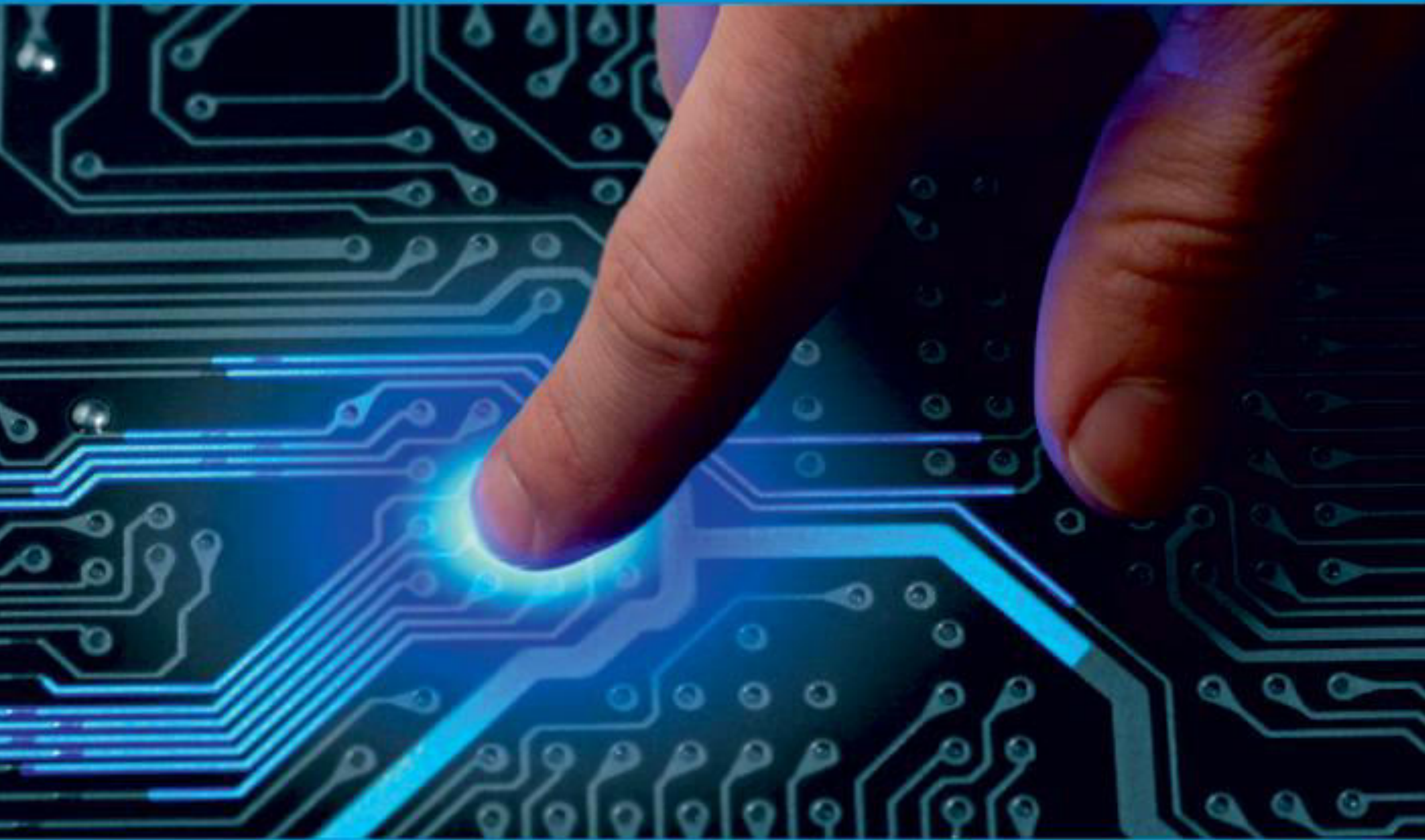
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 8, August 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.625

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Deep Learning Based Image Enhancement for Exposure Restoration

Manisha. T, Dr. Sumi M.S

Department of Electronics and Communication Engineering, Rohini College of Engineering and Technology, Kanyakumari, Tamil Nadu, India.

