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# ELIMINATION OF RAIN STREAKS IN VIDEO USING LOW RANK MATRIX COMPLETION AND KALMAN FILTER

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**Abstract: -** An innovative process for rain streaks, snow haze from a video i.e., sequence of frames using the two algorithms temporal correlation and low rank matrix completion as proposed in this paper. On discerning the rain streaks tiny and reckless that they upset the optical flow estimation between consecutive frames, we acquire a primary rain map by subtracting temporally warped frames from a current frame. Later we decomposed primary rain map into basis vectors based on sparse representation and then classify those basis vectors into rain streaks and outlier with a support vector machine. Then we refine the rain map by ignoring the outliers. Lastly we eliminate the spotted rain streaks by employing a low rank matrix completion technique. In addition, we prolong the proposed process to stereo de-raining. Experimental outcomes reveal that the proposed process detects and removes rain or snow streaks competently beating standard algorithms. In order to surge the resolution we customize two novel filters, kalman filter and particle filter which further more eases noise.

**Catalogue terms: -** video de-raining, de-snowing, rain streak removal, low rank matrix completion, sparse representation

## I.INTRODUCTION

For indoor environment, video is confined in ideal environment because artificial clarification is formed. On the other hand for open-air environment it is important to eradicate the various weather conditions such as static and dynamic. Static weather conditions are smog, mist and haze. The size of the streaks is about 1-10µm.The vibrant weather conditions are rain, blizzard and frozen rain. Its size is about 1000 times larger than that of static state of affairs i.e., 0.2-20mm. The concentration of the fastidious pixel will be the cumulative effect of large number of elements in the case of static weather state of affairs. In vibrant weather state of affairs since the droplets have the larger size the things will get motion. In distinct Image processing and computer vision systems including tracking and surveillance may not work accurately these degraded videos. Therefore challenges are made to reward for weather- dependent degradation and enhance outdoor video sequence. Rain prospect has property that an figure pixel is never eternally roofed by rain all over the complete video. Intensities produced by rain have tough spatial structure and depends on background brightness. When light permits through it gets reflected and refracted which makes clearer than background. Thus the concentration of the rain streak depends on the greatness of the drop, background view gleams and the integration time of the camera.

We have proposed an inventive video de-raining algorithm which uses temporal correlation and low rank matrix completion assuming that the adjoining frames, warped by the optical flows, are almost identical with the current frame excluding for rain streak sections. Here we generate an original rain map from the dissimilarities between the current frame and the warped adjoining frames. Then, we symbolize the initial rain map using sparse basis vectors which are dichotomized into rain streak ones and outliers using a support vector machine (SVM). By eradicating the outliers, we refine the rain map and perceive the rain streak. Finally, we put back the acknowledged rainy pixels using a matrix completion algorithm, which performs the expectation maximization (EM) iterations for low rank approximation. Moreover, we extend the proposed video de-raining algorithm to stereo de-raining. Experimental grades expose that the proposed algorithm out executes conventional algorithms by removing rain streaks competently and reconstructing the scene subjects faithfully.

This paper is organised as follows; section II surveys conventional de-raining algorithms. Section III describes proposed algorithms and section IV extends the proposed algorithm to stereo de-raining. Section V discusses experimental results. Section VI concludes the paper.

## II.RELATED WORKS

Garg and nayar "visualization and rain" in the year February 2007 successfully take apart rain streaks in videos but when rain is much heavy and light or rain is much away from from the lens, their method cannot perceive rain precisely. They made a widespread scrutiny about the attachment between rain's ocular effect and the camera constraints such as spotlight time, depth of field etc. They have over and done with that by adjusting the camera parameter, rain can be removed without clouding the background but in heavy rain clause this cannot be done and parameter cannot always be rehabilitated

K.Garg and S.K .nayar, "discovery and taking away of rain from videos" in the year 2004 designed method in which photometric model is held. The photometric model is based scheduled substantial properties of rain. They made a widespread exploration of ocular effects of rain and factor that upsetting it. They alleged that rain drops have an effect on only solitary frame and very few rain drop affect two successive frame. So if a rain drop shields a pixel then concentration modify owing to rain is one and the same to the intensity difference between the pixel in the current frame and repeated frame. This gives the lot of artificial recognition. Now to decline the artificially detect pixels, it is to be expected that the rain drops follow narrow photometric constraint. However in heavy rain, rain drops could affect the identical position in 2-3 successive frames. The novel algorithm could not categorize the defocused rain streak and streaks on the brighter background.

