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Image Decomposition Using Morphological Component Analysis: An Application to Automatic Rain Streak Removal of an Image

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ABSTRACT
Cloudiness, snow, or rain, haze are theclimate conditions which havingcritical visual impacts on images or videos.The performances of outdoor vision system deteriorate due to bad weather conditions. The perceptual quality of image and execution of the machine vision calculations are disturbed due to poor perceivability caused by rain in various application likedetection, surveillance, navigation and recognition tracking. The execution of open air vision system demeaned by raindrops and it creates problem item identificationand examination in a picture. Detection and removal of rain in an image is a quite critical issue because of the unpredictability of rain and its negative consequences for image. Rain streak removal widely used in various applications so it is necessary to develop algorithm to remove rain streaks from the images with preserving the original details. In this method, the detection and removal of rain streaks in an image is based on image decomposition which depends on Morphological Component Analysis (MCA) by performing dictionary learning.

INTROUCTION
Critical visual effects are present in spatial or temporal domains in images or videos due to various weather conditions [1]. Currently issue of eliminating streaks from videos is much trending [1]. A pioneering work on detecting and removing rain streaks in a video was proposed in [2], where the authors develop models for motion blur which depends on physics to identify the attributes of photometry of rain as well as catching the dynamics of rain. It was eventually shown in [3] that depth of field (DoF) and exposure time are used to retain the appearance of the scene with decreasing the proportion of effect of the rain. Furthermore, an improved video rain streak removal algorithm incorporating both temporal and chromatic properties was proposed in [4].While there is notable intensity change in a pixel through successive frames.it was supposed those pixels have good chance that rains might fall through and most of the rain streaks are relatively brighter.

In some instance, removing the rain from outdoor image is used to get original details of scene is important factor in many application. Nowadays Computer vision is a part our lives. One of the most important goals of computer vision is to achieve visual recognition. Recognition, segmentation, object detection and tracking can be used as feature information for various computer algorithms. This feature information the perceptual quality of image are degraded by dynamic climate condition and decreases the performance of k-means algorithms. A rain causes sharp intensity changes. A part hide by a falling down raindrop seems brighter than its original background. But it is difficult to detect rain only using the property of intensity changes. Because there exist so many objects which have similar linear edges with rain streaks.

Most of the rain streak removal has been done on video based approaches and with collection of training images. a few research works have focused on the more challenging task, that is, colour image based rain streaks removal [1-2] based on the actual requirement that if only a colour image is available, such as an image captured from a cell phone and camera or it might be downloaded from the Internet. In [2], a introducing work on colour image rain removal was proposed, which outlooks the rain removal task as the

image decomposition problem based on sparse characterization. In [2], a rain image was first isolate into low and high frequency parts via bilateral filtering [5]. The high frequency part was then decomposed into the rain component and non-rain component by performing dictionary learning using two associated sparse representation based dictionaries for representing rain and non-rain components, respectively. Since rain streaks customarily possess likely edge directions or gradients in an image, the rain dictionary is thus recognized by determining the variance of gradient direction for each dictionary atom. Additionally, as the rain streaks typically reveal similar and repeated patterns on an imaging scene [1], a low rank appearance model for eliminating rain streaks was proposed to seize the spatio-temporally correlated rain streaks. With the appearance model, rain streaks can be removed from a colour image or video in a uniform way.

PROPOSED RAIN STREAK REMOVAL BASED ON MCA VIA DICTIONARY LEARNING AND FEATURE SET

In this paper, The method propose a colour image based rain removal framework by formulating rain removal as an image decomposition problem based on sparse representation [6]. In this framework, an input colour image is first decomposed into low and high-frequency parts by using the bilateral filter [5] so that it can be consider the rain streak would be present in the high frequency part with non-rain textures/edges, and the high frequency part is then separated into a rain component and a non-rain component by performing dictionary learning and sparse coding. a feature set including histogram of oriented gradients (HoGs)[2], depth of field (DoF) [10], and Eigen colour [11], is employed to decompose the high frequency part. For boosting the non-rain part and retrieving rain part is done using this feature.

In the rain removal task, DoF is used as feature of the rain image. DoF [10] is calculated as a feature for a rain image. The focused subject(s) are less blurred than the rain streaks in an image. Their visual effects appears as fog and relatively weak. So employing the DoF feature is helpful for identifying the main subjects to be retained in a rain image. The rain streaks not possessing any colours so while analysing the atoms in an image for rain , they are considered to be neutral in colour. Hence, colour information is a key feature parameter. In this case the Eigen colour feature [10] is used. Similar to [2], this method is also fully automatic and self-contained, where no extra training samples are required in the dictionary learning stage. In addition, the usage of the DoF feature facilitates to enhance low frequency part of an image the qualities of the learned dictionary atoms for the high frequency part of an image and it also retrieve some non-rain information with similar orientations to the rain streaks, from the roughly reconstructed rain component.

