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RESTORATION OF LOW-LIGHT IMAGE BASED ON DEEP RESIDUAL NETWORKS

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Abstract

Images captured in low-light conditions usually suffer from very low contrast, which increases the difficulty of computer vision tasks in a great extent. Existing low-light image restoration methods still have limitation in image naturalness and noise. In this paper, we propose an efficient deep residual network that learns difference map between low-light image and original image and restores the low-light image. Additionally, we propose a new low-light image generator, which is used to train the deep residual network. Especially the proposed generator can simulate low-light images containing luminance sources and completely darkness parts. Our experiments demonstrate that the proposed method achieves good results for both synthetic and natural low-light images.

Keywords:

Low-Light Image, Image Restoration, Deep Residual Network

1. INTRODUCTION

In computer vision tasks such as object detection [1] and tracking [2], the image quality plays an important role in the performance of the entire system. Especially the light condition directly affects the quality of captured image. That’s because the images captured in low-light conditions such as morning and night makes the outline features of objects indistinct and overall luminance of the image poor. And also, in the case of images captured in low-light condition, electronic characteristic of the camera makes so much noise on images. This means the low-light condition decreases the image quality and furthermore degrades efficiency of visual recognition systems.

Therefore, the low-light image restoration comes up with an important task. For the first time, the enhancement methods including histogram equalization (HE) which enhances the global intensity of images had been studied and some of them aim to improve the HE performance by imposing different regularization terms on the histogram [3]-[5]. For instance, some contrast enhancement methods try to find a histogram mapping that pays attention on large gray-level differences, while other method achieves improvement by seeking a layered difference representation (LDR) of 2D histograms [6]. However, in nature, they focus on contrast enhancement instead of exploiting real illumination causes, the risk of over- and–under enhancement still remains.

Another solution is the Gamma correction, which is a nonlinear operation on images. But the main drawback is that the nonlinear operation of the Gamma correction is carried out on each pixel individually without considering the relationship of semantically linked pixels, and therefore enhanced results may be vulnerable and visually inconsistent with real scenes.

Retinex theory [7] is very popular in manipulating light correction tasks. In Retinex theory, the dominant assumption is that the image can be decomposed into reflection and illumination. Based on this assumption, single-scale Retinex and multi-scale Retinex methods using the reflection component are applied to improve the quality of the overall image. LIME [8] method tries to estimate the illumination of each pixel by finding the maximum value in R, G and B channels, then refines the initial illumination map by exploiting the structure of the illumination.

But these analytic restoration methods have limitations that they can’t consider the overall contextual information of image. So, the restored image is not natural and denoised sufficiently. Furthermore, the pixels at which the intensity is 0 can’t be restored.

By the reason, nowadays, CNN-based methods which shows good performance in computer vision tasks such as object recognition, scene understanding and face recognition [9], [10] are widely used for low-light image restoration. In fact, deep convolutional neural networks have achieved good result in other image restoration tasks, such as super resolution, denoising and inpainting. In this case, the CNN models are usually trained with the artificially generated low-light and noisy images [11]. Here, the low-light images are simulated by Gamma enhancement and the noisy image is simulated by adding Gaussian noise. So the trained restoration model takes any images to restored images which can be regarded as a normal-light images. In general, training data is important in CNN-based methods. The common method which is used to generate training samples is based on Retinex model.

However, using this method, it is impossible to simulate the characteristics of light (the extinction and the reflection) effectively. For example, even though captured in poor light, the brightness of an object gets darker from luminous source, but this property can’t be simulated by ordinary gamma adjustment. Thus, the generated training samples are not close to the natural low-light image and it directly affects the efficiency of model.

In this paper, we present a deep residual algorithm for the restoration of low-light image.

Our main contributions are as follows: First, we propose one method that generates low-light images containing the luminance sources and completely darkness parts for training CNN models. Second, we also propose the effective deep residual network that learns difference map between low-light image and original image and restores the low-light image.