ABSTRACT: Images and videos capture a vast amount of rich and detailed information about the scene. Intelligent systems use these captured images for various computer vision tasks, such as image enhancement, object detection, classification and recognition, segmentation, 3-D scene understanding, and modeling. Image restoration techniques process degraded images to highlight obscure details or enhance the scene with good contrast and vivid color for the best possible visibility. Poor illumination condition causes issues, such as high-level noise, unlikely color or texture distortions, nonuniform exposure, halo artifacts, and lack of sharpness in the images. This article presents a novel end-to-end trainable deep convolutional neural network called the deep perceptual image enhancement network (DPIENet) to address these challenges. The novel contributions of the proposed work are: 1) a framework to synthesize multiple exposures from a single image and utilizing the exposure variation to restore the image and 2) a loss function based on the approximation of the logarithmic response of the human eye. Extensive computer simulations on the benchmark MIT-Adobe FiveK and user studies performed using Google high dynamic range, DIV2K, and low light image datasets show that DPIENet has clear advantages over state-of-the-art techniques.

KEYWORDS: Deep Perceptual Image Enhancement Network(DPIENet)**,** MIT-Adobe FiveK, Convolutional Neural Network, Logarithmic Exposure Transformation.

I. INTRODUCTION

The growing importance of digital image processing systems from two principal application areas and they are (i) Improvement of pictorial information for human interpretation and (ii) Processing of scene data for autonomous machine perception. Digital image processing techniques are now used to solve a variety of problems. One such important problem in image processing is restoration. The goal of the restoration approach is to improve the given image, so that it is suitable for further processing. Restoration is a technique used to reconstruct or recover an image that has been degraded by using a prior knowledge of the degradation phenomenon. Removal of degradation is becoming increasingly important as image analysis and acquisition system finds more application in society. There are a variety of reasons that could cause degradation of an image, and image restoration is one of the key fields in today's Digital Image Processing due to its wide area of applications. Because of the imperfection of the physical imaging system and due to various physical limitations on every application a recorded image will always be a degraded version of an original image.

Blurring can be caused when an object in the image is outside the cameras depth of field during the exposure. Motion blur can be caused when an object moves relative to the camera during an exposure. Photographic defocusing is also a problem in many different imaging situations. This type o blurring is due to effects at the camera aperture, which spreads a point of incoming light across a circle of confusion. Noise is generally a distortion due to the imaging system rather than the scene recorded. Noise results in random variations to pixels in the image. Whatever be the degrading process, image distortions can fall into two categories, spatially invariant and spatially variant. In a space invariant distortion, all pixels have suffered the same form of distortion. This is generally due to the problems with the imaging system such as distortions in the optical system, global lack of focus or camera motion. In a space variant distortion, the degradation suffered by a pixel in the image depends upon its location in the image. This can be caused by internal factors such as distortions in the optical system or by external factors such as object, motion etc.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

II. REVIEW OF LITERATURE

Gu, F. Li, et al.(2022) proposed a Most LLIE algorithms focus solely on enhancing the brightness of the image and ignore the extraction of image details, leading to losing much of the information that reflects the semantics of the image, losing the edges, textures, and shape features, resulting in image distortion. In this paper, the DELLIE algorithm is proposed, an algorithmic framework with deep learning as the central premise that focuses on the extraction and fusion of image detail features. Unlike existing methods, basic enhancement preprocessing is performed first, and then the detail enhancement components are obtained by using the proposed detail component prediction model. Then, the V-channel is decomposed into a reflectance map and an illumination map by proposed decomposition network, where the enhancement component is used to enhance the reflectance map. Then, the S and H channels are nonlinearly constrained using an improved adaptive loss function, while the attention mechanism is introduced into the algorithm proposed in this paper. Finally, the three channels are fused to obtain the final enhancement effect. The experimental results show that, compared with the current mainstream LLIE algorithm, the DELLIE algorithm proposed in this paper can extract and recover the image detail information well while improving the luminance, and the PSNR, SSIM, and NIQE are optimized by 1.85%, 4.00%, and 2.43% on average on recognized datasets.

