ENHANCING SINGLE COLOUR IMAGE BY REMOVING RAIN OR SNOW

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Abstract

Outdoor vision system are used in various applications such as tracking, surveillance also in navigation. Rain introduces difficulty to the outdoor vision system. Rain/Snow is one of the types of weather condition and major component for the dynamic bad weather condition. Due to the rain/snow the visual quality of an image goes down so it is necessary to remove this rain/snow. In this paper, we propose an efficient algorithm to remove rain or snow from a single color image. Our algorithm takes advantage of two popular techniques employed in image processing, namely, image decomposition and dictionary learning. The effectiveness of our algorithm is verified through both subjective (the visual quality) and objective (through rendering rain/snow on some ground-truth images) approaches, which shows a superiority over several state-of-the-art works. We propose adaptive histogram equalisation technique for image enhancement to obtain the better quality of the image after removal of snow and rain. The results obtained are processed in matlab.

Keywords*: Rain and Snow Removal, Guided Filter, Trained Dictionary.*

I. INTRODUCTION

With the more and more growth in computer technology, outdoor vision system is widely used and it plays vital role in traffic surveillance and military surveillance. Weather can reduce the performance of outdoor vision systems. Outdoor vision systems are used in various purposes in many applications such as surveillance and navigation. We need to remove the effects of weather for making outdoor vision systems efficient that perform in every weather conditions. Rain creates poor visibility at outdoor vision systems. The images captured by outdoor vision system in the rain have low contrast and are blurred and it can creates serious degradation. Mainly the images captured in the rain have high pollution levels and are blurred, and the recognition of detail content makes it impossible to make application process together with the feature extraction and target recognition. So it has more importance to process the images acquired in the rain which can make outdoor vision system reliable.

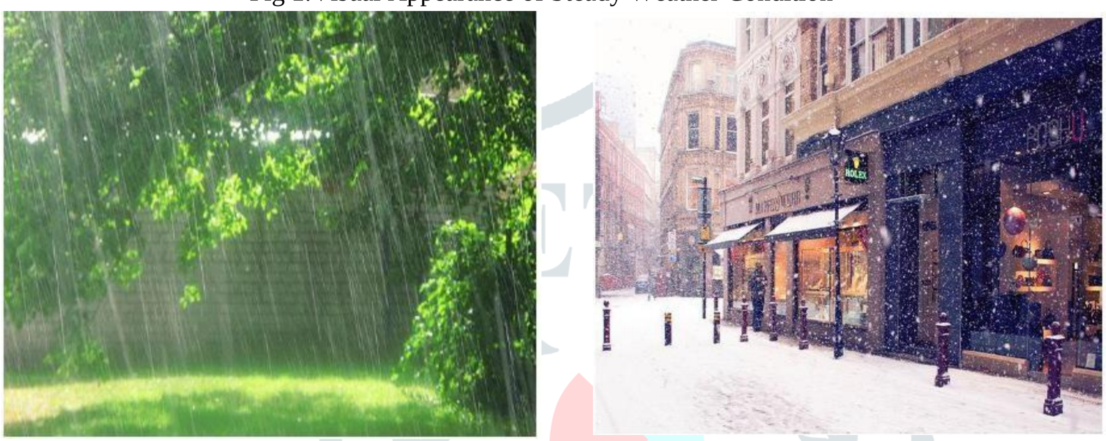
Images which are taken from an outdoor condition, bad weather like rain confuse human viewers also brings difficulty to image processing and also the performance of vision algorithms decreases. An area covered by a falling raindrop seems brighter than its original background. But it is very difficult to identify rain only using the property of intensity changes. Because there exist so many things which have similar linear edges with rain streaks. Though in some cases, there is essential application value to remove the rain from only outdoor image, this image is used to get more information. If rain steaks is exist in the climate which shows that, it will not only deteriorate the feature of the scene but also it will deteriorate the performance of computer vision algorithm. For example, examine the case when the object trackers may fail if small portion of the image become occluded.

Rain is one of the type weather condition. Reducing or removing the effects of rain while preserving image information is a difficult task, as rain streaks move very quickly through a image and are difficult to separate from other motion from the image. Additionally, the visual appearance of rain depends both on the background of the streak and other imaging lighting conditions, which makes it difficult to build a general appearance model.

