Deep Learning-based Image Restoration Algorithms in Display Devices

Jung-Hyun Kim[1] **and Suk-Ju Kang**[2]

[2]sjkang@sogang.ac.kr
[1,2]Department of Electronic Engineering, Sogang University, Seoul 04107, Republic of Korea
Keywords: Demoire, Moire, Image Restoration, Deep Learning.

ABSTRACT

This paper presents the deep learning-based demoire algorithms for image restoration. Specifically, several deep learning-based demoire techniques, which have currently been studied, are explained. In addition, we compare the performance of representative demoire methods.

1 Introduction

With the widespread use of mobile devices and the booming of social media, the digital images occupy an indispensable part in our life for capturing and sharing useful information. However, the captured images are contaminated by undesired aliasing effect. Aliasing can be caused by the interference between grids of color filter array in camera and arrangement of subpixel in screen (or some patterns of an object), thereby leading to moire artifacts. Moire artifacts degrade the image quality because it induces unnecessary patterns and color variations. Furthermore, the moire pattern is very diverse and complex, so demoireing is a challenging task. Other image restoration problems, including denoising [6], demosaicing [7], color constancy [8], sharpening [9], etc., much less attention has been paid to image demoireing, which is to recover the underlying clean image from an image contaminated by moire patterns. However recent studies [1,5] have tried to apply deep learning to image demoireing. This is because it is very difficult to recover moire artifacts due to the large variation of moire patterns in terms of frequencies, shapes, and colors. This paper describes the basic concept of the demoireing technology and the detailed operations.

2 Demoireing Methods

Generally, demoireing consist of differentiating moire patterns and texture patterns and extracting moire pattern from moire image. Texture's patterns are locally regular, and we remove the moire by applying the factor that the moire pattern and texture pattern are different. The way to extracting moire is 2 ways, one is using hardware devices, and the other is using demoireing algorithm. As a using hardware, a method of installation a low-pass filter in front of camera sensor has been proposed. However this method requires unusual hardware and the low-pass filter would remove the high-frequency component, resulting in smoothing image. Therefore, it is difficult moire images to remove moire pattern while maintaining the original quality of image, and require professional skills and high costs. The method of [2] propose an image decomposition model

