DEEP LEARNING NETWORK FOR LOW-LIGHT IMAGE ENHANCEMENT

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Abstract- Low-light image enhancement is a challenging task that has attracted considerable attention. Pictures taken in low-light conditions often have bad visual quality. To address the problem, regard the low-light enhancement as a residual learning problem that is to estimate the residual between low- and normal-light images and propose a novel Deep Lightening Network (DLN) that benefits from the recent development of Convolutional Neural Networks (CNNs). The proposed DLN consists of several Lightening BackProjection (LBP) blocks. The LBPs perform lightening and darkening processes iteratively to learn the residual for normal-light estimations. To effectively utilize the local and global features, propose a Feature Aggregation (FA) block that adaptively fuses the results of different LBPs and evaluate the proposed method on different datasets. Numerical results show that our proposed DLN approach outperforms other methods under both objective and subjective metrics.

I. Introduction

Capturing good quality images under poorly lit conditions is a difficult task. These images usually contain low illumination and brightness, poor contrast and noise. Certain operations such as increasing exposure, high ISO and flash could be used to improve the low light conditions of the environment. But these methods have some drawbacks. All these methods potentially destroy the naturalness of the image. Images taken in low-light conditions are usually very dim. This makes us difficult to recognize the scene or object. To obtain high-visibility images in the low-light conditions and can adopt three solutions.

A. To use flash
B. To increase the ISO (sensitivity of the sensor)
C. To take a photo with longer exposure time

Literature survey

2.1 Low Light Image Enhancement Recent literature shows that the CNN technology also benefits the low-light image enhancement. Some approaches (like Retinex-Net [20], LightenNet [21]) are based on the Retinex theory that contains two CNNs: One network decomposes the low-light image into illumination and reflectance, where reflectance is an inherent attribute of the scene which is unchangeable in different light conditions. The other network works as an enhancer to refine the illumination map of the low-light image. However, the definitions of ground-truth illumination and reflectance are not clear, which makes the decomposition difficult. Another problem is that these CNN-based approaches make use of shallow CNN structures that have few trainable parameters, which leads to a considerable limitation on the performance. For example, Retinex-Net [20] has only seven convolutional layers in the decomposition network, and LightenNet [21] has four convolutional layers only. It is obvious that the deep learning for low-light enhancement is still in its infancy stage. Some other approaches use Generative Adversarial Networks (GANs) that regard the lowlight enhancement as a domain transfer learning task by finding the mapping between low- and normal-light domains (e.g. EnlightenGAN [22]). Each GAN has a generator and a discriminator, where the generator estimates normal-light images from the lowlight ones, while the discriminator constrains the visual quality of the estimations and tries to distinguish the estimations from real normal-light images. However, the generator may collapse to a setting where it always outputs the same settings that are difficult for the discriminator to distinguish. In addition, the two models need to be trained simultaneously, but they have completely opposite targets that make it difficult to obtain the desired output [23].

• Interactive Low-light Enhancement: We resolve the low-light enhancement through a residual learning model that estimates the residual between the low- and normal-light images. The model has an interactive factor that controls the power of the lowlight enhancement. More details can be found in Proposed System

• Deep Lightening Network (DLN): We propose a novel DLN approach based on our residual model to enhance the low-light image in an end-to-end way. It contains several lightening blocks (see LBPs in Figure 2) that enhance the low-light image accumulatively. Our DLN is compared 4 with several state-ofthe-art approaches through comprehensive experiments. The results show that our proposed DLN outperforms all other methods in both subjective and objective measures.

• Lightening Back-Projection (LBP): Based on the idea of enhancing the low-light image iteratively, we propose a LBP block that iteratively lightens and darkens the low-light image to learn the residual for low-light enhancement. It is the first work that successfully introduces a new back-projection structure for low-light enhancement. More details can be found in Proposed System .

• Feature Aggregation (FA): Both global and local features are useful for low-light enhancement. We propose a FA block that aggregates the results from different lightening stages and provides more informative features for the following lightening process. More details can be found in Proposed System.

Existing System

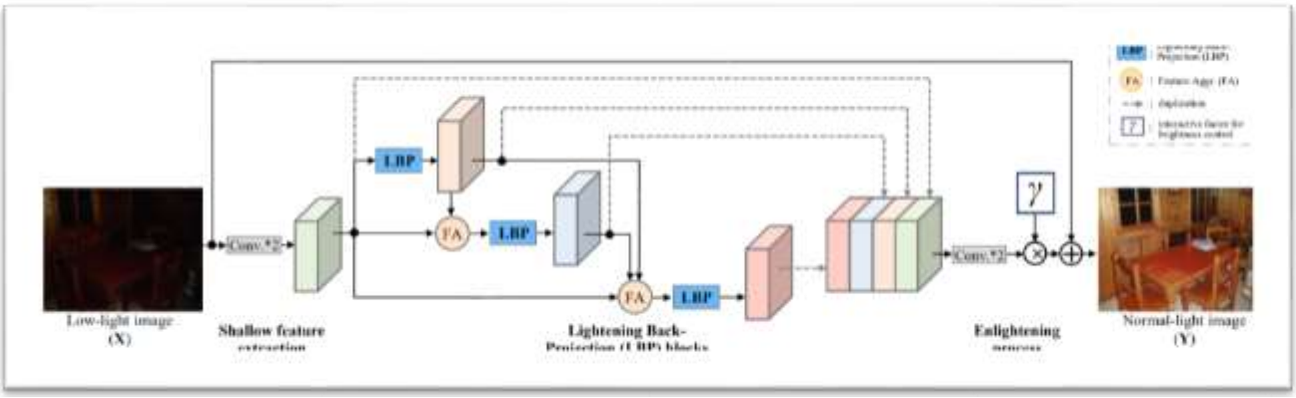
A large number of conventional approaches have been proposed to mitigate the degradation caused by low-light conditions. Histogram Equalization (HE) counts the frequency of the pixel values. By rearranging the pixels to obey uniform distribution. Retinex-based methods regard one image as a combination of illumination and reflectance, where the reflectance is an inherent attribute of the scene that is unchangeable in different lighting conditions, and the illumination maps store the differences between the low- and normal-light images.Image Super-Resolution (SR) is one of the similar topics, which reconstructs a high-resolution (HR) image from a low-solution (LR) image of different scales

