Enhancement methodology for low light image

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Abstract

In order to solve the problems such as low brightness, high noise and poor contrast in weak illumination images, there are several methods proposed to address this issue. Usually, these methods are categorized into two different ways. One is based on traditional light-based technology, the other is based on machine learning technology. The low-light image enhancement is often a challenging task because the noises in dark areas are amplified with the overall brightness and contrast of the image. With the development of machine learning techniques, deep learning networks are becoming the popular research topics recently to overcome the disadvantages of noisy dots. Based on the deep analysis of the current research work, we proposed a novel network and carried out lots of comparison experiments to analysis the performances of these methods. By training, validation and testing on the datasets, the evaluation criterious are defined and utilized to analysis the efficiency of the methods. With the results, we draw the conclusion that the efficient low-light image method can make up for the shortcomings of the environment, bring better viewers' experience and provide preprocessing for subsequent high-level computer vision tasks, such as target recognition, face recognition, semantic segmentation, etc.

Keywords: Low-light Image Enhancement, Retinex Theory, Convolutional Neural Network

1. Introduction

Due to unavoidable environmental or technical constraints such as inadequate lighting and limited exposure time, images taken under sub-optimal lighting condition are dissatisfied with backlighting, non-uniform lighting and low light. Such images taken in low-light conditions are of poor visual quality, thus affecting the visual experience. Lacking of light results in missing details in the image, the images are insufficient for many computer vision-related tasks.

Low-light image enhancement is aimed at improving image quality and restoring details lost details due to poor or uneven lighting conditions. Various image enhancement schemes have been proposed to address the issue. Traditional low light enhancement methods include histogram equalization[1][2] and Retinex models[3][4][5][6]. The former often produce unnatural image because they do not take into account the relationship of pixels to their neighbors under natural light. The latter has received relatively more attention. A typical Retinex model-based approach decomposes low-illuminance images into reflected and illuminated components by some priori or regularization. The estimated reflection component is regarded as the result of enhancement. But this method can not deal with color distortion and noise effectively.

Since the first pioneering work[7], deep learning-based low-light image enhancement has achieved great success in recent years. Compared with traditional methods, deep learning-based solutions have better accuracy, robustness, and speed, which has attracted the attention of researchers. Therefore, various deep learning methods have been proposed for low-light image enhancement for different applications. Here, we aim to explore various deep learning-centered efforts to improve poor and uneven lighting images and provide comparative analysis.

2. Related Work

Deep learning has been used for a variety of tasks over the years, including de-noising[8], de-fogging[9] and super-resolution[10]. The impressive performance of the depth model in these tasks is conducive to the application of low-light image enhancement (LIE) tasks. Compared with the end-to-end network enhancement, deep Retinex-based methods achieves better enhancement performance in most cases because of the Retinex physically explainable theory[11][12].

Since Retinex theory can well simulate color perception in human vision, LIE method based on Retinex theory has attracted wide attentions. According to Retinex theory, the image can be decomposed into two components: reflectance R and illuminance L. Mathematically, the observed image I can be expressed as Eq. (1)

$$\boldsymbol{I} = \boldsymbol{R} \cdot \boldsymbol{L} \tag{1}$$

Here R, L, and · represent reflectance, illuminance, and multiply operation, respectively. However, such decomposition is an underdetermined problem, which requires several priors and regularizers to constrain the decomposition process [13][14][15]. Designing explicit priors before fitting the data is key to getting the model to perform well. However, since Eq. (1) is an ill-posed problem, it is difficult to design a constraint function suitable for multiple scenarios.

In order to avoid the complex implicit priors in the traditional Retinex method, researchers proposed some learning-based Retinex decomposition methods and achieved good results. Shen et al.[16] proposed a three-phase model called Retinex-Net, which firstly extracted two components from low-light image, then applied denoising and brightness adjustment techniques, and finally obtained enhanced results.

In the next section, this paper will discuss some deep-learning-centered low-light level image enhancement methods, and then propose a new LIE method and compare it with the existing advanced methods for quantitative analysis. Lore et al.[7] cleverly design an autoencoder for low-light enhancement. This method uses the stacked sparse denoising automatic coding method to identify the signal features of low-light images, and two modules are designed for contrast enhancement and denoising learning. Inspired by Retinex theory, KinD [17] divides the network model into two parts, one is for regulating light and the other for eliminating noise. Subsequently, the Kind++[19] network was developed to illuminate the dark area with removing the hidden artifacts and suppressing the noise. Lv et al.[18] design a low-light image enhancement network, which is composed of multiple branches and fused features of different levels extracted from multiple subnets to finally complete the task of image enhancement. Jiang et al.[20] train a powerful unsupervised generative adversarial network (EnlightGAN) for image enhancement by using information extracted from the input itself to normalize unpaired data. However, unsupervised models require careful selection of training data, and sometimes the image will lose details after enhancement. Guo et al.[21] proposed a new zero-reference depth curve estimation network (Zero-DCE), which uses the depth network to take low light enhancement as the task of image specific curve estimation. Zero-DCE adapts the dynamic range of a given image by training a network for estimating pixel-level and higher-order curves.