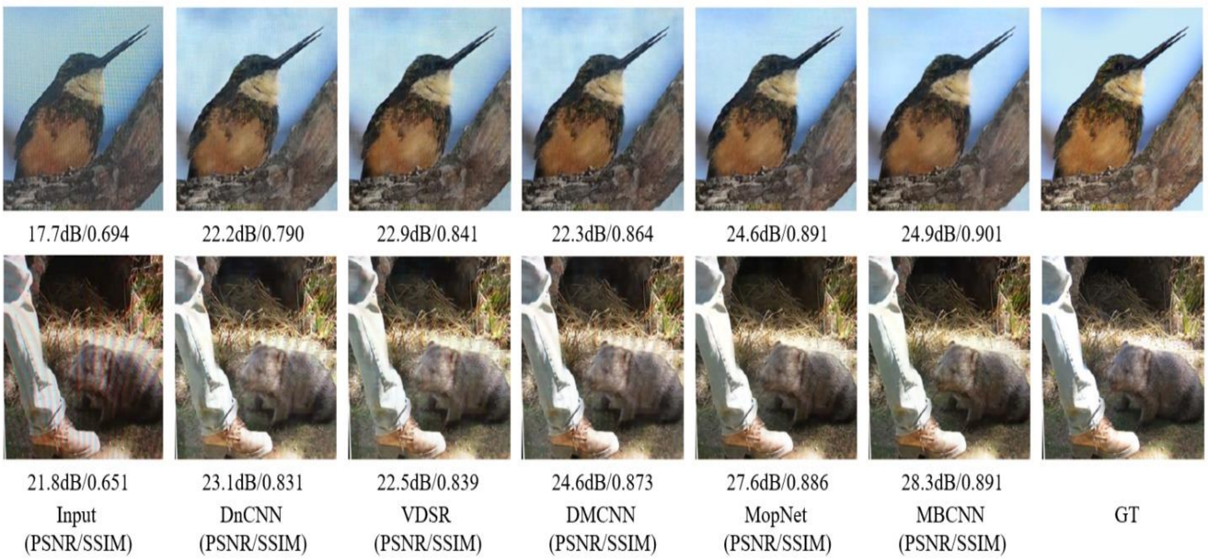

Figure 1 Demoire image results of various deep learning-based methods

Table 1 PSNR, SSIM comparison of the various deep learning-based methods

	DnCNN	VDSR	DMCNN[1]	MopNet[3]	MBCNN[4]
SSIM	0.834	0.837	0.871	0.895	**0.897**
PSNR	24.54	24.82	26.77	27.75	**30.03**

for moire pattern removal from texture images by utilizing the low-rank property of texture details and the sparsity constraint of moire patterns in DCT domain. However, since the moire pattern occurs not only at low frequencies, but also at high frequencies, [2] is not suitable to reduce all types of moire artifacts. Recently, several methods [1,3,4] have been proposed to solve these problems by applying the deep learning-based technology. DMCNN [1] tried to remove moire patterns of different frequency bands through multi-scale design. This method proposed a novel multi-scale CNN with multi-resolution branches, and summed up the outputs from different scales to obtain a final output. Input images are processed by DCT branch first, then passed into the pixel domain branch. The final restoration result in is the weighted sum of the input, the DCT branch estimation and the pixel branch estimation. MopNet [3] used a multi-scale feature aggregation sub-module to address the complex frequency, and two sub-modules to address edges and pre-defined moire types. Moreover Bin He et.al made additional annotation of attributes over benchmark datasets. However, this method did not try to model the moire patterns explicitly. It is difficult to get the frequency spectrum prior modeling the moire texture. To solve this problem, MBCNN [4] propose a learnable bandpass filter (LBF) to learn the prior from the moire images. MBCNN explicitly modeled the moire patterns by learning the frequency prior of moire patterns. In addition, MBCNN includes global and local tone mapping for accurate color restoration. The global tone mapping learns global color shift from moire images and local tone mapping makes local fine-grained color restoration. Also, MBCNN propose an advanced sobel loss to learn the structural high-frequency information. MBCNN performed both texture restoration and color restoration with in the same model.

3 Results and Discussion

For the performance evaluation of the deep learning-based demoireing techniques, the peak signal-to-noise ratios (PSNRs) and structural similarity index (SSIM) were calculated and compared quantitatively as shown in Table 1. [2] still has some limitations: the maze-like squiggles can not be removed well and in some cases, [2] ma inevitably smooth texture details. DMCNN is able to extract global information and eliminate JPEG compression artifacts. Mopnet still makes complex and irregular texture such as gavel or pavement surface in the background, and such erratic background will make the edge predictor fail to correctly distinguish the edges of background from moire gradients, leading to incomplete removal of moire patterns. MBCNN outperformed other state-of-the-art methods by more than 2dB and 0.002 in terms of PSNR and SSIM, respectively. In addition, for qualitative evaluation, the result images of various methods were compared as shown in Fig. 1. The visualized results shown in Figure 1 also demonstrated that MBCNN outperformed other methods. Comparing the various methods, we confirmed that the MBCNN's performance was quantitatively and qualitatively the best.

4 Conclusion

In this paper, we analyzed the performance of the recent deep learning-based demoireing techniques. Therefore, it was confirmed that the MBCNN method had excellent performance. Based on the analysis in this paper, the study of demoireing is expected to proceed.

Acknowledgement

This work was supported by LG Electronics and by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2021R1A2C1004208 and No. 2020M3H4A1A02084899).

References

[1] X. Zhang, W. Yang, Y. Hu and J. Liu, "DMCNN: Dual-Domain Multi-Scale Convolutional Neural Network for Compression Artifacts Removal," 2018 25th IEEE International Conference on Image Processing (ICIP), 2018, pp. 390-394.

[2] F. Liu, J. Yang and H. Yue, "Moiré pattern removal from texture images via low-rank and sparse matrix decomposition," 2015 Visual Communications and Image Processing (VCIP), 2015, pp. 1-4.

[3] B. He, C. Wang, B. Shi and L. Duan, "Mop Moiré Patterns Using MopNet," 2019 IEEE/CVF International Conference on Computer Vision (ICCV), 2019, pp. 2424-2432.

[4] B. Zheng, S. Yuan, G. Slabaugh and A. Leonardis, "Image Demoireing with Learnable Bandpass Filters," 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 3633-3642.

[5] X. Cheng, Z. Fu and J. Yang, "Multi-Scale Dynamic Feature Encoding Network for Image Demoiréing," 2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW), 2019, pp. 3486-3493.

[6] Zhang, K., Zuo, W., Chen, Y., Meng, D., & Zhang, L. "Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising," IEEE transactions on image processing, 26(7), 2017, pp. 3142-3155

[7] Gharbi, M., Chaurasia, G., Paris, S., & Durand, F. "Deep joint demosaicking and denoising," ACM

Transactions on Graphics (ToG), 35(6), 2016, pp. 1-12.
[8] Barron, J. T., & Tsai, Y. T. “Fast fourier color constancy,” In Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 886-894.
[9] Romano, Y., Isidoro, J., & Milanfar, “P. RAISR: rapid and accurate image super resolution,” IEEE Transactions on Computational Imaging, 3(1), 2016, pp. 110-125.