Garg and Nayar classified the weather based on the size of the weather particles into two types steady weather are fog and haze, and dynamic weather are rain and snow. In steady weather, particles are very small and steadily float in the air. In dynamic weather, rain drops are distributed anywhere in the scene and move all the time. This makes them difficult to identify and causes failures in vision applications. Outdoor vision systems are used for various purposes such as tracking, recognition and navigation. In order to develop vision systems that perform under all weather conditions, it is essential to develop algorithms that remove visual effects of the various weather conditions. Dynamic weather such as rain, snow, and haze normally brings unpleasant visual artifacts in outdoor vision system and would decrease the performance of vision tasks[1-2].

(a) Fog (b) Mist

Fig 1.Visual Appearance of Steady Weather Condition



(a) Rain (b) Snow

Fig 2 Visual Appearance of Dynamic Weather Condition

II. RELATED WORK

Many authors uses single image for rain streaks removal and proposed different techniques or methods. L-W Kang, C-W Lin and Y.-H. Fu proposed a single image based rain streaks removal framework by using image decomposition based on Morphological Component Analysis (MCA).Rather than directly applying a traditional image decomposition technique, the proposed method first decomposes input rain image into the low-frequency (LF) and high-frequency (HF) parts using a bilateral filter also called as smoothing filter. The LF part contains the most basic information and HF part contains rain streaks, edges or texture information. Dictionary learning and sparse coding is used for decomposing HF part into rain component and non-rain component. By combining non rain component of high frequency part with low frequency part they get the desired non rain image by separating rain component [3-6].

Y-L Chen and C-T Hsu proposed a generalized low-rank appearance model for rain streaks removal. This method does not required rain pixel detection nor dictionary learning stage. Instead as rain streaks generally release similar and repeated patterns on imaging scene. They proposed and generalized a low-rank model from matrix to tensor structure in order to represent the spatio-temporally correlated rain streaks. By using this appearance model they thus removed rain streaks from image[7].

X. Zheng, Y. Liao, W. Guo, X. Fu, and X. Ding proposed method for rain removal by using low frequency part of the image. This method depends on a key difference between clear background edges and rain streaks, normally low frequency part can determine the various properties. Low-frequency part is the geometric component, then this low-frequency part is then changed as a guidance image. The high-frequency part is treated as an input image of the guided filter, so that a non-rain component of the high-frequency part can be obtained. After getting non-rain component of high-frequency part and add low-frequency component in it they get desired image [8].

D-An Huang, L-Wei Kang, M-Chun Yang, C-Wen Lin, Wang proposed a learning-based structure for single image rain removal which primarily concentrates on the studying of context information from an input rain image and hence the rain patterns present in it can be automatically recognized and removed. This method for single image rain removal as the combination of image decomposition and self learning processes. More precisely, this method first implements context-constrained image segmentation on the input rain image, and they study dictionaries for the high-frequency part in distinct context categories by means of sparse coding for reconstruction value. For an image regions with the rain streaks, dictionaries of different context categories will allot common atoms which correspond to the rain patterns. By utilizing Principal Component Analysis and Support Vector Machine classifiers on the learned dictionaries, this structure focus at automatically recognizing the common rain patterns present in them, and thus rain streaks can be removed from the particular high-frequency components from the input image[9].

D-Yu Chen, C-Cheng Chen, and L-Wei Kang, proposed a single color image based rain removal structure by accurately designing rain removal as an image decomposition based on sparse representation. In this structure, initially an input rain image is partitioned into a low-frequency part and a high frequency part by applying the guided image filter so that the rain streaks present in the high-frequency part. High-frequency part contains with rain streaks, textures or edges. High-frequency part is again partitioned into a rain component and a non-rain i.e. geometric component by performing dictionary learning and sparse coding. After that split rain streaks from the high-frequency part, for this a hybrid feature set, together with the depth of field, eigen color and histogram of oriented gradients is implemented to moreover decomposed the high-frequency part. When they used hybrid feature set, almost all rain streaks can be removed; at the same time non-rain component can be enhanced. This method concentrates on the problem of single image rain removal and achieves good results with not only the entire rain component being eliminated more completely, but also the visual quality of deterioated images being improved[10- 11].

