

# Self-Learning Based Image Denoising and Rain Streaks Removal

B. Saranraj

Department of Electronics and Communication Engineering  
 P. A. College of Engineering and Technology  
 Coimbatore, India  
 E-mail: saranraj2011@gmail.com

**Abstract:** Image enhancement and an image denoising is the important task of an image processing applications. Decomposition of an image into multiple semantic components is used for done this task. In this paper we proposed to Self learning based image decomposition framework. In this framework first we separate the high frequency part from the input noisy image by using bilateral filter. Then learns the dictionary from the high frequency part of an image. To identify the image-dependent component with similar context information we perform unsupervised clustering on the observed dictionary atoms using Affinity propagation. Applying our proposed method we are able to automatically determine the “Gaussian noise or rain streaks” from the input image. Differ from the prior methods our proposed method does not need collection of training image data in advance. We conduct the experiments on Single-image denoising with Gaussian noise and rain streaks removal. As a result, the rain component and Gaussian noise can be removed from the image and preserving most original image details.

**Keywords:** Image Decomposition, Self-Learning, Rain removal, Denoising, Sparse representation.

## I. INTRODUCTION

An outdoor vision system is being more and more widely used and it plays an important role in traffic surveillance and military surveillance. Rain brings poor visibility at outdoor vision systems. The images acquired by outdoor vision system in rain have low contrast and noisy, it makes impossible to the process such as feature extraction and object recognition. To avoid this problem we use our proposed method for rain removal. An image is a linear mixture of multiple source components such as a texture, rain, etc.,. The proposed method identifies image component based on semantically similarity and thus can be easily applied to the application of image denoising. In this method there is no need of the collection of training image data, it advocates the self-learning of the input noisy image directly.

First we separate the high frequency part from the input noisy image by using bilateral filter. After observing the dictionary atoms with the high spatial frequency, we advance the unsupervised clustering algorithm of affinity propagation without any prior knowledge of number of clusters, which allow us to automatically identify the dictionary atoms which correspond to undesirable noise or rain components. By perform this we have to use Histogram of oriented gradients algorithm, which is used to separate rain component and non rain component. The major contribution of this paper is,

- (i) Perform Affinity propagation which identifies the similar context information;
- (ii) The learning of dictionary for decomposing rain streaks from an image is fully automatic and self contained, where no extra training samples are required;
- (iii) It preserving the most original image data

## II. PROPOSED TECHNIQUE

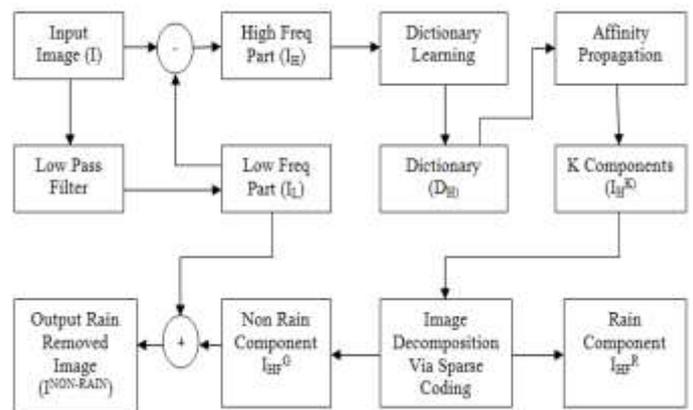
The Proposed system consists of 5 modules:

1. Decompose an image into LF part and HF part using

bilateral filter

2. Patch extraction and Dictionary Learning
3. Affinity propagation
4. Image Decomposition via sparse coding
5. Integration of Non-rain component and LF Image

## III. BLOCK DIAGRAM



## IV. BILATERAL FILTER

Using Bilateral filter an image is decomposed into Low frequency image ILF and High frequency image IHF. The most basic information is retained in LF part whereas rain streaks and other texture information is included in HF part of the image.

Apply the bilateral filter to obtain LF part ILF and HF part IHF of image, such that,

$$I = ILF + IHF$$

In case of decomposing image into two components, main step is to select two dictionaries built by combining two sub

dictionaries D1, D2 which can be either global or local dictionaries and those should be mutually incoherent.

