Image Deblurring of Video Surveillance System in Rainy Environment

Jinxing Niu[1, *], Yajie Jiang[1], Yayun Fu[1], Tao Zhang[1] and Nicola Masini[2]

Abstract: Video surveillance system is used in various fields such as transportation and social life. The bad weather can lead to the degradation of the video surveillance image quality. In rainy environment, the raindrops and the background are mixed, which lead to make the image degradation, so the removal of the raindrops has great significance for image restoration. In this article, after analyzing the inter-frame difference method in detecting and removing raindrops, a background difference method is proposed based on Gaussian model. In this method, the raindrop is regarded as a moving object relative to the background. The principle and procedure of the method are given to detect and remove raindrops. The parameters of the single Gaussian background model are studied in this article. The important parameter of the learning rate of Gaussian model is explored in order to better detection and removal of raindrops. Experiment shows that the results of removal of raindrops by using the proposed algorithm are better than that by using the inter-frame difference method. The image processing effect is the best when the learning rate is 0.6. The research results can provide technical reference for similar research on eliminating the influence of rainy weather.

Keywords: Inter-frame difference method, Gaussian model, raindrop, background difference.

1 Introduction

Outdoor vision systems are often used for many purposes. In a rainy-day environment, the captured video image will be blurred and dim. The raindrops will block important information, and sometimes cause color distortion. This series of problems has led to a reduction of usable information of video images, which has caused problems for vision effect. Therefore, detecting and removing raindrops in a video image is of great significance for image restoration.

The study of removing raindrops from video images has been started, and some scholars have proposed several algorithms based on the characteristics of raindrops. Garg et al.

[1] North China University of Water Resources and Electric Power, Zhengzhou, 450045, China.

[2] Institute of Science of Cultural Heritage, National Research Council, C. da Santa Loja, Tito Scalo (PZ), 85050, Italy.

[*] Corresponding Author: Jinxing Niu. Email: njx.mail@163.com.

Received: 16 April 2020; Accepted: 30 May 2020.

[Garg and Nayar (2007)] studied the physical, optical and dynamic properties of raindrops by analyzing their shape, size and distribution. They have found that a sudden change in light intensity occurs when a pixel is passed by a raindrop in the image. According to this, Dong et al. [Dong, Li and Chen (2013)] proposed an inter-frame difference method for detection and removal of rain in videos. The clear image is gained by two or more adjacent frames subtraction to eliminate the raindrops. However, this method can be used in the case where the same pixel does not have two or more consecutive frames affected. This method does not apply to heavy rain or rainstorm. Zhang et al. [Zhang, Li, Qi et al. (2006)] proposed a new rain removal algorithm that incorporates both temporal and chromatic properties of rain in video. Brewer et al. [Brewer and Liu (2008)] used the physical and optical properties of raindrops to detect pixels affected by raindrops, and then used the aspect ratio of raindrops for further detection. Barnum et al. [Barnum, Narasimhan and Kanade (2010)] analyzed the characteristics of raindrop in frequency domain in order to detect and eliminate raindrop, and then reversely transforms it to video image. Bossu et al. [Bossu, Hautière and Tarel (2011)] proposed a way which use of a histogram of orientation of streaks to detect rain or snow in image sequences. Tripathi et al. [Tripathi and Mukhopadhyay (2013); Tripathi and Mukhopadhyay (2014)] have found that the accuracy of algorithm to detection and removal of rain depends upon the discrimination of rain and non-rain pixels. This method can achieve real-time processing, but when it rains hard, the effect is not very good. Shorman et al. [Shorman and Pitchay (2016)] presented a review of restoration rain streaks detection and removal from single image which has different techniques used in video. Zhu et al. [Zhu, Fu, Lischinski et al. (2017)] proposed a novel method for removing rain streaks by decomposing it into a rain-free background layer B and rain-streaks layer R. They used a joint optimization process that alternates between removing rain-streak details for B and removing non-streak details from R. Huang et al. [Huang, Kang, Lin et al. (2012)] proposed a learning-based framework for single image rain removal, which focuses on the learning of context information from an input image. Guo et al. [Guo, Chen and Liu (2019)] proposed a novel deep learning architecture for rain removal from single image. Gui et al. [Gui and Zeng (2020)] regarded edit propagation as a multi-class classification problem and deep neural network to solve the problem. Zhang et al. [Zhang, Liang, Yang et al. (2018)] proposed a hybrid forensics strategy to detect object removal by exemplar-based inpainting. In this article, we propose a background difference method based on Gaussian model, which can be applied in moderate rain, heavy rain and snowy environment at the same time.

