Low-Light Image Enhancement Using Deep Lightening Network

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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, we regard the low-light enhancement as a residual learning problem that is to estimate the residual between low- and normal-light images. In this paper, we propose a novel Deep Lightening Network (DLN). The proposed DLN consists of several Lightening Back Projection (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, we also propose a Feature Aggregation (FA) block that adaptively fuses the results of different LBPs. We evaluate the proposed method on different datasets. Numerical results show that our proposed DLN approach outperforms other methods under both objective and subjective metrics.*

Keywords- Deep Lightening Network, Lightening Back Projection, Feature Aggregation

I. INTRODUCTION

Light is just one portion of the various electromagnetic waves flying through space. These waves have both a frequency and a length, the values of which are distinguishing light from other forms of energy on the electromagnetic spectrum. Light is emitted from a body due to Incandescence, Electric Discharge, Electro luminescence and Photoluminescence. Images cannot exist without light. To produce an image, the scene must be illuminated with one or more light sources. In this section we focus on interaction of light with surface and some artificial light source. Moreover determine general factors that affect on the light equality assessment.

A Radiometry is the science of measuring light from any part of the electromagnetic spectrum. In general, the term usually applies to the measurement using optical instruments of light in the visible, infrared and ultraviolet wavelength regions. The terms and units have been standardized in the American National Standards Institute publications (ANSI), whereas the Photometry is the science of measuring light within the visible portion of the electromagnetic spectrum in units weighted in accordance with the sensitivity of the human visual system.

Light is a form of radiometric energy, radiometry is used in graphics to provide the basis for illumination calculations which are(Radiant power, Radiant Intensity, Irradiance and Radiance) and the corresponding in Photometry units are (Luminous flux, Luminous intensity,Illuminance and Luminance). If we addressed in the simulation of light distribution it involves characterizing the reflections of light from surfaces. Various materials reflect light in very different ways, for example matt house paint reflects light many differently than the often highly specular paint used on a sports car.

There are many different types of lamps for everyday lighting and for color imaging lighting. Many of the major categories for everyday lighting are incandescent, tungsten halogen, fluorescent, mercury, metal halide, sodium and Lighting Emission Diodes (LEDs). For color imaging (photography), the major category is the electronic flash lamp. Two general characteristics of lamps that are important for color imaging are their spectral power distribution as a function of their life time and operating conditions. The light output of a lamp decreases during its life. Also, the spectral power distribution of a tungsten lamp depends on the voltage at which it is operated. Therefore, for critical color calibration or measurement, we cannot always assume that the spectral power distribution of a lamp will remain the same after hours of use or at various operating temperatures.

Taking photos is one of the most popular and convenient ways to record memorable moments of our life. Images taken in low-light conditions are usually very dim. This makes us difficult to recognize the scene or object. However, often it is inevitable to take photos in low-light conditions. To obtain high-visibility images in the low-light conditions, we can adopt three solutions.

To use flash: It is a direct way to solve the problem. However, it is not allowed in some public areas, such as the museum, cinema, and exhibition hall. To increase the ISO (sensitivity of the sensor): This method could increase the visibility of dark areas, but higher ISO will also bring more noise to the image, and the normal-light area will easily face the overexposure problem. To take a photo with longer exposure time: Capturing an image with longer exposures allows more light that enlightens the dark area. Nevertheless, long-time exposure may blur the image if there is camera shake or fast-moving objects.

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, it improves the dynamic range (i.e., better visibility) of the low-light image. 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. The Retinex-based methods enhance the illumination map of the lowlight image to estimate the corresponding normal-light image. Other methods adopt dehazing theory that decomposes the low-light image to ambient light, refraction, and scene information. Refining the refraction map can also enhance the visibility of low-light images.

Convolutional Neural Networks (CNNs) have achieved impressive results in many tasks, such as image classification, semantic segmentation, super-resolution, and object detection. Compared with conventional approaches, the CNNs have better feature representation that benefits from the large dataset and powerful computational ability. For CNNs, the information extracted from the shallow layers has detailed local information (like edge, texture), while deep layers have large receptive fields that can obtain more global features (like complex texture and shape).