The rest of this paper is organized as follows. In section 2, we review several related works. Section 3 describes about our low-light image generator and CNN-based low-light image restoration model. In section 4, we represent the efficiency of the proposed model by comparing with other methods. Finally, conclusion remarks and future research tasks are given in section 5.

2. RELATED WORKS

Many contrast enhancement methods for improving image contrast using histogram equalization [12], [13] are studied.

Wu [14] introduced OCTM to map the contrast-tone of an image by using of mathematical transfer function. Gonzalex et al [15] explored the available schemes using non-linear functions like the gamma function to enhance image contrast.

Agostinelli et al [16] introduced a multi-column architecture to denoise images by training the model with sorts of noise and testing on images with arbitrary noise levels.

To reconstruct clean images from noisy images by exploiting the multi-layer perceptron, Burger et al [17] used the stacked denoising autoencoders.

Fotiadou et al [18] intensified natural low-illumination images by applying the low-light image patches to approximate the corresponding daytime images.

Dong et al [19] proposed an algorithm, which inverts the dark input frames and performs de-hazing to improve the quality of the low light images.

Another method proposed by Yamasaki et al [20] decomposes the image into two elements and enhances the quality of images using the reflectance element.

3. PROPOSED METHOD

We simulation low-light images based on the consideration of the properties of images captured in the extremely poor-light condition. We configure the CNN based on residual network and train with the simulated low-light images. The characteristic of our model is that it can control the intensity of restoration.

3.1 LOW-LIGHT IMAGE GENERATOR

Our low-light image generator is based on the following Retinex model. Let I' represent the captured image, then it can be denoted by

$$I' = L \cdot I \tag{1}$$

where L represents illumination map, I represent original image and $\cdot$ represents element-wise multiplication. In general, Gamma correction is used for low-light image generation:

$$I' = \alpha I^{\gamma} \tag{2}$$

where γ is a constant determined by the image brightness and α is a constant determined by the maximum pixel intensity in the image.

If there is the luminous source or the highly bright part reflected from the luminous source, it is natural that the brightness is the max discrete value even though captured low-light condition. Therefore, we can represent the illumination map in the form of linear function as follows:

$$L = \alpha I^{\gamma} + \beta \tag{3}$$

If I=1 that is the luminous source or very bright part, we assume that the low-light image also has 1 value, so that L=1.

Therefore, $\alpha + \beta = 1, \beta = 1 - \alpha$ and L is represented as follows:

$$L = \alpha I^{\gamma} + 1 - \alpha \tag{4}$$

According, substituting Eq.(4) into Eq.(1) yields:

$$I' = (\alpha I^{\gamma} + 1 - \alpha) I = I - \alpha (1 - I^{\gamma}) I \tag{5}$$

If we define the difference map between the low-light image and original image as follows,

$$I^D = (1 - I^{\gamma}) I \tag{6}$$

Then the original image I is the sum of the low-light image and the weighted difference map αI^D:

$$I = I' + \alpha I^D \tag{7}$$

Here α is the parameter that represents low-light intensity.

If we can estimate the difference map I^D, it's possible to calculate I in the form of residual learning. The Fig.1 shows how the original pixel values change according to the α and γ by Eq.(5). Because some pixel values become smaller than zero, when α is larger than 1, in this case we change those pixel values into 0. These pixels can be regarded as the darkness parts in low-light condition, but they can be restored from the information of the neighbour pixel using the CNN.

3.2 DEEP RESIDUAL NETWORKS FOR LOW-LIGHT IMAGE RESTORATION

The CNN for restoring the low-light images is based on residual learning. First, we estimate I^D from the low-light input image in the front of the CNN. Then, the estimated difference map is weighted by α and the combination with original low-light input image and weighted difference map is used for the input of Enhance-Net, which removes the noise and improves the quality of the image for the contrast-enhanced image.

