ISSN: 2321-8169
4231 – 4235

Rain Streaks Removal from Single Image

Shalaka A. Mhetre, Research Scholar,
Vidya Pratishthan College of Engineering,
Baramati-413 133, S.P.Pune University
Maharashtra, India.
e-mail: mhetre.shalaka@gmail.com

Prof. P. M. Patil,
Dept of Computer Engg,
Vidya Pratishtan's College of Engineering,
Baramati-413 133, S.P.Pune University,
Maharashtra, India.
e-mail: Patil_pradeep1061@gmail.com

Prof Samir B.
National Institute of Technology,
Silchar, Assam,
India
e-mail: samirborg@gmail.com

Abstract— Rain removal from video is one of the challenging problems. There are very few methods which address the problem of rain removal from single image. Existing methods removes rain streaks from video not from single image. These methods capture non-rain data from successive images. This data is then utilized to replace rain-part in current images.
This approach removes rain streaks from single image. Morphological Component Analysis (MCA) [9 - 13] decomposes image into Low Frequency (LF) and High Frequency (HF) parts using bilateral filter. High frequency part is then decomposed into rain-component and nonrain-component by performing dictionary learning and sparse coding [2]. Non-rain component contains image features from which rain streaks are removed. Non-rain component is mixed with Low Frequency (LF) image component to form original image from which rain steaks are removed. The Morphological Component Analysis (MCA) [9 - 13] is a allows us to separate features contained in an image when these features present different morphological aspects. MCA can be very useful for decomposing images into texture and piecewise smooth (cartoon) parts or for inpainting applications.

Keywords- *Dictionary learning, image decomposition, morphological component analysis (MCA), rain removal, sparse representation.*

*****

I. INTRODUCTION

For detecting and removing rain streaks in video a correlation model is developed capturing the dynamics of the rain and physics based motion blur model characterizing photometry of rain. By adjusting camera parameters such as exposure time and depth of the field, effect of the rain streaks can be mitigated.

To remove rain streaks improves the performance of the image detection. For example, to identify pedestrians from rainy image[6]. In rainy image, not all the target objects will be detected. But performance accuracy of the rain removed version is better.

To remove noise from image, spatial adaptive filters, stochastic analysis, partial differential equations, transform-domain methods, splines, approximation theory methods, and order statistics are utilized. Use of sparse and redundant representation over learned dictionary has become one of the specific approaches for image denoising.

Before work of L.Kang,C.Ling & Y.Fu, rain streak removal has been mainly done on video based approaches that considers temporal correlation among multiple successive frames. However when only single image is available which is captures from camera or downloaded from internet such single image based rain streak removal method is needed. To add with, some video rain removal approaches based on adjusting camera parameters are not suitable for video camcorders.

Image based applications such as mobile visual search, object detection/recognition, image registration, image stitching, and salient region detection rely on the extraction of gradient based features that are rotation and scale invariant. To calculate image gradients, descriptors such as scale-invariant feature transform (SIFT) [3], speeded up robust features (SURFs) [4] and histogram of oriented gradients (HOGs) [5] – [7] are used.

Input image is rainy image and output is rain removed version of the input image [1]


(a) (b)

Fig 1: Input & Output

II. LITERATURE SURVEY

This is first approach which removes rain streaks from Single Image. Before this method rain streaks were removed from

 ISSN: 2321-8169
4231 – 4235

video i.e. a set of successive image. In this approach, non-rain atoms from successive images are captured to remove rain streaks from current image.
Before this proposed method, problem is addressed from many and diverse point of view using Spatial Adaptive filters, Approximation theory Methods [2] .

