QUALITY ASSESSMENT OF IMAGES AFTER RAIN REMOVAL

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ABSTRACT

Rain removal from images is an essential task and has been recently examined. Rain represents sharp power variations in images, which corrupt the quality as well as execution of outdoor vision systems. Hence firstly rain streak removal from images and then quality assessment of images after removing rain from it is very important. Quality assessment measures the perceived image degradation compared to an ideal or perfect image. In this paper the fundamental objective is to use a single-image-based rain removal framework via properly formulating rain removal as an image decomposition problem based on morphological component analysis (MCA) and then Quality assessment of rain removed image is done. After removing rain from images it is necessary to correlate with the perceived quality of an image. Hence quality assessment of rain removed images is performed by using various parameters.

Keyword: - *Rain Component, Rain detection and Rain removal, Bilateral Filter, Morphological Component Analysis (MCA), Quality assessment*

1. INTRODUCTION

Climate conditions i.e. rain, snow, mist, fog and haze decrease the quality as well as execution of outside vision framework. Rain is one of the kinds of climate condition and additionally rain is the real part for the dynamic bad climate[1]. Rain presents sharp intensity variations in pictures, which corrupt the quality or execution of outside vision frameworks. Rain removal has numerous applications in the field of security observation, vision based navigation, video or movie editing and video indexing or retrieval. In this way, it is vital to expel rain streaks from the pictures. The discovery and expulsion of rain streaks in a picture is performed by different techniques. After Removal of rain streaks and quality measurement, it is possible to effectively remove the rain components in the picture.

Now days, image de-noising is an important process in image processing. The proposed method focuses on rain streak removal frame work based upon morphological component analysis[2]. Bilateral filter is used in the de-noising stage. Then the filtered image is partitioned into low frequency and high frequency component. The high frequency component had undergone various processes such as patch extraction, dictionary learning and dictionary partitioning and sparse coding. The output of dictionary partitioning approach undergone morphological component analysis as an image decomposition process. As a result, the quality of rain removed image is checked via parameters such as MSE (Mean square error), PSNR (Peak signal to noise ratio) and SSIM (Structural similarity index). Image quality is a normal for an image that measures the perceived image degradation (compared to an ideal or perfect image). Imaging frameworks may present a few measures of distortion in the signal, so the quality assessment is an essential task. Hence the rain component can be successfully removed from the image while preserving most of the original image details by performing quality assessment of rain removed images.

In this paper, we investigate the problem of image de-noising. Here, the theory of morphological component analysis is employed to separate the image to be de-noised into some layers with different morphological components. In this paper, images are decomposed into two parts: smooth and textural parts. As noise only exists in the textural parts, we utilize bilateral filter to smooth textural parts. Finally, the smooth parts and the filtered textual parts are combined to get the image free of noise. The algorithm is tested experimentally, and the results show that it is superior to other state-of-art algorithms.

2. LITERATURE REVIEW

Due to the importance of rain removal, Researchers have developed a number of methods and several rain removal techniques. The literature survey of few of them is as follows:

Li-Wei Kanget, Chia-Wen Lin, Yu-Hsian Fu, et.al.[2], proposed a single-image-based rain removal framework via properly formulating rain removal as an image decomposition problem based on morphological component analysis. Instead of directly applying a conventional image decomposition technique, the proposed method first decomposes an image into the low- and high-frequency (HF) parts using a bilateral filter. The HF part is then decomposed into a "rain" and "non-rain component" by performing dictionary learning and sparse coding. As a result, the rain component was successfully removed from the image while preserving most original image details. They proposed a single-image-based rain streak removal framework by formulating rain removal as an MCA-based image decomposition problem solved by performing sparse coding and dictionary learning algorithms. The dictionary learning of the proposed method is fully automatic and self-contained where no extra training samples are required in the dictionary learning stage.