3. Methodology

The low light image enhancement problem can be regarded as consisting of several sub-problems, including enhancing dark areas, eliminating degradation and restoring details. The following are the core ideas of three current popular networks and the novel method we propose in this paper.

3.1. *LLNet*

LLNet presents a application that uses a class of deep neural networks-stacked sparse noise reduction autoencoders (SSDA) to enhance natural low-light level images. To the best of my knowledge, this is the first application of the depth architecture for natural low-light image enhancement. It is trained to capture the main signal features present in low-light images, and then de-noise and brighten them in an adaptive manner. This method uses the local patch-wise contrast improvement to enhance contrast such that the improvements are done relative to local neighbors to prevent overamplifying the intensities of already brightened pixels. In addition, it uses the same network to learn about noise structure and goes further to give brighter and less noisy images. They propose a method for generating training data by modifing the images from the Internet in a synthetic manner to provide simulations of low-light conditions.

LLNet examines two types of deep architectures -- (i) simultaneous learning for contrast enhancement and denoising (LLNet) and (ii) sequential learning for contrast enhancement and denoising using two modules (staged LLNet and S-LLNet). In conducting the experiment, both natural and artificial images were taken into account to estimate the performance of the network in removing noise and adjusting contrast.

The training of LLNet is the error back propagation process to minimize the reconstruction loss, which is defined by following Eq. (2):

$$L_{DA}(D;\theta) = \frac{1}{N}\sum_{i=1}^{n}\frac{1}{2}\|(\mathrm{y_i} - \hat{y}(\mathrm{x_i})\|_2^2 + \beta\sum_{j=1}^{K} KL(\hat{y}_j\|y) + (\|w'\|_F^2) + \frac{\lambda}{2}(\|W\|_F^2) \quad (2)$$

Where N is the number of patches, θ is the parameter of the model, and $KL(\hat{y}_j\|y)$ is the Kullback-Leibler divergence between y (target activation) and $\hat{y}_j$ (the empirical mean live of the j-th hiding unit), which can be expressed as Eq. (3)

$$KL(\hat{y}_j\|y) = \lambda log\frac{y}{\hat{y}_j} + (1-\lambda)log\frac{1-y}{1-\hat{y}_j} \quad (3)$$

Where $\hat{y}_j$ is defined by following Eq. (4)

$$\hat{y}_j = \frac{1}{n}\sum_{i=1}^{n} h_j(x_i) \quad (4)$$

After the decoder weight is initialized, the error back propagation algorithm is used to fine-tune the whole pre-training network. Experiments show that the depth autoencoder can effectively learn noise details from low-light images and understand important signal features. This method can enhance the contrast and reduce the noise well, but the processing capacity of the encoder is limited, and it is only suitable for small size image.

3.2. *KinD*

KinD fuses Retinex structures into efficient deep network designs to absorb the benefits of both Retinex (i.e., good signal structures) and deep learning (i.e., generally useful priors extracted from large datasets). KinD can be divided into three modules, namely layer decomposition, reflectivity recovery and illumination adjustment.

KinD first decomposed the low-light image into noisy reflectance and gradient-smooth illuminance, then uses U-Net to recover reflectance from noise and color distortion. KinD uses a shallow U-Net as a decomposition net, but recovering two components from an image without guidance from ground truth information is a very ill-posed problem. Since there is no real information, the decomposition network uses paired low-light and normal-light images $[I_l, I_h]$as constraints. The training loss function is given by following Eq. (5)

$$L^{LD} = L^{LD}_{rec} + 0.01L^{LD}_{rs} + 0.08L^{LD}_{is} + 0.1L^{LD}_{mc} \quad (5)$$

Where, L^{LD}_{rec} is the reconstruction error obtained by comparing the result of recombining the output reflectance and illuminance with the normal light image. L^{LD}_{rs} represents the L2 norm of reflection similarity of two reflection components $[R_l, R_h]$. L^{LD}_{is} measures the smoothness of illumination. L^{LD}_{mc} represents the mutual consistency of the output illumination of low and normal light images.