J-Hwan Kim, C Lee, J-Young Sim, and C-Su Kim proposed an adaptive rain streak removal algorithm for a single image. They notice that a specific rain streak has an elongated elliptical shape with a vertical direction. So, by using this algorithm they first need to recognize an area of rain streak by examine the rotation angle and the aspect ratio of the elliptical kernel at every pixel location. After this they perform the nonlocal means filtering on the recognized rain streak regions by choosing nonlocal neighbor pixels and their weights [12]. C-Hung Yeh, P-Hsian Liu, C-En Yu, and C-Yang Lin, proposed a NMF-based rain removal method. In this method for rain removal of single image, firstly rain image is divided into the high frequency part and the low frequency part by implementing Gaussian filter. Non-negative matrix factorization (NMF) is used to remove the rain streaks in the low frequency part.NMF is good noise filtering. Then, Canny edge detection is applied to deal with the rain in the high frequency and the block copy method is employed to preserve the image quality. After that, they applied a rain dictionary to further divide the high frequency into rain and non-rain parts**.** This method not only remove most of the rain, but also preserve the image quality using only single rain image[13].

S Yu ,W Ou , X You, Yi Mou , X Jiang ,Y Tang proposed a new algorithm for rain streaks removal from single image which is based on self-learning framework and structured sparse representation. This algorithm firstly divide and classifies input image into rain streaks regions and non-rain i.e. geometric regions through texture analysis. Meanwhile, we also decompose input image into high-frequency (HF) and low-frequency (LF) parts with bilateral filtering. Followed that, we introduced our newly proposed structured dictionary learning to decompose HF part into rain texture details and non-rain geometric details, where patches for training rain and non-rain sub- dictionaries are selected from rain streaks and non-rain geometric regions. Finally, they combine LF part with non- rain geometric details to get rain streaks-removal image [14].

III. METHODOLOGY

A. A Hierarchical Approach for Rain or Snow Removing in a Single Colour Image

In this work [2], they consider the rain/snow removal from a single colour image, in which several new designs are introduced. The main contributions of our work are summarized as follows: 1) They have outlined several common characteristics of rain and snow, from which two metrics are defined, namely, the sensitivity of variance across color channels (SVCC) and the principal direction of an image patch (PDIP). 2) A low-frequency part that is free of rain or snow almost completely has been generated, thanks to the use of a combination of rain/snow detection and a guided filter (as the low-pass filter), while the corresponding high-frequency part is made complementary to the low frequency part. 3) A 3-layer hierarchy of extracting image's details from the high-frequency part has been designed. Specifically, the first layer is a 3-times classification that is based on a trained dictionary (over-complete), the second layer applies another combination of rain/snow detection and a guided filter, and the third layer utilizes the SVCC to enhance the visual quality of the rain/snow-removed image.

B. Removing Rain/Snow from a Single Image Via Discriminative Sparse Coding

The paper [4] aims at developing an effective algorithm to remove visual effects of rain from a single rain image, i.e. separate the rain layer and the de-rained image layer from a rain image. Built upon a nonlinear generative model of rain image, namely screen blend model, we propose a dictionary learning based algorithm for single image de- raining. The basic idea is to sparsely approximate the patches of two layers by very high discriminative codes over a learned dictionary with strong mutual exclusivity property. Such discriminative sparse codes lead to accurate separation of two layers from their non-linear composite. The experiments show that the proposed method outperforms the existing single image de-raining methods on tested rain images.

C. Guided Image Filtering

This paper [5] presents a linear time fully connected guided filter by introducing the guided filter (GF). Since the intensity based filtering kernel of GF is apt to overly smooth edges and the fixed-shape local box support region adopted by GF is not geometric-adaptive, the filter introduces an extra spatial term, the tree similarity, to the filtering kernel of GF and substitutes the box window with the implicit support region by establishing all-pairs- connections among pixels in the image and assigning the spatial-intensity-aware similarity to these connections. The adaptive implicit support region composed by the pixels with large kernel weights in the entire image domain has a big advantage over the predefined local box window in presenting the structure of an image. They demonstrate the strength of the proposed filter in several applications.

