

Rain Streak Removal Using L_0 Gradient Minimization Technique

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Abstract: Removal of rain streaks from still images is a difficult process because of tiny regions in the image. The rain drops influences on a very micro region of an image, and consequently, results in a confusion to figure out which area need to be considered and which need not consider. To remove the rain streak pixels, L_0 Gradient Minimization is utilized. The minimization technique controls numbers of non-zero gradients about the image. Instead of considering the local features, salient edges are considered by the proposed method. These salient edges are preserved and at the same time low sufficiency and inconsequential details are decreased. Finally the rain streak removed images are enhanced in intensity using histogram adjustment technique to get better contrast images. Test results demonstrate that the proposed algorithm is exceedingly proficient as it eliminates rain streaks viably even under overwhelming rain conditions, without losing the details of the image.

Keywords: Rain streak removal, L_0 Gradient technique, Connected components.

1. INTRODUCTION

The efficiency of the image processing algorithm depends on the climate conditions whether it is harsh or not. The algorithms used for processing utilize features extracted from the image to deliver the outcomes. It is essential to integrate these algorithms such that they are strong enough against the changes in the climate.

The current rain streaks removal techniques are grouped into two types.

They are meant for recordings and still images. Zhou and Zhu [3] proposed a system to break down the spatio-transient and the chromatic property of rain streaks and also proposed an algorithm to effectively eliminate the rain streaks from recordings. Tripathi and Mukhopadhyay [4] proposed a method to remove rain streaks by utilizing the meteorological methodology. The rain streaks removal algorithm created for fixed camera can likewise be utilized for moving the camera as well. [5] Presents a foundation subtraction technique to remove the rain streaks pixels. Xu and Zhao et al. [6] utilized a guided filter, by which there was no pixel-based accurate data for distinguishing rain or snow are required is presented in the removal stage. Chen, Jie, and Lap-PuiChau [7] proposed an algorithm which is dependent on motion segmentation of dynamic scene. Cheng and Chen [8] proposed a rain removal framework for single color image by planning rain removal as a image decomposition issue utilizing sparse representation. Huang, De-An, et al [9] perceives the single image rain removal issue as the joining of image decomposition and self-learning forms. The technique in [9] first performs context-constrained image division on the information image. Fu, Yu-Hsiang, et al. [10] proposed another approach for rain streak removal as an image decomposition issue dependent on morphological component analysis(MCA). The initial step is to fragment the image into the low-recurrence and high recurrence parts utilizing a bilateral filter. The high-recurrence part is next fragmented into "rain segment" and "non-rain segment" by dictionary learning and inadequate coding. Also, the rain

streak segment can be effectively removed from the image. In any case, all the previously mentioned techniques deliver just elegant outcomes.

Section II talks about the System Design and its Implementations. Section III gives results of the original rainy image and the rain streak removed image. Section IV gives the conclusion.