A. Overview of Proposed Method

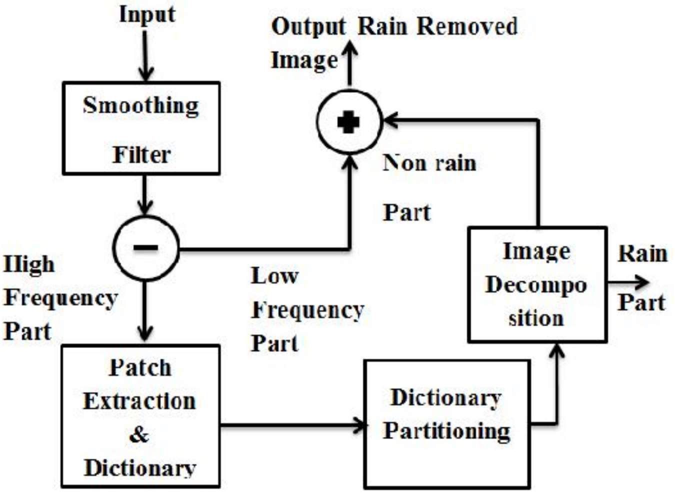

Figure.1 Block Diagram of Proposed Method

Fig.1 shows the proposed colour image based rain streak removal in which rain streak removal is performed via image decomposition. In this method, the rainy image is input image firstly parted into the low frequency

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(LF) part and the high frequency (HF) part using the bilateral filter [5], LF part contains the most basic information while in the HF part, it holds the rain streaks and the other texture details which are illustrated in Figure 1 after MCA based image decomposition, further HF part is divided into the rain component and the non-rain component. In decomposition stage, training samples are extracted from the HF part of the image that can be used to train dictionary can be divided by performing HOG [2] feature-based dictionary atom clustering into two sub dictionaries. Then, sparse coding is calculated [2] based on the two sub dictionaries to achieve MCA based image decomposition, in which the non-rain component in the HF part can be obtained, followed by integrating with the LF part of the image to obtain the rain-removed version of this image.

Isolation of the texture sample from the piecewise smoothing component can be done in inpainting applications by MCA. In general, it can be used to separate various elements which constituent unlike morphologies. The principal idea behind usage of MCA is to use the morphological diversity of the different features carried in the data to be imparted and to relate every morphology to a dictionary of atoms for which a fast transform is available.

B. Extraction of DoF

In executive photography, subjects are clearer than background or the other unfocused scenes and objects in the picture are blurred, such as rain streaks. So that, the visual appearance of rain streaks in an image would be comparatively weak and it may also act as fog. As a outcome, engaging to propose the feature and it can be named depth of field (DoF).For enhancing the performance of rain removal, Extraction of the area/region of interest (ROI) in a rainy image and simultaneously boosting the visual quality that can be perceived from rain removed images for that purpose DoF is used. The distance between the closest and farthest objects that glance satisfactorily spiky in the scene, it can be called as DoF which is shown in figure 3. In this method, to measure local correlative information in an image DoF is used. In DoF [10], The uniform blurring kernel fκ of size κ × κ (κ = {3, 5, 7} are initially enacted on the luminance component of Image then the vertical and horizontal derivatives are calculated respectively. Here the Kullback–Leibler (KL) divergence computed between the distributions for each pixel in the image. DoF is low when image is already blurred and it is not sensitive to kernel while the area under analysis is sharp as the distance between both distribution increases and probably DoF is high.

MCA-BASED IMAGE DECOMPOSITION

Suppose that Number of layers comprising of pixels of image I are superimposed. It is denoted bys^{th} component. This component can be geometric or textural component of image. The MCA algorithms [10] iteratively minimize the energy functions that can be used to decompose the image into s^{th} component. Wavelets or curvelets are traditional energy functions can be used as the dictionary for geometric component. Representation of the textural component can be done with global discrete cosine transform (DCT) basis functions are used as the dictionary. In MCA, to decompose the image into two components a crucial step is to appropriately select a dictionary built by combining two sub-dictionaries. Global or local dictionary should be mutually incoherent. Sparse representation is used to break down the global wavelet/curvelet and the global/local DCT for geometric and textural components respectively [2]–[10]-[13].