2 Rainy day video image restoration algorithm

For the detection and removal of raindrops, this paper firstly selects an efficient processing algorithm-inter-frame difference method, which can detect and remove raindrops effectively in the video, and achieve certain effects, but the image after processing still has raindrops, and there are certain deficiencies. In view of the shortcomings of the algorithm, this paper proposes a background difference method based on Gaussian model. The following is a principle analysis of the two algorithms and simulation experiments.

2.1 Inter-frame difference method

The inter-frame difference method is the most common method for detecting moving objects [Lin, Yu, Zhang et al. (2008)]. The basic principle is to subtract the gray value of the corresponding pixel of the two frames before and after. The background is assumed to have little change, the gray value of the corresponding pixel is not change. If some areas in the image have a large difference in gray value of corresponding pixel, it can be determined that there are raindrops passing through the area, and then the areas are calibrated to detect the position of the raindrops. Generally speaking, the image of two adjacent frames of the video is subtracted to represent the difference between the two frames of images. If there is a difference or a moving raindrop passes, the brightness values of the affected pixels of the two frames will change. The absolute value of the brightness difference can be obtained. According to many experiments, a threshold is set, the absolute value of brightness difference is compared with the threshold to distinguish the raindrop between the two frames. Raindrops can be detected by difference value between the two adjacent frames. The raindrops can be regarded as moving objects when the camera is fixed, that is, the detection and removal of raindrops are realized in the static scene.

In the inter-frame difference method, the most important step is to determine the difference between two frames. First, the luminance value I_t of each pixel in one frame of image at time t in the video sequence is extracted, and is subtracted by the luminance value $I_{t\text{-}1}$ of the pixel corresponding to one frame of image at time t-1. If the calculated absolute difference is greater than the selected threshold TH, it can be determined that the pixel is affected by the raindrop, and the luminance value is set to 1; if the calculated absolute difference is smaller than the selected threshold TH, then it can be assumed that there is no raindrop at the pixel, and the luminance value is set to 0.

The specific steps of the inter-frame difference method are as follows:

(1) Calculate the absolute difference between the brightness values of the t frame image and the t-1 frame image, as shown in the following formula:

$$D_t(x,y)=\left|I_t-I_{t-1}\right| \tag{1}$$

where $D_t(x, y)$ represents a difference value; I_t represents the value of the image frame at time t; $I_{t\text{-}1}$ represents the value of image frame at time t-1.

(2) $D_t(x, y)$ is binarized as shown in the following formula:

$$R_t(x,y)=\begin{cases}1 & D_t(x,y)\geq TH\\ 0 & D_t(x,y)< TH\end{cases} \tag{2}$$

where R_t (x, y) represents a binarized image; TH represents a threshold value, which is generally selected by experimental results, the value of which is the key of the inter-frame difference method. If the threshold is too low, it will be very sensitive, as long as a little change of the brightness value will be extracted, and the detected raindrops will be more; If the value is too high, the detected raindrops will be fewer. The threshold of the image can be divided into a global threshold and a local threshold. The change of the brightness value caused by the difference of the illumination area in the image will also be different. In general, the local threshold can be used to better detect the position of the raindrop.

(3) The clear image is obtained by subtracting the binarized image containing the raindrops from the current frame image.

The advantage of the inter-frame difference method is that the speed of detecting raindrops is fast and the algorithm is simple. The disadvantage is that it is easily affected by the external environment, and the selection of the threshold is also very important. It is difficult to grasp the threshold value, which will seriously affect the accuracy of raindrop detection.