The second stage is to improve the degradation problems in the reflectance, such as noise and color distortion problems. For this purpose, the KinD uses the reflectance component obtained from the input image of normal light as the ground-truth benchmark to train the restoration network, and its loss function is given by following Eq. (6)

$$L^{RR} = \left\|\hat{R} - R_h\right\|_2^2 - SSIM\left(\hat{R}, R_h\right) + \left\|\nabla\hat{R} - \nabla R_h\right\|_2^2 \quad (6)$$

Where, SSIM(·,·) is the structural similarity, and R corresponds to restored reflectance. The third item focuses on the tightness of the texture.

In the final stage, KinD designed a illumination adjustment net to flexibly convert one lighting condition to another in order to meet different needs. It uses a lightweight network with three convolutional layers and one sigmoid layer to improve lighting conditions, and its loss function is given by following Eq. (7)

$$L^{IA} = \left\|\hat{L} - L_t\right\|_2^2 + \left\||\nabla\hat{L}| - |\nabla L_t|\right\|_2^2 \tag{7}$$

$\hat{L}$ and L_t are the adjusted illuminance map and the target illuminance map, respectively. The illumination adjustment net is more sensitive to real dark parts by adding light to relatively dark areas while leaving already-bright areas almost unchanged. Compared with traditional gamma correction, the luminance information can be adjusted more flexibly.

3.3. *Zero-DCE*

Zero-DCE does not carry out the image-to-image transformation task, but redefines the enhancement as an image-specific curve estimation problem. Specifically, Zero-DCE takes low-light images as input and produces higher-order curves as output. These curves are then used to make pixel-level adjustments to a dynamic range to enhance the input image.

The method uses L-E curves to learn the mapping between low-light images and improved quality images, where the curve parameters depend only on the input images. A quadratic L-E curve can be expressed as Eq. (8)

$$LE(I(x);\beta) = \beta I(x)(1 - I(x)) + I(x) \tag{8}$$

Where x represents the position of each pixel in the image. β is a trainable curve parameter that can adjust the curvature of the L-E curve to control the exposure level. In this method, a seven-layer simple convolutional neural network is used to learn the mapping relationship between the input image and its optimal curve parameter map. To train DCE-Net in a zero-reference manner, it uses a compound non-reference loss function as shown in Eq. (9)

$$L_{total} = L_{exp} + L_{spa} + W_{col}L_{col} + W_{tv_A}L_{tv_A} \tag{9}$$

Spatial consistency loss L_{spa} prevents loss of original information by maintaining differences between adjacent areas of the input image and the enhanced image. Exposure control loss L_{exp} can solve the common problem of underexposure in low light images. Color constant loss L_{col} is used to correct potential color deviation in enhanced images. L_{tv_A} is the total variation loss. W_{col} and W_{tv_A} are the weights of the corresponding loss function.

In order to verify the effect of this algorithm on improving application performance, the latest FACE detection algorithm DSFD[22] was used as the basic model to conduct verification experiments on DARK FACE[23] data set. After Zero-DCE enhancement, the brightness and visibility of faces in dark areas are significantly improved, and the performance of face detection is also greatly improved.

3.4. *Ours module*

We propose a dual attention-guided generative adversarial network named DAGAN for fully unsupervised low-light image enhancement. Figure 1 shows the overall architecture of the proposed model DAGAN. We adopt the encoder-decoder architecture for the generator. A Double attention module is embedded in the generator to guide image enhancement and de-noising. The global discriminator D_g is a fully convolutional network composed of seven convolutional layers. It takes the entire image of the enhanced image (I_{fake}) and the normal light image (I_{real}) as input, and outputs the discriminant result with one channel. The local discriminator is similar to it. It is a fully convolutional network composed of six convolutional layers. It takes the local image blocks of the enhanced image (I_{fake}) and the normal illumination image (I_{real}) as input, and outputs a discriminative result with one channel

For discriminators, PatchGAN is used for global and local true/false authentication. For both global and local discriminators, we use relative discriminator LSGAN as the adversarial loss which is defined by following Eq. (10)

$$L_G = W_g L_{G_g} + W_l L_{G_l} + W_c L_c \tag{10}$$

Where, L_{G_g} and L_{G_l} is the generator of global adversarial loss and local adversarial loss. L_c represents content loss. W_g, W_l and W_c are the weights of the above loss functions, respectively.