X. Zhang, H. Li, Y. Qi, W. K. Leowand T. K. Ng" rain elimination in video by combine temporal and chromatic properties" in the year 2004. Zhang proposed a method in which mutually temporal and chromatic constrains are studied. According to temporal property due to the direction of random allocation of rain, the same pixel may not contain rain over the intact video. Based on chromatic constraints it is alleged that variation in R, G and B colour components due to rain drops or same. These deviations are to be anticipated by a small threshold. The restraint of chromatic constraints is that it will not make out the rain streaks in gray region and insignificant motion of gray region. They have alleged that the camera is stationary When the camera is vibrant they have recommended video stabilization earlier than removes rain and subsequent to remove rain again deterioration have to be done and that would be a demanding method .

Peter C. Barmun, SrinivasaNarasimhan, TakeoKanade" The analysis of rain and snow in frequency region" in the year 2010. To begin with they have analysed for definite rain streak and snow. This representation is then athletic to a video and is used to perceive rain or snow streaks first in frequency region and revealing effect is assigned. The interference is that it is not significant for light rain, Since the sample fashioned in frequency space is not apparent.

Ming Zhou, Zhichao Zhu, Rong, Deng, Shuai Fang, "detection and crossing out of chronological images" in the year 2011.They have used spatial temporal and chromatic property. According to spatial temporal property rain is detected using enhanced k-means then a new chromatic constraint is residential to mend detection results. They have measured the image or video in which rain is blocked to the camera. Rain video is isolated while new image is little unclear.

Abhishek kumarthirupathi, Sudipta Mukopadhyay, "a probabilistic approach for recognition and deduction of rain from videos" in the year 2011. Proposed algorithm is robust to the rain moderation adjustments. Probabilistic advance mechanically adjust the threshold and remarkably discriminate the rain pixels and non-rain moving object pixels. Judgement between the rain and non rain moving objects is based on the time progression of pixels in alternate frame.

## III.PROPOSED ALGORITHM

First we attain a principal rain map by estimating the difference between the current frame and an optimally wrapped frame. Second, we sooner the initial rain map using sparse basis vectors into proper ones and outliers we then reconstruct advanced rain map by employ the valid vectors only. Finally, we restore rainy pixels with rain free values, by formulate the rain streak removal as a matrix completion problem.

### A. Primary rain detection

The current frame $I_k$ and its prior frame $I_{k-1}$ in the video sequence "Mail box". We see that rain streaks appear arbitrarily and each streak occupies a rather small area in a frame and moves fast between repeated frames. Also, when a rain streak passes transversely over a pixel, the pixel value becomes brighter than its inventive colour. Hence, we detect a rainy pixel, which has great value in a current frame than in adjacent frames. This advance, however, is prone to forged detection, since the same pixel harmonize in different frames may not signify the equivalent scene point .A video sequence may contain vibrant objects or to be captured with a poignant camera.

To give back for these mismatches between successive frames, we warp the preceding frame into the current frame by estimating the ocular flow field. An ocular flow estimation algorithm finds a extreme motion field between two successive image frames. For each pixel in a reference frame, a shift vector is resolute to find the most similar pixel in a objective frame, while maintaining the association of the shift vectors among adjacent pixels. The ocular flow estimation is often originate as a minimization problem, in which an energy function E is given by

$$E(U) = E_d(U) + \lambda E_s(U)$$

Where U is a flow field and λ is a regularization parameter. The data term $E_d$ measures the similarity between analogous pixels in the indication frame $I_1$ and the objective frame $I_{2,}$

$$E_d(U) = \int \Psi\left(I_2(x + u(x)) - I_1(x))^2\right) dx$$

Where u(x) is the ocular flow vector of pixel x, and Ψ is a penalty function. The smoothness term $E_s$ constraint adjoining vectors to be similar,

$$E_s(U) = \int \Psi\left(\|\nabla u(x)\|^2\right) dx$$

Where ∇u(x) denotes the gradient of u(x).

### B. Rain Map Refinement

We can acquire a binary rain mask by thresholds an primary rain map FIG 5. shows an primary rain map and the consequential binary rain masks using diverse thresholds. Note that the binary rain mask contain mistakenly detected outliers, caused by warp errors or brightness changed between frames, or fall short to perceive some applicable rain streaks. In general, as we diminish the threshold, many outliers are wrongly detecting outliers as rain streaks. On the divergent, as we augment the threshold, we can condense such outliers but also miss valid rain streaks. Moreover, outliers often be related with applicable rain streaks. Therefore, to detect legitimate rain streaks again and again while suppress outliers, we refine a primary rain plot before the thresholding.

