

Rain Removal Algorithm Based on Retinex in Low Light Automatic Driving Scenario

Yang Qiyuan¹

¹School of Software, Yunnan University, Kunming, Yunnan 650091, China

qqq1277@mail.ynu.edu.cn

Abstract. In the field of automatic driving, clear image is one of the important prerequisites for the decision-making system relying on computer vision to make correct decisions. Rainy days and low illumination environment are two common scenes that seriously affect image quality. Researchers have proposed many effective methods for these two research fields. However, few applications have been studied in the field of automatic driving comprehensively. To solve the problem, a low illumination image enhancement method in rainy days is proposed, which combines the two scenes and can be applied to the field of automatic driving. This algorithm takes good advantage of the fact that raindrops cannot appear in the same frame at different times to eliminate the noise of raindrops in the image. And its main process is to fuse continuous image frames by maximum method through multi-scale Gaussian filtering. Thus, the fused image is used as the illumination map and the original image to be denoised is used as the input of Multi-Scale Retinex(MSR) method. Finally, the reflection image which can be directly applied in automatic driving is obtained.

Keywords: low light, rain removal, Retinex.

1. Introduction

In autonomous driving domain, it is important to extract clear images or videos from visual camera equipment. But due to the complex environment and weather, it can be possible that any irregular disturbance will cause the degradation of the quality of the image. The resulting loss of the image accuracy will lead to deviation in the decision of the autopilot system, which may produce more serious security problems. For instance, when dealing with human detection [1] or lane detection[2], if the images affected by some noise, the results may be biased or wrong, making the deviate from the correct path. For rainy days, both of rain streaks and drops often obturate or blur the important information of the images captured by camera outside the car. As usual, nearby rain drops/streaks tend to obstructor distort the key background scene contents and distant rain streaks tend to generate atomspheric veiling effects like mist or fog and make the image contents blur [3, 4, 5]. Therefore, it is essential to complete the rain removal task for image or video, which can be able to process the image in advance for vehicle. An efficient rain removal algorithm can offer help to deliver more accurate detection and recognition [6]. At present, there are two main types of rain removal tasks: video rain removal(VRR) and single image rain removal(SIRR)[7]. According to this classification, in recent studies, various methods have been made public for the task to eliminate rain whether it's video or single image[5]. However, it is noted that an image pixel is not always covered by rain in the whole

video about the temporal property. The chromatic property states that the changes of R, G, and B values of rain-affected pixels are approximately the same [8]. Thus for the field of autonomous driving, when tackle the rain removal task, the consecutive video frame information taken by cameras can be more useful and adaptive. Besides, as the results of the changeable environmental conditions, especially influenced by the light, for the most part video image frequency from gathering equipment, are too bright or dark, and some partial details of the image are lost [9], thereby has a great influence on the images' quality, which has a serious effect on safety and accuracy for the application of autonomous vehicles(AVs). So how to use the images with seriously damaged by the illumination are important for AVs.

Many researchers have proposed techniques to realize the improvement of image quality in these cases [10, 11, 12]. However, there is little work on these kinds of issue in automatic driving scene, especially combining both of the rain removal and low-light image enhancement. Consequently, it could be deemed to find one synthetical method, which be feasible and adaptive for the issues mentioned above. To solve those problems, and taking into account the relevance of adjacent video images for the autonomous driving, This paper proposed a new algorithm to solve the video rain removal in low-light with the Retinex theory, which can be used to enhance the image quality in the automatic driving scene with rain at night that has a low-light. In this regime, it is expected to get timely video frame, which has can be effectively used in the vision system of AVs. The main structure of this paper is as follows: Section 2 described the related work of video rain removal and Retinex theory in low illumination enhancement. Section 3 explained the method based on Retinex for images rain removal at low-light. And Section 4 lead a discussion about why MSR is better method to solve this issue. At Section 5, it included a briefly summary and conclusion.