III IMPLEMENTED METHOD

Symbol	Meaning
I	Input rain Image
I_{LF}	Low frequency part of input image
I_{HF}	High frequency part of input image
D_{HF}	Dictionary learned from each patch of image
D_{HF_R}	Rain sub dictionary of dictionary D_{HF}
D_{HF_G}	Geometric sub dictionary of dictionary D_{HF}
$I_{HF}{}^{G}$	Geometric component of I_{HF}
$I_{HF}{}^{R}$	Rain component of I_{HF}
y^k	Set of image patches
$b^k{}_{HF}$	k-th image patch extracted from I

Table 1:Notations

Removing rain streaks from image improves efficiency of the image. Fig 2 shows architecture to remove rain streaks from single image. Thereare many techniques to remove rain streaks from video. This method proposes approach which removes rain streaks from single image. It uses concept of Morphological Component Analysis (MCA) [9]–[13] to decompose image based on different features of the image. Where input image is first decomposed into Low Frequency, High Frequency images. Edges are extracted from input image using edges detection algorithm.

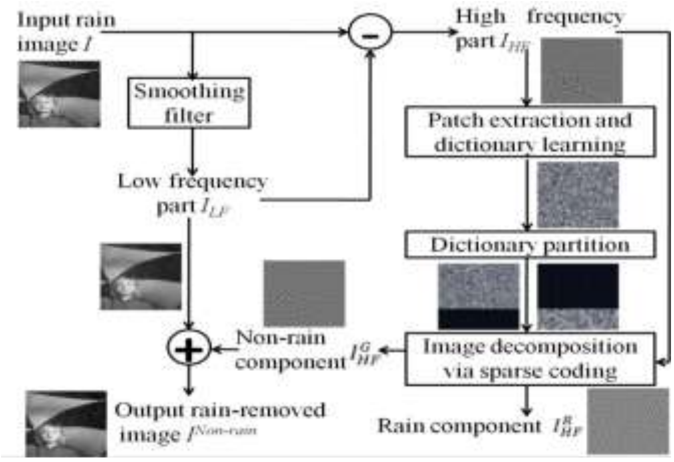


Fig. 2. Rain removal framework.

This model consists of 5 modules :
1. Decompose image into LF and HF parts using bilateral filter
2. Patch Extraction and Dictionary Learning
3. Patch Extraction
4. Image Decomposition via Sparse Coding [14] [15].
5. Integration of Non-rain component and LF Image.

1. Bilateral Filter

Low Pass Filter, High Pass Filter comprises Bilateral Filter [16] [17].Using bilateral filter image is decomposed into Low Frequency Image I_{LF} and high frequency image I_{HF} .The most basic information is retained in LF part whereas rain streaks and other texture information is included in HF part of the image. Image I is supposed to be comprised of s layers which is called as Morphological Components. In case of decomposing I into two components , main step is to select two dictionaries built by combining two
sub dictionaries D_1 , D_2 which can be either global or local dictionaries and those should be mutually incoherent.

2. Dictionary Learning

High frequency image is extracted from rainy image, patches are extracted from HF image for example 16 * 16 patches are extracted.
For each patch, dictionary is learned D_{HF} using dictionary learning algorithm-SVD [8] algorithm is used for dictionary learning.
Fig 3 shows dictionary learned from the patches extracted from HF patch via K-SVD Dictionary Learning algorithm.

Fig 3: Dictionary Learned from patch

3. Dictionary Partition

Dictionary learned in previous stage, can be further divided into two clusters which represents two components of the image rain (textural) and non-rain(geometric) component of the image. In this rain removal method, HOG descriptors [5] are used to describe each atom in D_{HF} .To extract HOG feature from the image, image can be divided into several small regions. For each region a local 1-D histogram of gradient direction or edge orientation over the pixels of cell are collected. The combined histogram entries of all the cells form HOG representation of the image.
Two sub dictionaries representing rain D_{HF_R} and Non-rain D_{HF_G} component are obtained. Below Fig 4 shows Dictionary partition. Fig (4.a) represents rain sub dictionary and fig (4.b) represents Non-rain sub dictionary.