D. A Generalized Low-Rank Appearance Model For Spatio-Temporally Correlated Rain/Snow

In this paper [6], propose a novel low-rank appearance model for removing rain streaks. This method needs neither rain pixel detection nor time-consuming dictionary learning stage. Instead, as rain streaks usually reveal similar and repeated patterns on imaging scene, they propose and generalize a low-rank model from matrix to tensor structure in order to capture the spatiotemporally correlated rain streaks. With the appearance model, thus remove rain streaks from image/video (and also other highorder image structure) in a unified way.

E. An Improved Guidance Image Based Method To Remove Rain And Snow In A Single Image

Rain and snow bring poor visibility to outdoor vision systems. The commonly used image processing methods may be not suitable for a degraded image. In this paper [7], a guidance image method is proposed to remove rain and snow in a single image. To removal rain and snow only using one image, a guidance image is derived from the imaging model of a raindrop or a snowflake when it is passing through an element on the disk of the camera. Since only using this guidance image may lose some detailed information, in this paper, a refined guidance image is proposed. This refined guidance image has a similar contour with the un-degraded image and also maintains the detailed information which may be lost in the guidance image. Then a removal procedure is given by the use of the refined guidance image. Some comparison results are made between different methods using the guidance image and the refined guidance image. The refined guidance image can be used to get a better removal result. In this paper first, analyse the imaging model of rain and snow formation to find a guidance image. Second, propose a refined guidance image such that this novel image could keep detailed information and at the same time remove the linear edges caused by rain and snow. Thereby use filtering method to remove rain and snow from this guidance image.

IV. PROPOSED ALGORITHM

The pipeline of our proposed rain/snow removal is shown in Fig. 3. Specifically, our algorithm consists of two steps. In the first step, the input image is decomposed into the low frequency part I_L and high-frequency part I_H. Note that I_L is free of rain or snow almost completely but usually blurred, while I_H contains rain/snow components and some or even many details of the image. In the second step, we design a 3-layer hierarchy of extracting non-dynamic components (i.e., the image's details) from I_H, which are denoted as I_H^{ND1}, I_H^{ND2} and I_H^{ND3} respectively. The final rain/snow-removed image is obtained as:

$$\hat{I} = I_L + I_H^{ND1} + I_H^{ND2} + I_H^{ND3}$$

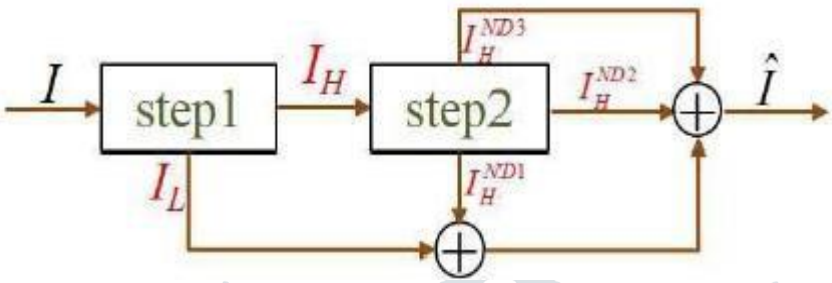


Fig.3. The simplified pipeline of our algorithm - the details of each step will be shown later.

In this section, we pay attention to the first step and the details of the second step are described in the next section. Fig. 4 shows the details of the first step. First, a rain/snow detection is performed to produce a binary location map M_I and the Hadamard product between I and M_I yields an output image I_M. Because the location map is binary, holes appear at the rain/snow locations. Then, we fill each hole with the mean value of its neighboring non- rain/snow pixels. At last, a guided filter is utilized to generate the low-frequency part I_L , and the high-frequency part is obtained as $I_H = I - I_L$.

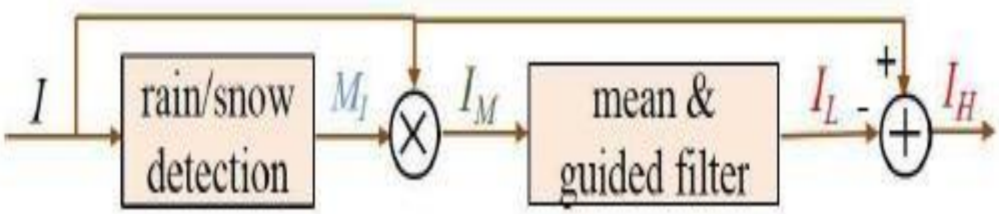


Fig. 4. The flow chart of the first step: I is the input rain/snow image; M_I is the location map; I_M is the Hadamard product of I and M_I ; I_H and I_H are, respectively, the low-frequency and high-frequency parts obtained after the decomposition.

