ISSN 2616-5775 Vol. 6, Issue 2: 100-103, DOI: 10.25236/AJCIS.2023.060213

Research on Brightness Enhancement of Street View Data Set Using DLN

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Abstract: *Low-brightness image enhancement is a challenging and difficult task. Photos taken under dark conditions often have poor visual quality. In order to solve the problems of low contrast and high noise in low illumination images, this paper uses deep illumination network technology to analyze nighttime street scene images taken under low illumination conditions. Different from the traditional method, this method regards weak light enhancement as a residual learning problem on the basis of deep learning, that is, the residual between estimates. The experimental results show that the PSNR of the algorithm we use is 20.63567452, and the SSIM is 0.2153426. The algorithm not only improves the brightness of the low-light image, but also improves the color depth and contrast. In the objective evaluation index, it has better low-light enhancement effect.*

Keywords: *Low light enhancement; DLN; Retinex; CNN*

1. Introduction

In recent years, face recognition technology has been widely used. This technology is a biometric identification technology based on human facial feature information. In traditional criminal investigation cases, staff need to monitor surveillance video for a long time, and capture face information of criminals through manual comparison, which is inefficient. Therefore, by enhancing the image in the street video and using the face recognition technology, the efficiency and accuracy of the crime locking can be greatly improved. Under the conditions of insufficient illumination, uneven illumination or shadow occlusion, the images collected by monitoring generally have problems such as excessive noise and weak contrast, which will not only have a negative impact on the quality of the images, but also hinder the progress of some machine vision tasks. Enhancement of low-light images helps to improve advanced visual performance, such as image recognition, semantic segmentation, target detection, etc. It can also improve the performance of intelligent systems in some practical applications, such as visual navigation, autonomous driving, etc. Therefore, enhancing the low light image can better serve the subsequent machine vision tasks[1].

In order to improve the clarity and contrast of low-brightness street view images, common methods include: histogram equalization-based methods, defogging-based methods, Retinex-based methods, and linear enhancement.

In this paper, the low illumination street scene image is analyzed and tested by using the depth lighting network technology. Compared with traditional image enhancement methods, this method uses learning model to generate image enhancement based on deep learning. Through experimental verification and comparison, this algorithm can not only improve the image clarity and contrast, but also improve the effect much more than Binary mask and Linear enhancements. The experimental effect is good.

2. Related work

Low-light image enhancement has important research significance in the fields of face recognition[2], automatic driving[3], and emotion recognition[4].

In the traditional image enhancement methods, in 1987, a histogram equalization method was widely used. This method can change the gray value of the image one by one. In the early days, this method was

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mainly used for low noise enhancement, but the histogram equalization method also has problems such as color distortion and loss of details.

The image masking method recalculates the value of each pixel in the image according to the mask matrix, and improves the contrast and brightness by processing the selected image.

The linear enhancement method ignores the reason for the decline of image quality, selects only the obvious features in the image for enhancement, and shields the unimportant features. This method is mainly used to improve the image clarity. The disadvantage of this method is that it is unable to automatically determine the appropriate requirements for different brightness conditions in different scenes, and it needs to manually adjust the contrast and brightness of the image, and the error is large, so it is unable to obtain an accurate and appropriate image.

With the continuous development of computer technology, low light level image enhancement has become an important achievement. Based on the histogram equalization method, the overall contrast is improved by changing the histogram of some areas of the image. This method is simple and easy to implement, but the image enhancement effect is not obvious due to artifacts caused by over enhancement and over stretching of gray scale. The method based on Retinex theory enhances the image by increasing the illumination brightness while maintaining the consistency of reflectivity. This method not only improves the contrast of the image, but also reduces the impact of noise. However, the relevant parameters of the algorithm should be manually set according to experience, and different types of images cannot be enhanced adaptively. Wang [5] et al. proposed a new mutually enhanced Retinex framework to sense light intensity and noise. However, the environment considered by this method is relatively mild, not bad enough, and its applicability is not strong. Ren [6] et al. proposed a hybrid network to recover scene content. But this method often leads to the problem of blurring the veil. In this paper, a new depth enhancement network method is used to control image noise.

3. Method

Through comprehensive experiments, our DLN is compared with several commonly used image enhancement methods in PSNR and SSIM. The experimental results show that the DLN method we use is superior to all other methods in subjective and objective measurement, and the image enhancement effect is obviously better than other methods, and the effect has been significantly improved.

3.1 Low light enhancement

First of all, we carry out residual learning on the image to estimate the residual between the low light level image and the ordinary light level image through the residual learning of the image, which lays the foundation for the follow-up experiment and solves the problem of low light level enhancement.