ISSN: 2321-8169
4231 – 4235

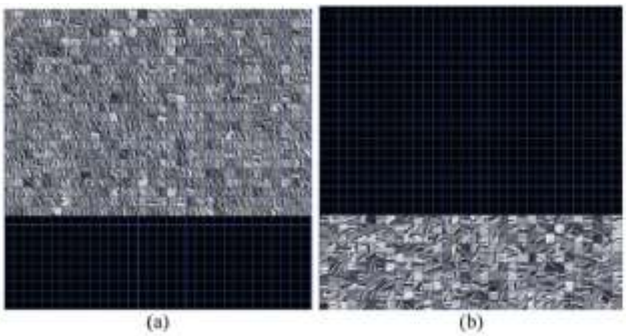


Fig 4: Rain & Non-rain Sub dictionary

4. Sparse Coding

Based on two sub dictionaries, Sparse Coding [14] [15] is applied using Orthogonal Matching Pursuit (OMP) for each patch of HF Image to find its sparse coefficient vector. Each constructed patch is used to recover either geometric or rain component of the image.
Non Rain Component of the High Frequency image is obtained from this step and Low frequency image obtained in the first step are combined to form Non-rain version of the original rainy image.

Extended Dictionary
In this approach, dictionary learning step is self explained where no extra training samples are required. Dictionary is learned from input image itself. Decomposition performance can be further improved by collecting set of patches from HF part of some non-rain training images to learn extended dictionary D_E. Then integrate D_E with Non-rain Sub dictionary D_{HF_G} of each image to form geometric sub dictionary of the image.

Algorithm: **Rain Streaks Removal from Single image**

Input: Single rainy image
Output: Input image with removed rain streaks

1. Apply the bilateral filter to obtain LF part I_{LF} and HF part I_{HF} of image, such that

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

2. Extract set of image patches y^k (k = 1,2. . P) from I_{HF} . Apply K-SVD online dictionary learning to obtain dictionary D_{HF} consisting of atoms that can sparsely represent y^k (k = 1,2 P).

3. Extract HOG feature descriptor for each atom in $D_{HF.}$ Apply k-means algorithm to classify all of the atoms into two clusters based on their feature descriptor.

4. One of the two clusters is identified as rain sub dictionary $D_{HF_R}$and other as geometric sub dictionary D_{HF_G}.

5. Apply MCA for each patch $b^k{}_{HF}$ by performing OMP(OrthogonalMatching Pursuit) for each patch in I_{HF} with respect to D_{HF} .

6. Reconstruct each patch $b^k{}_{HF}$ to recover either geometric component or rain component of I_{HF} based on corresponding sparsecoefficient.

