

An Approach To Analyse Rain Removal From Single Frame Image

Anjolly Pandey¹, Prof Laxmikant Dewangan²

¹Dept of ECE

²Professor, Dept of ECE

^{1,2}CSVTU

Abstract- Rain streaks can be hard to detect and remove as they are a very dynamic phenomenon dependent on camera settings and weather conditions. This thesis aims to research some already invented rain removal algorithms and compare and evaluate them. Surveillance cameras supply video in real-time so it is not possible to access the whole video and perform heavy computations relying on information from the future.

Keywords- single-image rain removal, entropy maximization, level of streak suppression.

I. INTRODUCTION

The thesis is done in the context of surveillance cameras and real-time modification of the frames from a camera recording a scene with rain- or snowfall. The streaks produced by rain or snow can be disturbing for both human observers and image analysis algorithms which might be operating on the video stream from the surveillance camera. A surveillance camera does not want its motion detection to trigger on different weather phenomena. The streaks may also cause failure in face recognition algorithms when raindrops occlude parts of the face. If a solution should be viable in a surveillance camera context the algorithm removing the streaks should only utilize the images from the past and the present. Time complexity of the work performed becomes another important factor as well as the quality of the processed images. Before starting the thesis it was concluded from limited research that complete removal of rain is very challenging. The aim was to implement and evaluate some existing algorithms. If possible, combinations of algorithms would be tested to improve the results. The resulting algorithm should be fitted for Axis cameras and be useful in real-time and use no information unavailable to a typical surveillance camera.

Removal of rain streaks has recently received much useful for object identification in rainy images. There are the lots of topics that the researcher focuses that cover the field of image and signal processing. The field extends from the basic level first the basic images are improved and then the images

in the bad weather as the rain, snow or fog (or haze) etc. The removal of rain streaks has recently received much attention [1–6] in the research work in the field of image processing. The rain removal is just like the image enhancement and may come in the category of image noise removal or image restoration. Garg et al [2] in 2004 worked on dynamics of correlation based rain droplets detection and removal in videos. In the next subsequent year 2005 author shown in [3] that by altering some camera parameters as exposure time and depth of field the appearance can be enhanced and mitigate the effects of rain without the scene appearance alteration. Furthermore, Barnum et al. [1] presented model of single image rain or snow streak detection. Bossu et al. [7], presented a selection rules based on photometry. The photometry and size are used in selection rules to select the latent rain streaks in a video, in which the rain streaks orientations histogram is estimated with computed geometric moments. Meanwhile some researchers [8-10] focused on raindrop recognition in images or videos that is different from rain streaks detectio

The rain and non-rain parts in a single image are very closely mixed up and the identification of rain streaks is not an easy task. In this paper, we compare a single-image rain streak removal based on morphological component analysis (MCA) by decomposition of rain streaks [11]–[12]. The signal and image processing for the filtering and region specification are discussed in the previous works [13-22]. In this method, a bilateral filter is applied for an image to decompose it into the low-frequency (LF) and high-frequency (HF) parts. The HF part is then decomposed into rain component and non-rain component by performing sparse coding and dictionary learning on MCA. While the saturation and visibility feature (SVF) based rain removal uses high pass filter and the orientation filter [23].

II. RELATED WORK

A camera has many different parameters and many of them can be adjusted. In [5] it is proposed that these parameters can be set so that the rain effects are minimized or removed. Exposure time and field of vision, among others, are used to lower the effects of rain

In [2] the properties of rain and snow in the frequency plane is analysed. It is found that the visual effect of rain in an image is consistent in the Fourier transform of the image. This can later be used to create a model of rain and snow which is used to remove frequencies similar to the rain or snow frequencies in an image. The model uses several parameters such as exposure time, focal length, droplet size, brightness and orientation of the rain. All these parameters need to be adjusted for the video and rain at hand, so that the model can be accurate. To improve the result, the temporal aspect of the video is utilized and pixels which are both rain like in the frequency space and are changing rapidly in the time domain are marked as rain. After the rain is detected, an alpha blending between the image containing rain and an estimated rain-free image is made in order to remove the rain. This rain-free estimate is made by using a median filter on the same image.

