International Journal of Progressive Research in Science and Engineering
Volume-1, Issue-4, July-2020
www.ijprse.com

A Deep Single Image Contrast Enhancer from Multi Exposure Images

Akhila T[1], Sunil Chakravarthi Kaippada[2]

[1]Student, Department of Computer Science Engineering, MCET, Thrissur, Kerala, India.

[2]Assistant Professor, Department of Computer Science Engineering, MCET, Thrissur, Kerala, India.

Corresponding Author: akhilavenugopalt96@gmail.com

Abstract: - The natural scene with good contrast, vivid color and rich details is an essential goal of digital photography. The acquired images, however, are often under-exposed or over-exposed because of poor lighting conditions and the limited dynamic range of imaging device. The resulting low contrast and low quality images will not only degenerate the performance of many computer vision and image analysis algorithms, but also degrade the visual aesthetics of images. Contrast enhancement is thus an important step to improve the quality of recorded images and make the image details more visible. Due to the poor lighting condition and limited dynamic range of digital imaging devices, the recorded images are often under-/over-exposed and with low contrast. Most of previous single image contrast enhancement (SICE) methods adjust the tone curve to correct the contrast of an input image. Those methods, however, often fail in revealing image details because of the limited information in a single image. On the other hand, the SICE task can be better accomplished if we can learn extra information from appropriately collected training data. In this work, we propose to use the convolutional neural network (CNN) to train a SICE enhancer. One key issue is how to construct a training dataset of low-contrast and high contrast image pairs for end-to-end CNN learning.

Key Words:- SICE, CNN, contrast-enhancement, training data.

I. INTRODUCTION

A Super Resolution System where the images are taken into our algorithm and outputs us a super resolution images. One central problem remains largely unsolved: how do we recover the finer texture details when we super-resolve at large up-scaling factors? The behavior of optimization-based super-resolution methods is principally driven by the choice of the objective function. Recent work has largely focused on minimizing the mean squared reconstruction error. The resulting estimates have high peak signal-to-noise ratios, but they are often lacking high-frequency details and are perceptually unsatisfying in the sense that they fail to match the fidelity expected at the higher resolution. In this paper, we present SRGAN, a generative adversarial network (GAN) for image super-resolution (SR). To our knowledge, it is the first framework capable of inferring photo-realistic natural images for 4x up-scaling factors. To achieve this, we propose a perceptual loss function which consists of an adversarial loss and a content loss. The adversarial loss pushes our solution to the natural image manifold using a discriminator network that is trained to differentiate between the super-resolved images and original photo-realistic images.

II. METHODOLOGY

The methodology for this concept will consist of mainly five steps. The first step is the Database collection then preprocessing the third step is Feature Extraction after that Training and final step is Testing. These steps can be described as below:

A. Preprocessing:

Preprocessing of images. Noise removals, Conversion of images to array formats.

B. Feature Extraction:

Feature extraction of images is basically the datas or arrays that is taken from the images after preprocessing.

C. Training:

Deep learning neural network models learn to map inputs to outputs given a training dataset of examples. The training process involves finding a set of weights in the network that proves to be good, or good enough, at solving the specific problem.

IJPRSE
Progressive Research
International Journal of Progressive Research in Science and Engineering
Volume-1, Issue-4, July-2020
www.ijprse.com

D. Testing:

Testing is done so that we can assure the training for the system is accurately done. Testing process gives us a proper understanding of the project detection. It shows us the accuracy level.

E. Prediction:

The predicted results will be shown in this module.

III. Convolutional Neural Network

The utilized neural network architecture is based on Mobile Nets. This network is built on depth wise convolution layers which are further divided into depth wise and point wise convolution, except for the first layer which is a fully connected layer. Depth wise convolution is used for applying a single filter on every input channel while point wise convolution is used to form a linear combination of the output from the depth wise layer. There are two non-linearity used: batch norm and ReLU after each layer. Depth wise convolution is a way to filter the channels but it does not combine them in order to generate new features. So for combining we use 1×1point wise convolution. The MobileNets training is done in Tensor flow with the help of RMS prop and asynchronous gradient descent. The layer architecture of the MobileNets model is given in comparison to other models such as Inception, the MobileNets uses less regularization and data augmentation. In fact, the size of the input to the network is also small. In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery.

