Restored Damaged JPEG via Deep Neural Network

VVLC Final Project Report

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1. INTRODUCTION

Recent years has seen an increased amount of research in image compression. Most of effort, however, has focused on how to use convolution neural network (CNN) to enhance image compression. One of them effort to use neural network to decrease the artifact of lossy image compression.

Ringing and blocking effect are two common, important, and unavoidable artifact of lossy image compression . Even though there are complex deblocking filters in recently compression techniques, for example H.264, there isn't similar deblocking approach in wide used JPEG

In this report, we will propose a convolution neural network which input is a decompressed image and output is a restored image to suppress ringing and blocking effect and also have a satisfying performance.

2. PROPOSED METHOD

2.1 Network Architecture

Yu et al. (2016) proposed Fast-ARCNN[1] which is a light model and performs well, but the performance can be better, our neural network is based on Fast-ARCNN to make the neural network can have a better performance. To solve this problem we use Conv Unit which contains a convolutions layer with 3 x 3 kernel size followed by an 1x1 convolutions layer and a PReLU then followed by another 3 x 3 a convolutions layer and a PReLU. After three sequential Conv Unit, connect a 1x1 convolutions layer, 5 x 5 convolutions layer, and a PReLU.

2.2 Loss Function

The mean-square error (MSE) is commonly used to compare image compression quality. We use MSE as our comparison standard and as our loss function, the formula is defined as:

$$MSE = \frac{1}{WH}\sum_i(\hat{x}_i - x_i)$$

Where x_i and $\hat{x}_i$ are the values of the *i*-th pixel in X and $\hat{X}$, *W* and *H* are the width and height of *X*. *X* denotes the original image and $\hat{X}$ denotes the restored image.

2.3 Hyper Parameters

In the training phase, we train our networks using Adam optimizer with momentum $\beta_1 = 0.8$. The neural network is trained with 20 epochs with learning rate of 10^{-3}, 20 epochs with learning rate of $5 * 10^{-4}$, 20 epochs with learning rate of 10^{-4}. To ensure the stability we normalize image in 0 to 1.

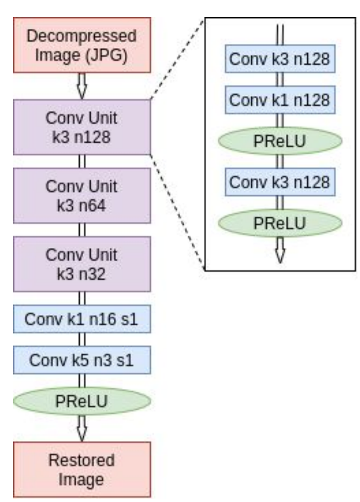

Fig. 1.

3. EXPERIMENT AND RESULT

3.1 Dataset

The training dataset we used are Open Images 2019 (Google), BSR, and DIV2k. The training data is more than 10 million,contain lots of kinds of situations, and the size of validation date is about 10 thousand 2k images. At the training phase we also augmented the images with rotation and resizing for trying to make the training more comprehensive.

3.2 Result

In this section, we compare restored images with original images and decompressed images(Fig. 3.). It not only has a higher PSNR, which is usually used to measure the quality of reconstruction of lossy compression than decompressed images, but also has a better quality as perceived by human.Also, Ringing and blocking effect improve a lot due to our neural network(Fig. 2.)

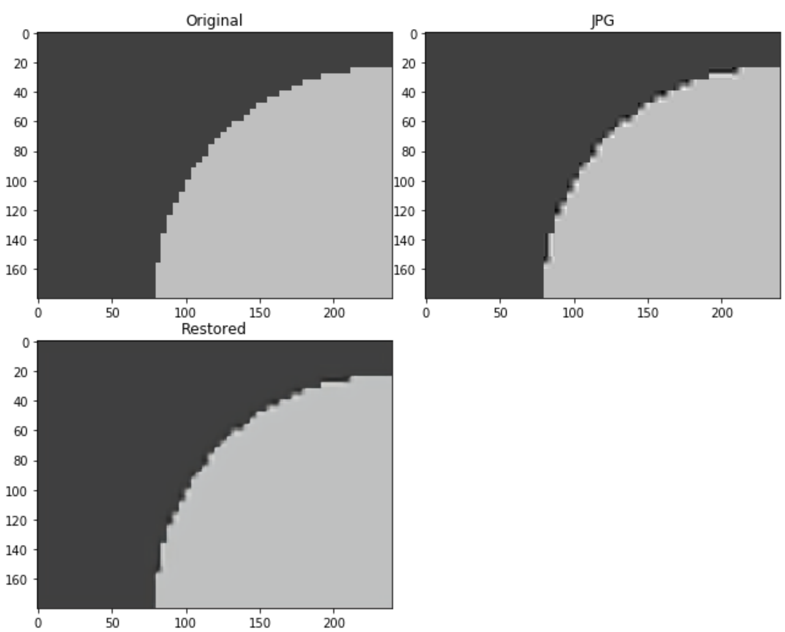

Fig. 2.