The CNNs tend to have more convolutional layers and complex structures to obtain more powerful learning abilities. The low-light enhancement can be regarded as an image restoration task. 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. Some SR networks adopt an end-to-end structure that minimizes the mean squared error between the reconstructed SR and HR images. Other approaches add backProjection structures that iteratively up- and down-sampling the LR images. It improves the efficiency of the network that is widely used in the field. For example, Deep Back-Projection Network (DBPN) approach has several BP stages that iteratively reconstruct the SR image. Back Projection and Residual Network (BPRN) refines the DBPN structure by injecting the advantages of Residual Network structure.

Low light conditions have no assistant light source, images obtained on rain day, at night or in the mine usually have poor quality and blurred details, these images are not applied to machine recognition and target tracking, so the resulted is unusable for practical applications. As image acquiring systems are demanded to work under low light conditions, the image enhancement and noise reduction is highly desired. Conventional image processing techniques such as histogram equalization which is the most widely used, it enhances contrast through simple computing, but leads to structure information loss. The Retinex can maintain color constancy of human vision. However, it causes some problems, such as halo effect, gray-out result and noise amplification. In addition a spatial domain enhancement method combined gradient transform with high boost filter, adopted bilateral filter and luminance statistics in order to compensate brightness, A nonlinear contrast enhancement based on human visual system was presented, Space-variant luminance map has been used in to enhance the low illumination image, A homomorphic filtering based on HSV space in solves the problem of color cast, these methods do not consider the characteristics of low illumination image, the results are not ideal.

II. LITERATURE SURVEY

Image quality assessment (IQA) aims to use computational models to measure the image quality consistently with subjective evaluations. The well-known structural similarity index brings IQA from pixel- to structure-based stage. In this paper, a novel feature similarity (FSIM) index for full reference IQA is proposed based on the fact that human visual system (HVS) understands an image mainly according to its low-level features. Specifically, the phase congruency (PC), which is a dimensionless measure of the significance of a local structure, is used as the primary feature in FSIM. Considering that PC is contrast invariant while the contrast information does affect HVS' perception of image quality, the image gradient magnitude (GM) is employed as the secondary feature in FSIM. PC and GM play complementary roles in characterizing the image local quality. After obtaining the local quality map, we use PC again as a weighting function to derive a single quality score. Extensive experiments performed on six benchmark IQA databases demonstrate that FSIM can achieve much higher consistency with the subjective evaluations than state-of-the-art IQA metrics.

Low-light image enhancement is highly demanded in various applications. The images captured in low-light condition usually suffer from both low contrast and much noise. Various low-light image enhancement methods were proposed, most of them focused on contrast enhancement. However, these methods usually imposed a uniform enhancement on the whole image which tended to cause over enhancement for very bright regions or under enhancement for very dark regions. In this project, a novel united low-light image enhancement framework for both contrast enhancement and denoising is proposed. First, the low-light image is segmented into superpixels, and the ratio between the local standard deviation and the local gradients is utilized to estimate the noise texture level of each superpixel. Then the image is inverted to be processed in the following steps. Based on the noisetexture level, a smooth base layer is adaptively extracted by the BM3D filter, and another detail layer is extracted by the first order differential of the inverted image and smoothed with the structural filter. These two layers are adaptively combined to get a noise-free and detail-preserved image. At last, an adaptive enhancement parameter is adopt into the dark channel prior dehazing process to enlarge contrast and prevent over/under enhancement. Experimental results demonstrate that our proposed method outperforms traditional methods in both subjective and objective assessments.

A simple and adaptive single image dehazing algorithm is proposed in this work. Based on the observation that a hazy image has low contrast in general, we attempt to restore the original image by enhancing the contrast. First, the proposed algorithm estimates the airlight in a given hazy image based on the quad-tree subdivision. Then, the proposed algorithm estimates the transmission map to maximize the contrast of the output image. To measure the contrast, we develop a cost function, which consists of a standard deviation term and a histogram uniformness term. Experimental results demonstrate that the proposed algorithm can remove haze efficiently and reconstruct fine details in original scenes clearly.

