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Poster

SDALIE-GAN: Structure and Detail Aware GAN for Low-light Image Enhancement

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Abstract

We present a GAN-based network architecture for low-light image enhancement, called Structure and Detail Aware Low-light Image Enhancement GAN (SDALIE-GAN), which is trained with unpaired low/normal-light images. Specifically, complementary Structure Aware Generator (SAG) and Detail Aware Generator (DAG) are designed respectively to generate an enhanced low-light image. Besides, intermediate features from SAG and DAG are integrated through guided map supervised feature attention fusion module, and regularizes the generated samples with an appended intensity adjusting module. We demonstrate the advantages of the proposed approach by comparing it with state-of-the-art low-light image enhancement methods.

CCS Concepts

• ***Computing methodologies*** → ***Computational photography;***

1. Introduction

Due to the lack of high-quality paired data, recent data-driven low-light image enhancement neural networks, i.e., Zero-DCE [GLG*20] and EnlightenGAN [JGL*21] are committed to reducing the dependency of paired data through self-regularized training. However, Zero-DCE predicts dynamic range adjusting curve of pixel intensity in the fixed local neighborhood which ignores the global structure consistency. EnlightenGAN regularizes the training of Generative Adversarial Networks (GAN) with self feature preserving loss between input and enhanced image, while the pooling and interpolation operation in U-Net discard the crucial details and lead to unnatural enhanced results.

In this poster, we propose an unsupervised *Structure and Detail Aware Low-light Image Enhancement Generative Adversarial Network (SDALIE-GAN)* trained with unpaired low/normal-light images. Specifically, we design complementary *Structure Aware Generator* (SAG) and *Detail Aware Generator* (DAG) respectively to acquire an enhanced low-light image. In SAG, enhanced illumination guidance map facilitates the structure adaptive enhancement of illuminance. DAG is composed of convolutional layers that do not change the input feature size to preserve all detail information, and integrate the intermediate feature of SAG through guidance map supervised *Feature Attention Fusion Module* (FAM). Moreover, the new *Intensity Adjust Module* (IAM) is appended to regularize the generate samples. Finally, global discriminator and local discriminator are utilized as EnlightenGAN [JGL*21] in adversarial training to close the gap between the real and output normal-light image distribution.

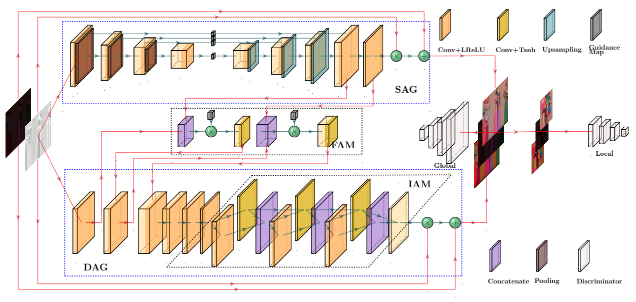

Figure 1: *The inputs are a low-light image and a corresponding enhanced illumination guidance map. The proposed SDALIE-GAN consists of two generators, i.e., SAG and DAG.*

2. Our Approach

The architecture of the proposed SDALIE-GAN is shown in Fig. 1, which consists of dual generators (SAG/DAG) and dual discriminators (global/local discriminator). In this section, we introduce the the newly designed generators SAG and DAG along with important

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modules FAM and IAM. Since we adopt the same discriminators as EnlightenGAN, readers can refer to [JGL*21] for more details.

Structure Aware Generator. The architecture of U-Net powered SAG is shown in the upper part of Fig. 1. Compared with EnlightenGAN, we simplify the architecture while achieving the same performance. The enhanced output E_{SAG} of SAG can be written as $E_{SAG} = L + I_{SAG}$, where L represents the low-light input image and I_{SAG} is the estimated intensity compensation map of SAG. We enhance L in four aspects: brightness, color, contrast, and sharpness with basic image processing operations to restore the structural information and empirically use $1-(0.299R+0.587G+0.114B)$ to get the enhanced illumination guidance map. The enhanced guidance map is integrated in skip connection and FAM as attention map to facilitate the structural aware I_{SAG} estimation.