L_{G_g} is given by following Eq. (11)

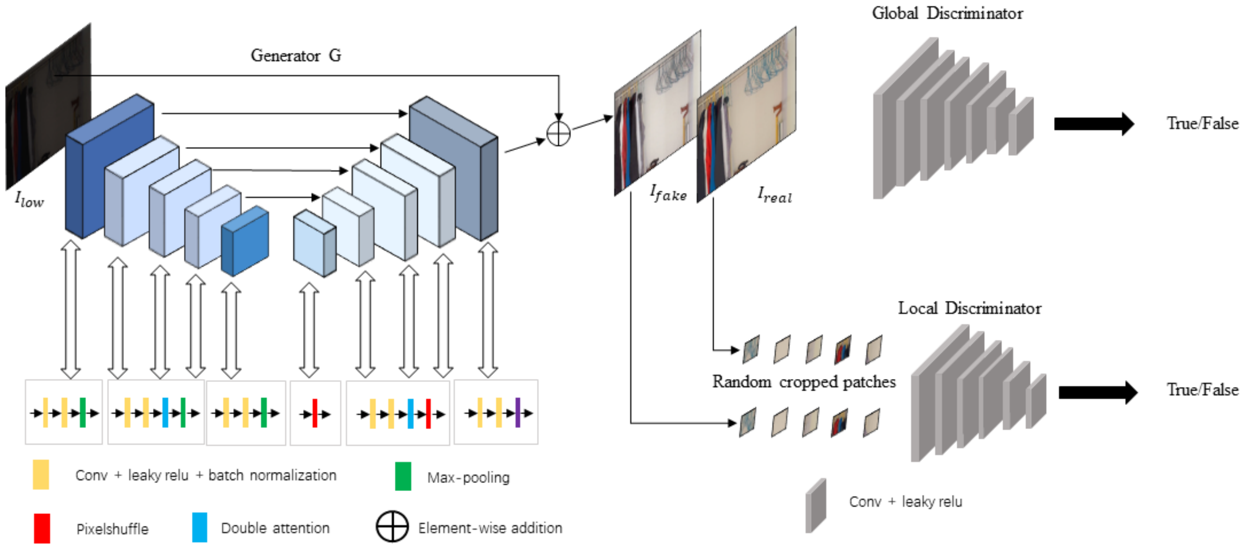

Fig. 1 An overview of DAGAN consisting of one generator and two discriminators. The generator is an encoder-decoder architecture that contains a double attention module layer. The global discriminator takes the entire image as input, while the local discriminator takes patches cropped randomly from both the output image and the real reference image as input.

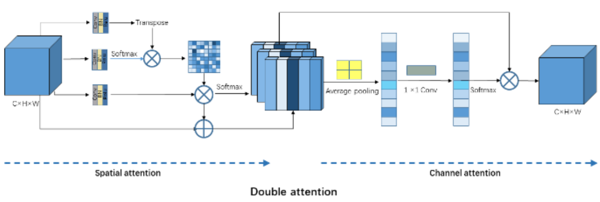

Fig. 2 Double attention module layer structure diagram. It consists of two attention modules: spatial attention module and channel attention module

$$L_{Gg} = E_{x_r \in P_{real}}\left[(D_g(x_r) - E_{x_f \in P_{fake}}(D_g(x_f)))^2\right] + E_{x_f \in P_{fake}}[(D_g(x_f) - E_{x_r \in P_{real}}(D_g(x_r)) - 1)^2] \quad (11)$$

Where, D_g is the global discriminator, E(·) is the mean calculation, P_{real} is the distribution of real natural light image data distribution, P_{fake} is the distribution of image data generated for the network, and x_r and x_f are the samples in the corresponding data distribution.

L_{D_l} is given by following Eq. (12)

$$L_{D_l} = E_{x_f \in P_{fake\_patch}}[(D_l(x_f) - 1)]^2 \quad (12)$$

Where D_l is the local discriminator, and P_{fake_patch} is the image block data distribution generated by the network. In this article, the size of the image block is 32×32.

L_c is given by following Eq. (13)

$$L_c = \frac{1}{WH}\sum_{i=1}^{W}\sum_{j=1}^{H}(\varphi_l(I(i,j)) - \varphi_l(R(i,j))) \quad (13)$$

Where, W and H represent the width and height of the feature map, respectively. $\varphi_l(\,)$ represent the output of the first convolution layer after the fifth maximum poolings layer of the pre-trained VGG-16 model. I represents the input image and R represents the image generated by the network.