4. CONCLUSION

We have implemented the proposed neural network for the task of removing compression artifacts. The result shows that neural network has its potential to remove artifact of compression, and the reconstruction image has good performance not only in object evaluation but also in subjective evaluation.

5. REFERENCES

[1] Compression Artifacts Reduction by a deep Convolutional Network
[2] Deep Convolution Networks for Compression Artifacts Reduction,2016
[3] Near-lossless l_∞-constrained Multi-rate Image Decompression via Deep Neural Network, 2018.

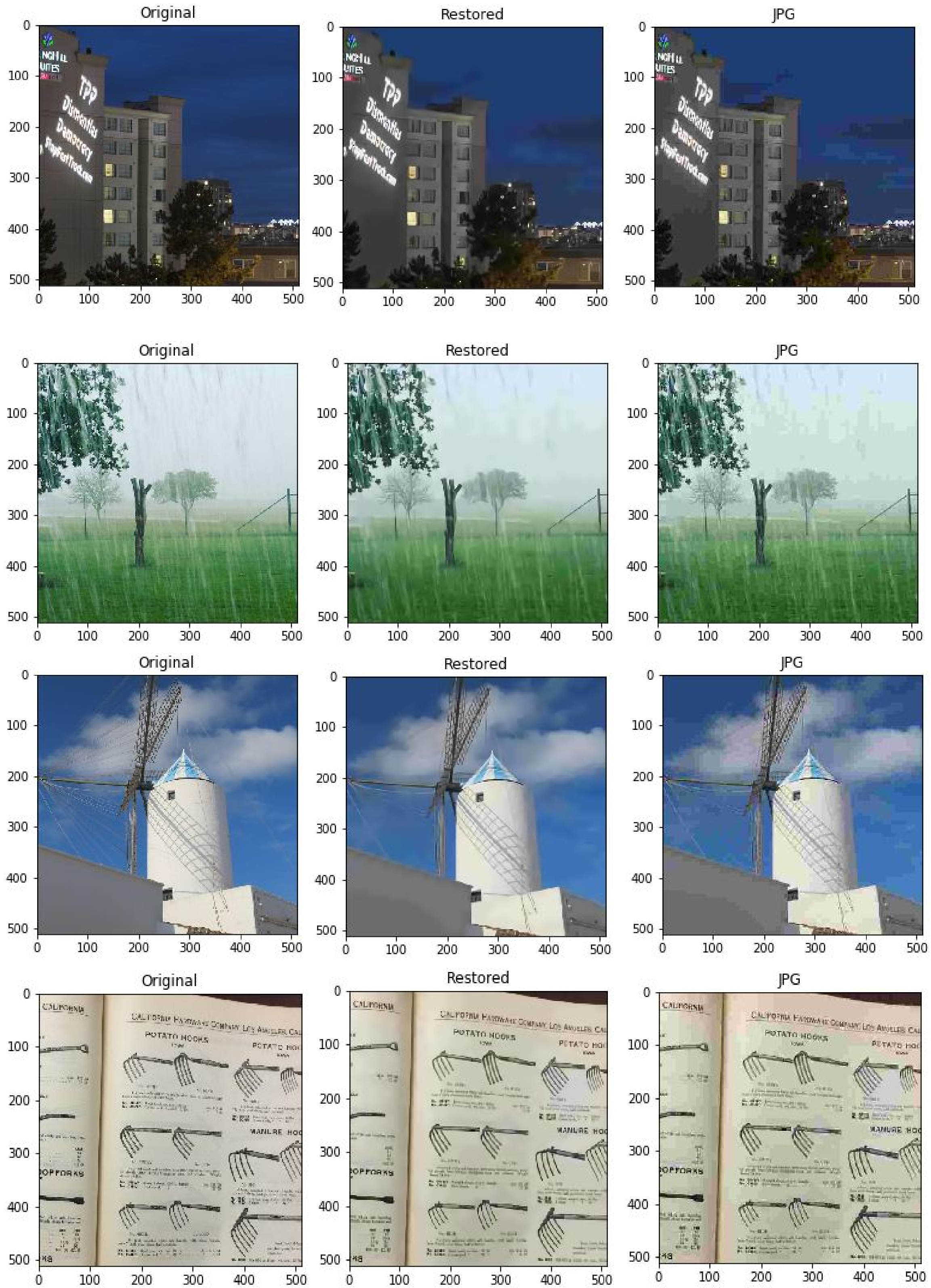
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Fig. 3.