Detail Aware Generator. Although skip connections are adopted to combine fine-grained and coarse-grained feature maps in U-Net, the down/up-sampling operation inevitably causes the loss of detail information. We design the DAG (the lower part of Fig. 1) to maintain high-resolution representation in the process of the low-light image enhancement with both rich structure and detail information. DAG integrates the illumination structure information learned by SAG with FAM to achieve the final illumination compensation I_{DAG} through IAM as shown in Fig. 1. The high-resolution feature maps of the last two expansion convolutional blocks of SAG and the first two convolutional blocks of DAG are concatenated respectively to maximally retain structure and detail information under the guidance of enhanced guidance map. Moreover, inspired by [SGB18], IAM is composed of two branches. The branch with ReLU activation is designed to extract features, and the branch with Tanh activation is devised to adjust intensity.

Loss Function. Similar to [JGL*21], we use both global and local perceptual loss and adversarial loss on both SAG and DAG.

3. Experimental Results

We verify the advantages of SDALIE-GAN with recent works on standard dataset, which include MEF, DICM, LIME, NPE, LOL and VV following [JGL*21]. Our proposed method is evaluated by both visual and quantitative comparisons with state-of-the-art low-light image enhancement methods, including [FWYL20], [GLG*20] and [JGL*21]. The results are shown in Fig. 2 and Tab. 1. We can observe over-exposure and detail missing artifacts in the enhancement results of [FWYL20], [GLG*20] and [JGL*21] in Fig. 2. SDALIE-GAN achieves the best effect in restoring the illumination and detail of low-light image which can also be validated through superior numerical results of image quality measurement NIQE (Naturalness Image Quality Evaluator) and PI (Perceptual index) in Tab. 1.

4. Conclusion and Future Work

We propose a novel network for low-light image enhancement, called SDALIE-GAN. Two complementary generators, i.e., SAG and DAG are used in the network. The intermediate features of SAG and DAG are merged through FAM, which IAM is designed to regularize the generated sample. Finally, experiments on real low-light images validate that our SDALIE-GAN can achieve more aesthetically pleasing and natural results than existing methods. In the future, we plan to investigate adaptive guidance map construction to deal with more complicated and diversified illumination conditions.

Input [FWYL20] [GLG*20] [JGL*21] Ours

Figure 2: *Visual comparisons with the state-of-the-art.*

Methods	MEF	LIME	NPE	VV	DICM	LOL	AVE
[GLG*20]	3.28	3.77	3.54	3.82	3.72	7.77	3.91
	2.35	**2.80**	2.86	2.67	3.13	4.44	2.99
[FWYL20]	3.80	4.00	3.39	3.38	3.92	**3.30**	3.60
	2.85	3.13	2.92	2.80	3.48	2.52	3.05
[JGL*21]	3.23	3.71	3.61	3.48	3.55	4.68	3.63
	2.32	2.90	2.98	2.61	3.16	2.89	2.93
Ours	**3.00**	**3.57**	**3.09**	**2.80**	**3.26**	3.77	**3.17**
	2.22	**2.90**	**2.74**	**2.29**	**3.05**	**2.47**	**2.73**

Table 1: *NIQE(Above) and PI(below) scores on the image sets (MEF, LIME, NPE, VV, DICM, LOL and Average(AVE)). The smaller value of NIQE and PI indicates more naturalistic and better perceptual quality. Bold for best results.*

5. Acknowledgement

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References

[FWYL20] Fan M., Wang W., Yang W., Liu J.: Integrating semantic segmentation and retinex model for low-light image enhancement. In *Proc. of the ACM Inte. Conf. on Mult.* (2020), ACM, pp. 2317–2325. 2

[GLG*20] Guo C., Li C., Guo J., Loy C. C., Hou J., Kwong S., Runmin C.: Zero-reference deep curve estimation for low-light image enhancement. *In Proc. of the IEEE Conf. on Comp. Visi. and Patt. Reco.* (2020). 1, 2

[JGL*21] Jiang Y., Gong X., Liu D., Cheng Y., Fang C., Shen X., Yang J., Zhou P., Wang Z.: EnlightenGAN: Deep light enhancement without paired supervision. *IEEE Trans. on Imag. Proc. 30* (2021), 2340–2349. 1, 2

[SGB18] Schwartz E., Giryes R., Bronstein A. M.: DeepISP: Toward learning an end-to-end image processing pipeline. *IEEE Trans. on Imag. Proc. 28*, 2 (2018), 912–923. 2