De-An Huang, Li-Wei Kang, Yu-Chiang Frank Wang, and Chia-Wen Lin et.al.[3], described the Deterioration of an image into multiple semantic components that has been an effective research topic for various image processing applications such as image de-noising, image enhancement, and image in-painting. In this paper, they have presented a novel self-learning based image decomposition framework. Based on the recent success of sparse representation, the proposed framework firstly learns an over-complete dictionary from the high spatial frequency parts of the input image for reconstruction purposes. Also they proposed framework that first observes the dictionary atoms from the input image for image representation.

Duan-Yu Chen, Chien-Cheng Chen, Li-Wei Kang et.al.[4],they proposed a single-color image-based rain removal framework by properly formulating rain removal as an image decomposition problem based on sparse representation. In their framework, an input color image was first decomposed into a low-frequency part and a high frequency part by using the guided image filter so that the rain streaks would be in the high-frequency part with non-rain textures/edges, and the high-frequency part is then decomposed into a rain component and a non-rain component by performing dictionary learning and sparse coding. In the future work, the proposed method can be extended to color-video-based rain streak removal.

Qingsong Zhu, JieYuan, Ling Shao et.al.[5], presented that Rain removal from videos is among the key technologies in image processing and video surveillance because of the complex visual effects caused by rain. With the rapid development of computer vision technologies, rain removal has attracted increasing interests in both academic and industrial communities. In this they firstly reviewed the main rain removal methods by classifying them into four categories based on the exploited rain properties. Some possible Challenges are also pointed out. And then, some constructive suggestions and prospects for the future research are brought forward.

Yi-Lei Chen, Chiou-Ting Hsu et.al.[6], showed an algorithm to remove rain streaks from single color image. Firstly, the guided filter, cooperated with rain pixel detection is used to separate a color image into low-frequency and high-frequency parts so that most rain components exist in the high-frequency part. Then, they focused on the high-frequency part to extract the non-rain details according to the characteristics of the rain for which a dictionary learning method is used. The simulation results showed that the proposed method can remove rain, especially heavy rain from single image more efficiently than some other state of the art methods.

Yu Luoet, Yong Xu, Hui Ji et.al.[7], aimed at developing an effective algorithm to remove visual effects of rain from a single rain image, i.e. separate the rain layer and the de-rained image layer from a rain image. Built upon a non-linear generative model of rain image, namely screen blend model, they proposed a dictionary learning based algorithm for single image de-raining. The basic idea was to sparsely approximate the patches of two layers by very high discriminative codes over a learned dictionary with strong mutual exclusivity property. Such discriminative sparse code gives accurate separation of two layers from their non-linear composite. The experiments showed that the proposed method outperforms the existing single image de-raining methods on tested rain images.

Zhou Wang, Eero P. Simoncelli and Alan C. Bovik et. al.[8], showed that the measure of structural similarity can provide a good approximation to perceived image quality. They proposed a multi-scale structural similarity method, which supplies more flexibility than previous single-scale methods in incorporating the variations of viewing conditions. Also developed an image synthesis method to measure the parameters that define the relative necessity of different scales. Experimental comparisons demonstrate the effectiveness of their proposed method.

Nisha, Sunil Kumar et. al.[9], proposed that, Image quality assessment is a fundamental and challenging problem with many interests in a variety of applications, such as dynamic monitoring and adjusting image quality, optimizing algorithms and parameter settings of image processing systems, and benchmarking image processing system and algorithms. So full reference(FR) methods like structural similarity index metric(SSIM),mean structural similarity index metric(MSSIM) are more efficient because some mathematical formula like peak signal to noise ratio(PSNR), mean square error(MSE) become unstable if image has a significant amount of degradation.

3. SYSTEM ARCHITECTURE

The fundamental objective of removal of rain streaks in an image is that it completely removes the rain streaks from the image while it preserves the original (non-rain) image as it is. Firstly in the removal of rain streaks from an image there is use of MCA as image decomposition[23]. Morphological Component Analysis (MCA) will use to separate the texture from the natural part in images. The important idea of MCA is to decompose the different features contained in the data or in the image. Removal of rain streaks is done by MCA based image decomposition by performing dictionary learning and sparse coding. Also Image Quality assessment plays an important role in various image processing applications. It is still an active area of research. It helps greatly to measure the perceived quality of an image. In this paper quality assessment is performed by using Means square error, Peak signal to noise ratio and Structural similarity index.