Colour Based Rain Streaks Removal Algorithm

Input:- Rainy image

Output:- Input image with removed rain streaks.

1. Low frequency part I_{LF} and high frequency part I_{HF} is to retrieve from image by employing bilateral filter, such as

$I = I_{LF} + I_{HF}$

2. The sparse coding is calculated over group of patches yk that take off from the high frequency part (k = 1,2. . P) to obtain dictionary D_{HF} consisting of atoms that can sparsely represent yk (k = 1,2 P).

3. Employ k-means algorithm for characterizing all of the atoms into two clusters based on their nature and its nature is given by HOG feature descriptor which is obtained from each atom in D_{HF}.

$$\min_{D_{HF}\in R^{n\times m},\theta^k\in R^m} \frac{1}{P}\sum_{k=1}^{P}\left(\frac{1}{2}\|y^k - D_{HF}\theta^k\|_2^2 + \lambda\|\theta^k\|_1\right)$$

4. Dictionary is made up of the two clusters from which one is said to be rain sub dictionary D_{HF_R} and other one is said to be geometric sub dictionary D_{HF_G}.

5. Orthogonal Matching Pursuit is implementing on each patch bk_{HF} for employing MCA in I_{HF} with respect to D_{HF}.

$$\min_{\theta_{HF}^k\in R^m} \|b_{HF}^k - D_{HF}\theta_{HF}^k\|_2^2 \; s.t. \; \|\theta_{HF}^k\|_0 \le L$$

6. Either geometric component or rain component of I_{HF} is reclaimed respective to sparse coefficient for reassembling each patch bk_{HF} .

7. Return image without rain.

$I_{Non\text{-}Rain} = I_{LF} + I_{HF\_G}$

DISCUSION & RESULT

Rain removal from color image by performing MCA based image decomposition via sparse coding and dictionary learning algorithms. In this method, the rainy image is input image firstly parted into the low frequency (LF) part and the high frequency (HF) part using the bilateral filter. The application ofthe bilateral filter is done with the help of spatial domain and intensity domain standard deviations in MATLAB. Spatial domain and intensity domain standard deviations set to 5 and 0.1 between 3 respectively. It guarantees that most rain streaks in a rain image can be removed. Flow the system is given in figure 2.Input image is converted into double format and resized according to input parameter given in table 1. Outcome of bilateral filter is intermediate low and high frequency part. Preprocessing is done on intermediate low frequency part as well as high pass MCA decomposition performed on intermediate high frequency part. Outputs of these processes are combined to obtained rain removed image shown in figure 3. Rain removed image undergo through DoF shifting which adjusts over all focus of the output image which leads to better quality of the image. Output parameters are calculated which are shown in table 2