To refine an primary rain plot, we exploit the directional property of rain streaks: rain streaks be predisposed to have cryptic shapes, whose foremost axes revolve aside modest from the perpendicular direction. In distinction, wrongly perceived outliers have subjective shapes or yield indiscriminate direction of foremost axes. Therefore, we can stumble on outliers by comparing the horizontal components with the vertical components of detected ellipses. However eliminating elliptical regions with large horizontal components may miss actual rainy pixels, since rain streaks and outliers occur simultaneously and may overlap each other.

To split valid rain streak vectors from outliers, we employ an SVM classifier by taking the rotational angle $\theta_i$ and the two Eigen values $\mu_i$ and $v_i$ as a feature vector. An SVM determines the maximum-margin hyperplane to split input data into two classes. For guidance the SVM, we use 3,072 positive samples of valid basis vectors from synthetic rainy frames. We also create 3,072 negative samples of outlier vectors by taking the difference between a frame and its warped adjacent frame in a rain-free sequence, which is erratically selected from the traced dataset.

Note that we may attempt to differentiate valid vectors from outliers by simply thresholds the rotational angle and the two Eigen values. However, it is not to find optimal thresholds for these parameters, and the finest thresholds vary according to input sequences. We confirmed experimentally that the SVM organization outperforms the simple threshold with various choices of thresholds. Moreover, the computational complexity of the SVM organization is much lower than that of the SVM guidance. It is worthy to point out that the guidance is performed only once offline.

After the SVM organization, we replace all outlier vectors in the original dictionary D with the zero vector to get a new dictionary next we refine the primary rain map R into the more perfect rain map Ř to this end, we restructure the matrix Ř by multiplying the pioneering dictionary Ď with the coefficient matrix $A^*$,

$$\hat{R} = \check{D}A^*.$$

We superimpose each patch, corresponding to a column vector in R̂, around the consequent pixel in R̂. Then, we set each pixel value in R̂ to be the standard of the overlapped values.

Finally, we generate a binary rain mask M from the refined rain map R̂, given by

$$M(x) = \begin{cases} 1 \; if \; \hat{R}(x) > € , \\ 0 \;\; otherwise, \end{cases}$$

Where the threshold € = 3 in the default setting, which was shown to yield consistent performance on most rainy sequences. Compares the initial rain map and the superior rain map, where the refined map suppresses most outliers in the initial map effectively. From the binary rain mask M, we further remove outliers by erasing small connected components of size 5 or less. Then, we perform the dilation operation on the rain mask, since the refinement procedure may warp the boundaries of rain streaks.

**C. Rain streak removal**

We renovate pixel values, detected as rainy, by exploiting temporal redundancies in adjacent frames. Specifically, we formulate the rain removal as a low rank matrix completion problem . We first separate the current frame $I_k$ into dislodge blocks. For each block b, we search for the most similar blocks from each of the four adjacent frames: $I_{k-2,}$ $I_{k-1}$, $I_{k+1}$ , $I_{k+2}$. Notice that we do not find similar blocks from the current frame. This is because similar blocks in the current frame tend to be selected near the given block b and affected by the same rain streak, debasing the de-raining performance. To measure the similarity between two blocks, we compute the sum of the squared differences between rain free pixels only. Then, we define a matrix B, by concatenating the given block b in the current frame and its 4l most similar blocks$b_i$ ‘s in the adjacent frames, B = [b, $b_1$,$b_2$ ,.....,$b_{4l}$]

Where each block is represented by a column vector. Note that we subtract the mean value from each block to compensate for the differences in enlightenment. We also define the binary rain mask matrix M for B, given by

M = [m,$m_{1,}$, $m_2$, ...,$m_{4l}$]

which consists of consequent mask values.

We adopt the low rank matrix completion techniques to find a filled-in matrix X from the unfinished matrix B. The required matrix X should minimize the nuclear norm $\|X\|$ subject to a constraint.

(1-M ) ° X = ( 1- M) ° B

Where 1 is the matrix whose all elements all elements are 1, and ° denotes the element –wise multiplication of two matrices.

## IV.EXPERIMENTAL RESULTS:

**I .Pre-processing:**

Image pre-processing is the term for operations on images ( or video frames) at the lowest level of analysis. First, we are converting the video into frames and then the input frame is transformed into gray scale image.