This System consists of five modules:
1. Decompose image into LF and HF parts using bilateral filter.
2. Patch Extraction and Dictionary Learning.
3. Dictionary Partition.
4. Image Decomposition via Sparse Coding.
5. Integration of Non-rain component and LF Image.
6. Quality assessment of rain removed image

The steps for removal of rain streaks:

Step-1: Preprocessing
For the input rain image in the pre-processing step we have to apply edge preserving smoothing filter called bilateral filter[13]. Smoothing filter is edge preserving and noise-reducing filter. After applying smoothing filter the input rain image is decomposed into LF (Low-frequency) and HF (High-frequency) part, where the basic information is in the low frequency part while the rain drops or rain streaks and the other edge or texture information will be in the high frequency part of the image.

Step-2: Patch extraction
For learning dictionary of HF part (DHF) a set of overlapping patches are extracted from HF part. Then separate atoms in the dictionary into two sub-dictionaries for representing rain component and textural component of HF part[21].

Step-3: Partitioning

For representing the rain and geometric component of HF part, the atoms which consists of dictionary of HF part is divided into two sub-dictionaries i.e. rain and geometric sub-dictionaries. Image gradient is used for extracting the most significant feature of rain atom[20]. The HOG (Histogram of Oriented Gradient) feature descriptor is used to describe each atom in DHF.

Step-3: Removal of rain streaks

Sparse coding is implemented on these two sub-dictionaries for finding sparse coefficients for each patch extracted from the HF part[11]. At that point we get the rain expelled version of the input rain image by joining Low frequency and non-rain image of High frequency part by separating rain component.

Step-5: Quality assessment of rain removed image

Quality index is performed on rain removed images collected from dataset. Image quality is a characteristic of an image that measures the perceived image degradation (typically, compared to an ideal or perfect image). Imaging systems may introduce some amounts of distortion or artifacts in the signal, so the quality assessment is an important problem[16].

