Single Image Rain Removal by Canny Edge Detection

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Abstract—In Today's era of image processing many vision applications such as surveillance and navigation are present for image. But one of the challenges is rain removal, especially the rain removal from a single image. In this research paper, a single rain image is divided into the high frequency part and the low frequency part by the Gaussian filter method. For quality enhancement Non-negative matrix factorization (NMF) is deployed to remove the rain streaks in the low frequency part. After That, Canny edge detection is applied to deal with the rain in the high frequency and the block copy method is implemented to enrich the image quality. After that, we applied a rain dictionary to further divide the high frequency into rain and non-rain parts. The experimental results show that the proposed method is better than the state-of-the-art methods, especially in the high frequency part.

Keywords – ***Gaussian Filter, Non-negative matrix factorization (NMF), canny edge detection, block copy, rain dictionary.***

I. INTRODUCTION

Different vision applications such as surveillance and navigation are used for different purposes. Some weather Conditions, such as rain [6] and haze, may influence computer vision functions. Rain removal in a single image is more difficult than in video since there is no temporal information for a single image. It is still a challenge up to date. [2] The rain interference is mainly in the middle frequency with specific angles.

Therefore, we can simply adjust the corresponding frequency coefficients to remove rain interference. However, if we do this, the detail part of the image and the image quality would not be desirable. Moreover, the precise angles of the rain in the middle of frequency are not easily found and the rain fallen in the low frequency and high frequency still remains. There is another research [1] which is concentrated on sparse representation. The raindrop directions in images could be learned by applying dictionary learning. Nevertheless, the results depend on extended dictionary heavily. That means the database must collect many different kinds of non-rain images to train a high quality dictionary. That would be a time-consuming process and the image quality significantly depends on collected non-rain images. In this paper, we will propose another learning strategy for rain removal based on non-negative matrix factorization (NMF). We adopt different viewpoints to remove rain in the image and do not used extra non-rain images to improve the image.

A. Non-negative Matrix Factorization (NMF)

Principal components analysis (PCA) and vector quantization (VQ) are unsupervised learning algorithms. They can be known as matrix factorization subject to different constraints, so that it leads to a very distributed representation which uses cancellations to generate variability. VQ applies a winner-takes-all constraint, so the data is clustered into the prototypes. NMF

[3, 4] doesn't allow you any negative entries in the matrix factors. It is a useful constraint to learn the part-based representations of the input data because these constraints allow only additive combination. The equation of NMF is shown in Eq. (1).

$$V = WH \quad (1)$$

The given image database which is a set of n-dimensional multivariate data vectors is regarded as a matrix V with n×m elements, and then it is approximately factorized into matrix W with n×r elements and matrix H with r×m elements. The dimension r is chosen to be smaller than m or n such that the result is compressed for the given data matrix. Since NMF is an approximate and iterative way to reconstruct V, an updating process for W and H is required for V. The following equations show the update rules for W and H based on Kullback-Leibler divergence.

$$H_{au} \longrightarrow H_{au} \frac{\sum_i W_{ia} V_{iu} / (WH)_{iu}}{\sum_k W_{ka}} \quad (2)$$

$$W_{ia} \longrightarrow W_{ia} \frac{\sum_u H_{au} V_{iu} / (WH)_{iu}}{\sum_v H_{av}} \quad (3)$$