7. Return rain removed version of I , $I^{NonRain} = I_{LF} + I_{HF\_G}$.

Step by Step result [1] is shown in Fig. 5

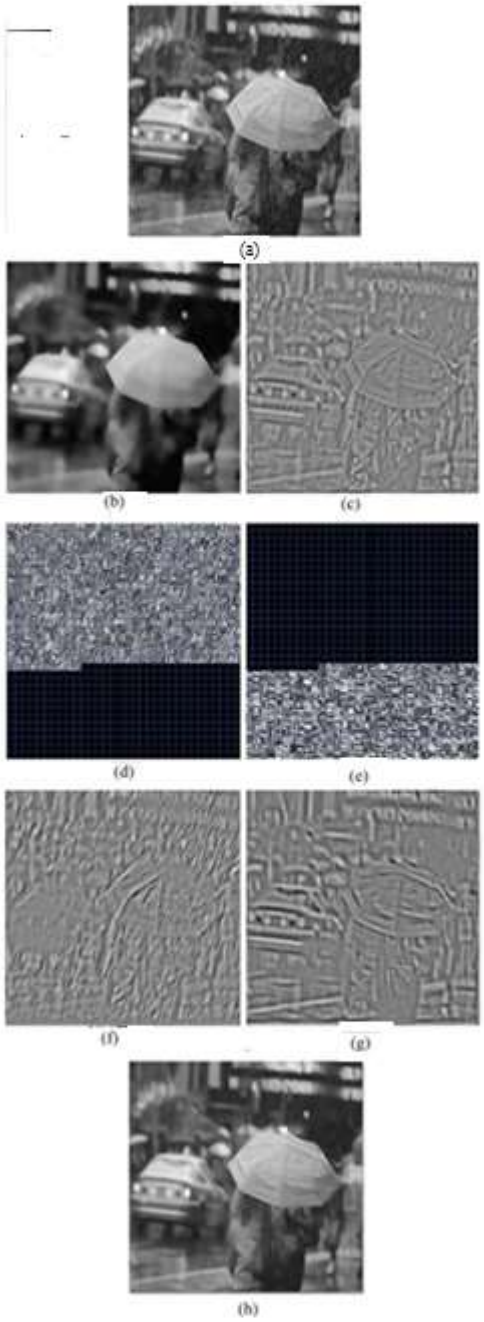


Fig 5: Step by Step result

ISSN: 2321-8169
4231 – 4235

Where

a) Input rain image
b) Low frequency part of rain image
c) High Frequency part of rain Image
d) Rain Sub dictionary
e) Non rain sub dictionary
f) Rain component
g) Non Rain component
h) Rain removed version of the image

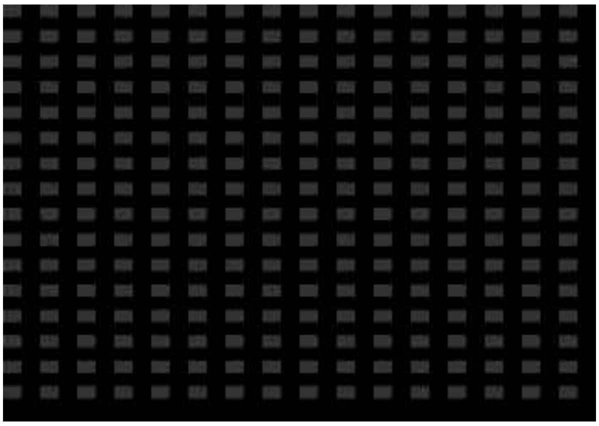
IV. RESULT ANALYSIS

The following images are the screenshots of the implemented system.
Screenshot-a shows input image. Screenshot (b),(c) shows Low Frequency & High frequency images. Screenshot-(d) shows Patched image of high frequency image. Screenshot-(e),(f) shows Rain Component & Non component of HF part of image. Screenshot (g) shows Rain removed version of input image. Screenshots (h),(i) shows improved quality of image by applying Filter & denoising techniques.

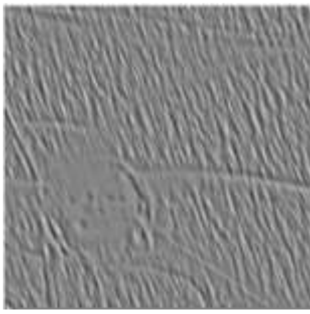
(a) Rain Image

(b) High pass image

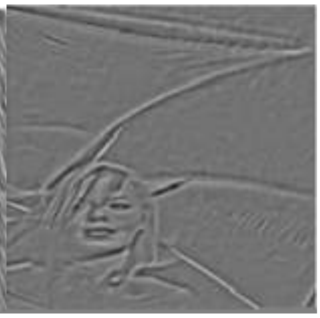
(c) Low pass image



(d) Patched Image



(e) Rain component of HF



(f) Non rain component of HF

(g) output combined with LF part(b)

(h) After Deblur

(i) After denoising (Non rain image)

Image output of my approach is compared with the output of the author's method. Please find below results.

	Our Approach
Mean Squared Error	719.0
Peak Signal to Noise Ratio	19.56

V. CONCLUSION

This approach by L.kang is among the first to achieve rain streak removal from single image, while preserving geometrical details in a single frame, where no temporal or motion information among successive images is required. This is first automatic MCA-based image decomposition framework for rain steak removal is proposed.

Learning of the dictionary [8] for decomposing rain steaks from an image is fully automatic and self-contained, where no extra training samples are required in the dictionary learning [8] stage.