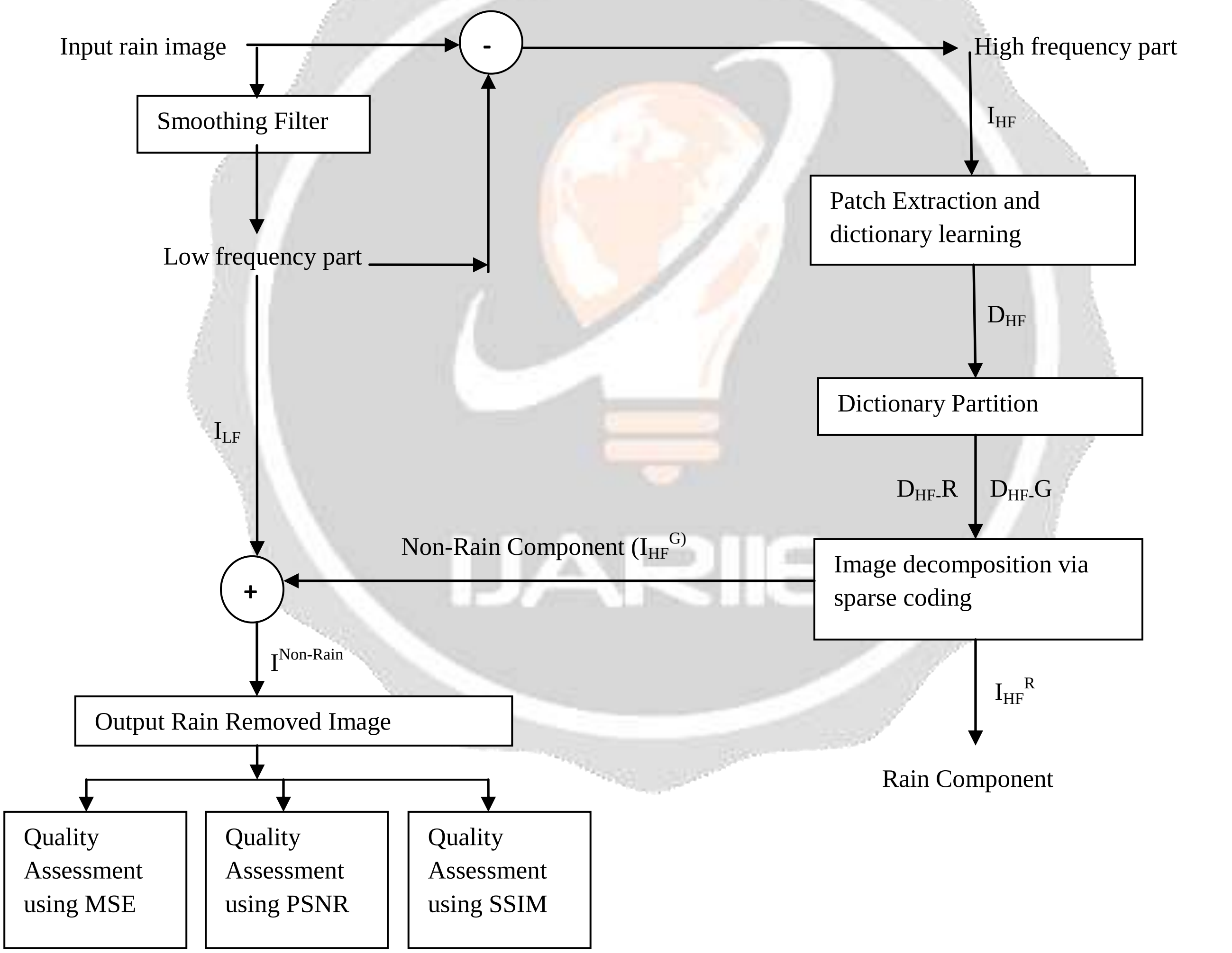

Figure1. System Architecture

4. IMPLEMENTATION

Visual changes on images due to bad weather conditions can have a bad impact on the performance of some outdoor vision systems. One of the mostly seen bad weather is rain which causes important yet complex local intensity fluctuations in images. An effective algorithm can be developed to remove visual effects of rain from a single rain image, i.e. separate the rain layer and the de-rained image layer from a rain image. In this Paper we propose a dictionary learning based algorithm for single image de-raining[23].