The chromatic and temporal properties of rain are investigated in [4]. The temporal property states that a pixel is not always covered by rain throughout the entire video. With this fact in mind a histogram of pixel intensity is created for every pixel and two intensity peaks are identified; the intensity peak for the background and the intensity peak for the rain. It is stated that for this to work the camera has to be stationary or video stabilization has to be performed. The chromatic property says that the change of the red, green and blue values of a pixel are roughly the same from frame to frame if it was covered by a raindrop.

A. IMPLEMENTATION METHOD

Barnum and Narasimhan's research about frequency space [2] showed promise so that was where the thesis started. After an algorithm was familiarized with, a running implementation was developed. The development time for the different algorithms varied greatly. During the development of the algorithms some evaluation occurred all the time as the end results could be seen directly and be analysed.

The proposed method find the rain drops from the orientation filter and after the orientation filtering the entropy maximization based remaining rain drops are detected and the background is estimated for the rain removal. The step by step procedure is explained in the figure 1 .

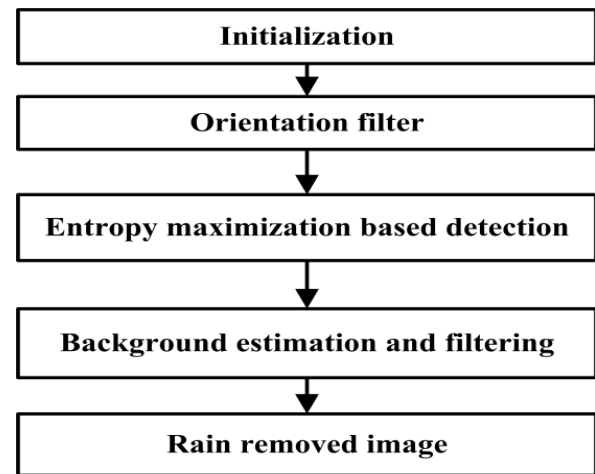


Fig 1. The flowchart of the proposed method

The decomposition based rain removal is based on the orientation of the rain drops. The vertically oriented [13, 22] rain drops are separated by the decomposition base method [23, 24].

A) TOOL

This section will provide a brief summary of the tools used during the thesis. For the image analysis part, Octave was the main development tool used in this master's thesis. Octave is an open-source alternative to the similar proprietary software called Matlab, and shares many functions. Since Octave provides very efficient ways to handle matrices, Octave was the program of choice. Matlab was also utilized for the morphological algorithms where Octave lacked some useful functions.

Java was used to load videos which could not be loaded in Octave. The Java implementation was closely intertwined with Octave and the software package Java Octave was also used as a bridge between the two.

The camera used to record the evaluation video presented at section 4 is an AXISP3367 Network Camera. It supports 5 megapixels or HDTV 1080p (2592x1944) quality. A lot of footage from other cameras supplied by Axis were also inspected.

They are presented below.

A.1.a Frequency

The frequency domain algorithm A.1. Detection algorithms

Five algorithms were implemented and compared in order to find the most suitable algorithm. It was investigated first out of the five algorithms. Unlike some of the other algorithms, the process of removing rain with information regarding their presentation of the frequency of rain consists of several steps.

Streak model: Uses theory to construct a rain streak similar to the streaks falling rain make in an image.

Rain model: A Fourier transform of the streak model created to imitate rainfall.

Fitting model to video: A big part and a big obstacle is the various parameters of the models which need to be adjusted to fit a particular rainfall.

Detection Use the model to identify the frequencies of rain in the image and remove them.