2. SYSTEM DESIGN

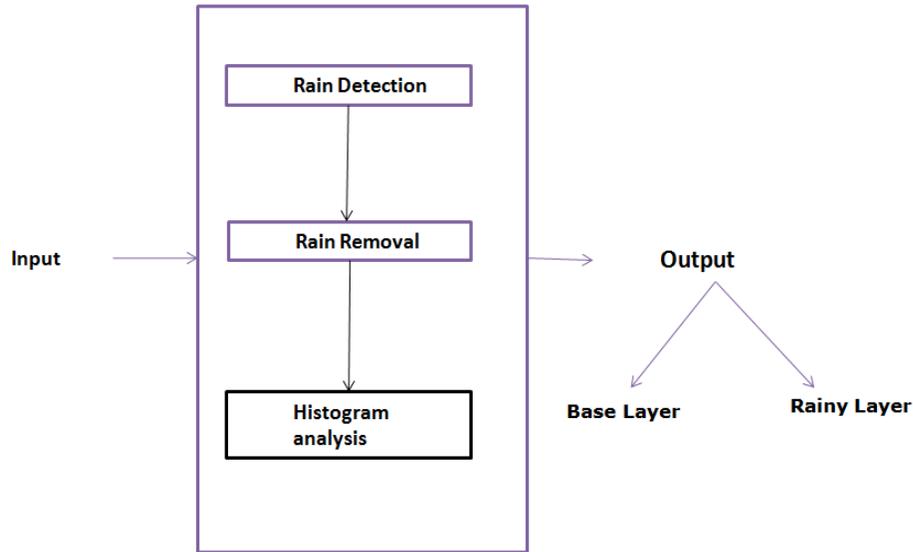


Fig. 1 Workflow Diagram

Image with rain streaks is the input to the system as shown in Fig. 1 which explains the proposed system design. Here the image is read and then detected through regional maxima. The image is processed with erosion and dilation for larger view. Thus their complements are used for image reconstruction and thus we obtain the regional maxima i.e, the rain streaks available in the original image. Then the detected rain image undergoes shift strategy in case of non-vertical rain streaks. Now smoothing operation is performed using L_0 gradient minimization technique. After completing the smoothing operation, adjustment limits are set as the intensities at the top and bottom 1% of the range by stretching. Because of the gamma correction factor, the mapping of the image which is inputted to the resultant image may be nonlinear. The mapping is linear, when the value of gamma is one, and it is weighted toward more resultant values, when gamma is < 1 . When the value of gamma is greater than one, the mapping is weighted closer to minimum resultant values. The peak signal-to-noise ratios for both the original image and the image which is rain free resultant image are obtained. Thus, peak signal-to-noise ratio is maintained without any modification from the original image.

Rain Detection

Rain streaks have two intrinsic properties for the still images named chromatic and spatial. Following headings elaborate on these properties.

- Spatial

Rain is imaged as an accumulation of circular H_2O drop that is conveyed in the space randomly. Rain falls rapidly when it is close to the ground because of the gravitational force. The

rain streaks are unable to image when they are far from the camera and it results in fog or haze like appearance. In this work, still images of rain streaks are considered. Rain streaks circulate in each image arbitrarily [3]. Because of the rapid, a similar drop may not show up in the two progressive image outlines. Rain streaks over the whole image cannot generally secure any pixels. The pixels being secured by rain streaks have their equivalent intensity distribution [3]. The inward and outward circles explain the distribution of intensity for the pixel respectively enclosed and not enclosed by rain streaks. Circles are evaluated in view of the fluctuations in the environment illumination. The spatial properties of rain streaks in single image are:

1. Rain streaks discontinuously secure a pixel.
 2. Similar background adjoining pixels have their intensity fluctuations similar to some degree.
 3. Rain streak unsecured pixels obtain uniform distribution of intensity.
- Chromatic

A droplet of fixed rain streak resembles a straightforward circle and that circle refracts light. The reflection of the surface and the internal reflection make the pixel which is secured by rain streaks more brilliant. In an image, the projection of rain streaks droplets may result in a haze because of the speed of rain streaks and the camera's properties.

Rain streak pixels have their intensity value smaller than that of stationary droplets. The intensity is specified by the following expression [10].

$$I_b(x, y) = \int_0^T E_r(x, y)dt + \int_t^T E_m(x, y)dt \quad (1)$$

here T - presentation period

t - interim that a drop remains on a pixel,

E_m - time-arrived at the midpoint of irradiance because of the foundation

E_r - the time-arrived at the midpoint of irradiance because of the droplet

I_b - power of the pixel secured by rain streaks.

In the discrete area: $I_b = E_b * T$,

$I_r = E_r * T$. From these,

$$I_{br}(x, y) = \beta * I_r(x, y) + (1 - \beta) * I_b(x, y) \quad (2)$$

here $\beta = t/T$. There is a mixing of the separate foundation and the stationary drop forces along a streak.

Rain streak removal using L_0 gradient minimization, can find edges comprehensively and control what number of non zero slopes are brought about to rough important structure in a way of sparsity-control [2].

The image is eroded and then dilated for larger view. Thus their complements are used for reconstructing the image and we also obtain the regional maxima i.e., the rain streaks available in the original image.

Framework for Rain Removal

Evacuation of the rain streaks is accomplished by smoothing activity. Remarkable regions are distinguished by this smoothing task, for example the most elevated difference edges by keeping the count of non-zero angles in a worldwide way.

Here rain detected image is given as input. Rain detected from the image is given as output. The input image undergoes the following process as shown in Fig. 2. The following framework consists of three sub modules. They are

- Shifting Strategy
- Smoothing Operation
- Contrast Enhancement

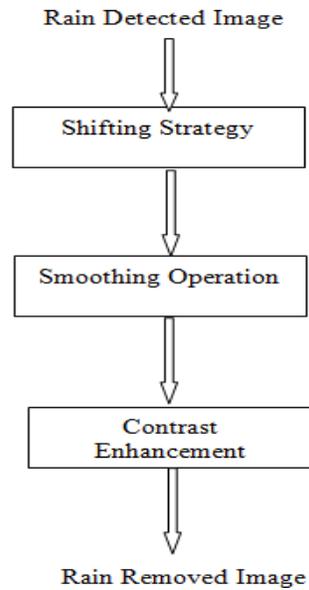


Fig. 2 Process of Rain Removal

- Shifting Strategy

Always the rain streaks are not vertical in a real rainfall-affected scene. For digital videos, double-edged sword directional property is utilized in the model. Depending on orientation, the rainy images are divided into different cases. If the orientation of the rain streaks is close to 0^0 , L_0 gradient minimization technique is directly applied.