A. Detection of Dynamic Components

In general, some low-pass filter (e.g. the guided filter) can be used to decompose a rain or snow image into the low- frequency part and high-frequency part. However, such a low-pass filtering can hardly filter out all dynamic components (i.e., rain or snow). To solve this problem, we propose to first perform a rain/snow detection to obtain the coarse locations of these dynamic components and then apply a guided filter to obtain the low-frequency part that would become free of rain or snow almost completely. Rain/snow detection belongs to the category of object detection, to which many algorithms have been developed, including several very recent ones by Pang et al. In this part of our work, we wish to keep the detection as simple as possible, which can be achieved by utilizing some intrinsic characteristics of rain/snow, as described below.

Notice that the rain/snow detection used here is a very strong one and will unavoidably lead to some over- detection mistakes. Nevertheless, such a detection usually includes all rain streaks for rain images or snowflakes for snow images, especially the rain streaks or snowflakes with high intensities. On the other hand, rain streaks or snowflakes with low intensities in an image may be missed by our detection. However, even missed, this kind of rain streaks or snowflakes can be filtered out by a low-pass filter easily. A much more challenging problem associated with over detection mistakes is that some or even many details of the image are detected as rain/snow components because they also have high intensities as compared with their neighbors.

B. Image Decomposition

For a given image I , we calculate the Hadamard product of I and the binary location matrix M_I as

$$I_M = I \circ M_I$$

Since M_I is binary, holes exist in image I_M at the locations of all detected rain streaks or snowflakes. To fill these holes, the value of the dynamic pixel $I_M(i, j)$ is substituted with the mean value of non-dynamic pixels in the patch centered at $I_M(i, j)$. Then, we use the guided filter [26] to further filter out the remaining dynamic components with low intensities from IM and get the low-frequency part I_L as

$$I_L = \mathscr{F}_g\{\mathscr{F}_m\{I_M\}\} = \mathscr{F}_g\{\mathscr{F}_m\{I \circ M_I\}\}$$

Finally, the high frequency part IH is obtained as $I_H = I - I_L$, i.e., I_L and I_H are completely complementary to each other.

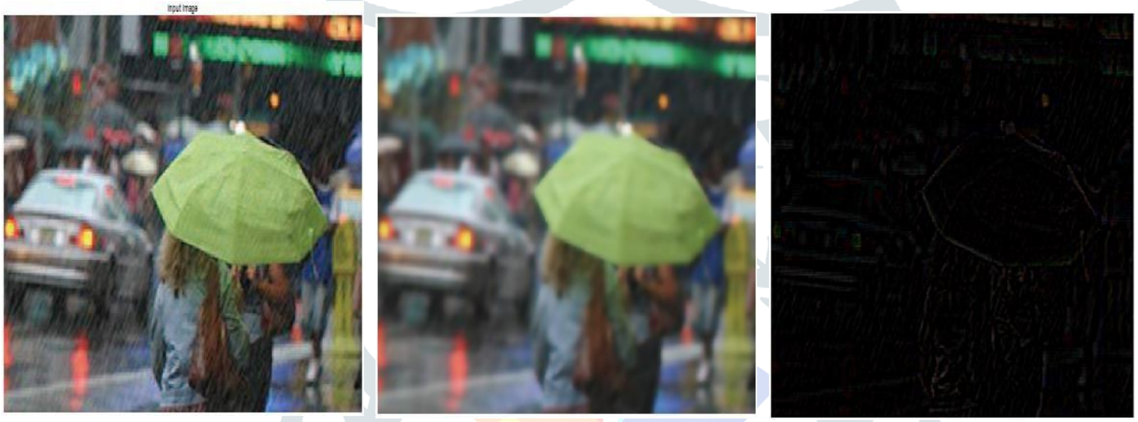
C. Image Enhancement

The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide better input for other automated image processing techniques.Image Enhancement (IE) transforms images to provide better representation of the subtle details. It is an indispensable tool for researchers in a wide variety of fields including (but not limited to) medical imaging, art studies, forensics and atmospheric sciences. It is application specific and IE technique suitable for one problem might be inadequate for another.