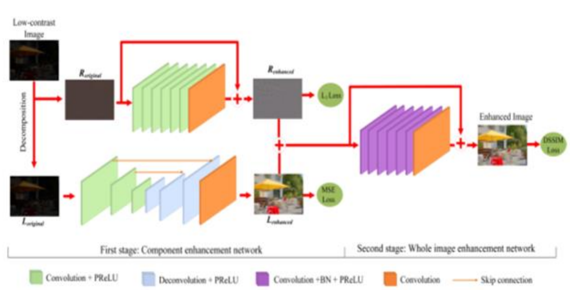

Figure.1. CNN Model

IV. Result

The result of the proposed system is again an image without noise and with enhanced contrast. And there is another option is there that a registration system.

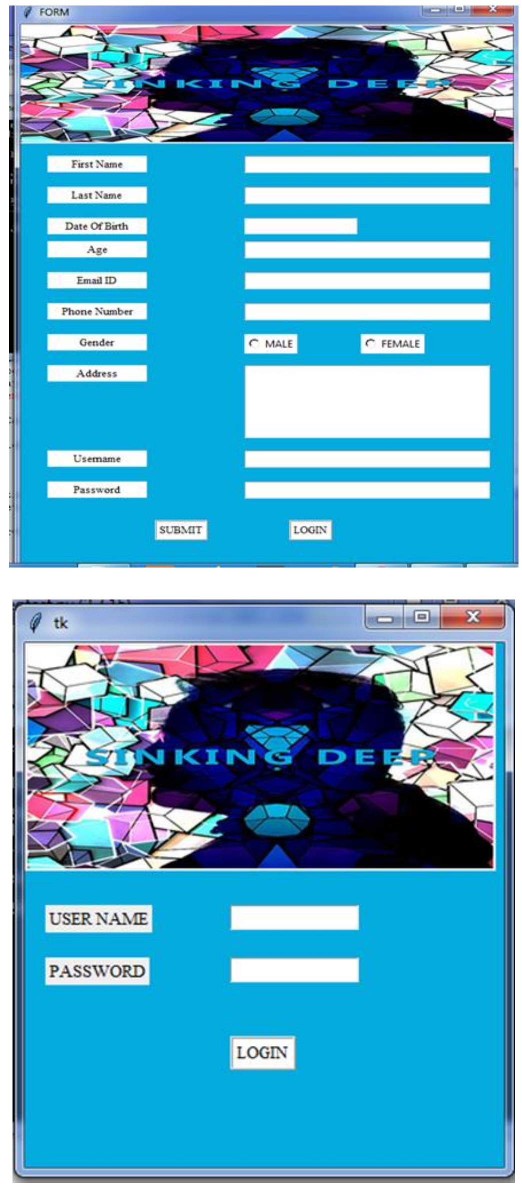

Figure.2. Registration and Login pages

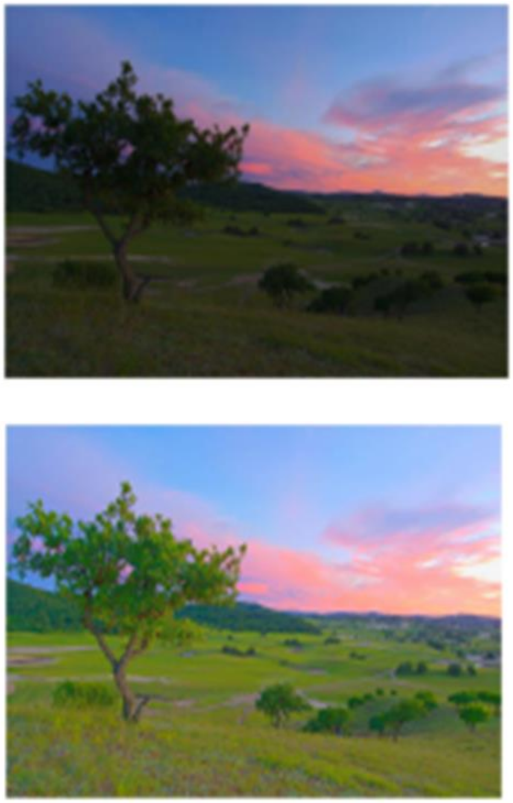

Figure.3. Input image and the output image

V. CONCLUSION

We built a multi-exposure image dataset, which has 589 image sequences and high-resolution images of different exposures. For each sequence, a corresponding high quality reference image was generated by using MEF and stack based HDR algorithms. Subjective tests are also conducted to screen the best quality one as the reference image of each scene. As a demonstration, we developed a simple yet powerful CNN-based SICE enhancer, which is capable of adaptively generating high quality enhancement result for a single over-exposed or underexposed input image. Our experimental results showed that the developed SICE enhancer significantly outperforms state-of the-art SICE methods, and even outperforms MEF and stack based HDR methods for dynamic scenes. Video enhancement is another important application. To apply the proposed methods to videos, we could consider enlarging our dataset and learning an LSTM (long short-term memory) based CNN enhancer to convert the conventional videos to HDR videos. This will be one of our future works.

REFERENCES

[1]. Wang, D., Khosla, A., Gargeya, R., Irshad, H., & Beck, A. (2016). Deep Learning for Identifying Metastatic Breast Cancer. ArXiv: 1606.05718.

[2]. Abadi, Agarwal, Barham, Brevdo, Chen, Citro, Zheng. (2016). TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems.arXiv:1603.04467.

[3]. M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen,C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, et al. Tensorflow: Large-scale machine learning on heterogeneous systems, 2015. Software available from tensorflow. Org, 1, 2015. arXiv:1603.04467.