J. Liang, et al. (2021) proposed a Low-light images, i.e. the images captured in low-light conditions, suffer from very poor visibility caused by low contrast, color distortion and significant measurement noise. Low-light image enhancement is about improving the visibility of low-light image. As the measurement noise in low-light images is usually significant yet complex with spatially-varying characteristic, how to handle the noise effectively is an important yet challenging problem in low-light image enhancement. Based on the Retinex decomposition of natural images, this paper proposes a deep learning method for low-light image enhancement with a particular focus on handling the measurement noise. The basic idea is to train a neural network to generate a set of pixel-wise operators for simultaneously predicting the noise and the illumination layer, where the operators are defined in the bilateral space. Such an integrated approach allows us to have an accurate prediction of the reflectance layer in the presence of significant spatially-varying measurement noise. Extensive experiments on several benchmark datasets have shown that the proposed method is very competitive to the state-of-the-art methods, and has significant advantage over others when processing images captured in extremely low lighting conditions.

Zhen Hua, et al. (2022) proposed Images collected in haze or other weather have problems of quality degradation, blurred details, and low recognition, which seriously affect the application and development of related image application fields. The dark channel prior method is the typical method of image dehazing, but it is not suitable for sky region. The wavelength of near-infrared is longer than that of visible light, which makes it more penetrating, less affected by the scattering of suspended particles in the air, and carries more detailed information. This paper uses near-infrared information to distinguish between sky region and non-sky region, improve the dark channel prior method, enhance the visibility of the image, and restore the contrast of the image. A large number of experiments have proved that our method has achieved satisfactory results in solving problems such as sky region and darker scene. This method has strong pertinence and stability for image dehazing, and the effect is relatively natural and efficient. Therefore, our method is better than the existing method of image dehazing.

Jiangfan Feng, et al. (2021) proposed a Motion deblurring and image enhancement are active research areas over the years. Although the CNN-based model has an advanced state of the art in motion deblurring and image enhancement, it fails to produce multitask results when challenged with the images of challenging illumination conditions. The key idea of this paper is to introduce a novel multitask learning algorithm for image motion deblurring and color enhancement, which enables us to enhance the color effect of an image while eliminating motion blur. To achieve this, we explore the synchronization of processing two tasks for the first time by using the framework of generative adversarial networks (GANs). We add L1 loss to the generator loss to simulate the model to match the target image at the pixel level. To make the generated image closer to the target image at the visual level, we also integrate perceptual style loss into generator loss. After a lot of experiments, we get an effective configuration scheme. The best model trained for about one week has achieved state-of-the-art performance in both deblurring and enhancement. Also, its image processing speed is approximately 1.75 times faster than the best competitor.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

CHAI Gaixia, et al. (2022) proposed a failure of existing evaluation methods of infrared and visible fusion image caused by high brightness halation information in night vision halation scene, a novel fusion image quality evaluation method based on adaptive partition is proposed. In this method, the adaptive coefficient is automatically determined according to the halation degree o visible image, and then, the fusion image is divided into halo regions and non-halo region by iterative calculation of the critical halation gray value. In the halo region, the effectiveness of halation elimination is evaluated by halation elimination index designed, while in the non-halo region, the enhancement effect of detailed information such as texture and color is evaluated from three aspects including characteristics of fusion image itself, retention degree of original image information and human visual effect. Based on evaluation and analysis of fusion images obtained by 4 different anti-halation algorithms, nine objective indexes are selected to construct a quality evaluation system of night vision anti-halation fused image. Experimental results in different night vision halation scenes show that the proposed method could evaluate anti-halation image quality of infrared and visible fusion comprehensively and reasonably, and could solve the problem that the more thorough halation elimination of fusion image, the worse objective evaluation results. This method could also be suitable for evaluating merits and demerits of different anti-halation fusion algorithms.