Streak Model

Firstly the model was built with the formulas. The streak model is handled as a matrix containing the values for the streak. The streak can easily be visualized as seen in figure 2. The dimensions of the matrix, which contains the streak are the same as the intended matrix dimension of the input image.

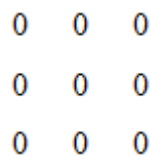


Figure: 2. Binary Mask of Dilation

Rain model

To get an approximation of the mean streak as a number of streaks were generated and added together. These streaks were created with parameters drawn

Detection

By applying equation below a gray scale matrix is constructed. This gray scale matrix indicates where rain exists in the picture. One model per frame is created, but with manual fitting of the model parameters the model is rarely updated. The aim was to go further and implement a way to automatically estimate the parameters needed for the model.

$$p_2(x, y, t) = \mathcal{F}^{-1} \left\{ \frac{R^*(u, v, \Lambda, \theta_{min}, \theta_{max})}{\|M(u, v)\|} \times \exp(i\phi M(u, v)) \right\}.$$

Skewness:

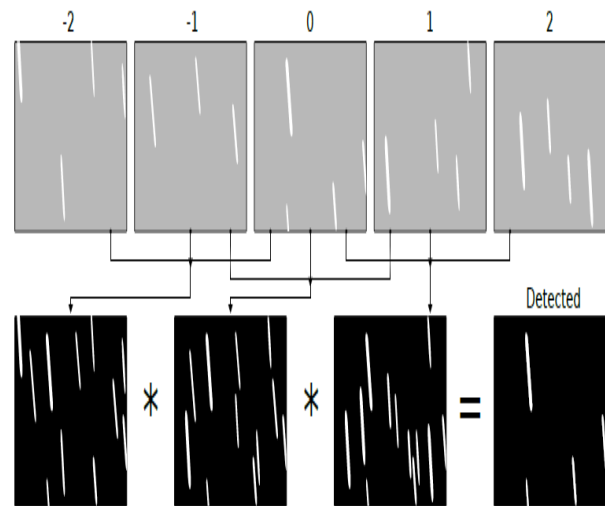


Figure 2: Illustration of how skewness can be used to detect the rain streaks from a single frame.

Intensity: The intensity property of rain is a very central property of the phenomena and as such it is a powerful tool. The approach is straightforward but can be varied by introducing different thresholds

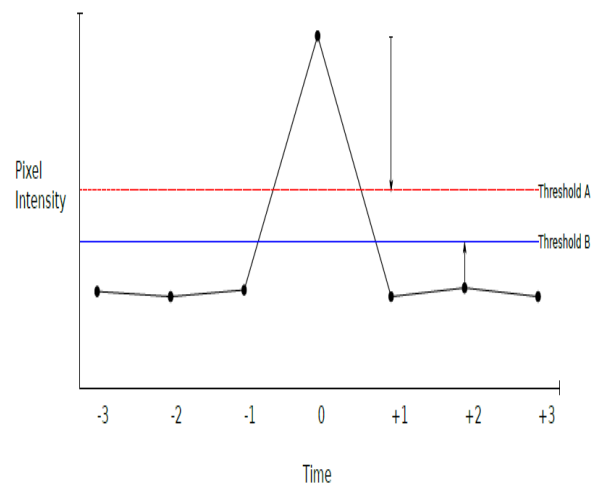


Figure 3: Intensity spike with thresholds determining if the spike is rain-like. Temporal neighbours to the pixel at time 0 have to be on the correct side of the thresholds if the pixel at time 0 shall be counted as a rain pixel.



Figure 4: Going from top to down, left to right. Image 1 is the original snow covered frame. Image 2 is image 1 with the snow removed. Notice the piece of the red umbrella being removed by mistake. Image 3 is image 1 with the snow removed. Notice unaffected umbrella. This is because color neutralization has been applied to the detection frame. But some very small areas are a bit pixelated and this can be removed with blurring. Image 4 is image1 with the snow removed. Color neutralization and blurring has been applied.



