

The dictionary-based MCA algorithms are easy to extract the features through sparse coding with patches. The actual geometric high-frequency components are removed in the rain streak region for the minimum.

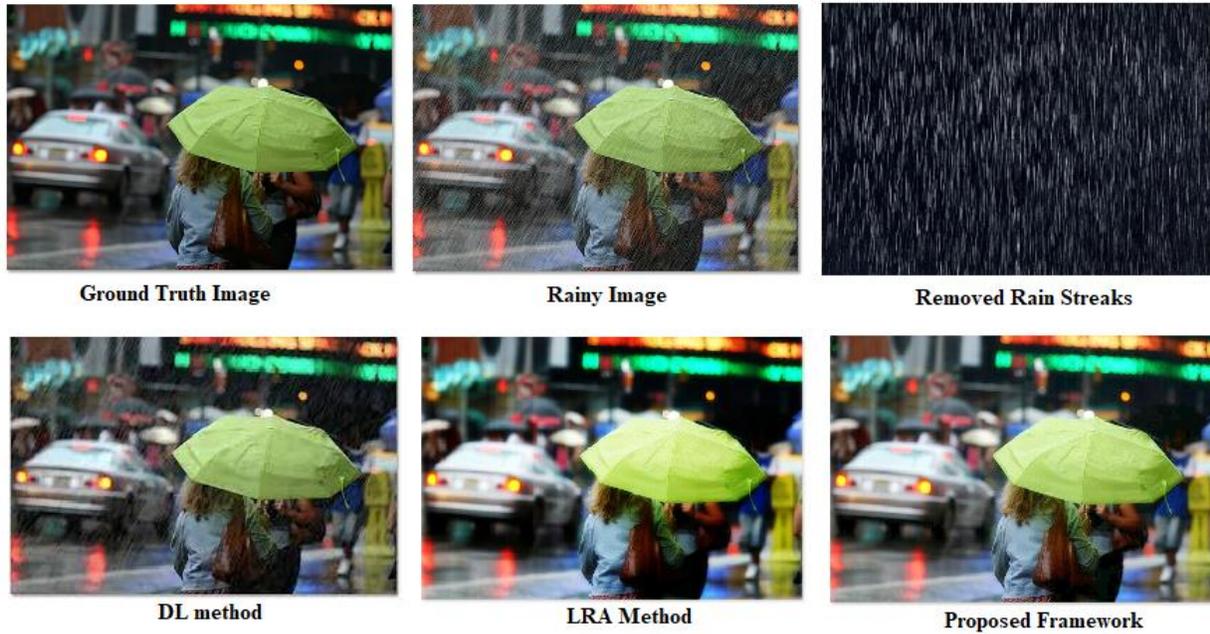
**Step 7:**

Evaluate the final performance comparison with PSNR, MSE and SSIM metrics.

## 5. Results & Discussion

Using both synthetic and actual pictures, we assessed the proposed technique and then the results are compared to those obtained by other approaches, such as the sparse representation-based dictionary learning method and low-rank appearance method (also known as LRA). The figure 4 shows our ground truth image, rainy image and rain streak alone image on the top. The bottom three pictures are showing the traditional and proposed methods in this research article.