2.2 Gaussian model based on background difference method

In application, the background image is constantly changing over time, and there are many factors that cause the background image to change, briefly as the following:

(1) There are many interference factors in the scene, such as the shaking of branches and leaves in the background scene, the fluctuation of the water surface ripples, etc. These interference factors cannot be simply judged as moving objects-raindrops.

(2) In rainy scenes, light and weather changes may affect the detection of raindrops.

(3) Changes of the background in the scene, such as a car leaving in the background, a person entering the background from outside the scene, changing the position of the original object in the background, which will affect the accuracy of the raindrop detection.

These factors are unavoidable in real life, and there is an urgent need for a way to avoid the impact of these factors. Therefore, a background difference method based on Gaussian model is proposed to achieve the purpose of removing raindrops. The algorithm can update the background in real time, which can avoid the influence of the above factors.

Because the background of the video image is relatively simple and static considering the speed of the algorithm, the background difference method of the single Gaussian model can be used. The single Gaussian model is a classic background modeling method with pixel values as the main feature, the parameter iterative method is adopted in the model. It is not necessary to model the background every time, just update the parameters. The complexity of the algorithm is reduced, and the processing speed of the algorithm is improved, which can well meet the real-time performance of the video background update. The background difference method of Gaussian model is mainly divided into two steps: one is the establishment of Gaussian model; the other is background difference method.

(1) Establishment of single Gaussian background model

The single Gaussian background model considers that the value of each pixel in the video image will be a little disturbed over time, and the distribution of disturbance satisfies Gaussian model [Yang and Shi (2009)]. If a raindrop passes, the pixel value will change greatly, and the pixel value will not obey the Gaussian distribution. According to this, the raindrops can be determined whether the pixel value at a certain moment satisfies the Gaussian distribution, and if it is satisfied, it is determined as the background, otherwise, it is judged to be a raindrop. The establishment of the Gaussian model mainly includes background modeling, background updating and background extracting.

1) Background modeling

The single Gaussian background model $\eta(x_t, \mu_t, \sigma_t)$ is established for each pixel in one frame of the video sequence image:

$$\eta(x_t, \mu_t, \sigma_t) = e^{-\left(\frac{x_t - \mu_t}{2\sigma_t^2}\right)^2} \tag{3}$$

where x_t represents the pixel value of a pixel of the t frame image; μ_t and σ_t represent the mean and variance of the pixel values of a pixel respectively.

The threshold can be obtained according to large number of experiments, which is obtained empirically. Then, comparing the threshold with the value of Gaussian model, if the value of Gaussian model is greater than the threshold, it can be determined that the corresponding pixel is a raindrop; if the value of Gaussian model is smaller than the threshold, it can be determined that its corresponding pixel is the background. It can be concluded from Eq. (3) that each Gaussian model is determined by the mean and variance of the value at that pixel.

2) Background updating

In real situation, the background changes slightly over time, so you need to update the pixel mean and variance for each pixel：

$$\mu_{t+1} = (1 - \alpha)\mu_t + \alpha x_t \tag{4}$$

$$\sigma_{t+1}^2 = (1 - \alpha)\mu_t^2 + \alpha x_t^2 \tag{5}$$

where α represents the model learning rate, that is the speed of the background change, and the value range is 0~1, which is determined according to the experimental effect. The Gaussian distribution parameters of the pixel points in one frame of image at time t+1 can be updated by using Eqs. (4) and (5).

3) Background extracting

The Gaussian distribution can be obtained by updating α according to the update formula. The average and variance value currently are the mean and variance of the background frame image. The background image obtained can better maintain the smoothness of the image edge. The algorithm is simple and fast, and the obtained result is also expected.

(2) Background difference method

After the background image is updated, the background difference method can be used to detect the raindrop. If the current frame image is $f_k(x, y)$, the background frame image $f_{bk}(x, y)$, and the difference $D_k(x, y)$ is：

$$D_k(x, y) = |f_k(x, y) - f_{bk}(x, y)| \tag{6}$$

The binarized image $R_k(x, y)$ is:

$$R_k(x, y) = \begin{cases} 1 & D_k(x, y) \geq T \\ 0 & D_k(x, y) < T \end{cases} \tag{7}$$

where T represents the threshold; if a pixel value of the image is larger than the threshold, it is determined to be a raindrop; if a pixel value is smaller than the threshold, it is determined to be the background.