Proposed System

The use of back-projection block has shown outstanding performance in the image restoration field (e.g., image Super-Resolution(SR)). Based on the idea of enhancing the image iteratively, and proposed a novel CNN structure (i.e., the Deep Lightening Network (DLN)) that achieves remarkable enhancement for the low-light image, the novelty of our proposed method as follows:

- Interactive Low-light Enhancement
- Deep Lightening Network (DLN)
- Lightening Back-Projection (LBP)
- Feature Aggregation (FA)

IV SYSTEM ARCHITECTURE



Modules

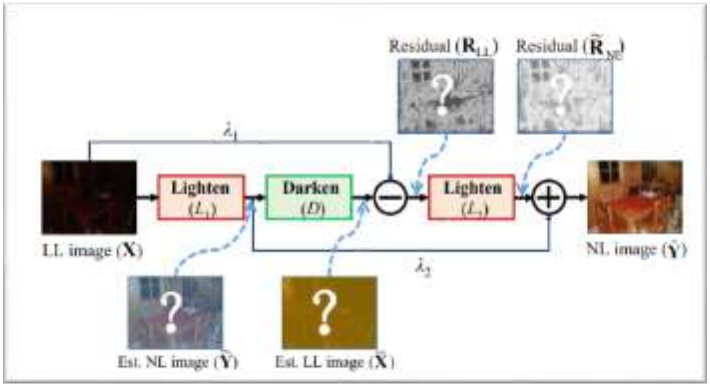
1) Shallow Feature Extraction

Upload a low light image that we want to enhance and DLN takes the LL image as the input. It firstly enters into the shallow feature extraction part that consists of two convolutional layers (the Conv.*2 at the left side of System Architecture), where each layer has 64 3- by-3 filters with stride of 1, padding of 1.

2) Lightening Back projection blocks

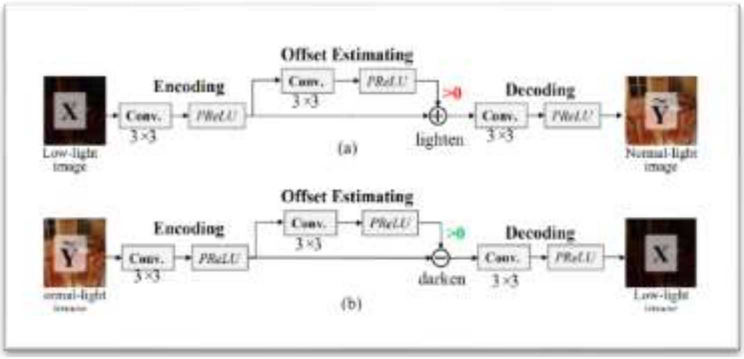
the multiple LBPs (with feature aggregation (FA) blocks) scheme starts to enhance the LL image accumulatively.
It consists of LBPs and Feature Aggregation Block.

i. LBP-LBP block iteratively lightens and darkens the low-light image to learn the residual for low-light enhancement



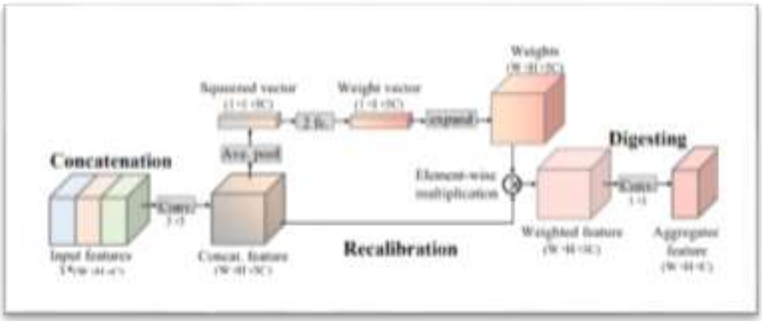
Lightening and Darkening Operations in LBP -

They are used as part of residual learning. Low light images have smaller pixel values and normal light images have high pixel values. Lightening operator is used for increasing the mean value of the low light images to map it to normal light image. Darkening Operator works in reverse



ii) Feature Aggregation block

Both global and local features are useful for low-light enhancement. We propose a FA block that aggregates the results from different lightening stages and provides more informative features for the following lightening process



Conclusion:

Introduced our proposed Deep Lightening Network (DLN) for low-light image enhancement. Unlike the previous methods that either learn the mapping between the low- and normal-light images directly for reconstruction, and propose a novel Lightening Back-Projection (LBP) block which learns the differences between the low- and normal light images iteratively. To strengthen the representation power of the input of the lightening process, we use Feature Aggregation (FA) block ,that investigates both the spatial and channel-wise dependencies among different feature maps. Benefited from the residual estimation of LBP and the rich features of the FA, the proposed DLN gives a better reconstruction of the normal-light condition.

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