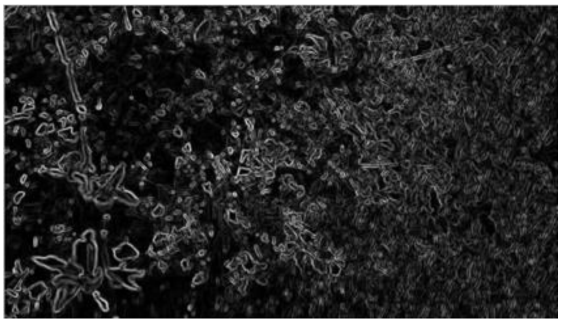
a. Input image

Grey scale images are distinct from 1-bit bitonal black-and –white images which in the context of computers imaging are images with only two colours black and white. Grey scale images have many shades of gray in between. These are always the result of measuring the intensity of light at each pixel in a single band of electromagnetic spectrum and in such cases they are monochromatic proper when only a given frequency is captured.

b. grey scale image

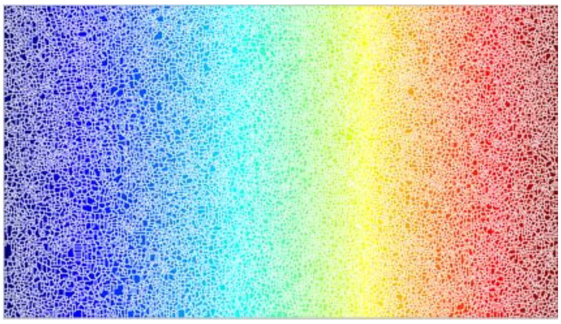
**II. Segmentation:**

This process is used for the separation of foreground and background of the images.



c. Gradient image

Watershed segmentation is used in the determination of RGB values from the image.



d. Watershed transformation of gradient magnitude (LRGb).

e. dilution of image

f. image reconstruction

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When a rain a streak passes across a pixel, that pixel values becomes brighter than its original colour. In order to remove rain streaks we, replace each rain pixel value with the weighted average of non-locally neighbouring pixel values.

g. Morphological process

**III. IMAGE RESTORATION:**

In order to acquire an image without rain streaks low rank reduction completion matrix is used. Our algorithm to achieve state-of-the-art space performance in low rank matrix recovery with theoretical guarantees. The reconstruction is accomplished by minimizing the nuclear norm of the hidden matrix subject to agreement with the provided entries.

h. image restoration

i. Image restoration (LLR)

**IV Post- processing**

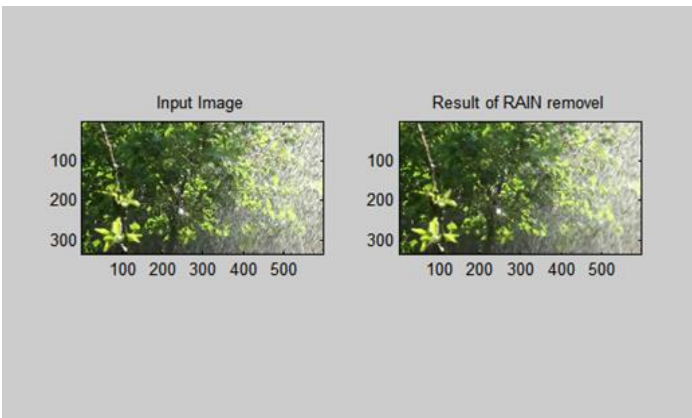
This is the final step of our paper, we already obtain an output image without rain streaks but it failed to obtain the image quality and the pixel resolution. In order to overcome this, we use kalman filter and particle filter.

j. Noisy image

**Kalman filter:**

In an unstructured complex environment or multiple tracking application kalman filter is applied for each of the objects to track.
Particle filter:
This filter is used to predict or to track variable number of objects and for position estimation of the objects.

Output image




Comparison of input image and output image

## CONCLUSION:

We proposed a video de-raining algorithm which exploits temporal correlation in a video progression based on the low rank matrix completion. The proposed algorithm obtains an initial rain map, by warping preceding and next frames and comparing those warped frame with the current frame. It then refines the initial rain map by removing outliers based on the sparse representation and organization. Finally, the proposed algorithm fills in rainy pixels using the EM based low rank matrix completion. We also extend that the projected algorithm into stereo video de-raining. Extensive experimental results established that the proposed algorithm removes rain and snow streaks more efficiently, at the same time as preserving scene structures more faithfully than the conservative algorithms.

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