RESTORATION OF VIDEO BY REMOVING RAIN

Sajitha Krishnan[1] and D.Venkataraman[1]

[1]Computer Vision and Image Processing, Department of Computer Science, Amrita Vishwa Vidyapeetham University, Coimbatore, India

saji_krishnagiri@yahoo.co.in,d_venkat@cb.amrita.edu

ABSTRACT

The objective is to remove rain from videos without blurring the object. The algorithm helps to devise the system which removes rain from videos to facilitate video surveillance, and to improve the various vision-based algorithms. Rain is a noise that impairs videos and images. Such weather conditions will affect stereo correspondence, feature detection, segmentation, and object tracking and recognition. In video surveillance if any problem is found due to weather conditions the object cannot be tracked well. In this paper we have considered only rain falling in static environment, i.e., the object is not moving.

KEYWORDS

Properties, Symmetry, Temporal Intensity Waveform, Blending Parameter

1. INTRODUCTION

In indoor environment, video is captured in ideal environment because artificial illumination is formed. On other hand in outdoor environment, it is important to remove weather effect. In surveillance outdoor vision systems are used. Many algorithms such as feature extraction, object detection, segmentation etc use outdoor vision systems. Based on the physical properties there are two kinds of weather conditions: steady and dynamic [1]. Figure 1 and 2 show the steady and dynamic weather conditions respectively. The steady weather conditions are fog, mist and haze. The size of those particles is about 1-10µm. The dynamic weather conditions are rain, snow and hail. Its size is 1000 times larger than that of steady conditions i.e., about 0.1-10mm. The intensity of a particular pixel will be the aggregate effect of a large number of particles in case of steady weather conditions. In dynamic weather conditions, since the droplets have larger size, the objects will get motion blurred. These noises will degrade the performance of various computer vision algorithms which use feature information such as object detection, tracking, segmentation and recognition. Even if a small part of the object is occluded, the object cannot be tracked well. Rain scene has property that an image pixel is never always covered by rain throughout the whole video. For the purpose of restoration, the dynamic bad weather model is investigated. Rain is the major component of the dynamic bad weather.

DOI : 10.5121/ijcsea.2012.2202

Individual rain drop acts as spherical lens [1]. Intensities produced by rain have strong spatial structure and it depends strongly on background brightness. When light passes through it get refracted and reflected which make them brighter than background. But when it falls at high velocity, it gets motion blurred. Thus the intensity of the rain streak depends on the brightness of the drop, background scene radiances and the integration time of the camera. Analysis of rain and snow particles is more difficult. Some scene motions can produce spatial and temporal frequencies similar to rain. Median filtering of the frame partially only removes rain, and also the object gets blurred. Hence mere image processing techniques cannot suffice the problem.

a) Mist

b)Fog

Fig 1: The visual appearance of steady weather conditions

(a) Rain

(b) Snow

Fig 2: The visual appearance of dynamic weather conditions

The proposed work contains two modules: detection of rain and removal of rain. The detection of rain is too complex. Rain produces sharp intensity changes in images and videos that can severely impair the performance of outdoor vision systems. Each rain drop is in spherical shape. When light passes through the rain drop it get reflects and refracts from a large field of view towards the camera, creating sharp intensity patterns in images and videos. A group of such falling drops results in complex space and time varying signals in videos. In addition, due to the long exposure time of a camera, the intensities produced by rain are motion-blurred and hence depend on the background. After detecting rain pixels, it is replaced by α-value computed for each pixel.

2. LITERATURE SURVEY

Garg and Nayar successfully removed rain in videos [1]. But when rain is much heavier or lighter or when rain is much farther from the lens, their method cannot detect rain accurately. They made a comprehensive analysis about the relationship between rain's visual effect and the camera parameters such as exposure time, depth of field and so on. They have concluded that by adjusting the camera parameters rain can be removed without blurring the background. But in heavy rain condition this cannot be done and parameters cannot always be changed.