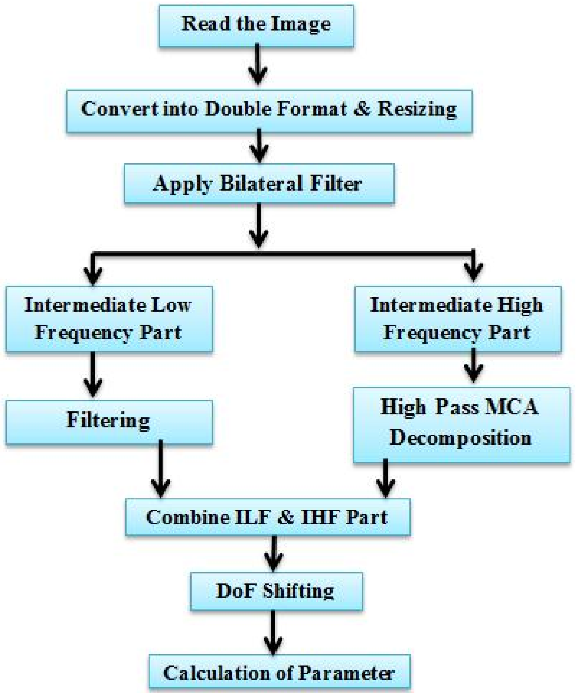


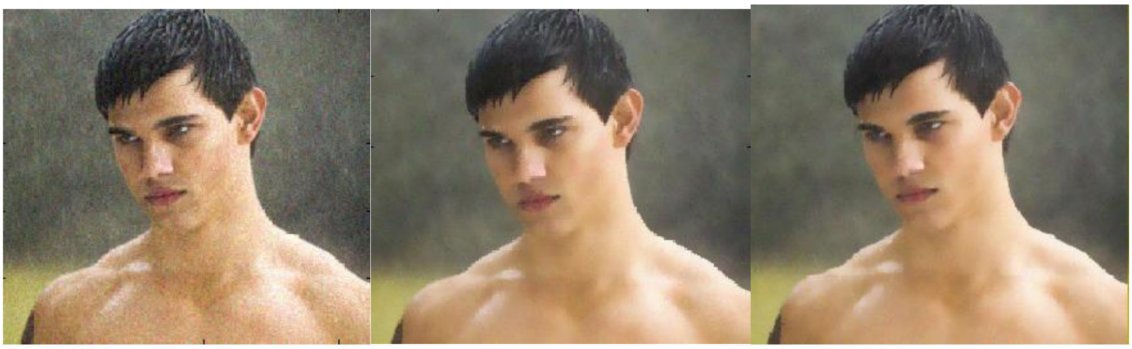
Figure No.2 Flow the function proceeds in system.

In the dictionary learning, intermediate high frequency part from input image is used to retrieve patches from it. The size of patches is as per mentioned in table 1. Dictionary is trained D_{HF} using SVD [8] algorithm is used for dictionary learning. Dictionary learned from the patches extracted from HF patch via Online Dictionary Learning algorithm. For each input image, image size, the patch size, number of training patches, dictionary size, and the number of training iterations are given in table 1. Rain component are significantly differ from the geometrical component in most parts of the image and rain streaks are generally coherent. The rain atoms and non-rain atoms from the input image contain rain atoms and non-rain atoms which is used to train dictionary itself for sparsely representing the rain and non-rain components of the image. In this case only input image sufficient to train the dictionary and it contains the rain patches that itself used to learn the rain dictionary. The gradient vector (HOG features) of rain patches in an image has similar statistics in terms of gradient magnitude and directions.

Table 1. Input parameter for all image input images remains constant.

Input Parameter	Image Height	Image Width	Patch Image	No. of Iteration	Dictionary Size	Bilateral Filter Width
For all input Image	256	256	16	100	1024	5 X 5

Orthogonal Matching Pursuit is implementing on each patch bk_{HF} for employing MCA in I_{HF} with respect to D_{HF}on two sub dictionaries, Sparse Coding isapplied using Orthogonal Matching Pursuit (OMP) for eachpatch of HF Image to find its sparse coefficient vector. Geometric and raincomponent of the image are recovered using eachconstructed patch.Non Rain Component of the HF image obtained from thisstep and low frequency image obtained in the first step arecombined to form Non-rain version of the original rainy image. Dictionary learning is self-trainedwhere no extra training samples are required. Input imageis itself used to learn dictionary. Decompositionperformance can be further improved by collecting set ofpatches from HF part of some non-rain training images tolearn extended dictionary DE.Then integrate DE with Non-rainSub dictionary DHF_G of each image to form geometricsub dictionary of the image.Better visual quality achieves with extended geometric dictionary while it also widens computationalcomplexity of sparse coding .the extended dictionary provides more non-rain atoms for sparse coding to recover rain removed version with more image details. The main reason is that D_E is a much richer dictionary learned by several non-rain image patches and can be used to speculatively recover some texture information behind the rain streaks in the rain image while applying the MCA image decomposition. the performances of system subjectively evaluated by using some output parameter mention in table 2. To analyze the quality of a rain removed image the visual information fidelity (VIF) metric in the range of [0, 1]. Visual information fidelity (VIF) is related to peak signal to noise ratio which is shown in table 2.



(a) (b) (c)

Figure 3 (a) Rainy Image (b) Rain Remved Version (c) Rain Remved Version with DoF Shifting

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CONCLUSION

In this method, rain removal from color image is implemented using image decomposition via sparse coding. A rainy color image is isolated into high frequency component and low frequency component using bilateral filter. Thehigh frequency component is then partedinto a raincomponent and a non-rain component by accomplishing sparse coding and dictionarylearning. HoGand DoF arerecruited to eliminate rain streak from HF part and also non-rain component can be enhanced.It is itself enough to train dictionary.

Table 2.Calculation of parameter for analyzing output image

Sr.No.	Input Image	Output Image	PSNR	SNR	Mean
1			13.4896	-1.0812	0.6835
2			18.6902	-0.3065	0.5005
3			12.7700	-0.6602	0.7980
4			15.4308	-0.6293	0.5791

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