The next step is to remove the raindrops. After obtaining the current frame image and the detected raindrop image in the video, we perform a subtraction operation, then the clear image is obtained after removal the raindrops.

3 Simulation experiments and results analysis

In raining day, the details of the image are blurred, the occlusion of the raindrops causes the desired image details to fail to meet the clarity requirements of the original image. In this article, the above two algorithms are used to simulate experiments for the rainy video images by MATLAB in the hardware environment of CPU Core i5-3210M processor and 4G memory.

3.1 Simulation experiment

The static scene in the rain is studied in this article, that is say, the background is fixed, no camera movement or jitter. When the Gaussian model background difference method is used, the processing effect will be different with the different learning rate α in the algorithm. The smaller the learning rate value is, it has the lower ability to adapt to environmental changes, and takes enough time to update the background model. The larger the learning rate value is, it has the stronger the ability to adapt to environmental changes and quickly update the model. If the learning rate value is bigger, a target is easily regarded as a background which stays for a period in the scene. In some situation, the learning rate value in the algorithm needs to be adjusted, that is, different values are set at different positions in the image to adapt the changes of the environment. However, in this paper, because of the rapid falling of the raindrop, it is not a period time for raindrops staying at the same scene, so we only need to set a fixed value.

(1) Relationship between learning rate value α and running time t

Simulation experiments were performed on the MATLAB platform by selecting different learning rate values. A total of 100 sets of data were selected to obtain the relationship between the learning rate value α and the time t, as shown in Fig. 1.

As can be seen from Fig. 1, the learning rate α is about 0.3, the curve is undulating, and there is no rule to follow. But when it is bigger than 0.3, the whole curve shows a downward trend, that is, the larger the learning rate α is, the shorter the program running time is.

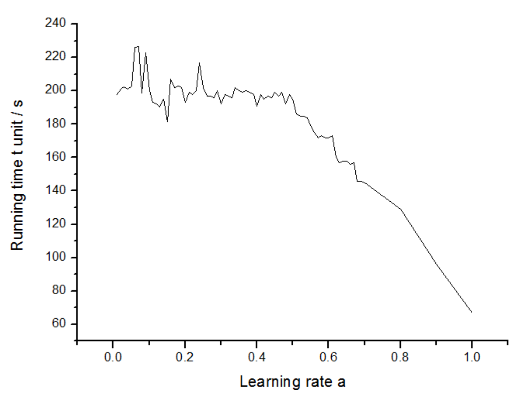


Figure 1: Relationship between learning rate α and running time t

(2) Simulation results

The following is the result of the Gaussian model background difference method, three representative effect images are selected here to present with different learning rates α, as shown in Fig. 2.

From the following three images, it can be seen that as the learning rate α increases, the effect of removing raindrops is getting better. When α is taken as 0.6, the effect is the best, and basically all the raindrops are removed. However, in the process of increasing the learning rate α from 0.6 to 1, the effect of removing raindrops is getting worse. Especially when it is 1, basically no effect is seen.

α =0.1 α =0.6 α =1

Figure 2: Result image at different learning rate α

We can draw a conclusion by combining analysis of running time and visual effects: when the learning rate α of the algorithm is 0.6, the processing result is the best, and the running time is relatively fast, which is about 172 seconds.

3.2 Analysis of simulation results

According to the above simulation experiment results, the update parameter of the background difference method of Gaussian model is 0.6, the video images of medium and heavy rain are studied. The difference between medium and heavy rain is that the rain line of heavy rain is longer and denser than that of medium rain. Because the characteristics of raindrops and snowflakes are very similar, the simulation results show that the algorithm is also suitable for the detection and removal of snowflakes. The simulation results of the background difference method of Gaussian model and the inter-frame difference method are shown in the Figs. 3-7.