Garg and Nayar [2] proposed a method in which photometric model is assumed. The photometric model is based on the physical properties of rain. They have made a comprehensive analysis of the visual effects of rain and factors that affecting it. They assumed that raindrops affect only single frame and very few raindrops affect two consecutive frames. So, if a raindrop covers a pixel, then intensity change due to rain is equal to the intensity difference between the pixel in the current frame and in the consecutive frame. This gives lot of false detections. Now, to reject the false detected pixels, it is assumed that raindrops follow the linear photometric constraints. But in heavy rain, raindrops could affect the same position in two or three consecutive frames. Photometric model assumed that raindrops have almost the same size and velocity. It is also assumed that pixels that lie on the same rain streak have same irradiance because the brightness of the drop is weakly affected by the background. This gives a large number of miss detections. The reason could be the variation of the size and velocity of raindrops that violates the assumptions of the photometric model. The algorithm could not identify defocused rain streaks and streaks on brighter background. Thus, all the rain streaks do not follow the photometric constraints.

Zhang [3] proposed a method in which both temporal and chromatic constraints are considered. According to temporal property, due to the random distribution of rain, the same pixel may not contain rain over the entire video. Based on chromatic constraint, it is assumed that variations in R, G, and B color components due to raindrops are same. These variations are bound by a small threshold. The limitation of chromatic constraint is that it will not identify rain streaks in gray regions and slight motion of gray regions. They have assumed that the camera is static. When camera is dynamic, they have suggested video stabilization before removing rain and after removing rain again destabilization has to be performed, but that will be a difficult method.

Barnum [4] proposed a method in frequency space. First they have analyzed for individual rain streak and snow. This model is then fit to a video and is used to detect rain or snow streaks first in frequency space, and the detection result is then transferred to image space. The disadvantage is that it is not applicable for light rain, since the pattern formed in frequency space is not distinct. Zhou [5] proposed a method for rain removal in sequential images. They have used spatial-temporal property and the chromatic property. According to the spatio-temporal property, rain is detected using improved k-means. Then a new chromatic constraint is advanced to mend detection results. They have considered the image or video in which rain is close to the camera. Rain in video is removed, although new image is a little blurry.

Bossu [9] proposed a method in which detection of rain is done using histogram of orientation of streaks. In this the orientations of the different connected components are obtained by the method of geometric moments. The data of this histogram are then modeled as a Gaussian-uniform mixture. A decision criterion on the smoothed histogram then allows detecting the presence or absence of rain. When rain is detected, the rain pixels can be detected accurately and easily in the images and rain intensity can be estimated as well. The disadvantage is that rain with small intensity is difficult to be seen for human eyes, and thus to be detected with the proposed method. In the presence of light rain, the Mixture of Gaussian is no longer relevant. However, in the absence of rain, this method may also detect rain presence.

In our proposed method it is able to remove rain without blurring the background. This works in any rain conditions such as light rain, heavy rain, rain in reflection, rain with wind etc. The method does not assume the size, shape and orientation of rain. This requires only 15 or less consecutive frames for detection and removal process. Here we have taken into consideration only videos of static background.

In this paper, we first present the comprehensive analysis of the rain effects. The next section is the algorithm. The algorithm part includes both detection and removal of rain. This algorithm is experimented in complex static background scenes with different rain intensity variations and rain in reflection conditions. The experimental results are also shown.

3. RAIN ANALYSIS

3.1 Properties of Rain

3.1.1 Spatio-temporal Property

Rain randomly distribute in space and fall at high speeds when they reach at the ground. Due to high speed any pixel may not always covered by rain in two successive frames. The pixels which are covered by rain have similar intensity distribution [5].

3.1.2 Chromatic Property

A stationary drop is like spherical lens, so when light passes through the drop it gets some internal reflections and thus the drop becomes brighter than background. The increase in chrominance values is dependent on the background. The difference in three planes between two consecutive frames will be almost same. These variations are bound by a small threshold [3].

3.1.3 Photometric constraint

The photometry deals with the physical properties of the rain. The intensity of the rain streak depends on the brightness of the drop, background scene radiances and the integration time of the camera. Photometric model assumed that raindrops have almost the same size and velocity. It is also assumed that pixels that lie on the same rain streak have same irradiance because the brightness of the drop is weakly affected by the background [1, 2].

3.2. Challenges

The challenges in the detection of rain are heavy wind during rainfall, reflection in rainfall, misclassifications between text and rain, time-varying textures such as water ripples and when foreground is too cluttered. The following figures show examples.