In the last published concept (1986) for a Retinex computation, Edwin Land introduced a center/surround spatial form, which was inspired by the receptive field structures of neurophysiology. With this as our starting point we have over the years developed this concept into a full scale automatic image enhancement algorithm| the Multi-Scale Retinex with Color Restoration (MSRCR) which combines color constancy with local contrast/lightness enhancement to transform digital images into renditions that approach the realism of direct scene observation. The MSRCR algorithm has proven to be quite general purpose, and very resilient to common forms of image pre-processing such as reasonable ranges of gamma and contrast stretch transformations. More recently we have been exploring the fundamental scientific implications of this form of image processing, namely: (i) the visual inadequacy of the linear representation of digital images, (ii) the existence of a canonical or statistical ideal visual image, and (iii) new measures of visual quality based upon these insights derived from our extensive experience with MSRCR enhanced images. The lattermost serves as the basis for future schemes for automating visual assessment a primitive first step in bringing visual intelligence to computers.

III. PROPOSED SYSTEM

Firstly, model the low-light enhancement as a residual learning task. Then, we present our proposed Deep Lightening Network (DLN) that learns the residual for the low-light enhancement. 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 that enhance the low-light image accumulatively.

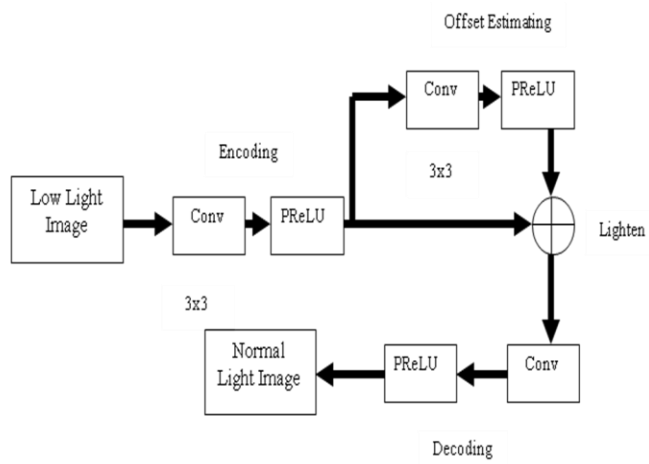

Fig 1 Proposed Block Diagram

Fig 1 shows our proposed lightening and darkening operations, where each operator consists of three parts: encoding, offset estimating, and decoding process. To take the lightening operation for example the LL image (actually, it is the features of the LL image) firstly enters into an “Encoding” structure to extract representative features from the low-light image by using a convolutional block (Conv.+PReLU, which reduces the number of feature channels from 64 to 32). As we mentioned before, the lightening operation is to increase the mean values of the image. The “Offset” structure adopts a convolutional layer to learn the differences between the LL and NL images. Consider that the NL images usually have larger pixel values compared with the LL images. Note that the PReLU activation layer has the effect to remove the negative values of the offset. Then, adding the offset to the LL image can increase the pixel values of the LL image, i.e., lightening the LL image. Subsequently, the “Decoding” process is conducted to reconstruct the NL image (actually, increase the number of the feature channels from 32 to 64).

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MODULES DESCRIPTION

Input Image

The input image is get from the a dataset collected from Internet. The uiget function file is used to get the image from the source folder. Imshow() This syntax can be useful for scanning through images. Note, however, that when you use this syntax, imread does not store the image data in the workspace. If you want to bring the image into the workspace, you must use the getimage function, which retrieves the image data from the current image object.

Encoding

The LL image (actually, it is the features of the LL image) firstly enters into an "Encoding" structure to extract representative features from the low-light image by using a convolutional block (Conv.+PReLU, which reduces the number of feature channels from 64 to 32).

Offset Estimation

The "Offset" structure adopts a convolutional layer to learn the differences between the LL and NL images. Consider that the NL images usually have larger pixel values compared with the LL images. Note that the PReLU activation layer has the effect to remove the negative values of the offset.

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.

Making use of the hierarchical structure, CNNs have inherent multi-scale feature representations, where the features extracted from the shallow layers usually contain detailed information (like edge and texture), and the features extracted from deep layers provide global components (like complex texture and shape). For low-light enhancement, both global and local information is essential. The global information is helpful for the evaluation of the illumination condition, and the local features benefit the detail restoration. Nevertheless, features from different layers play distinct roles in the feature representation. Stacking the feature maps may simply lose some representation power. Hence, further investigation for the channel-wise dependencies is needed. However, very few papers in the literature focus on seeking for a better representation from different layers. Based on the idea of squeeze-and-excitation, we propose a Feature Aggregation (FA) block that strengthens the feature representation power from multiple intermediate layers, which fuses both spatial and channel-wise information to the same block.