III. PROPOSED SYSTEM

This project proposes a deep learning-based perceptual image enhancement network (DPIENet). DPIENet comprises of three main components: 1) logarithmic-based exposure transformation; 2) joint local and multiblock global feature extraction; and 3) dynamic channel attention (DCA) blocks. A unified network that can ensure global uniformity by generating perceptually similar enhanced images for input images of both standard and low exposure setting by utilizing dilated convolutions to preserve spatial resolution in convolutional networks. A combination of a classical log-based synthetic multi exposure image generation technique-logarithmic exposure transformation (LXT) that employs trainable parameters to improve the performance of the network. A novel loss function "multi scale human color vision (MHCV) loss". This loss aims at improving the quality of the reconstruction by considering human perception. This loss function promotes the model to learn complicated mappings and effectively reduces the undesired artifacts, such as noise, unrealistic color or texture distortions, and halo effects a multiscale loss function that works on the principle of the Retinex theory is proposed. According to this, the low-frequency information of the image represents the global naturalness, and the high-frequency information represents the local details. By decomposing the image into a low-frequency luminance component and a high-frequency detail component, the loss function incorporates both the local and global information. This loss is driven by the close to the logarithmic response of the human visual system (HVS) in large luminance range areas.

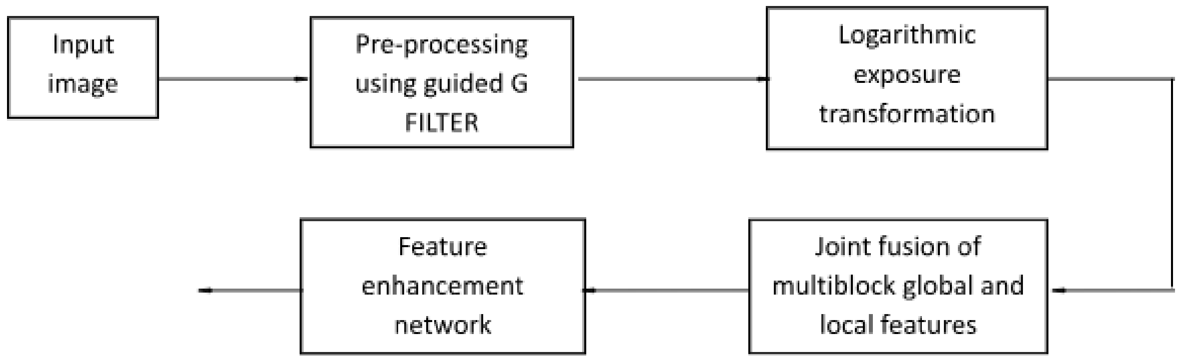


Fig 3.1 Block Diagram

A deep learning-based perceptual image enhancement network (DPIENet) to address these issues. This network has a U-shaped structure similar to the U-Net architecture. It consists of two stages: a feature condense network (FeCN) that aims to acquire compact feature representation of the spatial context of the image and feature enhance network (FeEN) that performs nonlinear up sampling of the input feature maps to reconstruct an enhanced image. The architecture is

© 2024 IJIRCCE | Volume 12, Issue 8, August 2024| DOI: 10.15680/IJIRCCE.2024.1208005

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

equipped with skip connections between these two networks to use high-resolution image details during the reconstruction. An example of the result obtained using the network is illustrated in Fig. 3.1. Some of the notable contributions of DPIENet include the following. A unified network that can ensure global uniformity by generating perceptually similar enhanced images for input images of both standard and low exposure setting by utilizing dilated convolutions to preserve spatial resolution in convolutional networks and improve spatial image understanding. Furthermore, it incorporates a channel attention mechanism that aims to adaptively rescaling channel wise features by extracting the channel statistics to enhance the network's discriminative ability. A combination of a classical log-based synthetic multi exposure image generation technique logarithmic exposure transformation (LXT) that employs trainable parameters to improve the performance of the network. A novel loss function "multiscale human color vision (MHCV) loss". This loss aims at improving the quality of the reconstruction by considering human perception. This loss function promotes the model to learn complicated mappings and effectively reduces the undesired artifacts, such as noise, unrealistic color or texture distortions, and halo effects.