3.2 Deep Lighting Network

The DLN method we used includes three parts: shallow feature extraction, illumination back projection block (LBP) and illumination processing. DLN takes the low brightness image as the input and enters the shallow feature extraction part composed of two convolution layers, each of which has 64 × 3 Filter, step 1, fill 1. Then, multiple LBP algorithms start to perform cumulative enhancement on low brightness images. The illumination process then receives the LBP results and estimates the residuals of the common brightness image through two convolutions. Finally, the residual is enhanced by adding interaction factors. We conducted a comprehensive experiment to compare our DLN with some of the most advanced methods.

3.3 Brightening BP

Based on the back projection theory, we can obtain the normal light version from the low light image of the dimming operation. The target enhancement for this version is to find the lighting operation used to predict the image. Objectively, we can also obtain the estimated version of the image from the dimming operation. If the lighting and dimming operations are in the ideal state, the two images will be the same. Under actual conditions, the remaining items are used to represent the weak point operation of lighting and dimming. The brightening operation and illumination operation in the residual are estimated based on the residual theory. Finally, estimates can be added to the residuals.

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3.4 Feature combination

DLN has multiple short connections between LBPs, which can propagate features from the former to the latter. In order to use features more effectively, we use feature aggregation blocks to enhance feature representation based on multiple intermediate results. The first FA block on the left has two inputs, merging information from two feature maps, and the second FA block on the right combines three input feature maps.

4. Result

The training set in the experiment is LOL dataset and the test set is DARK FACE dataset. In this paper, a total of 500 test data sets, including different locations and different lighting conditions of the street view pictures. In the training, each picture was cycled 500 times and the results were taken for the fifth hundred times. The entire network model CPU model is i7-11370, frequency 3.30GHz processor, 16GB of memory, GPU model RTX 3050 GPU, comparative experiments were completed on pycharm2021 and matlab2020a. The measurement of illumination conditions lacks objective evaluation methods, and it is difficult to evaluate the performance of different low-light enhancement methods. We believe that the enhanced LL image should be close to the real NL image. Therefore, we use Peak Signal-to-Noise Ratio (PSNR) and Structure Similarity (SSIM) , which are widely used in the field of image restoration, to measure the quality of estimation.

The experimental content is mainly divided into two parts. One is to use the deep illumination network to batch brighten the data set of the street view image, and use other methods (binary Mask and linear enhancements) to brighten the data set of the street view image. Second, the brightened images obtained by different methods are compared with the original images to obtain the corresponding PSNR and SSIM data.

The evaluation on real datasets compares DLN with existing methods, and the results are shown in the table. It can be concluded from the table that the DLN method has achieved the best performance in both PSNR and SSIM. The average PSNR score is 20.636 dB and the average SSIM score is 0.215. Both of them are superior to other methods in terms of PSNR and SSIM.The results show that the proposed DLN method has good brightness enhancement ability and achieves the best low illumination enhancement effect among all the comparison methods(as shown in Figure 1 and Table 1).

input Ours binary Mask linear enhancements

Figure 1: Comparison of image enhancement results obtained by different lighting methods

Table 1: PSNR and SSIM values of different image brightening methods

id	Method	PSNR	SSIM
1	Binary mask	16.3113456	0.160148072
2	Linear enhancements	15.51949159	0.141317326
3	Ours	20.63567452	0.2153426

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5. Conclusions

Aiming at the problems of low brightness, high noise and weak contrast in the visual effect of low light image, DLN model is used. In this paper, a new illumination back projection (LBP) block iterative learning is proposed to learn the difference between low-illumination images and normal-illumination images. We compare the performance of the proposed DLN with other methods from both subjective and objective aspects. Extensive experimental results show that our proposed method outperforms other state-of-the-art methods (traditional method, cnn-based method and gan-based method) both quantitatively and qualitatively. In further work, we can continue to explore more effective CNN structures to improve the performance of low-light enhancement, and study low-light enhancement methods for optical video enhancement. Experiments show that compared with Binary mask and Linear enhancements, DLN has achieved the highest values in objective indicators PSNR and SSIM.In terms of enhancing the visual contrast of images, DLN not only improves the contrast of images and suppresses noise, but also obviously eliminates the degradation problem and achieves better visual effects.

In the future research work, we will collect more images on the street at night, and combine the data set used in this method with the data set taken on the street. This research will play an important role in criminal investigation, which will greatly reduce the time for staff to lock in suspect. In addition, driving at night is easy to cause driver fatigue due to low visibility, fewer vehicles and other reasons. Next, we will analyze the night video, such as the vehicle video system. Through this method, the video taken in the vehicle at night will be highlighted, and the driver's appearance will be analyzed, especially the eye features. At present, this work has been planned.

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