2. Related work

2.1. Video rain removal method

In 2004, it was raised by Garg and Nayar firstly that remove rain streaks[13]. Subsequently, more video derain methods based on different rain situation were proposed, and quite a few of them won excellent results[5]. Early methods usually depended on some properties of rain, including geometric property, brightness property, chromatic property spatial and temporal property[14]. It is noteworthy that falling raindrop at a high speed will cause shape distortions, and these distortions often influenced by the factors mentioned including above but not limited. But for the discussion of this article, it mainly focus on the spatial and temporal characteristics. As we all know, raindrops captured by camera are appeared in image area randomly, and due to raindrops move at high velocities, intensity fluctuations will occur in time and space, and for every video frame, not all the time the raindrops covered a specific pixel[8], which mean throughout the entire video, it only exhibits one peak that the intensity histogram of a pixel haven't been covered by raindrops before, and a pixel at particular position is not always covered by these raindrops in every frame[8, 15]. However, sometimes the intensity histogram for the pixel covered by rain shows two peaks, one is the background intensity distribution, the other is the rain intensity distribution. Therefore, the multi-scale information on these serial images can be used, then by exploiting the difference between adjacent images the rain streaks can be eliminated [16].

2.2. Low-light image enhancement method

In general, there are two main groups of low-light image enhancement can be used: method based on histogram and Retinex. It may be the most intuitive way to illuminate the dark image by directly expanding the low light level image through histogram transformation. One of the histogram equalization techniques is histogram equalization (HE), which makes the histogram of the image more balance as much as possible. However, another method called Retinex is mainly considered by this paper. This theory was proposed by Land[17], which gave a description about the color perception

characteristics of human visual system[18]. In Retinex theory, the image data obtained by human is dependent on the incident light and the reflection of the object surface.

3. Proposed algorithm

In this paper, the novel algorithm based on Retinex tries to fused the multi-scale information captured by visual sensor on AVs. On the one hand, it points to improve the quality of serial video pictures, on the other hand, it takes advantages of the continuous image to restore the rain streaks caused by temporary rain drops. There are main methods used include Gaussian Filtering, Retinex and Algorithm based on MSR.

3.1. Gaussian filtering

Gaussian filter is a smooth linear filter, which applies normal distribution in image processing. Using Gaussian filter to filter the image has the effect of reducing the “sharp” change of image gray, that is, making the image “fuzzy”, but the image noise obeying normal distribution is suppressed. As for the Gaussian filter, it can also be regarded as a process of averaging numerically for the digital image in a pixel matrix and it produces the effect of blur on the original image. Before calculating, Gaussian filter needs a template also called kernel, and this kernel will be used to match the pixel matrix for one image, and this kernel obey the Gaussian function as follow:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}} \quad (1)$$

σ is the parameter means standard deviation that we need to set, After calculation and normalization using the specified Gaussian, we can get the smooth image.

3.2. Retinex

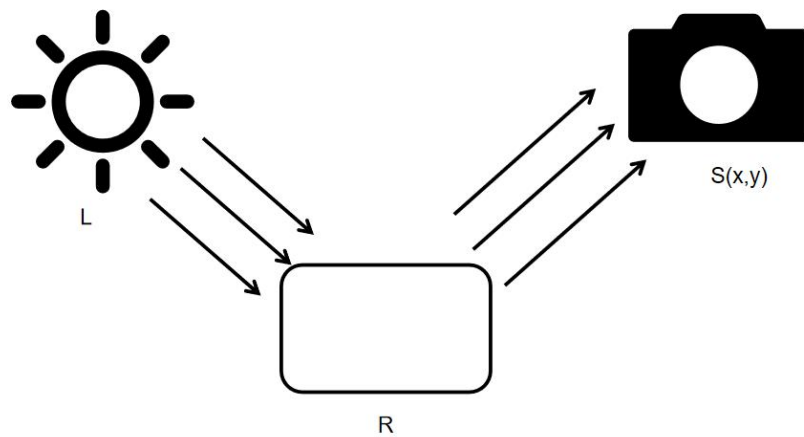


Figure 1. Schematic diagram of Retinex

Retinex is a classic theory to Remove or reduce the influence of incident image, so as to retain the information reflecting the essence of the object as much as possible called reflection image. As shown in the above Figure 1, $R(x,y)$ is the image data we finally get by Retinex. First, it is illuminated by the incident light, and then reflected into the imaging system through the object to finally form the image we see. The process can be expressed by formula:

