LEUGAN: Low-Light Image Enhancement by Unsupervised Generative Attentional Networks

Yangyang Qu, Chao Liu and Yongsheng Ou

Abstract—Restoring images from low-light data is a challenging problem. Most existing deep-network based algorithms are designed to be trained with pairwise images. Due to the lack of real-world datasets, they usually perform poorly when generalized in practice in terms of loss of image edge and color information. In this paper, we propose an unsupervised generation network with attention-guidance to handle the low-light image enhancement task. Specifically, our network contains two parts: an edge auxiliary module that restores sharper edges and an attention guidance module that recovers more realistic colors. Moreover, we propose a novel loss function to make the edges of the generated images more visible. Experiments validate that our proposed algorithm performs favorably against state-of-the-art methods, especially for real-world images in terms of image clarity and noise control.

Index Terms—Generative attentional networks, image enhancement, unsupervised learning

I. INTRODUCTION

In recent years, due to the rapid popularity of cameras equipped in various devices, image acquisition and vision algorithms are more and more widely used. While the images taken under low-light conditions may cause problems, such as low contrast, blurred edges, poor color, and noise further producing negative impacts in the depth estimation and semantic segmentation. Raising ISO is capable of increasing the image sensor sensitivity, but it will also amplify the noise in the meantime.

Histogram equalization (HE) [1] is one of the most widely adopted techniques to enhance low-light images because of its simplicity and effectiveness. However, there are some shortcomings, such as excessive contrast adjustment, noise amplification, and contour distortion. Various studies have been carried out to address these disadvantages. Wang et al. [2] proposed a novel contrast enhancement algorithm based on the layered difference representation of 2D histograms. Another algorithm [3] enhances the contrast of an input image using interpixel contextual information.

Retinex theory [4] is another popular low-light enhancement technique, which assumes that images can be decomposed into reflectance and illumination. Wang et al. [5] presents a brightness filter to decompose the observed image and then preserves the naturalness while enhancing the image details. In [6], the brightness of each pixel is replaced by the maximum value in R, G, and B channels to generate an enhanced map.

Learning-based methods have been studied extensively in the past few years. Gharbi et al. [7] consider a convolutional neural network that directly learns an end-to-end mapping between dark and bright images. Chen et al. [8] developed an unpaired learning model for photo enhancement based on a two-way generative adversarial network (GAN). Lv et al. [9] propose a multi-branch low-light enhancement network via multiple subnets and multi-branch fusion. Wang et al. [10] calculates a global illumination estimation for the input and adjust the illumination under the guidance of the estimation.

To solve these issues, we propose a novel unsupervised generative attentional network for low-light enhancement. The contributions of this work are summarized as follows:

- We develop an unsupervised generative attentional network that can be trained with unpaired image sets.
- We design an edge enhancement module that recovers sharper edges and an attention module that improves the color and texture restoring at focused areas.
- The experimental results demonstrate the effectiveness of the proposed network in terms of image clarity and noise control.

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II. LOW-LIGHT IMAGE ENHANCEMENT BY UNSUPERVISED GENERATIVE ATTENTIONAL NETWORKS

In unsupervised image-to-image translation, a joint distribution is yielded through models where the network encodes images from two domains into a shared feature space. Our goal is to map from a source domain $\alpha$ (defined by low-light images) to a target domain $\beta$ (defined by normal-light images) only by unpaired samples via a network model that consists of two generators and two discriminators, as shown in Fig. 2.

We integrate an edge-enhanced module and an attention module into the networks. The edge module focuses on recognizing edges and generating clearer textures, while the pixel and channel attention module leads the networks to mark particular areas for restoring richer details and better colors.

A. Network Architecture of Generative Model

As shown in Fig. 2, our generator model $G_{\alpha \rightarrow \beta}$ consists of an edge-enhancement module $ED_G$, an encoder $E_G$, a decoder $D_G$, and an attention module $U_G$ which focuses on particular regions.