REFERENCES

[1] L. Kang, C. Lin and Y. Fu "Automatic Single-Image-Based Rain Streaks Removal via Image Decomposition" IEEE Trans. Image Process, vol. 21, no. 4, April 2012

[2] M. Elad and M. Aharon, "Image denoising via sparse and redundant representations over learned dictionaries," IEEE Trans. Image Process., vol. 15, no. 12, pp. 3736 3745, Dec. 2006.

[3] D. G. Lowe, "Distinctive image features from scale-invariant keypoints," Int. J. Comput. Vis., vol. 60, no. 2, pp. 91 - 110, Nov. 2004.

[4] H. Baya, A. Essa, T. Tuytelaarsb, and L. V. Gool, "Speeded-up robust features (SURF)," Comput. Vis. Image Understand., vol. 110, no. 3, pp. 346 - 359, Jun. 2008.

[5] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., San Diego, CA, Jun. 2005, vol. 1, pp. 886 - 893.

[6] O. Ludwig, D. Delgado, V. Goncalves, and U. Nunes, "Trainable classifier-fusion schemes: An application to pedestrian detection," in Proc. IEEE Int. Conf. Intell. Transp. Syst., St. Louis, MO, Oct. 2009, pp. 1 - 6.

[7] S. Maji, A. C. Berg, and J. Malik, "Classification using intersection kernel support vector machines is effcient," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Anchorage, AK, Jun. 2008, pp. 1 - 8.12

[8] M. Aharon, M. Elad, and A. M. Bruckstein, "The K-SVD: An algorithm for designing of over complete dictionaries for sparse representation," IEEE Trans. Signal Process., vol. 54, no. 11, pp. 4311 - 4322, Nov. 2006.

[9] J. M. Fadili, J. L. Starck, J. Bobin, and Y. Moudden, "Image decomposition and separation using sparse representations: An overview," Proc. IEEE, vol. 98, no. 6, pp. 983 - 994, Jun. 2010.

[10] J. M. Fadili, J. L. Starck, M. Elad, and D. L. Donoho, "MCALab: Reproducible research in signal and image decomposition and inpainting," IEEE Comput. Sci. Eng., vol. 12, no. 1, pp. 44 - 63, Jan./Feb. 2010.

[11] J. Bobin, J. L. Starck, J. M. Fadili, Y. Moudden, and D. L. Donoho, "Morphological component analysis: An adaptive thresholding strategy," IEEE Trans. Image Process., vol. 16, no. 11, pp. 2675 - 2681, Nov. 2007.

[12] G. Peyr, J. Fadili, and J. L. Starck, "Learning adapted dictionaries for geometry and texture separation," in Proc. SPIE, 2007, vol. 6701, pp.67 011T.

[13] J. L. Starck, M. Elad, and D. L. Donoho, "Image decomposition via the combination of sparse representations and a variational approach," IEEE Trans. Image Process., vol. 14, no. 10, pp. 1570 - 1582, Oct. 2005.

[14] B. A. Olshausen and D. J. Field, "Emergence of simple-cell recep tive field properties by learning a sparse code for natural images," Nature, vol. 381, no. 65-83, pp. 607 - 609, Jun. 1996.

[15] S. Mallat and Z. Zhang, "Matching pursuits with time-frequency dictionaries," IEEE Trans. Signal Process., vol. 41, no. 12, pp. 3397 - 3415,Dec. 1993.

[16] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in Proc. IEEE Int. Conf. Comput. Vis., Bombay, India, Jan. 1998,pp. 839 - 846.

[17] M. Zhang and B. K. Gunturk, "ultiresolution bilateral filtering for image denoising,"IEEE Trans. Image Process., vol. 17, no. 12, pp.2324 - 2333, Dec. 2008.

[18] Y. Jia, M. Salzmann, and T. Darrell, "Factorized latent spaces with structured sparsity," in Proc. Conf. Neural Inf. Proc. Syst., Vancouver,BC, Canada, Dec. 2010, pp. 982–990.