

A Review on Removal of Rain Streaks in an Image by using Image Decomposition

Sneha Wandale¹, Prof.P.A.Tijare², Prof.S.N.Sawalkar³

¹Student, Computer Science and Engineering, CSE Department,
Sipna Collage of Engineering, Amravati

²Associate Professor, CSE Department,
Sipna Collage of Engineering, Amravati

³Assistant Professor, CSE Department,
Sipna Collage of Engineering, Amravati

Abstract: *Weather conditions i.e. rain, snow, fog, mist and haze degrade the quality also performance of outdoor vision system. Rain is one of the type of weather condition as well as rain is the major component for the dynamic bad weather. Rain introduces sharp intensity variations in images, which degrade the quality or performance of outdoor vision systems. These intensity variations depend on various factors, such as the brightness of the scene, the properties of rain, and the camera parameters. Rain removal has many applications in the field of security surveillance, vision based navigation, video or movie editing and video indexing or retrieval. So, it is important to remove rain streaks from the images. The detection and removal of rain streaks in an image is done by image decomposition which depends on Morphological Component Analysis (MCA) by performing dictionary learning and sparse coding. Rain streaks removal is fall into the category of image noise reduction. After Removal of rain streaks we can easily identify feature in the image.*

Keywords: Image decomposition, Morphological component analysis, Sparse coding, dictionary learning

1. INTRODUCTION

Weather can impair the performance of outdoor vision systems. Outdoor vision systems are used in various applications such as surveillance and navigation. To make outdoor vision systems robust to perform in all weather conditions we need to remove the effects of weather [1].

With the rapid development of computer technology, outdoor vision system is being more and more widely used and it plays important role in traffic surveillance and military surveillance. However, robustness and practicability of outdoor vision system in adverse weather conditions are influenced greatly. Rain bring poor visibility at outdoor vision systems. The images acquired by outdoor vision system in the rain have low contrast and are blurred, and it can cause serious degradation. Especially the images acquired in the rain have high pollution levels and are blurred, and the ambiguous recognition of detail content makes it impossible to make application process including feature extraction and target recognition. So it has important significance to process the images acquired in the rain which can make outdoor vision system have greater reliability and adaptability.

processing and decreases the performance of vision algorithms. Both rain bring complex intensity changes. A region covered by a falling down raindrop seems brighter than its original background. But it is hard to detect rain only using the property of intensity changes. Because there exist so many objects which have similar linear edges with rain streaks. However, in some cases, there is important application value to remove the rain from only one outdoor image is used to get more information.

Computer vision is a part of everyday life. One of the most important goals of computer vision is to achieve visual recognition. Bad weather degrades the perceptual image quality as well as the performance of various computer algorithms which use feature information such as object detection, tracking, segmentation and recognition. Thus, it is very difficult to implement these computer vision algorithms robust to weather changes.

There are different types of bad weather conditions, e.g. rain, snow, fog, mist, hail. Based on the type of visual effects, there are two types of bad weather conditions: steady and dynamic [1]. Figure 1 and 2 show the steady and dynamic weather conditions respectively.

In images taken from an outdoor condition, bad weather like rain annoys human viewers, brings difficulty to image



(a)Mist



(a)Fog

Figure1 The visual appearance of steady weather conditions



(a)Rain



(b)Snow

Figure2 The visual appearance of dynamic weather conditions

The steady weather conditions are fog, mist and haze. The size of steady weather particles is about 1-10 μ m. The dynamic weather conditions are rain, snow and hail. Its size is 1000 times larger than that of steady conditions i.e., about 0.1-10mm. At such sizes, individual particles become visible to a

camera. The intensity of a particular pixel will be the aggregate effect of a large number of particles in case of steady weather conditions.

2. LITRETURE REVIEW

Zhou [2] proposed a method for rain removal in sequential images. They have used spatial temporal property and the chromatic property. As per the spatial-temporal property, rain is detected by using improved k-means. Then a new chromatic constraint is advanced to mend detection results. They have considered the image in which rain is close to the camera. Rain in image is removed, but new image means non-rain image is a little blurry.

Bossu [3] proposed a method in which detection of rain is done using histogram of orientation of streaks. In this the orientations of the different connected components are obtained by the method of geometric moments. The data of this histogram are then modeled as a Gaussian-uniform mixture. A decision criterion on the smoothed histogram then allows detecting the presence or absence of rain. When rain is detected, the rain pixels can be detected accurately and easily in the images and rain intensity can be estimated as well. The disadvantage is that rain with small intensity is difficult to be seen for human eyes, and thus to be detected with the proposed method. In the presence of light rain, the Mixture of Gaussian is no longer relevant. However, in the absence of rain, this method may also detect rain presence.

3. RELATED WORK

The main objectives 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 in an image there is use of MCA as image decomposition. Morphological Component Analysis (MCA) will use to separate the texture from the natural part in images. The important idea of MCA is to decomposed the different features contained in the data or in the image. Removal of rain streaks is done by MCA based image decomposition[8] by performing dictionary learning and sparse coding.

3.1 MCA-Based Image Decomposition

MCA can be used for separating the texture from the piecewise smooth component, for inpainting applications or more generally for separating several components which have different morphologies. The main idea for using MCA is to use the morphological diversity of the different features contained in the data to be separated and to associate each morphology to a dictionary of atoms for which a fast transform is available.