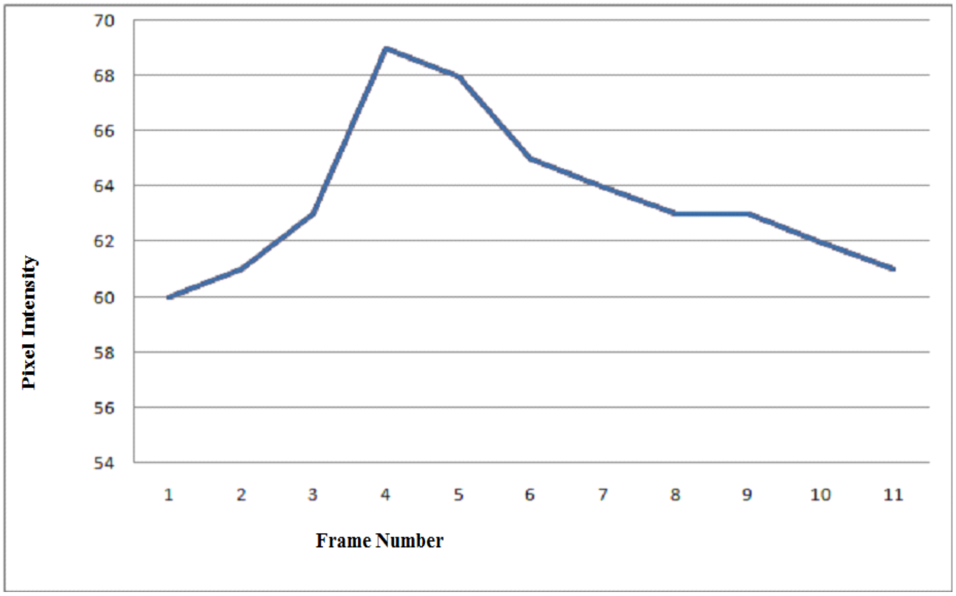
Fig 3: A frame of video containing heavy wind and rain. Rain is removed, but due to change in the orientation of rain streaks, some of leaves can be seen in the third column. In this case due to heavy rain, it forms a steady effect.

Fig 4: A frame containing light rain with too cluttered foreground. Rain is removed, but some portions of trees are misclassified as rain pixel. Time-varying textures such as ripples is also another challenge in this example.

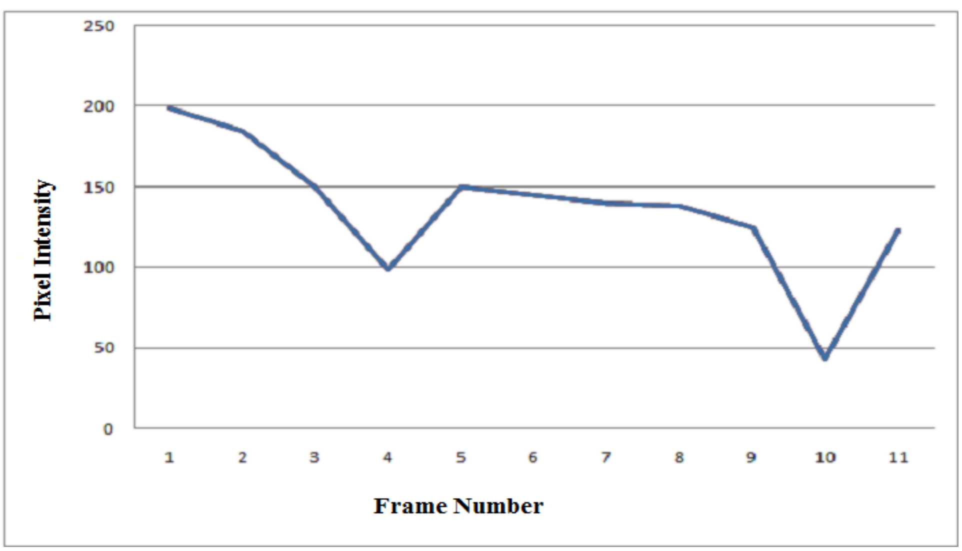
Some scene motions form similar temporal and spatial variations like rain. If foreground is too cluttered it is difficult to correctly detect rain. When rain streak is reflected, the intensity of rain pixel will change, but still the algorithm should be able to detect rain disregarding the chrominance and size of the rain particles. If there is heavy wind the orientation of the rain streaks may change, so we cannot assume the size and orientation of rain streaks.