It is used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. Ordinary histogram equalization simply uses a single histogram for an entire image. Consequently, adaptive histogram equalization is considered an image enhancement technique capable of improving an image's local contrast, bringing out more detail in the image. However, it also can produce significant noise. A generalization of adaptive histogram equalization called contrast limited adaptive histogram equalization, also known as CLAHE, was developed to address the problem of noise amplification.

V. RESULTS

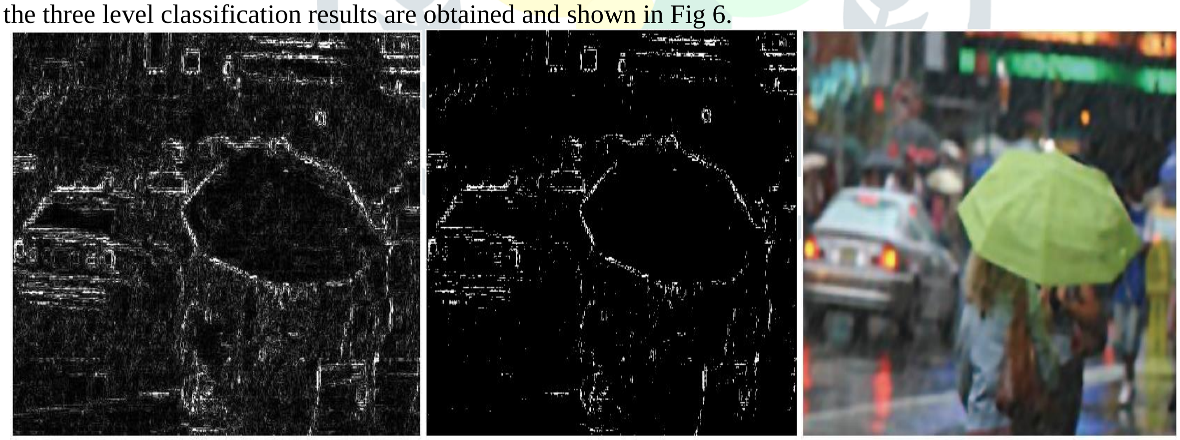
we consider a rain or snow image as input and process the image to remove the rain / snow and enhance the image to obtain better quality.



(a) (b) (c)

Fig 5. (a) Input Image (b) Low Frequency Components of Rain Image (c) High Frequency Components of Rain Image

Now the three level classification results are obtained and shown in Fig 6.



(a) (b) (c)

Fig 6. (a) Classification Result of Non Rain Component □□ □2 (b) Classification Result of Non Rain Component □□ □3

(c) Classification Result of Non Rain Component □□□1

Fig 7. Rain Removed Image

Fig 8. Enhanced Image using AHE

The performance metrics of the obtained images are PSNR(Peak Signal to Noise Ratio) and SSI(Structural Similarity Index). The results obtained after removing rain. snow from image and the results obtained after image enhancement is compared and tabulated.

Table 1. Comparison of Performance Metrics

	PSNR	SSI
Rain Removed Image	41.045	0.821
AHE Enhanced Image	58.35	0.852

VI. CONCLUSION

This project has attempted to solve the rain/snow-removing problem from a single color image by utilizing the common characteristics of rain and snow. To this end, we defined the principal direction of an image patch (PDIP) and the sensitivity of variance of color channel (SVCC) to describe the difference of rain or snow from other image components. We acquired the low and high frequency parts by implementing a rain/snow detection and applying a guided filter. For the high frequency part, a dictionary learning and three classifications of dictionary atoms are implemented to decompose it into non dynamic components and dynamic (rain or snow) components, where some common characteristics of rain/snow defined earlier in our work are utilized. Moreover, we have designed two additional layers of extracting image details from the high frequency part, which are based on, respectively, the SVCC map and another combination of a rain/snow detection and a guided filtering. Finally, we have presented a large set of results to show that our method can remove rain or snow from images effectively, leading to an enhanced visual quality in the rain/snow-removed images. Finally to improve the quality of image we have performed image enhancement using adaptive histogram equalization. The results obtained after performing AHE has an improvement in PSNR and SSI.

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