$$S(x, y) = R(x, y) * L(x, y) \quad (2)$$

where $S(x, y)$ represents the image signal observed or received by the camera. $L(x, y)$ represents the irradiation component of ambient light. $R(x, y)$ represents the reflection component of the target object carrying image detail information. In the field of image processing, this theory is often used for image enhancement in order to get a better image. At this time, $R(x, y)$ represents the image after image enhancement, and $S(x, y)$ represents the original image. In the process of image processing, $L(x, y)$ is often the result of $R(x, y)$ go through high pass filtering, and it also means a process of image smoothing, which has been introduced above. It can be concluded that the equation of Single Scale Retinex(SSR) in logarithmic space:

$$r(x, y) = \log R(x, y) = \log \frac{S(x, y)}{L(x, y)} \quad (3)$$

and the $r(x, y)$ is the output of image, then the incident image estimated as a convolution space smooth image can be expressed as a convolutional calculation, thus the $r(x, y)$ will be transformed:

$$r(x, y) = \log S(x, y) - \log[F(x, y) * S(x, y)] \quad (4)$$

where $F(x, y)$ represents central surround function. Multi-Scale Retinex(MSR) is derive from the SSR. Its advantage is that MSR can keep high image fidelity and realize compression on the image about the dynamic range meanwhile. MSR can also realize color enhancement, color constancy, local dynamic range compression and global dynamic range compression.

3.3. Algorithm based MSR

The main technological process is follow:

Traditional Retinex methods mainly are composed to two components: estimation and normalization of illumination. And the key of problem is how to gather the background illumination more accurately. After this process to the image, which produces a reflection image corresponding to it. And this reflection image can be used for other algorithms in the practical application of automatic driving. Hence, it can achieve an accurate image by enhancing and denoising.

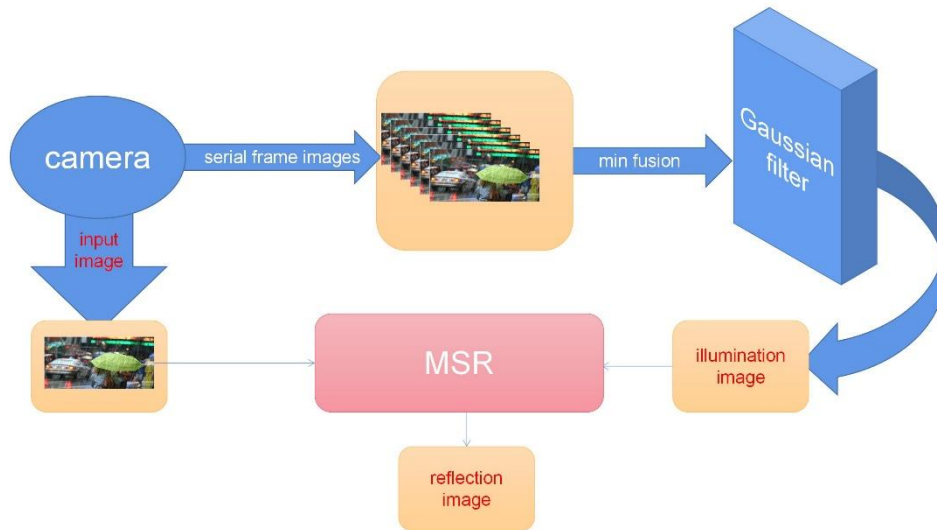


Figure 2. Flow path of algorithm

step1: Extract the backgrounds for every single image using multi-scale Gauss masks.