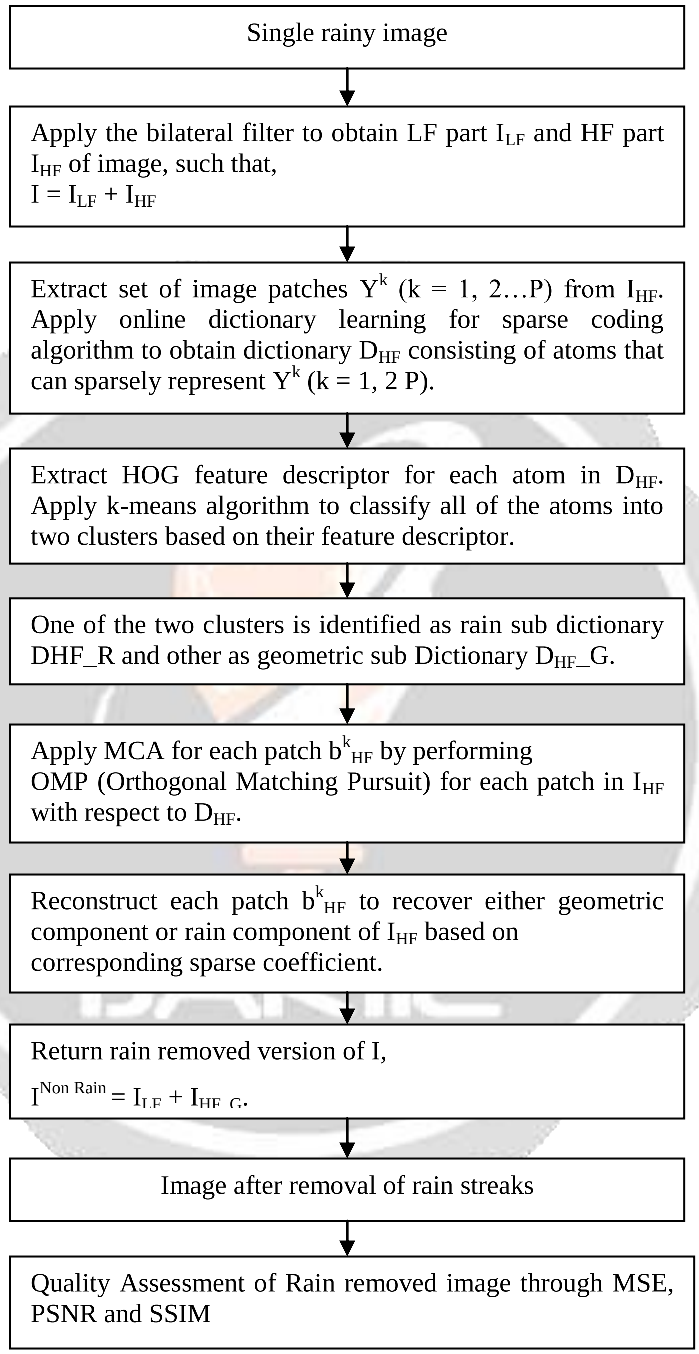

Figure 2: General Algorithm for Rain Detection

The basic idea is to sparsely approximate the patches of two layers by very high discriminative codes over a learned dictionary with strong mutual exclusivity property. Such discriminative sparse codes lead to accurate separation of two layers from their non-linear composite. The experiments show that the proposed method outperforms the existing single image de-raining methods on tested rain images. The quality assessment of rain removed images is performed through following parameters:

MSE (Mean Square error): It stands for the mean squared difference between the original image and distorted image[9]. The mathematical definition for MSE is:

$$MSE= \frac{1}{MN} \sum_{y=1}^{M} \sum_{x=1}^{N} \left[I(x,y) - I'(x,y) \right]^2$$

PSNR (Peak signal to noise ratio): The PSNR is most easily defined via the mean squared error. PSNR is a classical index defined as the ratio of the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation[9]. PSNR can be calculated easily and more quickly and is therefore a very popular quality measure, widely used to compare the 'quality' of compressed and decompressed images. It is given by:

$$PSNR= 10 \log_{10} (255^{2}/ MSE) \text{ dB}$$

Where 255 is the maximal possible value the image pixels when pixels are represented using 8 bits per sample, and MSE (mean square error) is the Euclidian distance between the original and the degraded images. The major advantages of these metrics are its simplicity and mathematical tractability, but they are not correlating well with perceived quality measurement because the Human Vision System characteristics are not considered in their models. PSNR is more consistent in the presence of noise compared to the SNR.

SSIM (Structural Similarity Index): It is a novel method for measuring the similarity between two images. The SSIM index can be viewed as a quality measure of one of the images being compared provided the other image is regarded as of perfect quality. It is an improved version of the universal image quality index[10]. The Structural Similarity (SSIM) Index quality assessment index is based on the computation of three terms, namely the luminance term, the contrast term and the structural term. The overall index is a multiplicative combination of the three terms.

$$SSIM(x, y) = [l(x, y)]\, \alpha \cdot [c(x, y)]\, \beta \cdot [s(x, y)]\, \gamma$$

5. RESULT AND DISCUSSION

i. The major contribution of this paper is to detect and remove rain streaks from an image based on MCA based image decomposition by performing dictionary learning and sparse coding.
ii. For preprocessing stage bilateral filter is used which smooth's images while preserving its edges, by means of a nonlinear combination of nearby image values.
iii. After removing rain streaks by proposed method, quality index of rain removed image is checked.This gives good results as shown.
iv. The parameters evaluated for quality assessment are shown through following table.