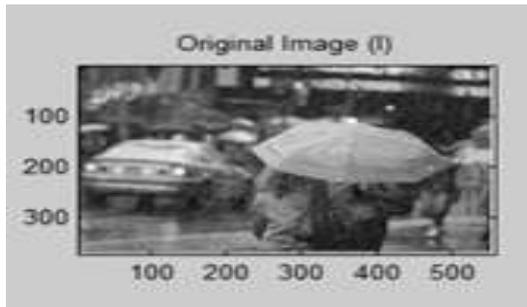


Figure1. Original Image(I)

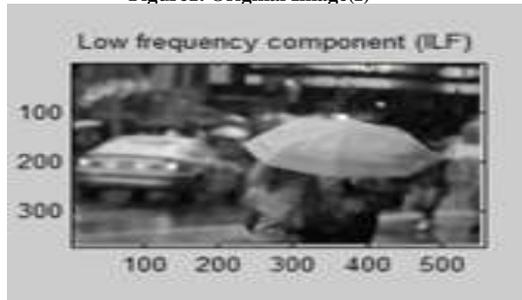


Figure2. Low frequency component (ILF)

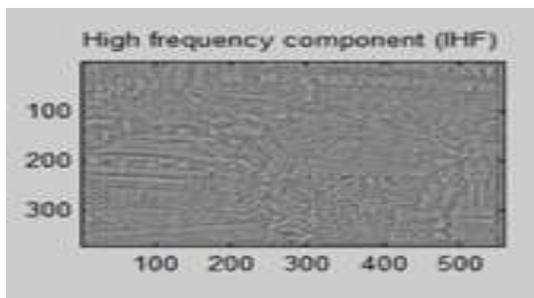


Figure3. High frequency component (IHF)

## V. DICTIONARY LEARNING

After getting high frequency image from rainy image, patches are extracted from HF image for example 16\*16 patches are extracted. The dictionary is learned by using an algorithm K-SVD or Online Dictionary Learning. Once such dictionary is observed, the remaining task is automatically identifying the undesirable components which correspond to noise, so that one can perform an image reconstruction without using such components for achieving an image denoising.

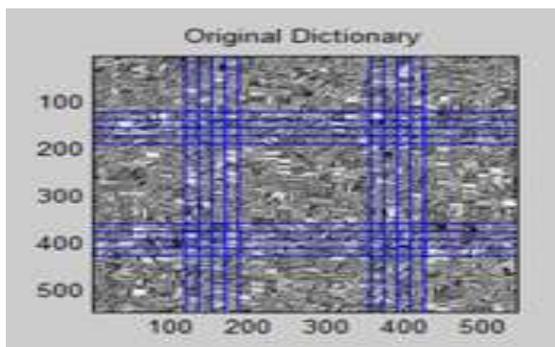


Figure4. Original Dictionary.

## VI. AFFINITY PROPOGATION

When estimate the undesirable image components in using the observed dictionary atoms are not easy. We proposed to separate these atoms into disjoint groups i.e., those within the same group are semantically similar to each other. Thus it will be possible to determine the group associated with the noise of interest.

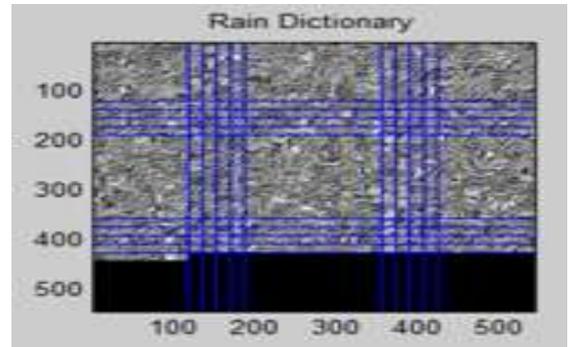


Figure5. Rain Diction

We group the aforementioned atoms into different clusters, so that the atoms within the same group will share similar edge or texture information. The M different atoms are grouped into K different clusters is called unsupervised clustering. In this the K is not known, we apply affinity propagation to solving this problem. In this we have to group different clusters based on Histogram of Oriented Gradient feature via Affinity propagation. To identify the high spatial frequency rain streak pattern we consider the variance of gradients for each dictionary atoms associated with each cluster. The variance of the atoms in that cluster would be smallest then that is corresponds to noise patterns, remaining is non rain component of an image.

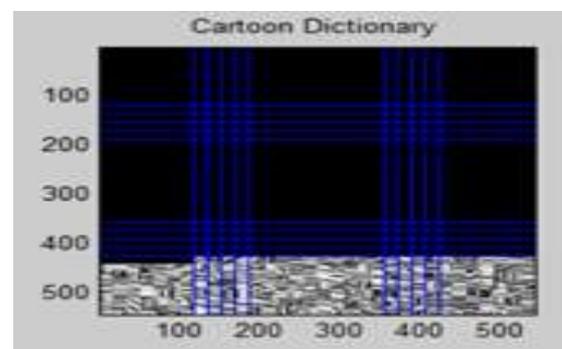


Figure6. Cartoon Dictionary.