Morphological Component Analysis (MCA) which is a novel decomposition (separation) method based on sparse representation of images. The basic idea is separating various morphological characteristics included in the image on the basis of image morphological composition differences (which can be sparsely represented by different dictionaries). The MCA can be applied in image compression, reconstruction, noise suppression and feature extraction, and it's extremely useful in the respect of image segmentation and image inpainting. The following diagram shows the steps for removal of rain streaks.

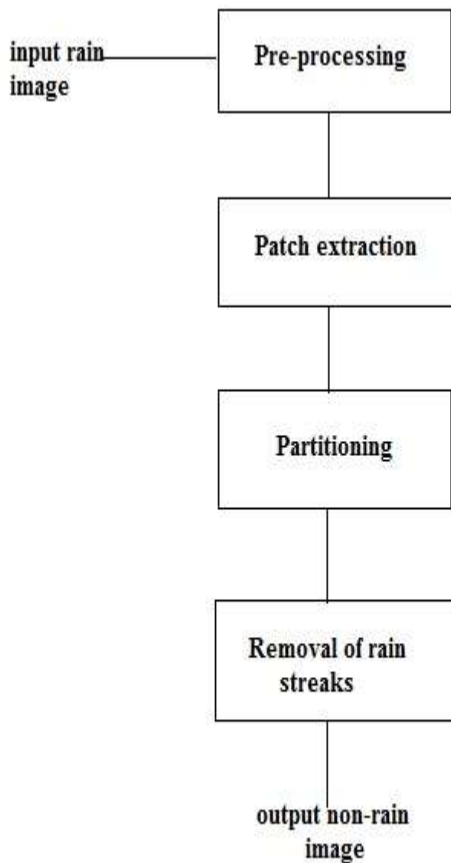


Figure 3 Steps for removal of rain streaks

Step 1: Pre-processing

For the input rain image in the pre-processing step we have to apply edge preserving smoothing filter called bilateral filter [4]. 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 LF part while the rain drops or rain streaks and the other edge or texture information will be in the HF part of the image.

Step 2: Patch extraction

For learning dictionary of HF part (D_{HF}) a set of overlapping patches are extracted from HF part. Then separate atoms in the dictionary into two sub-dictionaries [6-7] for representing rain component and textural component of HF part.

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. The HOG (Histogram of Oriented Gradient) feature descriptor [5] is used to describe each atom in D_{HF} .

After extracting the each atom in D_{HF} by using HOG feature, then applying K-means algorithm for separating all of the atoms in D_{HF} into two sub-dictionaries D_1 and D_2 based on HOG feature descriptors. For identifying which cluster consists of rain atoms and which cluster consists of geometric atoms, for that we calculate the variance of gradient direction for each atom d_{ij} , $j=1,2,\dots,N$, in cluster D_i , as VG_{ij} , also $i=1, 2$. Then, calculate the mean of VG_{ij} for each cluster D_i as MVG_i . Based on the fact that edge directions of rain streaks in an atom are mostly consistent, means the rain atom has the small variance of gradient direction, then after this we identify the cluster with

the smaller MVG_i as rain sub-dictionary D_{HF_R} and other one as geometric (or non-rain) sub-dictionary D_{HF_G} .

Step 4: Removal of rain streaks

Sparse coding is performed on this two sub-dictionaries for finding sparse coefficients for each patch extracted from the HF part. Then we get the rain-removed version of the input rain image by combining LF and non-rain image of HF part by separating rain component.

4. CONCLUSION

The proposed method uses single image for removal of rain streaks and it is suitable for only rain streaks removal. Non-rain image shows that this method could reduce the degradation caused by dynamic weather and also maintain some detailed information of the image. By using image decomposition we are able to separate rain and non-rain part from the image.

The single image rain streak removal framework is done by formulating rain removal as an MCA based image decomposition problem solved by performing sparse coding and dictionary learning. After removal of rain streaks the object can be detected easily.

For future work, the visual quality or visibility of the non-rain image will improve by using image enhancement technique. Image enhancement improve the image quality so that the resultant image is better than original image.

REFERENCES

- [1] K. Garg and S. K. Nayar, "Vision and rain," *Int. J. Comput. Vis.*, vol.75, no. 1, pp. 3–27, Oct. 2007.
- [2] Ming Zhou, Zhichao Zhu, Rong, Deng, Shuai Fang, "Rain Detection and Removal of Sequential Images", IEEE Chinese Control and Decision Conference (CCDC), pp. 615-618, 2011.
- [3] J. Bossu, N. Hautière, and J. P. Tarel, "Rain or snow detection in image sequences through use of a histogram of orientation of streaks," *Int. J. Comput. Vis.*, vol. 93, no. 3, pp. 348–367, Jul. 2011.
- [4] 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.
- [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] L.-W. Kang, C.-W. Lin, and Y.-H. Fu, "Automatic single-image-based rain streaks removal via image decomposition," *IEEE Trans. Image Process.*, vol. 21, no. 4, pp. 1742–1755, Apr. 2012.
- [7] Y. H. Fu, L. W. Kang, C. W. Lin, and C. T. Hsu, "Single-frame-based rain removal via image decomposition," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process.*, Prague, Czech Republic, May 2011, pp. 1453–1456.
- [8] 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.