Table: Experiment Results

Image Name	Resultant PSNR	Resultant MSE	Resultant SSIM
Rain Image 1	65.1471	0.0198779	0.8112
Rain Image 2	64.8766	0.0211555	0.949949
Rain Image 3	64.8241	0.0214127	0.936889
Rain Image 4	66.6102	0.0141925	0.83301
Rain Image 5	62.3606	0.0377587	0.879511

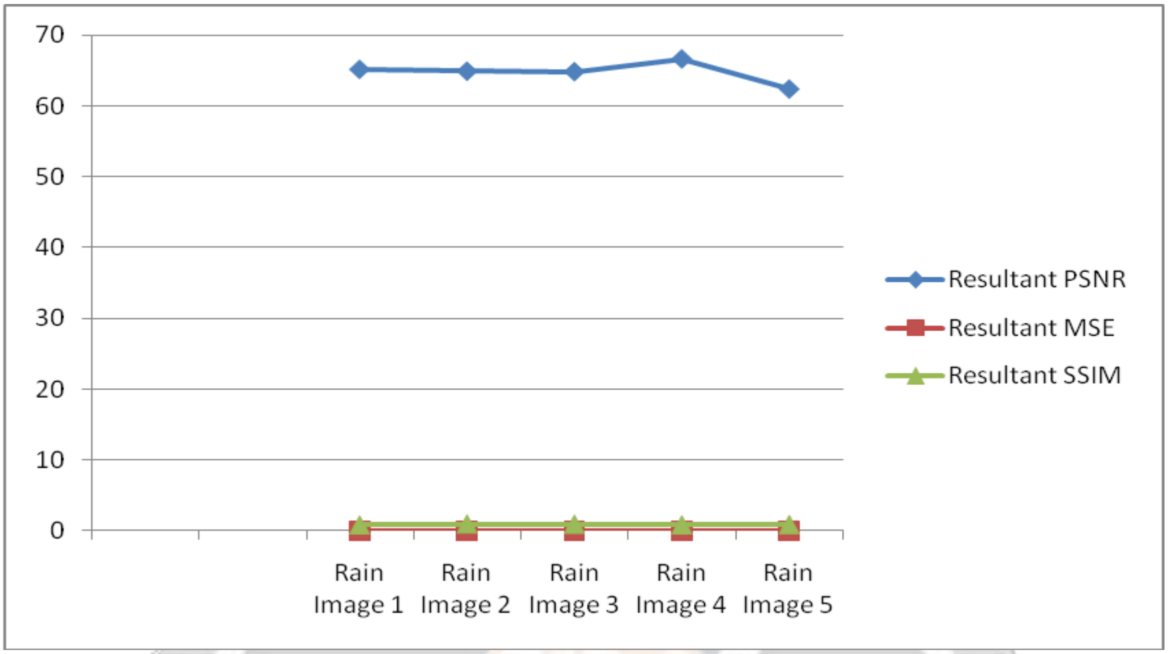

Figure 3: Curve of resultant values for MSE, PSNR and SSIM

SNAPSHOT OF EXPERIMENTAL RESULT

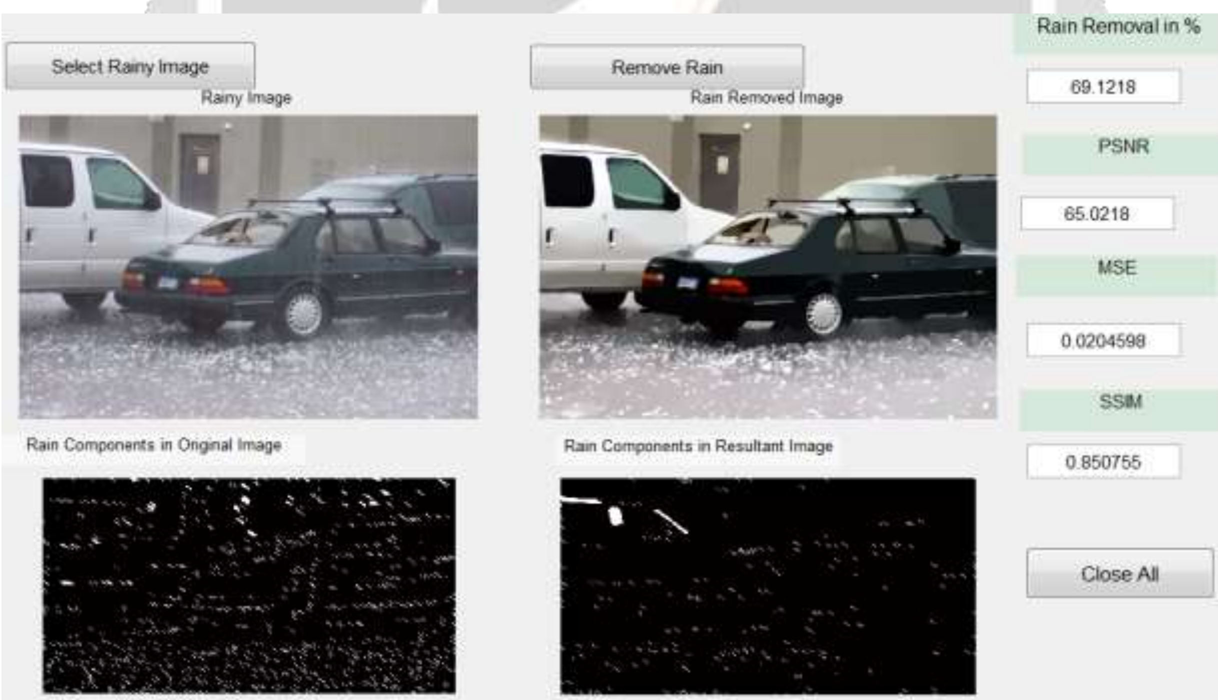

Figure 4: Rain image 1and its rain removed image with resultant values

6. CONCLUSION

This paper presents an extensive method for rain streak removal. Currently, many new schemes are proposed in the field of rain Detection. So the best method among all should be found out. The proposed method is among the efficient method of all to achieve rain streak removal while preserving geometrical details in a single frame. This is an automatic MCA-based image decomposition framework for rain steak removal. Learning of the dictionary for decomposing rain steaks from an image is fully automatic and self-contained, where no extra training samples is required in the dictionary learning stage. Many techniques are proposed for measuring the quality of an image but none of it is considered to be perfect for measuring the quality. Image quality assessment plays a crucial role in the field of image processing. In this paper quality assessment is performed using three parameters. From the estimated results it is found that a lower value for MSE means lesser error. Logically, a bigger value of PSNR is good because it means that the ratio of signal to noise is higher. Higher PSNR indicate that the reconstruction is of higher quality. From the observed results it is also seen that high PSNR values do not always correspond to signals with perceptually high quality. The Structural similarity index has been proved to be better objective quality assessment metric. Experimental results also show that improved SSIM index is closer to subjective perception.

7. ACKNOWLEDGEMENT

First and the foremost I, take this opportunity to express gratitude to my guide, Mrs. H.H. Kulkarni, for her constant encouragement and support throughout the project implementation. I sincerely thank Prof. S. P. Agnihotri, Head of Department of Electronics & Telecommunication Engineering for his advice and support during course of this work.

With deep sense of gratitude I thank to our Principal Dr. P. C. Kulkarni and Management of Gokhale Education Society for providing all necessary facilities and their constant encouragement and support. I also express my thanks to all teaching and non-teaching staff for their kind co-operation and guidance also.

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