Our generator contains two branches. For the upper branch, our purpose is to obtain the attention map $I_{att}$ of the image. Firstly, the original low-light image $I_{low}$ is down sampled by encoder module $E_G$. Then we input the encoder result $e_r$ into attention module $A_G$ to calculate the important distribution of features. For another branch, we input $I_{low}$ to the edge module $ED_G$ to get the edge image $I_{edge}$. Then we use the same encoder module $E_G$ for down sampling. We calculate the attention map $I_{att}$ from the result of down sampling, and get the final normal-illumination image $I_{nor}$ via decoder $D_G$.

1) Attention Module: Considering the uneven distribution of light, the pixel attention would be more attentive to the informative areas, such as the texture-rich regions. For the pixel attention, we calculate the feature map of each channel after the pixel attention. The typical attention modules used in other networks handle images on only pixel level without taking advantage of interrelation between color channels. Therefore, we add a channel attention part inspired by the Squeeze-and-Excitation networks [11], which aims to adaptively recalibrate channel-wise feature responses.

Firstly, we calculate an auxiliary feature $u \in \mathbb{R}^{H \times W \times C}$ from the encoded result, $E_r \in \mathbb{R}^{H' \times W' \times C'}$. By using a three-dimension convolution kernel $v$, we can get the convolution output $u = v \ast E_r$.

After that, we calculate the pixel attention. After getting the important distribution through global average pooling $f_{ave}$ and maximum pooling $f_{max}$, we can get the feature map $f_G = [f_{ave}^T, f_{max}^T]^T$. And then we can get the standard attention map $I_{att}$:

$$I_{att} = f_G \ast u,$$
(1)

and the visualization of attention map can be seen in Fig. 2.

In order to make our model more flexible to adjust the attention map and improve the training effect of the model, we add residual connection after the attention map which is inspired by [12]. Assuming that the result of our encoder is $E_r$, we can get the dynamic $E_{ro}$:

$$E_{ro} = \lambda \ast I_{att} \ast E_r + E_r,$$
(2)

where $\lambda$ is a trainable parameter that dynamically adjusts to the relationship between the feature map $I_{att}$ and the original result $E_r$, e.g. When $\lambda=0$, results from attention module are discarded, and the encoder output is directly passed to the decoder.

2) Edge Module: To extract edge information from low-light images, we first convert the input to gray-scale image, and then we get the oriented gradient via convolution with a improved sobel operator for for horizontal direction and
vertical direction respectively. Being different from [13], we add edge module in the process of generator and discriminator.

B. Network Architecture of Discriminator Model

Similar to the generator models, our discriminator model $D_{\alpha \rightarrow \beta}$ consists of edge-enhancement module, an encoder $E_D$, a decoder $D_D$, an attention module $A_D$ and a classifier $C_D$. With the help of these modules, the model will discriminate whether $x$ comes from the target domain or the translated source domain $G_{\alpha \rightarrow \beta}$. When we get an image $x$, $D_{\alpha \rightarrow \beta}(x)$ uses attention map to get:

$$c_r(x) = e_D \ast I_{att.D}(x),$$

(3)

where $e_D$ is the meaning of encoder result, $I_{att.D}(x)$ is the attention maps which is trained by $A_D$, and $c_r$ is the classifier result.

C. Loss function

The loss function comprises five loss terms which contains a new loss function proposed by us.

1) Structural Loss.: We propose a loss function by further considering the structural information of the image. $\mu_x$ and $\mu_y$ represents the pixel value averages of the image, $\lambda_x$ means the standard deviation of the image, and $\lambda_y$ has the same meaning as $\lambda_x$. $\theta$ is a constant and we set it to 1. We formulate the loss functions as:

$$\lambda_x = \sqrt{\left(\frac{1}{N-1} \sum_{i=1}^{N} (x_i - \mu_x)^2\right)},$$

(4)

$$\lambda_{xy} = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \mu_x)(y_i - \mu_y),$$

(5)

$$L_{str} = \frac{\lambda_{xy} + \theta}{\lambda_x \lambda_y + \theta},$$

(6)

where $N$ is the number of pixels in the image.