For the other cases, shift strategy is introduced to handle the minimization technique. It is assumed that rain streaks have same orientation without loss of generality. The angle between vertical direction and rain streaks is represented by θ . Angle θ normally distributes in $(-90^0; 90^0)$. Suppose the angle $\theta \in (-90^0; 0^0)$, it is converted into the limits $(0^0; 90^0)$ by flipping left-right all the frames. Suppose $\theta \in (45^0; 90^0)$, it is changed to the range of $(0^0; 45^0)$ by performing the transpose operation (in the matrix swapping rows and columns) to all the frames. So focus is made only for the range of angles $[0^0; 45^0]$.

- Smoothing Operation

Consequence of smoothing by f and discrete flag is signified by g . The strategy checks adequacy changes discretely, composed as in Eq. (3).

$$c(f) = \# \{ p \mid f_p - f_{p+1} \neq 0 \} \quad (3)$$

Where p & $p+1$ are lists of the neighboring examples (or pixels). $|f_p - f_{p+1}|$ is the slope based on p as forward contrast. $\#\{\}$ is the operator to count which yields the number of p 's that fulfills that the value of $|f_p - f_{p+1}|$ being not equal to zero. The capacity, $c(f)$ is not dependent on inclination extent, and subsequently won't be influenced if any adjusts its difference. This discrete counting capacity is vital to the strategy. The target work is expresses as in Eq. (4).

$$\min \sum_f (f_p - g_p)^2 \text{ s.t } c(f) = k \quad (4)$$

$c(f) = k$ demonstrates that there exists k number of nonzero slopes for the outcome. Eq. (4) is incredible to extract structural data. The details are flattened the main edges are sharpened by the resulted signal. A bigger k yields a better estimation, as yet portraying the most unmistakable differentiation areas. Quadratic distinction term $(f_p - g_p)^2$ in Eq.(4) yields the expense. An important component of this system is regardless of the set value of k , no edge haziness will be produced because of the shirking of nearby separating and the averaging activity. Practically speaking, value of k in above Eq. (4) can be from 10s to 1000s, particularly in two dimensional images with various goals. To manage it, a common structure is utilized to look for a harmony between structure straightening and output closeness with the data, and compose it as

$$\min \sum_f f_p - g_p)^2 + \alpha \cdot c(f) \quad (5)$$

here α - smoothing parameter that controls weight of $c(f)$ straightforwardly. The large value of λ influences the outcome not to have many edges. Non-zero angle quantity is monotone as in $1/\lambda$.

In two dimensional, any input image is characterized as I and the outcome of image smoothing as S . Inclination is assessed for all the pixels as shading contrast between the adjacent pixels along both the x and y directions. The angle measurement is calculated as:

$$C(S) = \#\{ p \mid |\partial_x S_p| + |\partial_y S_p| \neq 0 \} \quad (6)$$

Eq. (6) checks p for which the extent $|\partial_x S_p| + |\partial_y S_p|$ is not equivalent to zero. Keeping such information, S is evaluated by using Eq. (7).

$$\min_s \sum_p S_p - I_p)^2 + \lambda \cdot C(S) \quad (7)$$

By tradition, the slope greatness $|\partial S_p|$ is only the whole of angle extents in the entity RGB plane. The term $\Sigma(S-I)^2$ represents structure of image comparability. There are 2 subproblems in L_0 smoothing because of the non-continuous nature. For example limiting the auxiliary variables and resultant image.