In this work, we have improved the double attention mechanism[24] and cleverly embedded it in the generator for low light enhancement. In a low-light image, there are some darker or under-exposed areas. Channel attention can reassign different weights to different areas, and spatial attention can better extract spatial information of images. Therefore, the attention mechanism can extract global information from low-light images and expand reception domain. This method skillfully integrates the redistributed channel feature information and spatial feature information. Figure 2 shows the structure of the double attention module layer, where H, W and C represent the dimensions of the feature map.

In this paper, the spatial attention module[25] is used to expand the current feature diagram, as shown in the left half of Figure 2. In the right half of Figure 2, the

Fig. 3 Face detection results of a group of low light images before and after enhancement

interdependencies between channel feature maps are used to build the channel attention module[26].

4. Experimental Evaluations

In this section, we will conduct quantitative and qualitative experiments on the models mentioned above. It verifies the effect of the proposed DAGAN on the DSFD dataset for face detection under dark conditions.

4.1. *Dataset and Metrcis*

We trained DAGAN on the unpaired dataset collected in reference[20], which contained 914 low-light images and 1016 normal-light images. To evaluate the performance of DAGAN, we conduct quantitative analysis on three public datasets (LOL[27], DICM[28] and NPE[29]). The LOL dataset contains the low/normal light image pairs, while the other two DICM and NPE don't contain paired images.

We compare the performance of LLNet[7], KinD[17], MBLLEN[18], Zero-DCE[21], Kind++[19], Enlight GAN[20] and the proposed DAGAN.

4.2. *Quantitative Assessment*

As the LOL dataset has paired images, we conducted a quantitative comparison between PSNR, SSIM and LPIPS[30] on the LOL dataset. Since neither DICM nor NPE datasets have paired reference images, we calculated no-reference metrics NIQE[31]. Among these metrcis, PSNR and SSIM are widely used image quality assessment metrics in low-level visual tasks to evaluate the similarity between enhanced results and real reference images.

Method\ Metrics	PSNR	SSIM	LPIPS
LLNet	28.12	0.51	0.34
KinD	27.99	0.77	0.16
MBLLEN	28.07	0.78	0.21
Zero-DCE	27.82	0.66	0.31
Kind++	28.16	0.76	0.18
EnlightGAN	27.80	0.73	0.29
DAGAN(Ours)	**28.31**	**0.79**	**0.15**

Comparison of LOL Datasets based on PSNR, SSIM and LPIPS metrics

Method	DICM	NPE
LLNet	4.50	4.29
KinD	4.79	4.45
MBLLEN	3.98	4.30
Kind++	4.57	4.13
DAGAN(Ours)	**3.77**	**3.90**

Comparison of DICM and NPE Datasets based on NIQE metrics

Learning perceptual image patch similarity (LPIPS) is also known as perceptual loss. Compared with traditional metrics, LPIPS is obtained by computing the distances between features, which is more suitable for human visual perception of texture. The lower LPIPS indicates that the enhanced image has higher perceptual similarity with the corresponding ground truth.

Natural Image Quality Evaluator (NIQE) is a well-known non-reference image quality assessment metric for evaluating image restoration performance without ground truth. The lower the NIQE value, the closer the enhanced image is to the natural image.

5. Conclusions

Through a detailed analysis of LLNet, KinD, MBLLEN, Zero-DCE, Kind++, EnlightGAN and DAGAN, it can be found that each method has its advantages and disadvantages. Some give better results in terms of visual appeal, but at the cost of fuzzy details. LLNet, KinD and KinD++ generally fall into this category. On the other hand, some methods focus on details, such as EnlightGAN and MBLLEN, but bring color distortion and noise amplification problems due to over-focus on detail restoration. In extremely dark conditions, Zero-DCE can enhance images quickly and achieve good results. From the calculation results, the proposed DAGAN can effectively improve image quality and restore color and detail better. In order to further prove the practicability of DAGAN, the application experiment in this paper is carried out on the DARK FACE dataset. The DARK FACE dataset consists of

10,000 outdoor images taken in the dark. This paper randomly selects 100 images from the validation set for evaluation. After DAGAN preprocessing, the average face detection (AP) accuracy of the detector DSFD increases from 7.1% to 45.0%, which shows that DAGAN can improve the performance of computer vision tasks. Figure 3 shows an example of the face detection results. It can be seen that DAGAN algorithm improves the brightness and visibility of faces in dark areas, thus improving the performance of face detection.

Acknowledgment

This work was supported by the "Tianjin University of Science and Technology-Ansoft Technology Intelligent edge computing Joint Laboratory"

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