In a rain video taken from a static camera, raindrops are randomly distributed in the space. Due to the random distribution of raindrops, a pixel at a particular position is not always covered by the raindrops in every frame. It is a common practice to analyze the rain pixels. To analyze the nature of rain, time evolution of pixel variations is exploited. There can be positive fluctuation in intensity variations. The intensity values of a pixel at a particular position present in the rain region for consecutive frames is quite different from that of the pixel present in moving object region. For the rain pixel, intensity values below and above mean are more rhythmic than those for the moving object pixel. Intensity variations produced by the raindrops are somewhat symmetric about the mean of the intensities of consecutive frames at particular pixel position.

Comparison of temporal intensity waveform between rain region and non-rain object motion is shown in Figure 1. The figures show the intensity at a particular position for 11 consecutive frames.



a)



b)

Figure: 5 a) shows the temporal intensity waveform for pixels in rain region b) shows the temporal intensity waveform for pixels in non-rain moving object region.

4. DETECTION AND REMOVAL OF RAIN

Extent of symmetry [6] of the waveforms above and below mean can be quantitatively measured by the skewness. The skewness [7, 8] of the data sample $x_1, x_2, x_3, \ldots, x_n$ can be given by Equation (1) as follows:

$$Skew\ (x_1, \ldots, x_n) = \frac{1}{N} \sum_{i=1}^{n} ((x_i - \bar{x}) \ / s)^3 \tag{1}$$

$\bar{x}$ is the mean and s is the standard deviation. Symmetry is considered to understand the variability of intensity values. The skewness value can be positive or negative, or even undefined. Qualitatively, a negative skew indicates that the tail on the left side of the probability density function is longer than the right side and the bulk of the values (possibly including the median) lie to the right of the mean. A positive skew indicates that the tail on the right side is longer than the left side and the bulk of the values lie to the left of the mean. A zero value indicates that the values are relatively evenly distributed on both sides of the mean. But in real time applications, it is not possible to get skewness value zero for the data items. When the background is static, we can see that there will not be any change in the intensity value for particular positions at some consecutive frames, but when rain is present the difference in the change of intensity values between consecutive frames will be small. The rain pixels will have low value of skewness than non-rain moving object pixels. For finding the discrimination between rain and non-rain pixels, this difference in the intensity waveform is considered.

4.1 Detection Of Rain

The difference in the temporal intensity waveform of rain and non-rain object pixel is considered. After finding the skewness for some consecutive frames, a threshold is set for skewness, say 100 and the intensity values less than the threshold is set as 1, i.e. rain pixel, otherwise 0 i.e. non-rain pixel.

4.2 Removal Of Rain

When rain drops fall at high velocity, the object gets motion blurred. In Garg and Nayar [2] the rain affected pixel is replaced by taking the average of temporal mean of consecutive frames. But if rain is very heavy, we cannot assume that the same pixel may contain rain for three consecutive frames only. In that case we cannot replace the rain pixel with average value, since that can be again a rain pixel. The velocity of the rain drop is higher than the exposure time; hence the same pixel position may contain different rain drops in consecutive frames. The consecutive frames may get degraded due to noise, low brightness, out-of-focus etc. In Zhang [3] the rain removal is done using α-blending. Dilation and Gaussian-blurring is applied on the detected rain pixels and it is used as α-channel. The new color of a pixel is replaced by α-blending of K-means clusters. The value of α may not be suitable for the entire image [5]. The value of α is determined by the exposure time of camera T and the time interval τ for the raindrop to stay over the pixel. The τ interval varies depending on the distance between camera and the object. Hence the α_i parameter for each pixel is calculated as

$$\alpha_i = \frac{\sum N_b}{\sum N_b + N_{br}}$$

where N_b is the element number of background cluster and N_{br} is the element number of the streak cluster.

5. SIMULATION AND RESULTS

To demonstrate the effectiveness of the algorithm, it is applied in following different videos.