[4]. T. Tieleman and G. Hinton. Lecture 6.5-rmsprop: Divide the gradient by a running average of its recent magnitude. COURSERA: Neural Networks for Machine Learning, 4(2),2012.

[5]. K. Goatman, A. Charnley, L. Webster, S. Nussey, “Assessment of automated disease detection in diabetic retinopathy screening using twofield photography,” PLoS One, vol. 6, no. 12, e27524, 2011.

[6]. Philip S, Fleming AD, Goatman KA, Fonseca S, McNamee P, “The efficacy of automated disease/no disease grading for diabetic retinopathy in a systematic screening programme”, Br. J. Ophthalmol., vol. 91, no. 11, pp. 1512–1517, 2007.

[7]. Fleming AD, Goatman KA, Philip S, Williams GJ, Prescott GJ, “The role of hemorrhage and exudate detection in automated grading of diabetic retinopathy”, Br. J. Ophthalmol., vol. 94, no. 6, pp. 706-711, 2010.

[8]. Fleming AD, Goatman KA, Philip S, Prescott GJ, Sharp PF, “Automated grading for diabetic retinopathy: a large-scale audit using arbitration by clinical experts”, Br. J. Ophthalmol., vol. 94, no. 12, pp. 1606-1610,2010.

[9]. M. Lalonde, M. Beaulieu and L. Gagnon, "Fast and robust optic disc detection using pyramidal decomposition and hausdorff-based template matching", IEEE Trans. Medical imaging, vol. 20, no. 11, pp.1193-1200, 2001.

[10]. S. G. Mallat, "A theory for multiresolution signal decomposition: The wavelet representation", IEEE Trans. Pattern Anal. Machine Intell., vol. 11, pp.674-693, 1989.

[11]. Sharath Kumar P N, Rajesh Kumar R, Anuja Sathar, Sahasranamam V, “Automatic Detection of Exudates in Retinal Images Using Histogram Analysis,” in IEEE International Conference on Recent Advances in Intelligent Computational Systems (RAICS), pp. 277-281, December 2013.

[12]. Y. Hatanaka, T. Nakagawa, Y. Hayash, A. Fujita, Y. Mizukusa, M. Kakogawa, K. Kawase, T. Hara, and H. Fujita, “CAD scheme for detection of hemorrhages and

exudates in ocular fundus images," in Proc. SPIE Medical Imaging 2007: Computer-aided Diagnosis, San Diego, 2007, vol. 6514, pp. 65142M-1-65142M.