2) Identity Loss.: After considering the structural information, we use identity loss for the generator to ensure that the color distributions of input image $x$ which is from $\beta$ domain (normal-light image) and output image generated by $G_{\alpha \rightarrow \beta}$ is similar. The loss function is given by:

$$L_{idt} = \mathbb{E}_{x \sim X_{\beta}} \left[|x - G_{\alpha \rightarrow \beta}(x)|\right],$$

(7)

where $|\cdot|$ indicates absolute value.

3) Adversarial Loss: We adopt the adversarial loss to minimize the distance between the real and output normal light distributions.

$$L_{adv} = \mathbb{E}_{x, y \sim X_{\beta}} \left[\log(D_{\beta}(x))\right] + \mathbb{E}_{x \sim X_{\alpha}} \left[\log (1 - D_{\beta}(G_{\alpha \rightarrow \beta}(x)))\right].$$

(8)

4) Cycle Consistency Loss: This loss is proposed to tackle the unpaired translation problem [14], and it has been used wildly to prevent the network from generating random images in the target domain. We also put it in our network, and formulate the objective functions as:

$$L_{cyc} = \mathbb{E}_{x \sim X_{\alpha}} \left[|x - G_{\alpha \rightarrow \beta}(G_{\beta \rightarrow \alpha}(x))|\right].$$

(9)

5) Auxiliary Loss.: Here we adopt the auxiliary loss to get to know where is the most difference between two domains in the current state, $\eta_{D_{\beta}}$ represents the auxiliary classifiers, and it is defined as:

$$\mathcal{L}_{aux} = \mathbb{E}_{x \sim X_{\beta}} \left[\mathbb{E}_{y} \left[\eta_{D_{\beta}}(x)\right]^2\right] + \mathbb{E}_{x \sim X_{\alpha}} \left[2 \log (1 - \eta_{D_{\beta}}(G_{\alpha \rightarrow \beta}(x)))\right],$$

(10)

where $\eta_{D_{\beta}}$ is calculated as:

$$\eta_{e}(x) = \sigma \left(\sum_{k} \omega^k \sum_{i} E_{r}(x)\right),$$

(11)

where $\sigma(\cdot)$ is softmax function [15].

The overall loss function for training LEUGAN is written as follows:

$$L_{all} = \omega_{st}L_{str} + \omega_{idt}L_{idt} + \omega_{adv}L_{adv} + \omega_{cyc}L_{cyc} + \omega_{su}L_{aux}.$$  

(12)

where $L_{str}$, $L_{idt}$, $L_{adv}$, $L_{cyc}$, $L_{aux}$ represent the corresponding loss function, and $\omega_{st}$, $\omega_{idt}$, $\omega_{adv}$, $\omega_{cyc}$, $\omega_{su}$ are the corresponding coefficients of these losses. In the experiments, we empirically set $\omega_{st} = 1$, $\omega_{idt} = 10$, $\omega_{adv} = 10$, $\omega_{cyc} = 10$, $\omega_{su} = 100$.

III. EXPERIMENTS

To validate LEUGAN, we evaluate the performance on Low-Light(LOL) dataset [16], and we compare it with LIME [17], SRIE [18], CycleGAN [19], EnlightenGAN [20], MBLLLEN [9] and GLADNet [10] which are all trained on the LOL dataset.

A. Implementation Details

The proposed network is trained using the proposed dataset. The parameters of the networks were optimized using the Adabound algorithm [16]. As for the normalization method, we adopt the AdaLIN [12] whose parameters are dynamically computed from the attention map, and we train the model with a weight decay learning rate 0.0001.

In the generator, we use the instance normalization for the encoder to increase the accuracy of the auxiliary attention. We only use AdaLIN for the decoder. In the discriminator, we use spectral normalization, and we employ two different scales of PatchGAN [21] which classifies whether local $(70 \times 70)$ and global $(256 \times 256)$ image patches are real or fake. After that, we use ReLU [22] in the generator and leaky-ReLU with a slope of 0.2 for the activation function.

B. No-Reference Quality Assessment

The sharpness and the amount of noise are important indicators for measuring the quality of the image, and it can better correspond to human subjective feelings. For the non-reference image quality evaluation, we use several representative definition algorithms for discussion and analysis.