Algorithm: L_0 Gradient Minimization

Input: I – input image; λ - smoothing weight; k - smoothing rate; β & β_{\max} - parameters

Output: S - smoothed image

1. $S = I, \beta_{\max} = \beta, \kappa = 2.0, \lambda = 2E - 2$
 2. $\beta_{\max} = 1E5$
 3. $IF = FFT(I)$
 4. Use the variables h and v
 5. $\beta = 2 * \lambda$
 6. While ($\beta < \beta_{\max}$)
 - begin
 - $Solve (h,v) \text{ subproblem}$ $Solve S \text{ subproblem}$
 - Find IFFT
 - $\beta = \beta * \kappa$
 - end
 7. Enhance S
 8. Return S
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Algorithm 1 explains the gradient minimization technique. The attribute β is consequently refreshed during every cycle beginning from the underlying quality, and each time this parameter is multiplied by smoothing rate. In the execution the attributes β and β_{\max} are assigned with the

constants twice the smoothing weight and 1E5 respectively and smoothing rate is fixed to 2.0 for obtaining a decent balance among efficiency and execution time.

- Improving Contrast

Contrast is defined as a proportion of change of pixel brightness to the normal brightness. Contrast enhancement is performed by two tasks namely gamma correction and stretching.

1. First find the pixel esteems which are mapped to 0% and 100% of brightness. An assumption is made to keep the noise from impacting the stretching. Stretching sets the power esteems which speak to the top 1% (i.e., 0.01) and the bottom 1% (i.e., 0.99) of the range as far as possible. One can use large space in the balanced unique range of the remaining intensities by cutting the boundaries.
2. Mapping between qualities in the inputted and outputted images could be non-linear based on the estimation of gamma correction factor. Value of Gamma is in the range of 0 to infinity. Mapping is straight when gamma value is 1 (default). The mapping is weighted toward higher (more brilliant) yield esteems for gamma value under 1. The mapping is darker (lower values) output values for gamma value greater than 1.

Histogram Analysis

For both the original (image with rain streaks) and rain-free image, peak signal-to-noise ratio is calculated. Peak signal-to-noise ratio is maintained without any modification from the original image. PSNR is used for measuring the quality of reconstruction of lossy and lossless compression.

Reconstruction quality perceived by human is estimated by PSNR for comparing different compressions. Larger value of PSNR normally shows that the reconstruction is good. PSNR is defined through the mean squared error. Following algorithm shows the calculation of PSNR.

Algorithm: PSNR CALCULATION

Begin

 OriImg = double (OriImg);

 OutputImg = double (OutputImg);

 [S T] = size (OriImg);

 Err = OriImg - OutputImg;

 MSrErr = $\frac{\sum(\sum(\text{Err} * \text{Err}))}{(S * T)}$

 if (MSrErr > 0)

 PSNRVal = $\frac{10 * \log(255 * 255 / \text{MSrErr})}{\log(10)}$

 else

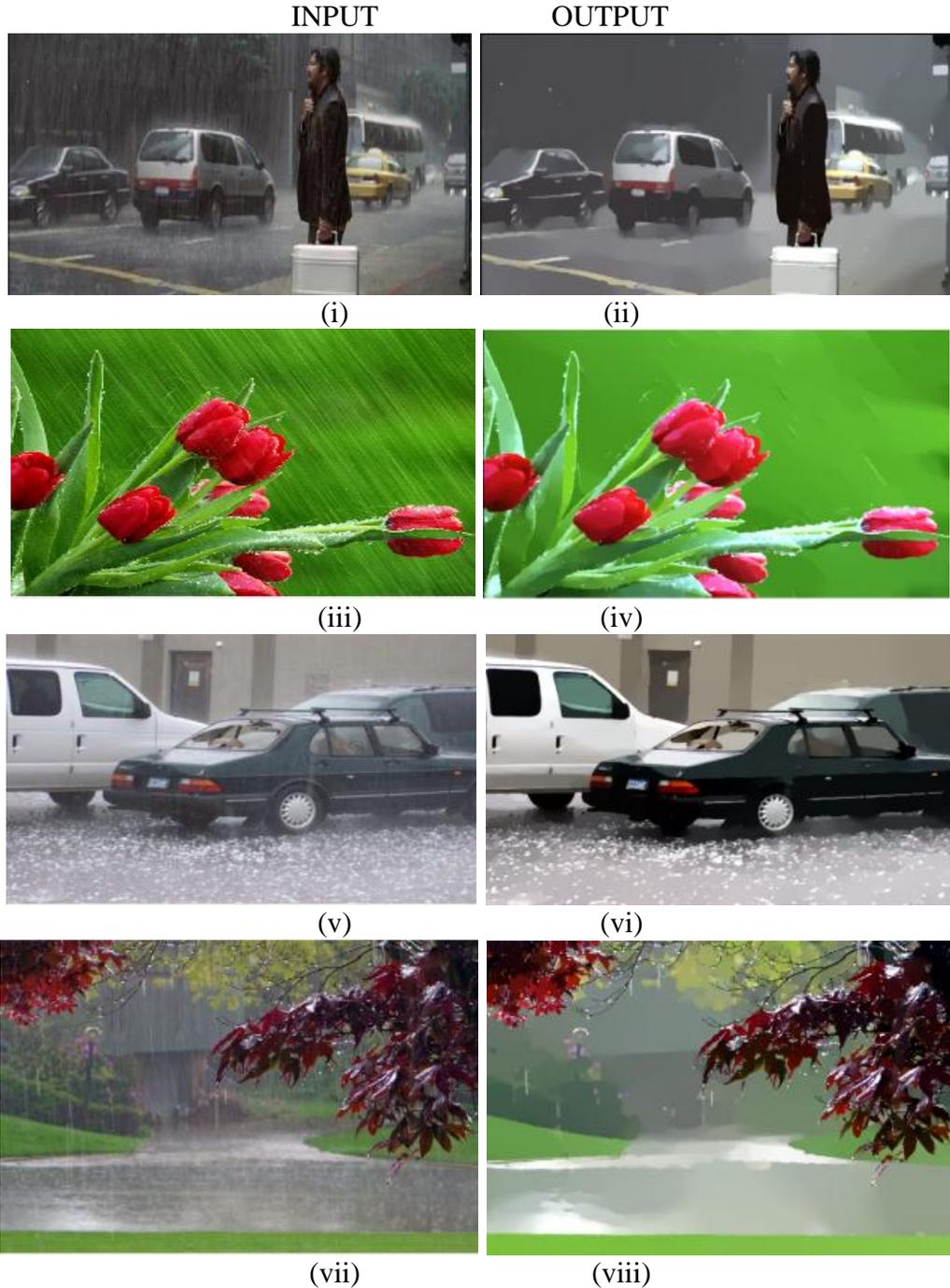
 PSNRVal = 99;