Decoding

Then, adding the offset to the LL image can increase the pixel values of the LL image, i.e., lightening the LL image. Subsequently, the "Decoding" process is conducted to reconstruct the NL image (actually, increase the number of the feature channels from 32 to 64).

Normal Light Image

Finally the lighting model is used to enhanced the input image The proposed DLN is inspired by the success of deep learning in low-level vision tasks. It produce the normal light image.

FEATURE AGGREGATION

The DLN has several short connections among the LBPs, which allows propagating features from the former to the latter LBPs. To use the features more effectively, we propose a feature aggregation (FA) block that strengthens the feature representation power based on multiple intermediate results. The first FA block in on the left has two inputs which fuses information from two feature maps, while the second FA block on the right fuses three input feature maps. Let us use the second FA block as an example which receives three feature maps, and each map has a size of W×H×C, where W, H, and C denote the width, height, and the number of channels of the feature map separately.

The FA block consists of three parts: feature concatenation, recalibration, and digesting process, as described below.

Feature concatenation

For a CNN network, the shallow layers extract the feature maps that contain detailed information. After the process of several layers, the neurons have larger receptive fields that extract more global information. Therefore, the filters of different layers can investigate the information on different sizes of spatial regions. As we mentioned above, for the low-light enhancement task, both local and global information are essential, because we need global information to evaluate the light condition of the whole image and the local features to refine the details. The FA block takes multiple feature maps that contain different spatial information as the input. It concatenates them together (with size: W×H×3C) and captures the spatial correlations in different scales through a convolutional layer, where the filter size is 3, with stride of 1 and padding of 1.

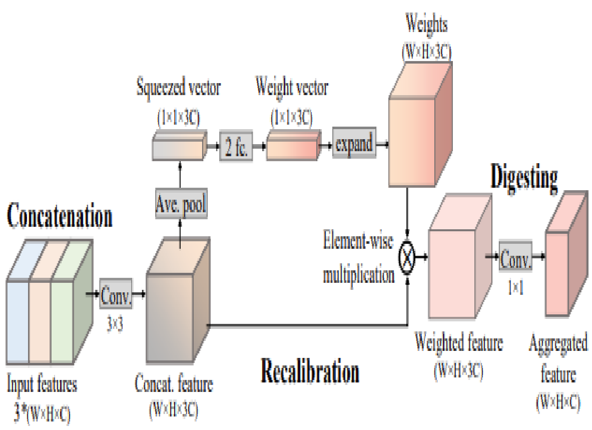


Fig 2 Structure of three-input Feature Aggregation (FA) block

Recalibration

Each channel of the feature map stores the information of a type of spatial pattern that is extracted by the convolutional filter. Based on the idea of constructing informative features by fusing the channel-wise information, we recalibrate the concatenated feature map by giving weights to different channels. The recalibration process contains a weighting branch and a short connection. For each channel (size: W×H), the weighting branch squeezes the information into a single value through global average pooling. Then, the feature map (size: W×H×3C) can be described by a squeezed vector with the size of 1×1×3C, and each value represents the information for one channel.

To investigate the channel-wised dependency, we make use of two fully-connected (fc) layers to assign weights for different feature channels, i.e., it estimates a weight vector (size: 1×1×3C), each attribute of which stores the weight for each channel. Next, it expands the weights at the width-height plane, and this changes the dimension to W×H×3C. Finally, the representational ability of the feature map is improved by multiplying the weights to the corresponding features. Note again that the recalibration process investigates channel-wise dependencies of the concatenated feature maps.

Digesting

Usually, the recalibration process has the effects to make the key features have large weights that are more important for the following process. The digesting block further improves the representation ability of the weighted features through a one-by-one convolutional layer which reduces the channels from W×H×3C to W×H×C.