We adopt natural image quality evaluator (NIQE) [23] which is a no-reference image quality evaluation standard to justify how "naturally" the image looks like. It has better
Fig. 3. Visual comparison with state-of-the-art low-light image enhancement methods. Zoom-in regions are used to illustrate the visual difference. It can be seen that our results contain little noise and obtain the most natural color of the image.

Fig. 4. Images enhanced by attention module, edge module and LEUGAN. (a) is the original image, (b) is without attention module, (c) is the attention map visualization, (d) is without edge module, (e) is our method. We can find that our results have little noise after the details are magnified, while most other images have higher noise.

consistent with human subjective quality evaluation. Lower the NIQE score, more natural the image looks. Besides, we also use Vdolath [24] to measure image sharpness, PCA-based [25] to measure the image noise. Higher Vdolath means better clarity, and lower PCA-based indicates less image noise.

Table I reports the quantitative results of the low-light image enhancement. Bold blue represents the best result, and bold black represents the second best result. The results show that our superiority in visual effects and noise control. From the results we can find that our method achieves the best results in terms of visual effect, and it is much better than other methods in terms of noise control. We also achieved the second best result in terms of clarity. We also confirmed our experimental results in the latter visual effect analysis.

C. Visual effect analysis

We give an example to illustrate the superiority of our method in Fig. 3; the last column is our method.

Through the results shown in Fig. 3, we can find that our method achieves good results in both color restoration and noise control. EnlightenGAN [20] which is an unsupervised method has achieved good results in terms of noise control, while it does not perform well in color. CycleGAN [19] generates darker result compared with our method. The results of other methods are also unsatisfactory in terms of color and brightness. As can be seen that our method restores more realistic image with clearer details, better contrast and normal brightness.

TABLE I

| Model         | NIQE(↓) | Vdolath(↑) | PCA-based(↓) |
|---------------|---------|------------|--------------|
| AMSR [26]     | 5.529   | 319.45     | 7.718        |
| BIMEF [27]    | 5.533   | 672.37     | 5.896        |
| BPDHE [28]    | 5.163   | 2160.22    | 7.022        |
| Dong [29]     | 5.669   | 1507.61    | 10.930       |
| LIME [6]      | 6.911   | 3248.44    | 13.660       |
| EnlightenGAN [20] | 4.784   | 1760.56    | 7.562        |
| Retinex-Net [30] | 5.808   | 872.54     | 10.268       |
| NPE [31]      | 5.678   | 1649.80    | 13.218       |
| MBLLEN [9]    | 4.670   | 2408.47    | 12.365       |
| GLADNet [10]  | 6.067   | 2380.35    | 5.542        |
| CycleGAN [19] | 4.263   | 2235.47    | 1.542        |
| SRIE [18]     | 5.633   | 608.43     | 5.140        |
| LEUGAN        | 4.216   | 2420.34    | 0.616        |

D. Ablation Study

We conduct ablation studies on the dataset to evaluate the effectiveness of different components in the method from visual effects and quantitative analysis based on the low-light dataset. Fig. 4 shows the ablation results of our different modules.

Attention module. Fig. 4 (b) illustrates an image that is enhanced via a network without attention module. Clearly, it is dull in color while edges are blurred. With the help of the attention maps shown in Fig. 4(c), the generator could capture the global structure (e.g., the brightness of the image) as well as pay more attention to some local important areas so that many previously lost image details can be recovered, and the colors become richer and more natural.

Edge module. Fig. 4(d) shows the result with edge module, and we can see that our result shown in Fig. 4(e) generates high-quality images with sharp edges and smooth surfaces under the guidance of the edge module.

IV. Conclusion

In this paper, we proposed a low-light image enhancement network using unsupervised generative attentional networks with designed attention and edge modules period, and these two modules help improve the image quality in terms of restoring color and sharpening edges. We test our method on the LOL dataset and compare it with some state-of-the-art
methods. Results show that our method outperform the others approaches in terms of image clarity and amount of noise.

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