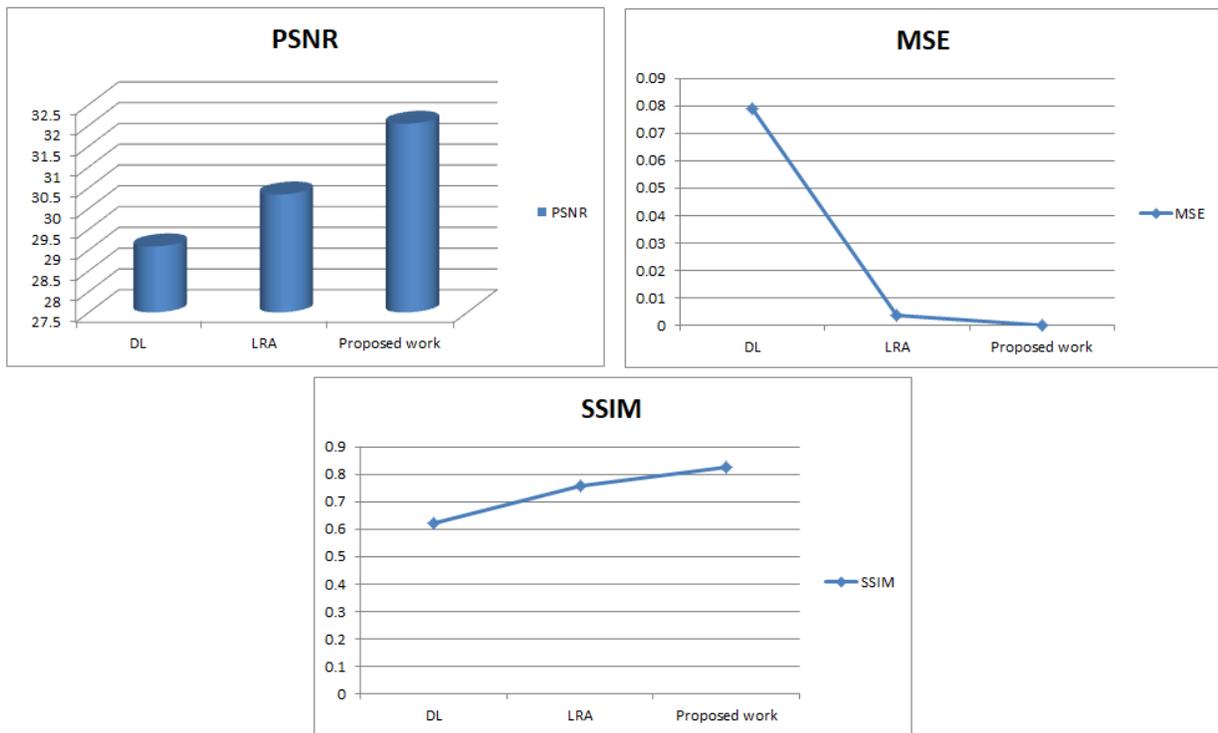
**Figure 4.** Results Obtained by Proposed Work

When we first apply the templates, it will be performed with default parameter values. We carefully followed the method given in the preceding part to implement MCA and we implemented the settings as specified to obtain the greatest overall quantitative performance.

**Table 1.** Computed Performance Metrics

S.No	Methods	PSNR(in dB)	MSE	SSIM
1	Dictionary learning method	29.09	0.07891	0.6229
2	Low rank appearance method	30.34	0.00345	0.7554
3	Proposed hybrid Sparsity coding	32.04	0.00016	0.8245

Using pictures as ground truth for synthetic data enables us to calculate SSIM and PSNR on the luminance channel (in both two metrics, a larger number indicates closer proximity to the ground truth). When error minimization is the goal, the MSE values are calculated. In the graph (Figure 5), clearly shows that our proposed algorithm is better performance than other traditional approach. Figure 4 also shows the better visual through our proposed work.



**Figure 5.** Overall Performance Graph

The performance metrics formulas are following,

$$PSNR = 10 * \log \left( \frac{255^2}{MSE} \right)$$

$$MSE = \frac{1}{M * N} \sum_{i=1}^N \sum_{j=1}^M [I(i, j) - \hat{I}(i, j)]^2$$
$$SSIM = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

## 6. Conclusion

Thus, the proposed work shows superiority in PSNR value from the reconstructed images. Besides, the MSE values are fewer than in other traditional approaches. The obtained images are very clear from the noisy image set. Due to perfect coarse estimation, the image is getting sparse free parameters from the rain streak. Since, actual rain is diverse and complicated; creating a unique framework to house the combination of model-driven and data-driven approaches is a challenging task. The strategic long-term view is known as the deep unroll approach, which has the potential to expand networks with greater explain ability and transferability. In the future, we should prioritize efficiency and real-time requirements to effectively support actual applications. Low temporal and spatial complexity and universality are particularly important for videos (available for complex video scenes). To quickly evaluate one picture, a rapid test speed is required [25-27].

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