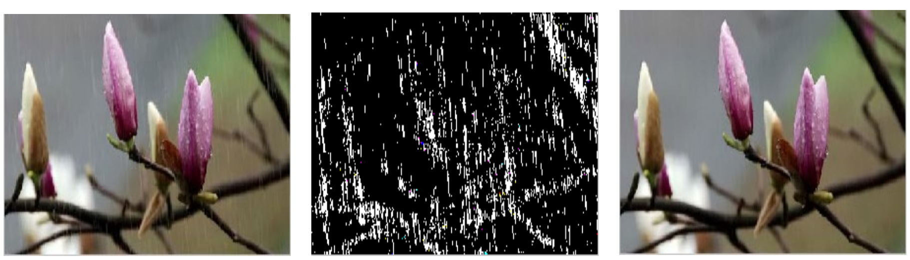
Figs. 3 and 4 show the experimental results after adopting the inter-frame difference method in medium and heavy rain environments respectively. It can be seen from the results that the algorithm has a certain effect on detecting and removing raindrops in the medium and heavy rain environment, and the image becomes clear after being processed, but there are still raindrops.

(a)original image (b)Raindrop image (c)Processing result

Figure 3: Effect of inter-frame difference method in medium rain

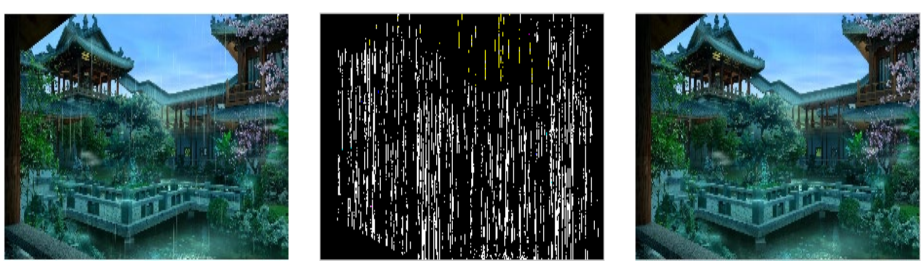
(a)original image (b)Raindrop image (c)Processing result

Figure 4: Effect of inter-frame difference method in heavy rain



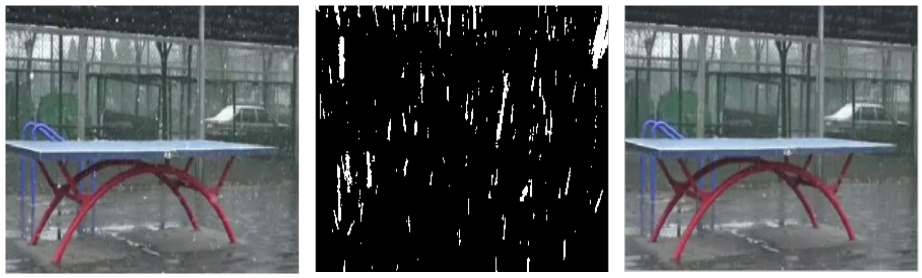
(a)original image (b)Raindrop image (c)Processing result

Figure 5: Effect of background difference method of Gaussian model in medium rain



(a)original image (b)Raindrop image (c)Processing result

Figure 6: Effect of background difference method of Gaussian model in heavy rain



(a)original image (b)Raindrop image (c)Processing result

Figure 7: Effect of the background difference method of Gaussian model in snow

Figs. 5 and 6 show the results after employing the background difference method of Gaussian model in medium and heavy rain environments respectively. We can see that it has great advantages compared with the inter-frame difference method. The image after being processed has few raindrops, and has good effects for the scenes of medium and heavy rain. Fig. 7 shows the results after adopting the background difference method of the Gaussian model in a snowy environment. The results show that the algorithm is also good for snowflake processing.

Therefore, the background difference method of Gaussian model has good effects on detecting and removing raindrops and snowflakes in the video, and can be applied to medium rain, heavy rain, and snowy environments at the same time.