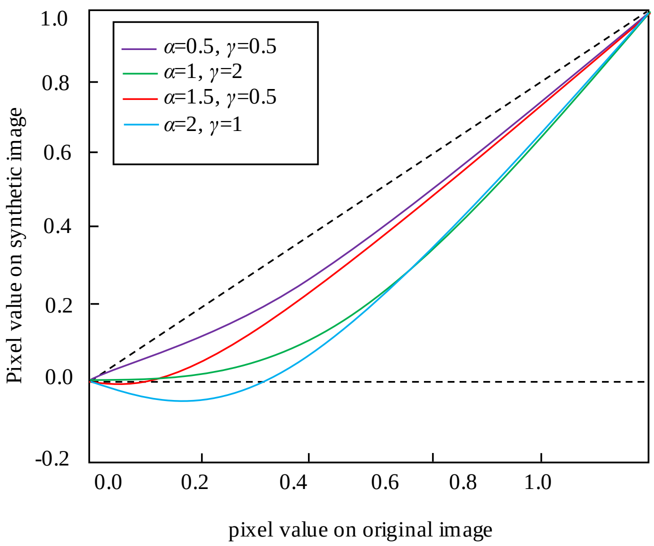
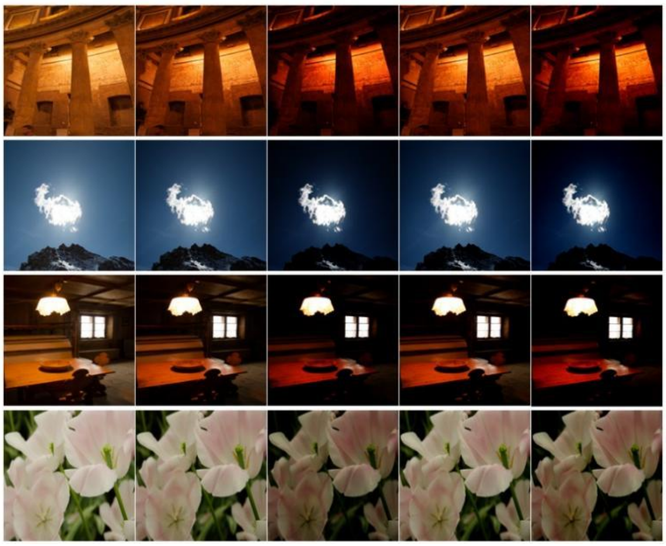


Fig.1. The pixel values the low-light image following α and γ

The structure of CNN is mainly based on residual network. Residual network is often used for image inpainting, super resolution, image generation because the features of the input image are directly delivered. We modify the structure and the position of BN and CNN in Resnet structure used for super resolution as follows:

First, we set the kernel size by combining 7×3 and 3×7 larger than 3×3, because dark parts on the image must be restored from the neighbor information and this can be performed as in inpainting.

Secondly, as shown in Fig.2, BN is added in the front and back of CN. Fig.2 shows the low-light sample images calculated by Eq.(5) when we set α as 0.5, 1, 1.5 and 2. As we can see in the Fig.2, the bright parts still approximately maintain its brightness after transformed by Eq.(5).



(a) (b) (c) (d) (e)

Fig.2. Several examples for synthetic low-light images (a)-original images, (b), (c), (d), (e)-synthetic images for α=0.5, γ=0.5, α=1, γ=2, α=1.5, γ=0.5, α=2, γ=1, separately

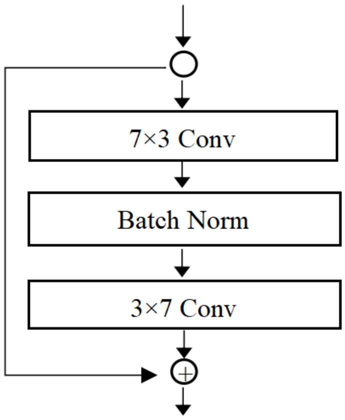


Fig.3. Residual block used in the CNN

Experiment results show that this achieves state-of-the art performance in image restoration. I^D map obtained in the convolutional neural network that estimates I^D is added to input image. We configure another CNN for denoising and improving the quality of the image after the CNN again based on the Resnet. The overall structure of the deep networks is as follows Fig.3.