IV. RESULT AND DISCUSSION

For training, RGB input patches of size 256×256 along with the corresponding ground truth were considered. The training data were augmented using random horizontal, vertical, and 90° rotations alon the center of the image. The merged images from the Google HDR dataset were utilized to show the effectiveness of DPIENet aims at exposure correction, the merged images were used as inputs to the systems. To compute the quality, no reference-based quality measure, such as CRME, Brisque, and Divine, were utilized. Comparative results are provided in Table V. Due to the supervised training of DPIENet, it has to be noted that it tries to enhance the image so that it is close to the reference image, and thus, it is not optimized for the no-reference-based measure. This is indicated by the marginally better results obtained by DPIENet in comparison to other methods.

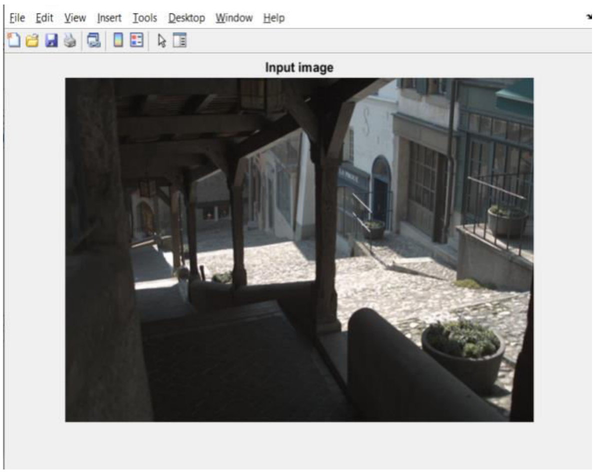


Fig. 4.1 Input image

An input image is a digital representation of a physical image or scene, which is used as an input to a computer vision system for further processing and analysis. An input image can be in various formats, such as JPEG, PNG, BMP, TIFF, etc. the input image is shown in figure 4.1.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

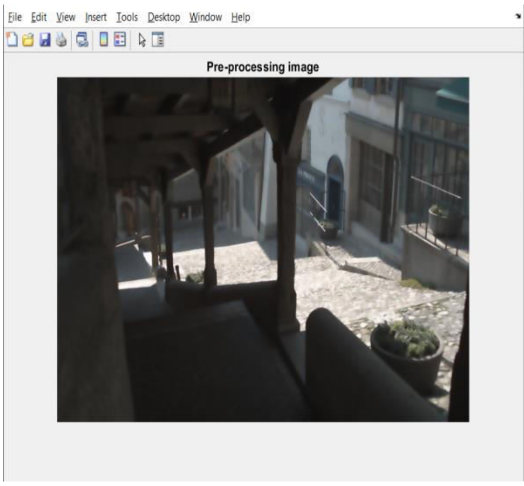


Fig. 4.2 Pre-processing image

The aim of pre-processing is an improvement of the image data that suppresses unwilling distortions or enhances some image features important for further processing, although geometric transformations of images. The pre-processing image is shown in figure 4.2.

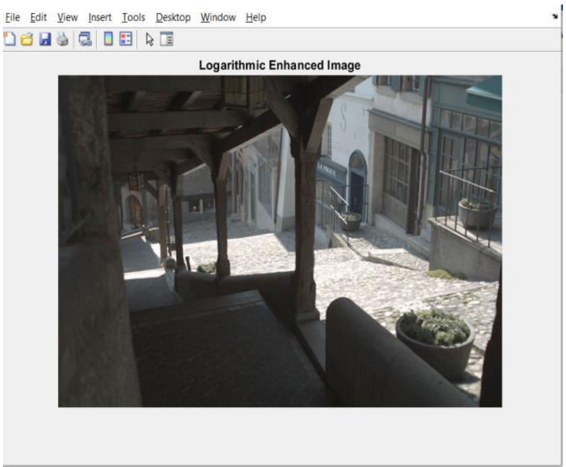


Fig. 4.3 Logarithmic enhanced image

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Logarithmic Image Processing (LIP) models provide a suitable framework for visualizing and enhancing digital images, acquired from various sources and obtained by transmitted/reflected light through absorbing/reflecting media, where the effects are naturally of a multiplicative form. The logarithmic enhanced image is shown in figure 4.3.