Figure 5: Going from top to down, left to right. Image 1 is the detection frame. Image 2 is image 1 with color neutralization applied. Image 3 is image 2 but with blurring applied. Image 3 is also the final detection frame. As can be seen, in every step the false detection (peoples, umbrellas) are reduced.

IV. RESULT

The detection algorithms’ usefulness is evaluated with detection quality and time complexity in mind. To measure the results of the algorithms two rough detection matrices were constructed for the selected frames. All rain streaks were manually marked in one frame to test rain detection. In another other all moving objects was marked to measure false detections in those objects. The two matrices can be seen in figure 3 To evaluate detection figure 3 and compare it to the algorithms’ outputs. Then each pixel can be categorized into the categories true_positive, false_positive, true_negative and false_negative. The category true_positive denotes all the rain pixels being correctly detected as rain. Similar to the category false_positive denotes all the non-rain pixels falsely detected as rain pixels.

The category true_negative denotes all the non-rain pixels correctly not being detected as rain. Finally the category false_negative denotes all the non-rain pixels falsely being detected as rain.

Using these values the following metrics the precision of an algorithm can be calculated as

$$precision = \frac{\sum true_positive}{\sum true_positive + \sum false_positive}$$

which gives a precision value which says how often the algorithm is correct when it outputs that a pixel is rain.

The sensitivity of an algorithm is a measure of how many of the actual rain pixels are correctly identified as such. It can be seen as how much of the rain in the frame that is covered by the algorithm,

$$sensitivity = \frac{\sum true_positives}{\sum true_positives + \sum false_negative}$$

Table1 Result comparison for the baseline [16], baseline [23], and proposed method

IMAGE	METHOD	PSNR	UIQI
Street image	baseline1	31.76	0.87
	baseline2	32.36	0.88
	proposed	33.34	0.93
Tree image	baseline1	31.26	0.86
	baseline2	31.87	0.89
	proposed	32.89	0.91

V. CONCLUSION

The purpose of our work has been to relieve the viewer or image processing algorithms from the specific noise the precipitation introduces. This hypothesis involved a subjective judgement of a video which could be difficult to objectively assess. During the thesis we have watched a lot of videos with rain removed and under some circumstances the algorithms do suppress the rain effect satisfactory, but this is not enough as an algorithm must work well in many cases, preferably in all cases. The false removal introduced by really aggressive rain removal algorithms could pose a problem if one attempts to analyze every detail in the image. If this is required then it is recommended that one should not remove the rain as aggressively by setting a higher threshold. If it is a video for watching then the possible noise being introduced might not even be noticeable by the viewer due to the high frame rate. In the algorithms implemented and tested in this thesis we found that the intensity algorithm coupled with morphological filter came closest to fulfilling the requirements. With regards to the time aspect several algorithms struggle. Especially frequency and aspect ratio with certain settings takes too long time. Frequency needs even more computations (scalar and orientation approximation) to be applicable there for we feel that it is not a candidate in real-time context with current computational power. The morphological algorithms' time consumption grows quickly under the wrong circumstances and this needs to be contained. If it can be optimized enough it removes a lot of false detections and should be considered.

Finally, we should say something about processing overhead. The algorithm was implemented in MATLAB[®] as a test implementation. It currently take several minutes to process an image; however, we hope to better this in future work.

VI. FUTURE SCOPE

In this section improvements to the algorithm are projected. To find out if the algorithms are truly applicable in an actual camera further evaluation is required. In particular, the algorithm should be implemented and evaluated in a camera. Automatically determine what the optimal parameters used in our algorithms should be set to in real-time if no setting is found to be good enough all around. The intensity threshold could e.g. maybe depend on the average intensity in the scene. The algorithms are different and some are more in need of this than others. Optimal parameters are parameters that will enable the rain removal algorithm to remove a lot more rain without falsely removing anything.

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