The Fig.4 shows the proposed whole framework for low-light image restoration. In Fig.4, I^D is estimated from the low-light input image by Estimate-Net, and the estimated difference map is weighted by α. Then, the combination with original low-light input image and weighted difference map is used for the input of Enhance-Net, which remove the noise and improve the quality of the image.

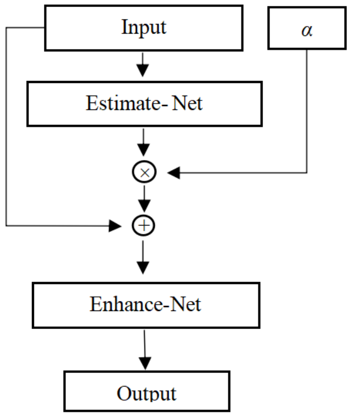


Fig.4. The proposed framework for low-light image restoration

4. EXPERIMENTS

We generate the original image and the corresponding low-light image following some α using the proposed method in section 3.1 and train with Tensor-flow. To evaluate the performance of the proposed method, we compare with the recent low-light image enhancement methods for the simulated images. And we analysis how some hyper-parameters of the CNN affect the result.

4.1 DATABASE

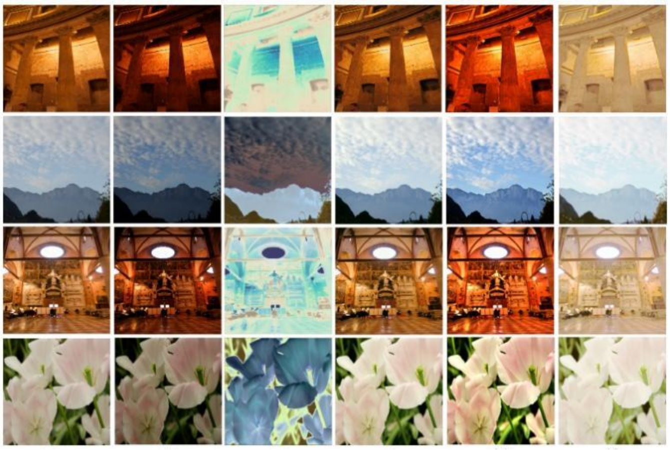
We collect 1000 images from RAISE database [21] and generate low-light images with the proposed method in section 3.1 to train CNN. We use original image to generate the low-light image by randomly selecting α and γ. Thus, we can simulate the low-light image associated the various α, the finally trained model can restore the low-light image effectively. Also, we add some Gaussian noise randomly to the generated low-light image to simulate the reality that lots of noise is generated when capturing images in low-light condition.

4.2 TRAINING SETTINGS

We set the depth of CNN to estimate I^D to 3 and to denoise and improve the image quality to 2. We use L2 norm between the original image and output image as loss function and use L2 weight regularization method to avoid over-fitting. The Adam optimization is adopted, and initial learning rate starts with 10-e^3 and reduces 10 times at every 50k steps. At each training epoch, we set α randomly between 0.5 and 2. We use randomly selected image patches of size 48×48 rather than the whole images. The input of the CNN is α and low-light image patch and the output image is the ordinary image patch. Training is performed on a TITAN XP GPU and the batch size is 32.

4.3 RESULTS ON SYNTHETIC IMAGES

In Fig.5 we illustrate 4 results on synthetic images from RAISE datasets, where α=1, γ=0.5. It is shown that our Estimate-Net can estimate difference map of low-light efficiently and Enhance-net enhance output image.