End

For color images with three RGB values per pixel, except the MSrErr is the sum over all squared value differences divided by image size and by three, the definition of PSNRVal is the same.

Thus the obtained PSNR's are plotted as histogram. Thus the proposed technique helps in ensuring the maintenance of PSNR's using histogram equalization.

3. RESULTS



In Figure. 3 (i),(ii),(iii),(iv),(v),(vi),(vii),(viii) the images before rain removal and after rain removal are shown.

Images captured under heavy rain are experimented with proposed technique. As mentioned before in Figure 3. (i), (iii), (v) and (vii) contain images with heavy rain. The images (ii), (iv),

(vi) and (viii) are the rain streak removed output images obtained by using the smoothing technique.

The work can be further extended by implementing the shift strategy of the oblique image to have the rainy image with more accuracy.

Connected Component Analysis

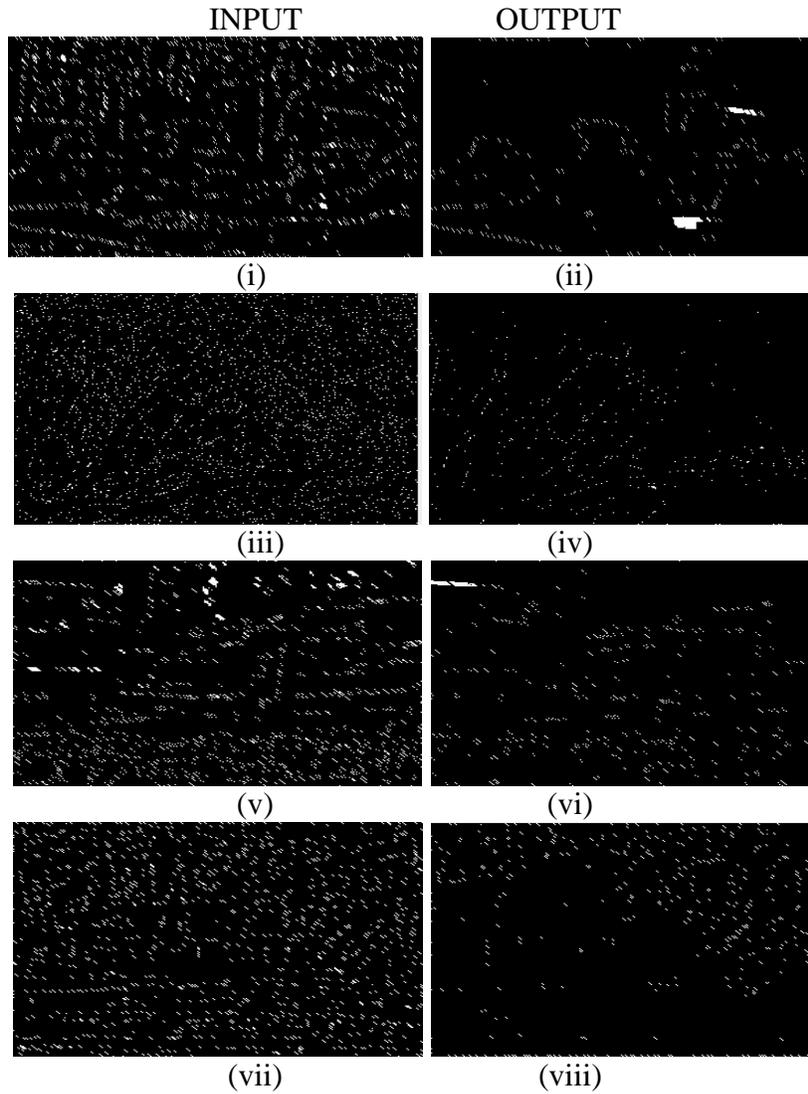


Figure 4 (i), (ii), (iii), (iv), (v), (vi), (vii), (viii) Shows the Connected Component Analysis of Images before Rain Removal and after Rain Removal

Table 1: Connected Component Analysis

Sl. No.	Number. of rain components in input image	No. of rain components in output image	% of Rain removal
1	2061	30	98.6
2	3009	142	96
3	2041	165	92

4	2968	196	93.4
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Figure 4 shows the images obtained by the proposed method using k-means smoothing technique for the original images and rainy images shown in figure3. A connected component analysis technique is applied on the images of Figure. 3 and the results are tabulated in Table I. The simulation results and the connected components analysis clearly showed that most of the rain streaks are well removed, the images are not blurred and the unwanted ghost effects are not formed. To improve the visual quality of the image the edges are well defined and maintained. The project is implemented in Matlab R2018a with minimum configuration set up.(i3 processor of 3.4 GHz and 4GB RAM). Simulation takes 3 seconds approximately to process and output the rain streak removed image of size 280*340.

4. CONCLUSION