1) Video containing rainfall in the presence of light. The rainfall is brighter, but still the rain is detected well. First column is the original frame of the video, second column is the rain removed frame, and the third column is the difference between the two.

a) Frame containing rain b) Rain removed frame c) Detected rain drops

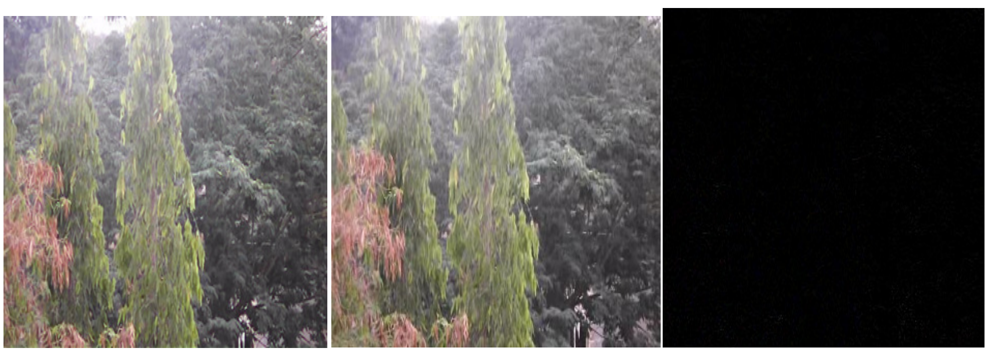
2) Video of pool - The video containing the rain falling to the pool. The video is taken in static background. First column contains the original frame and the second column contains the rain removed frame. The third column contains the difference between first and second column frames.

a) Frame containing rain b) Rain removed frame c) Detected rain streaks

3) Video containing number plate. In the second column the rain is removed. We can see in third column the rain is correctly detected.

a) Frame containing rain b) Rain removed frame c) Detected rain

4) Video of light rain. In the second column rain is removed. Even very light rain is well detected by the algorithm which is shown in the third column.



a) Frame containing rain b) Rain removed frame c) Detected rain

6. CONCLUSION

The proposed work does not assume the size, shape and orientation of the rain drops. It works in any rain conditions and also in case of reflected rain drop and scene containing text information. There is a significant difference in time evolution between the rain and non-rain pixels in videos. This difference is analyzed with the help of the skewness, which is the third central moment. Proposed algorithm uses this property to separate the rain pixels from the non-rain pixels. Here it is assumed that the camera is static and results are experimented using video with static background. In future work we wish to remove rain in dynamic background and also remove other dynamic weather conditions such as snow and hail.

REFERENCES

[1] Kshitiz Garg and Shree K. Nayar, “Vision and Rain”, International Journal of Computer Vision 75(1), 3–27, February 2007

[2] K. Garg and S.K. Nayar, "Detection and removal of rain from videos," in IEEE Conf. Computer Vision and Pattern Recognition, vol. 1, pp. 528-535, 2004.

[3] X. Zhang, H. Li, Y. Qi, W.K. Leow and T.K. Ng, "Rain Removal in Video by Combining Temporal and Chromatic Properties," in IEEE Int. Conf. Multimedia and Expo, pp. 461-464, 2006.

[4] Peter C. Barnum ,Srinivasa Narasimhan ,Takeo Kanade “Analysis of Rain and Snow in Frequency Space”, Springer International Journal of Computer Vision 86,256-274, 2010.

[5] Ming Zhou, Zhichao Zhu, Rong, Deng, Shuai Fang,Rain, “Detection and Removal of Sequential Images”, IEEE Chinese Control and Decision Conference (CCDC), pp. 615-618, 2011.

[6] Abhishek Kumar Tripathi, Sudipta Mukhopadhyay, “A Probabilistic Approach for Detection and Removal of Rain from Videos”, IETE Journal of Research, vol. 57, pp. 82-91, 2011.

[7] Stuart, A., and Ord, J.K., Kendall’s Advanced Theory of Statistics, 5th edition, 1987, vol 1, section 10.15.

[8] http://mathworld.wolfram.com/PearsonsSkewnessCoefficients.html

[9] Jeremie Bossu, Nicolas Hautiere, Jean-Philippe Tarel, “Rain or Snow Detection in Image Sequences Through Use of a Histogram of Orientation of Streaks”, Springer International Journal of Computer Vision, January 2011.