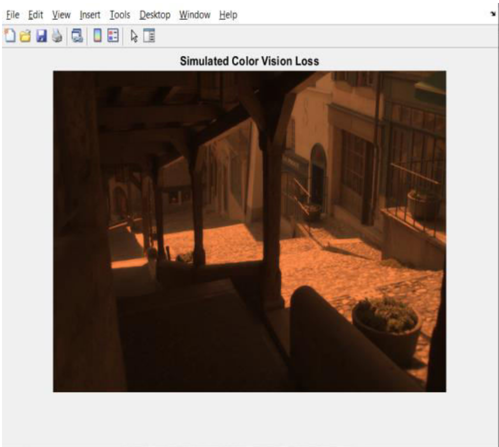


Fig. 4.4 Simulated color vision loss

Color blindly is an Chrome extension that helps developers and designers simulate different types of color blindness. There are different types of color blindness to simulate: here we used Blue Cone Monochromacy. Achromatomaly-Monochromacy. The simulated color vision loss is shown in figure 4.4

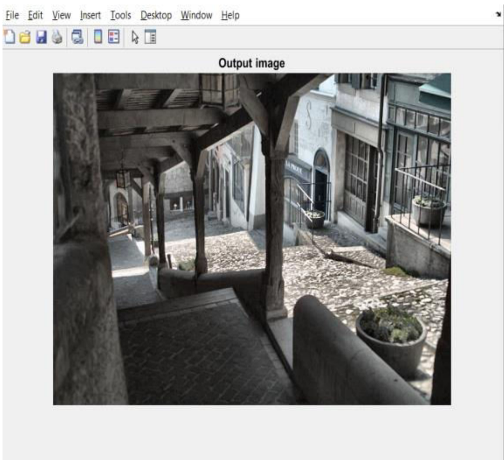


Fig. 4.5 Output image

Finally, the output enhanced image is shown in figure 4.5.

V. CONCLUSION AND FUTURE WORK

In this work, a novel deep learning-based image enhancement for exposure restoration is presented. The method is built on multi exposure simulation using LXT. The proposed DPIENet, which is an end-to-end mapping approach, comprises of a condense and enhance network, which leverages the idea of residual learning to reach a larger depth. Furthermore, the skip connection between these networks aids in recovering spatial information while up sampling. In

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.625| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

addition, to improve the network's ability to realize the context of the image, global features are exploited from each group in the condense network. A DCA mechanism to adaptively rescale channel wise features is employed to boost the network's channel inter dependencies further. To obtain realistic images that correlate to human vision, a novel multiscale human vision loss is presented these aid in accounting for the global variation in illumination, details, and colors.

Furthermore, DPIENet overcomes artifacts, such as halo effects, noise amplification in dark regions, and artificial color generation, which occur in a few existing techniques. As a part of the future work, intend to test the accuracy of the system for various low-level computer vision tasks, such as super-resolution, image recoloring, and image denoising.

REFERENCES

[1] A. Ignatov, N. Kobyshev, R. Timofte, K. Vanhoey, and L. Van Gool,"DSLR-quality photos on mobile devices with deep convolutional networks," in Proc. IEEE Int. Conf. Comput. Vis., 2017, pp. 3277–3285.

[2] A. K. Jain, *Fundamentals of Digital Image Processing*. Englewood Cliffs, NJ, USA: Prentice Hall, 1989.

[3] A. Voulodimos, N. Doulamis, A. Doulamis, and E. Protopapadakis,Deep learning for computer vision: A brief review," *Comput.Intell. Neurosci.*, vol. 2018, Feb. 2018, Art. no. 7068349,doi: 10.1155/2018/7068349.