(a) (b) (c) (d) (e) (f)

Fig.5. The results using different methods on synthetic images (a): natural images, (b): synthetic images, (c): estimated difference maps, (d): results using our method, (e): results using LIME method, (f): results using LLnet method

The bright parts of images are expressed as dark parts in difference maps. Because this means that the bright parts of images are enhanced small amount, it may satisfy the purpose of restoration. Our network can restore low-light image contains bright part and eliminate quantization noise, as illustrated in Fig.5.

Unfortunately, there is no general quantitative comparison method designed for low-light image restoration methods. Because there is no low-light image database with ground truth image pairs. Most of methods use the visual comparison methods, but it is hard to compare quantitatively since most of low-light image restoration methods can achieve good results.

We compare the differences between the restoration result and original image on synthetic images in terms of PSNR, SSIM.

We collect 100 natural images and then synthesize low-light images using our proposed method. We calculate PSNR and SSIM between the restoration result with previous methods and ground truth. We also process with our approach. The calculation results are shown in Table.1. For both PSNR and SSIM, the proposed method has the greatest values, and LLNet[11] has the smallest values. Thus, we can see that the quality of synthetic images is better in the proposed method than in other two methods, in terms of PSNR and SSIM.

Table.1. The PSNR and SSIM results on synthetic images.

Method	PSNR	SSIM
LIME [8]	17.23	0.78
LLNet [11]	16.35	0.73
Proposed method	18.12	0.85

4.4 RESULTS ON NATURAL LOW-LIGHT IMAGES

The Fig.6 shows visual comparison on four natural low-light images using different methods. As shown on images, our method brightens up the objects buried in dark lightness enough without overexposure, which benefits from the learning-based image enhance method with synthetic low-light images. Compared with LIME and LLnet, our results are not partially over-exposed for brighten part such as street lamp. As shown in Fig.6, details are better preserved by our network while LIME and LLnet blur the edges.

(a) (b) (c) (d)

Fig.6. The results using different methods on natural low-light images. (a): natural low-light images, (b): results using LIME method, (c): results using LLnet methods, (d): results using our methods.

5. CONCLUSION

In this paper, we present a deep residual algorithm for the restoration of low-light image. The proposed deep residual network learns difference map between low-light image and original image which is subsequently used to estimate the enhanced image. Especially our proposed architecture has an advantage that it can control the intensity of restoration by setting up α. Experimental results show that our method produced good results in terms of PSNR, SSIM and visual enhancement. Though our method has gained some development, a lot of research studies, such as training of quantization artifacts for more realistic situation and exploring of other deep architectures for the natural low-light image enhancement, need to be done in the future.

REFERENCES

[1] D. Oneata, J. Revaud, J. Verbeek and C. Schmid, "Spatio-Temporal Object Detection Proposals", *Proceedings of European Conference on Computer Vision*, pp. 737-752, 2014.

[2] K.H. Zhang, L. Zhang and M.H. Yang, "Real-Time Compressive Tracking", *Proceedings of European Conference on Computer Vision*, pp. 864-877, 2012.

[3] E.D. Pisano, S.Q. Zong, B.M. Hemminger, M. DeLuca, R.E. Johnston, K. Muller, M.P. Braeuning and S.M. Pizer,

"Contrast Limited Adaptive Histogram Equalization Image Processing to Improve the Detection of Simulated Speculations in Dense Mammograms", *Journal of Digital Imaging*, Vol. 11, No. 4, pp. 193-200, 1998.

[4] H.D. Cheng and X.J. Shi, "A Simple and Effective Histogram Equalization Approach to Image Enhancement", *Digital Signal Processing*, Vol. 14, No. 2, pp. 158-170, 2004.

[5] M. Abdullah-Al-Wadud, M.H. Kabir, M.A.A. Dewan and O. Chae, "A Dynamic Histogram Equalization for Image Contrast Enhancement", *IEEE Transactions on Consumer Electronics*, Vol. 53, No. 2, pp. 593-600, 2007.