LIGHTEN BACK-PROJECTION (LBP)

A low-light (LL) image (X) can be obtained from its normal-light (NL) version (Y) through a darkening operation (D, see the left green arrow in Fig. 3). The objective of LL enhancement is to find a lightening operation (L1), which predicts the NL image ($\tilde{Y} \in \mathbb{R}^{H\times W\times 3}$) from the observed LL image (X) (see the top red arrow in Fig. 3). Objectively, we can also estimate a version of the LL image ($\tilde{X} \in \mathbb{R}^{H\times W\times 3}$) from the estimated NL one ($\tilde{Y}$) through the darkening operation. If the lightening (L1) and darkening operations (D) are in an ideal situation, the ground-truth (X) and estimated ($\tilde{X}$) LL images will be the same. In real condition, their difference (a residual term $R_{LL} \in \mathbb{R}^{H\times W\times 3}$, for $R_{LL} = X- \tilde{X}$) indicates the weakness of the lightening (L1) and darkening (D) operations. Based on the residual information (RLL), it can estimate the residual ($\tilde{R}_{NL} \in \mathbb{R}^{H\times W\times 3}$, for $\tilde{R}_{NL} \approx Y-\tilde{Y}$) in the NL domain through a lightening operation (L2).

Finally, the intermediate NL estimation ($\tilde{Y}$) can be refined by adding the residual $\tilde{R}_{NL}$ to $\tilde{Y}$, i.e., $\hat{Y}= \tilde{Y} + \tilde{R}_{NL}$, where the term $\hat{Y} \in \mathbb{R}^{H\times W\times 3}$ is the refined NL estimation. Accordingly, we propose a Lighten Back-Projection (LBP) block that is shown in Fig. 4, where each LBP block consists of two lightening, and one darkening operator. The LL image (X) makes use of a Lightening operator L1 to estimate a NL image (Ỹ). Next, a Darkening operator (D) predicts the LL image (X̃) from the estimated Ỹ. For the LL image, the estimated (X̃) should be close to its ground truth (X). Then, it calculates the difference between X̃and X, i.e., the residual (RLL). Similarly, for the residual (RLL), another Lightening operator (L2) is used to estimate the residual (R̃NL) under NL conditions. The final estimation for the NL image (Ŷ) is obtained by adding the NL estimation (Ỹ) and its residual R̃NL. As we mentioned above, different from other approaches that directly learn the mapping function between LL and NL images, the proposed LBP blocks iteratively lightening and darkening the LL image to learn the residual term (R̃NL) for a better reconstruction.

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.

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 that enhance the low-light image accumulatively. Our DLN is compared 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.

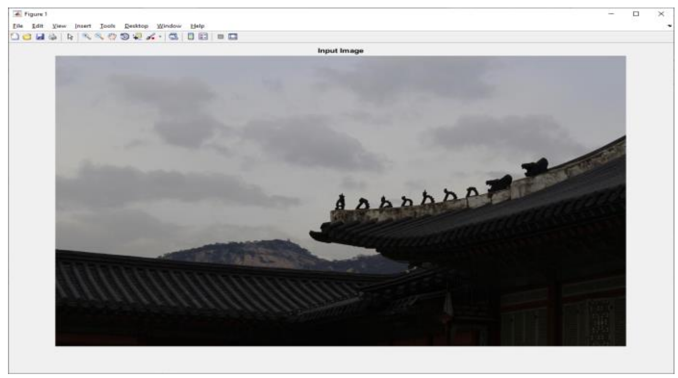
Feature Aggregation (FA)

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.

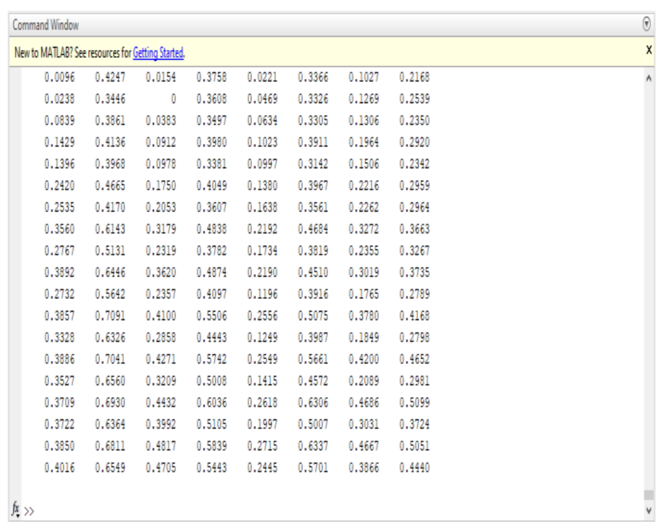
Making use of the hierarchical structure, CNNs have inherent multi-scale feature representations, where the features extracted from the shallow layers usually contain detailed information (like edge and texture), and the features extracted from deep layers provide global components (like complex texture and shape). For low-light enhancement, both global and local information is essential. The global information is helpful for the evaluation of the illumination condition, and the local features benefit the detail restoration.