[4] C. Chen, Q. Chen, J. Xu, and V. Koltun, "Learning to see in the dark," in*Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2018, pp. 3291–3300.

[5] C.-H. Lee, J.-L. Shih, C.-C. Lien, and C.-C. Han, "Adaptive multiscale retinex for image contrast enhancement," in *Proc. Int. Conf. Signal-Image Technol. Internet-Based Syst.*, 2013, pp. 43–50.

[6] D. J. Jobson, Z.-U. Rahman, and G. A. Woodell, "Properties and performance of a center/surround retinex," *IEEE Trans. Image Process.*,vol. 6, pp. 451–462, 1997.

[7] E. H. Land and J. J. McCann, "Lightness and retinex theory," *J. Opt.Soc. America*, vol. 61, no. 1, pp. 1–11, 1971.

[8] H. Jiang and Y. Zheng, "Learning to see moving objects in the dark,"in*Proc. IEEE/CVF Int. Conf. Comput. Vis.*, 2019, pp. 7324–7333.

[9] H. Sawant and M. Deore, "A comprehensive review of image enhancement techniques," *Int. J. Comput. Technol. Electron. Eng.*, vol. 1, no. 2,pp. 39–44, 2010.

[10] I. Goodfellow et al., "Generative adversarial nets," in Advances in Neural Information Processing Systems. Red Hook, NY, USA: Curran Assoc.,2014, pp. 2672–2680.

[11] J. C. Russ and F. B. Neal, *The Image Processing Handbook*. Boca Raton,FL, USA: CRC Press, 2018.

[12] J. Hu, H. Gao, Z. Zhang, G. Lin, H. Wang, and W. Liu, "A novel image enhancement method based on variational retinex approach," in *Proc.IOP Conf. Ser. Mater. Sci. Eng.*, vol. 452, Dec. 2018, Art. no. 042202,doi: 10.1088/1757-899x/452/4/042202.

[13] K. A. Panetta, E. J. Wharton, and S. S. Agaian, "Human visual system based image enhancement and logarithmic contrast measure," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 38, no. 1, pp. 174–188,Feb. 2008.

[14] K. G. Lore, A. Akintayo, and S. Sarkar, "LLNet: A deep auto encoder approach to natural low-light image enhancement," Pattern Recognit.,vol. 61, pp. 650–662, Jan. 2017.

[15] K. Panetta, S. Agaian, Y. Zhou, and E. J. Wharton, "Parameterized logarithmic framework for image enhancement," *IEEE Trans. Syst., Man,Cybern. B, Cybern.*, vol. 41, no. 2, pp. 460–473, Apr. 2011.

[16] M. Abdullah-Al-Wadud, M. H. Kabir, M. A. A. Dewan, and O. Chae,"A dynamic histogram equalization for image contrast enhancement,"*IEEE Trans. Consum. Electron.*, vol. 53, no. 2, pp. 593–600, May 2007.

[17] M. Aubry, S. Paris, S. W. Hasinoff, J. Kautz, and F. Durand, "Fast local laplacian filters: Theory and applications," ACM Trans. Graph., vol. 33, no. 5, p. 167, 2014.

[18] M. Gharbi, J. Chen, J. T. Barron, S. W. Hasinoff, and F. Durand, "Deep bilateral learning for real- image enhancement," ACM Trans. Graph.,vol. 36, no. 4, pp. 1–12, 2017.

[19] M. J. Nadenau, J. Reichel, and M. Kunt, "Wavelet-based color image compression: Exploiting the contrast sensitivity function," *IEEE Trans.Image Process.*, vol. 12, pp. 58–70, 2003.

[20] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in *Proc. Int. Conf. Med.Image Comput. Comput. Assist. Intervent.*, 2015, pp. 234–241.

[21] Q. Chen, J. Xu, and V. Koltun, "Fast image processing with fully convolutional networks," in Proc. IEEE Int. Conf. Comput. Vis., 2017,pp. 2497–2506.

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com

Scan to save the contact details

www.ijircce.com