Initially, it needs extract smooth background illumination information of different position and illumination power. In order to adapt to video in complex environment, it is necessary to fuse multi-scale image information. Therefore by using the multiparameter Gauss filters, each individual

image can get multiple levels of filtering results, which will be fused totally by minimum method. Then the backgrounds after multi-scale filtering are obtained. It is noted that the reasonable parameter for the radius of Gauss filters are 5, 9, 13, 25, and for their variance, which are set as 0.3, 0.5, 0.7, 1.0 in this paper.

step2: Fuse the illumination of some adjacent frame images by maximum method.

After obtaining the background information based on step 1, here arises a problem about how many images need to be fused. Considering the frame rate of video and the efficiency of the algorithm, it is workable to combine 6 consecutive images. Then the method of maximum is used to extract the uniform and optical background image for above images are selected, which takes advantage of the connection of these adjacent images in videos.

step3: Enhancement using MSR method.

At this step, the background image and subsequently the original input image captured by camera will be brought into the MSR method. As for why MSR is selected as the basic method instead of SSR or MSRCR, it will be discussed in Section 4. Firstly, the expression of MSR can be expressed as follows:

$$R(x, y) = \sum_K^k \omega_k \{ \log S(x, y) - \log [F_k(x, y) * S(x, y)] \} \quad (5)$$

$S(x, y)$ represents the input image, and $\log F_k(x, y)$ represents the Gauss masks. As for $R=R(x, y)$, it stands for the results of MSR, which also the enhancement image wanted. Go through step1 and 2, the mainly variables can be accessed. Then just need to transform the variables into the logarithms domain, the $\log R(x, y)$ also in logarithm, so it needs to be transformed $r=e^R$. With the results of MSR, the final image also called reflection image has been denoised and enhanced greatly. At this time, the image can be applied to other image processing process for autonomous driving.

4. Discussion

The basic theory of Retinex mentioned above has been introduced, but the MSR is feasible instead of SSR or MSRCR. There is a brief discussion to explain this option. SSR is the most fundamental algorithm in Retinex algorithms, When obtaining the filtered illumination picture, except the input image, it also needs the σ that indicates the radius of filter. There are many filtering methods, however, Gauss mask usually can be used to get the smooth image, which be used in this paper as well. And kernel is mentioned in the methodology above, it means σ . This constant is charge of the tune-up between the compression of dynamic range and total rendition, but SSR is defective in providing dynamic range compression and total rendition meanwhile due to the single scale which equals to the unique kernel for SSR. The MSR algorithm is derived from SSR algorithm. It uses multiple different values of σ , and then weights the different results, which solves the problem that a single kernel can not give consideration to dynamic rendering and dynamic compression range. But limitation still exist in this method. There is still a problem with image color. By using MSR we cannot judge that the color produced after processing the image whether it is right. Then another approach was presented as MSR with color Restoration (MSRCR) to overcome the limitation of MSR. This method aims to recover the color of the image by adding the color restoration factor to eliminate image color distortion as far as possible. However, the advantage of MSRCR fit human vision well at the color level. Instead for machine vision, the restoration of these colors does not make much sense. Usually, the image processing in autonomous driving will be converted into gray image, or a single color channel will be extracted for processing. Hence the MSR is accepted on the derain and low-light enhancement issue for this application scenario. In summary, Compared with other methods like SSR and MSRCR, MSR can achieve good image enhancement effect and reduce unnecessary parameter settings, so it is used in this method.

5. Conclusion

This algorithm make full use of the characteristics of rain and low-light, fusing the continuous information taken by visual sensor on autonomous vehicles. It can solve the problem of image rain removal in low illumination automatic driving scene. But there still exists some problems need to be explored about this paper, this algorithm only focused on light rain without heavy rain or strong wind, and these condition may make raindrops fluctuate greatly. Besides, some new noise generated in the image finally get by this algorithm. Therefore, it is necessary to further improve the quality of image.

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