The proposed model focuses on rain streaks expulsion from still images utilizing L_0 gradient minimization procedure. The method is successful and experimented on all images with substantial rain streaks. This strategy is free of the nearby properties, such as, spatial and chromatic feature, all inclusive holds and hones. The edges are not covered because of the absence of neighborhood sifting and averaging activities. Extensive simulation results on a variety of still images captured under various rain conditions showed that the proposed method gives better results.

5. REFERENCES

- [1] Manu B.N. "Rain streak removal using L_0 Gradient Minimization Technique". 7th *International Conference on Information Technology and Electrical Engineering (ICITEE)*, 2015.
- [2] Xu, Li, "Image smoothing via L_0 Gradient Minimization." *ACM Transactions on Graphics (TOG)*. Vol. 30. No. 6, 2011.
- [3] Ming Zhou, Zhichao Zhu, Rong Deng, Shuai Fang. "Rain detection and Removal of Ssequential Images." *Control and Decision Conference (CCDC)*, pp.: 615 - 618, 2011.
- [4] Abhishek Kumar Tripathi, Sudipta Mukhopadhyay, "Meteorological Approach for Detection and Removal of Rain from Videos". *Computer Vision, IET*, Volume: 7, Issue: 1, pp: 36 - 47, 2013.
- [5] Meibin Qi, Biao Geng, Jianguo Jiang, Tiao Wang, "A rain detection and removal method in video image". *Intelligent Visual Surveillance (IVS)*, 2011.
- [6] Xu, Jing, "Removing rain and snow in a single image using guided filter." *IEEE International Conference on Computer Science and Automation Engineering (CSAE)*, 2012.
- [7] Chen, Jie, and Lap-Pui Chau. "A rain pixel recovery algorithm for videos with highly dynamic scenes." *IEEE Transactions on Image Processing*, pp: 1097-1104, 2014.
- [8] Chen, Duan-Yu, Chien-Cheng Chen, and Li-Wei Kang. "Visual depth guided color image rain streaks removal using sparse coding." *IEEE Transactions on Circuits and Systems for Video Technology*, pp: 1430-1455, 2014.
- [9] Huang, De-An. "Context-aware single image rain removal." *IEEE International Conference on Multimedia and Expo (ICME)*, 2012.
- [10] Fu, Yu-Hsiang. "Single-frame-based rain removal via image decomposition." *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 2011.