4 Summary

Aiming to solve the problem of detecting and removing raindrops in image, this paper proposes a background difference method based on Gaussian model, which updates the background in real time to avoid the influence of background interference on raindrop detection. Results show that the method can achieve the purpose of raindrop detection and removal, and the effects are better than inter-frame difference method. The algorithm can be applied to medium rain, heavy rain and snow environments at the same time and it can be used in many engineering applications.

Acknowledgement: The authors thanks Dr. Jianrong Ma for his suggestions. The authors would like to thank the anonymous reviewers and the editor for the very instructive suggestions that led to the much-improved quality of this paper.

Funding Statement: This work was supported by Henan Province Science and Technology Project under Grant No. 182102210065.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

Barnum, P. C.; Narasimhan, S. G.; Kanade, T. (2010): Analysis of rain and snow in frequency space. *International Journal of Computer Vision*, vol. 86, no. 2-3, pp. 256-274.

Bossu, J.; Hautière, N.; Tarel, J. P. (2011): Rain or snow detection in image sequences through use of a histogram of orientation of streaks. *International Journal of Computer Vision*, vol. 93, no. 3, pp. 348-367.

Brewer, N.; Liu, N. (2008): *Structural, Syntactic, and Statistical Pattern Recognition*. Springer-Verlag Berlin Heidelberg.

Dong, R.; Li, B.; Chen, Q. (2013): A method for detection and removal of rain in videos. *Acta Automatica Sinica*, vol. 39, no. 7, pp. 1093-1099.

Garg, K.; Nayar, S. K. (2007): Vision and rain. *International Journal of Computer Vision,* vol. 75, no. 1, pp. 3-27.

Gui, Y.; Zeng, G. (2020): Joint learning of visual and spatial features for edit propagation from a single image. *The Visual Computer*, vol. 36, no. 3, pp. 469-482.

Guo, Y.; Li, C.; Liu, Q. (2019): R^2N: A novel deep learning architecture for rain removal from single image. *Computers, Materials & Continua*, vol. 58, no. 3, pp. 829-843.

Huang, D.; Kang, L.; Yang, M.; Lin, C.; Wang, Y. (2012): Context-aware single image rain removal. *IEEE International Conference on Multimedia & Expo*, pp. 164-169.

Lin, J.; Yu, Z.; Zhang, J.; Ma, A.; Chu, Y. (2008): A new moving detection method based on background differencing and coterminous frames differencing. *Chinese Journal of Scientific Instrument*, vol. 29, no. 4s, pp. 112-115.

Shorman, S. M.; Pitchay, S. A. (2016): A review of rain streaks detection and removal techniques for outdoor single image. *ARPN Journal of Engineering and Applied Sciences*, vol. 11, no. 10, pp. 6303-6308.

Tripathi, A. K.; Mukhopadhyay, S. (2013). Meteorological approach for detection and removal of rain from videos. *IET Computer Vision*, vol. 7, no. 1, pp. 36-47.

Tripathi, A. K.; Mukhopadhyay, S. (2014): Removal of rain from videos: a review. *Signal Image and Video Processing*, vol. 8, no. 8, pp. 1421-1430.

Yang, J.; Shi, Z. (2009): Improved single gaussian model for traffic background extraction. *Acta Photonica Sinica*, vol. 38, no. 5, pp. 1293-1296.

Zhang, D. Y.; Liang, Z. S.; Yang, G. B.; Li, Q. G.; Li, L. D. et al. (2018): A robust forgery detection algorithm for object removal by exemplar-based image inpainting. *Multimedia Tools and Applications*, vol. 77, no. 10, pp. 11823-11842.

Zhang, X.; Li, H.; Qi, Y.; Leow, W. K.; Ng, T. K. (2006): Rain removal in video by combining temporal and chromatic properties. *Proceedings of the IEEE International Conference on Multimedia and Expo*, Toronto, Canada, pp. 461-464.

Zhu, L.; Fu, C. W.; Lischinski, D.; Heng, P. A. (2017): Joint bi-layer optimization for single-image rain streak removal. *IEEE International Conference on Computer Vision*, pp. 2526-2534.