## VII. AFFINITY PROPOGATION

Based on two sub dictionaries, Sparse Coding is applied using Orthogonal matching pursuit for each patch of HF image to find sparse coefficient vector. Each constructed patch is used to recover either geometric or rain component of the image. The non rain component of the HF image obtained from this step and low frequency image obtained in the first

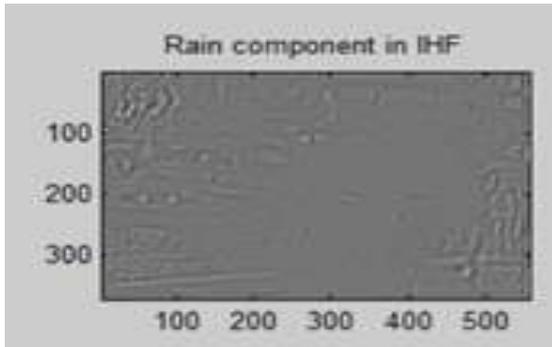


Figure7. Rain component in IHF.

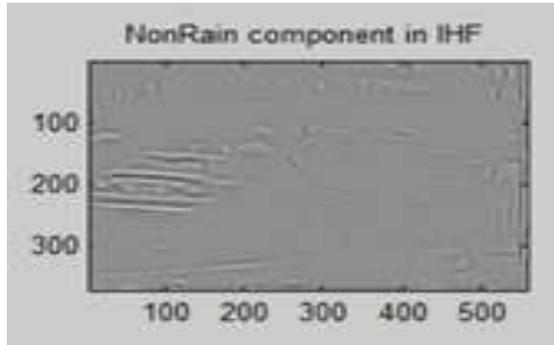


Figure8. Non Rain component in IHF.

step are combined to form Non rain version of the original rainy input image.

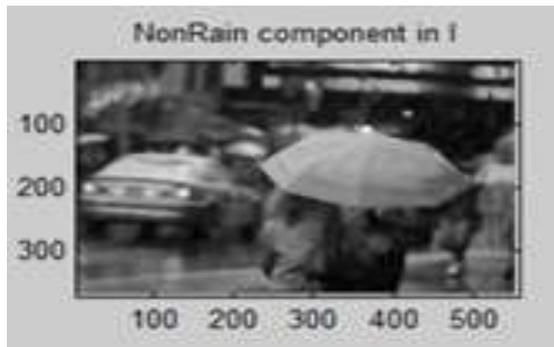


Figure9. Non Rain component in I.

### VIII. IMAGE DENOISING

We further apply our proposed decomposition method for removing Gaussian noise from the input image. In this we do not need standard deviation of such noise patterns to be given in advance, which makes our method more practical for the real world applications. Similar to rain removal, we first decompose an image into HF and LF part using Bilateral filter. Once is obtained, we learn the dictionary and extract the HOG features for each atom. The use of HOG still allows us to perform clustering of dictionary atoms. In the other words even the standard deviation of Gaussian noise is not given we are still able to identify the image component which corresponds to the presence of such noise using our proposed decomposition and clustering frame work. Once this noise component is identified and discarded, we can reconstruct the image using the remaining HF component and LF component. Then finally the Denoised image is obtained, it enhance the image quality.

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### IX. CONCLUSION

In this paper we presented a learning based image decomposition framework for single image denoising. The proposed frame work first observes the dictionary atoms from the input image directly. Image components associated with different context information will be automatically learned from the grouping of the derived dictionary atoms, which does not need any prior knowledge on the type of images nor the collection of training image data. The single image rain streaks removal framework is done by formulating rain removal as MCA based image decomposition problem solved by performing sparse coding and dictionary learning. To address the task of image denoising, our proposed method is able to identify image components which correspond to undesired noise patterns.

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### AUTHOR'S BIOGRAPHIES



B. Saranraj received BE degree in Electronics and Communication Engineering from Anna University Chennai, ME degree in Applied Electronics from Anna University Chennai. He is currently working as Assistant Professor of the Department of Electronics and Communication Engineering at P. A. College of Engineering and Technology, Pollachi, Coimbatore. His research interests include Image Processing and Communication Engineering.