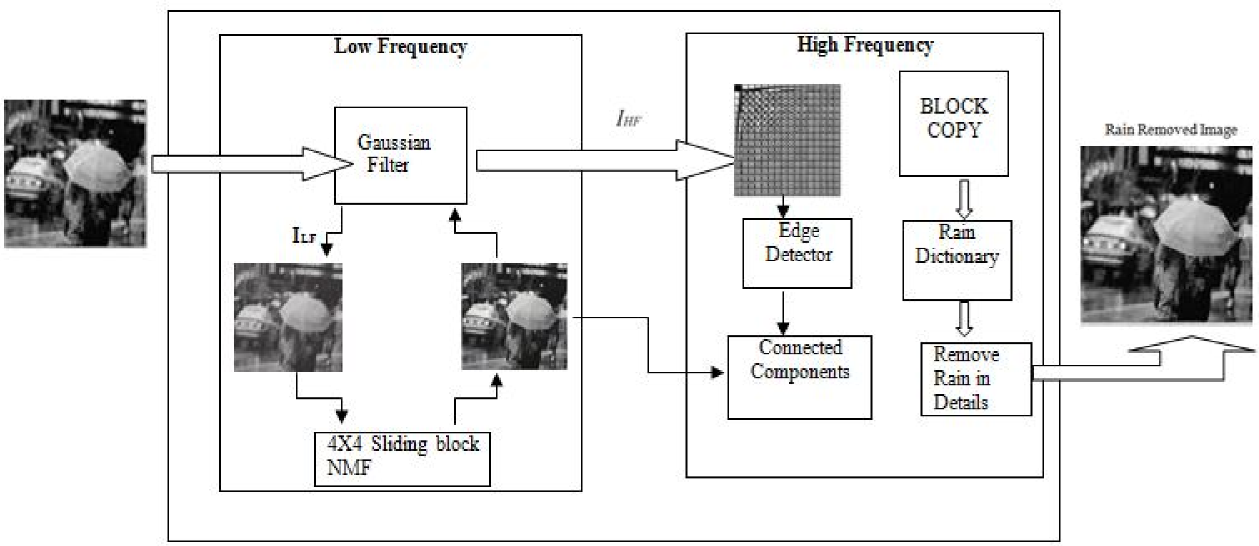

Fig. 1. Flowchart of rain removal

The rain removal flowchart is shown in Fig. 1. First, the Gaussian filter is applied to the input image I and the low frequency part of I can be obtained denoted as I_{LF}. Next, we can simply produce the high frequency part of I by I-I_{LF}, denoted as I_{HF}. Then, I_{LF} is divided into matrix W and matrix H by NMF in order to reduce the rain streaks in the low frequency part. This includes iterative steps, so I_{LF} will become better and better until the image quality couldn't be further improved. The edge detector and connected component would find the main edges in the image. For the vague edges or complicated blocks, block copy strategy is used to preserve the high frequency part [5]. After that, we apply Kang et al's dictionary to complement the details of the image. The detailed description is provided in the following subsections.

A. Frequency Separation and De-raining with NMF

Gaussian filter is applied to decomposed image into the low frequency part I_{LF} and the high frequency part I_{HF}. The main idea is that the human vision is sensitive to noise in the low frequency, and therefore, NMF is used to remove rain in the low frequency of the image. I_{LF} is partitioned into 4x4 overlapping blocks which are composed of matrix W. Then, H will be obtained by multiplicative update rules presented in Eqs. (2) and (3). Therefore, I_{LF} can be reconstructed by the linear combination of $W \times H$ straightforwardly. After that, the rain streaks are certainly smoothed out and softened, but the image details are also missing. The following subsections describe how the details can be reconstructed

B. Edge Detection, Block Copy, and Dictionary Filtering

Canny edge detector will be used to decide the actual edges and the pseudo edges which caused by rain in the image. In the proposed scheme, Canny is used for obtaining strong edge pixels, so some complicated edges are hard to be determined and hard to differentiate from rain. Therefore, in this paper, the complicated block, which is defined by the number of edge pixels in the block, will be completely copied to the reconstructed image to preserve the quality of the high frequency part. We denote this reconstructed image as *I*new. In order to further remove the rain in the high frequency of I_{new}, we introduce the dictionary trained by Kand et al's method (2) to the proposed method. First, the high frequency part can be obtained by subtracting *I*new from I, denoted as I_{newH}. The I_{newH} will be reconstructed by Kand et al's dictionary. The dictionary is trained only by the original rain image itself, instead of using extra non-rain images in the original Kand et al's method. Note that the dictionary of Kand et al's method is divided into two types, rain dictionary and non-rain dictionary, and the size of rain dictionary is much larger than that of non-rain dictionary. Here, only the rain dictionary is applied because it has better description of rain. Therefore, when *InewH* is reconstructed by the rain dictionary, denoted as I'_{newH}, it will contain most of the rain. Finally, the difference of $I_{newH} - I'_{newH}$ will be added to I_{new} to be our final result.

III EXPERIMENTAL RESULTS

We will present some of the experimental results of the proposed rain removal method in this section. The parameters are set as follows. A (3+j) × (3+j) size of block is utilized by Gaussian filter, where j is the number of iterations. The sigma is set to 5. Fig. 2 shows the comparison of results. It can be seen that our final result, shown in Fig. 2(f) preserves more detail components like hair and umbrella than other images.

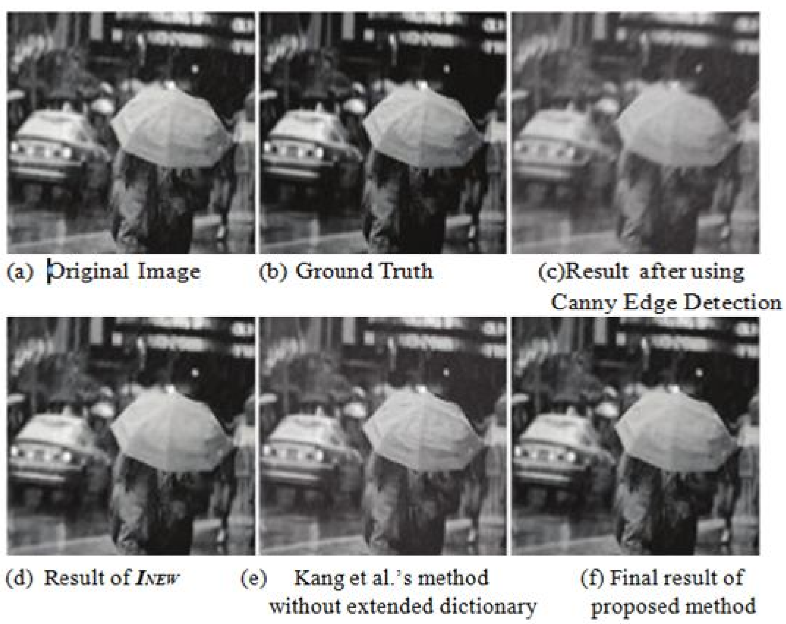

Fig. 2. Comparisons of experimental results

IV. CONCLUSION

In this paper, the NMF-based rain removal technique has been proposed. In order to remove rain, the proposed technique first partitions the image into low and high frequencies. The low frequency part is processed by NMF because NMF is good at noise filtering. On the other hand, the high frequency part goes through Canny edge detection, block copy, and dictionary filtering to remove rain and also maintain the edge details. The experimental results show that our method can not only remove most of the rain, but also keep the image quality using only single rain image. Compared to Kand et al's method if only single image is applied, our method has much better visual quality than theirs.

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