[6] T. Celik and T. Tjahjadi, "Contextual and Variational Contrast Enhancement", *IEEE Transactions on Image Processing*, Vol. 20, No. 12, pp. 3431-3441, 2011.

[7] E. H. Land, "The Retinex Theory of Color Vision", *Scientific American*, Vol. 237, No. 6, pp.108-129, 1977.

[8] X.J. Guo, Y. Li and H.B. Ling, "LIME: Low-Light Image Enhancement via Illumination Map Estimation", *IEEE Transactions on Image Processing*, Vol. 26, No. 2, pp. 982-993, 2017.

[9] E. Shelhamer, J. Long and T. Darrell, "Fully Convolutional Networks for Semantic Segmentation", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 39, No. 4, pp. 640–651, 2017.

[10] W.H. Yang, J.S. Feng, J.C. Yang, F. Zhao, J. Y. Liu, Z. M. Guo and S. C. Yan, "Deep Edge Guided Recurrent Residual Learning for Image Super Resolution", *IEEE Transactions on Image Processing*, Vol. 26, No. 12, pp. 5895-5907, 2017.

[11] K.G. Lore, A. Akintayo and S. Sarkar, "LLNet: A deep Autoencoder Approach to Natural Low-Light Image Enhancement", *Pattern Recognition*, Vol. 61, pp. 650-662, 2017.

[12] E. Pisano, S. Zong, B. Hemminger, M. DeLuce, E. Johnston, K. Muller, P. Braeuning and S. Pizer, "Contrast Limited Adaptive Histogram Equalization Image Processing to Improve the Detection of Simulated Spiculations in Dense Mammograms", *Journal of Digital Imaging*, Vol. 11, No. 4, pp. 193-200, 1998.

[13] M. Kaur, J. Kaur and J. Kaur, "Survey of Contrast Enhancement Techniques based on Histogram Equalization", *International Journal of Advanced Computer Science and Applications*, Vol. 2, No. 7, pp. 137-141, 2011.

[14] X. Wu, "A Linear Programming Approach for Optimal Contrast-Tone Mapping", *IEEE Transaction on Image Processing*, Vol. 20, No. 5, pp. 1262-1272, 2011.

[15] R. Gonzalex and R. Woods, "*Digital Image Processing*", Prentice Hall, 2001.

[16] F. Agostinelli, M.R. Anderson and H. Lee, "Adaptive Multi-Column Deep Neural Networks with Application to Robust Image Denoising", *Advances in Neural Information Processing Systems*, Vol. 29, pp. 1493-1501, 2013.

[17] H.C. Burger, C.J. Schuler and S. Harmeling, "Image Denoising: Can Plain Neural Networks Compete with BM3D?", *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2392-2399, 2012.

[18] K. Fotiadou, G. Tsagkatakis and P. Tsakalides, "Low Light Image Enhancement via Sparse Representations", *Proceedings of International Conference on Image Analysis and Recognition*, pp. 84-93, 2014.

[19] X. Dong, G. Wang, Y. A. Pang, W. Li, J. G. Wen, W. Meng and Y. Lu, "Fast Efficient Algorithm for Enhancement of Low Lighting Video", *Proceedings of IEEE International Conference on Multimedia and Expo*, pp. 1-6, 2011.

[20] A. Yamasaki, H. Takauji, S. Kaneko, T. Kanade, H. Ohki and A. Denighting: "Enhancement of Nighttime Images for a Surveillance Camera", *Proceedings of International Conference on Pattern Recognition*, pp. 1-4, 2008.

[21] D.T. Dang-Nguyen, C. Pasquini, V. Conotter and G. Boato, "Raise: A Raw Images Dataset for Digital Image Forensics", *Proceedings of ACM Conference on Multimedia Systems*, pp. 219-224, 2015.