Nevertheless, features from different layers play distinct roles in the feature representation. Stacking the feature maps may simply lose some representation power. Hence, further investigation for the channel-wise dependencies is needed. However, very few papers in the literature focus on seeking for a better representation from different layers. Based on the idea of squeeze-and-excitation, propose a Feature Aggregation (FA) block that strengthens the feature representation power from multiple intermediate layers, which fuses both spatial and channel-wise information to the same block.

IV. SCREEN SHOTS

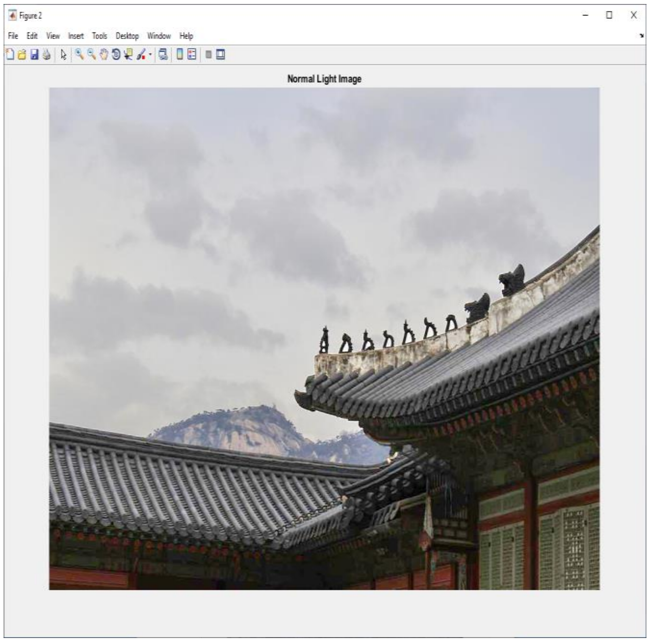


Input Image



0.0096	0.4247	0.0154	0.3758	0.0221	0.3366	0.1027	0.2168
0.0238	0.3446	0	0.3608	0.0469	0.3326	0.1269	0.2539
0.0839	0.3861	0.0383	0.3497	0.0634	0.3305	0.1306	0.2350
0.1429	0.4136	0.0912	0.3980	0.1023	0.3911	0.1964	0.2920
0.1396	0.3968	0.0978	0.3381	0.0997	0.3142	0.1506	0.2342
0.2420	0.4665	0.1750	0.4049	0.1380	0.3967	0.2216	0.2959
0.2535	0.4170	0.2053	0.3607	0.1638	0.3561	0.2262	0.2964
0.3560	0.6143	0.3179	0.4838	0.2192	0.4684	0.3272	0.3663
0.2767	0.5131	0.2319	0.3782	0.1734	0.3819	0.2355	0.3267
0.3892	0.6446	0.3620	0.4874	0.2190	0.4510	0.3019	0.3735
0.2732	0.5642	0.2357	0.4097	0.1196	0.3916	0.1765	0.2789
0.3857	0.7091	0.4100	0.5506	0.2556	0.5075	0.3780	0.4168
0.3328	0.6326	0.2858	0.4443	0.1249	0.3987	0.1849	0.2798
0.3886	0.7041	0.4271	0.5742	0.2549	0.5661	0.4200	0.4652
0.3527	0.6560	0.3209	0.5008	0.1415	0.4572	0.2089	0.2981
0.3709	0.6930	0.4432	0.6036	0.2618	0.6306	0.4686	0.5099
0.3722	0.6364	0.3992	0.5105	0.1997	0.5007	0.3031	0.3724
0.3850	0.6811	0.4817	0.5839	0.2715	0.6337	0.4667	0.5051
0.4016	0.6549	0.4705	0.5443	0.2445	0.5701	0.3866	0.4440

DLN Features



Normal Light Image

V. CONCLUSION

In this project have introduced the 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, or adopt GAN-based method for perception reconstruction, we 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, fuse the feature maps with different receptive fields through the Feature Aggregation (FA) block, which is an extension of the squeeze-and-extension structure 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. Besides, the network works in an end-to-end way, which makes it easy to implement. Have used both objective and subjective evaluations to compare the performance of the proposed DLN with other methods.

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