Project Report - CS7180

Color Constancy

By Di Zhang [002957246] & Prakriti Pritmani [002724130]

Abstract:

Bianco et al presented a paper "Color Constancy using CNNs" and is one of the first neural networks implementation to tackle this problem. The authors present a network consisting of one convolutional layer with max pooling, one fully connected layer and three output nodes to accurately predict the scene illumination. The patches are 32x32 and an average illumination for all patches is computed.

Introduction and prior work:

The authors state two methodologies to obtain reliable color description from image data: computational color constancy and color invariance. So far, only statistic methods have been used to approach color constancy where illumination is either kept constant or not considered. The values of a Lambertian surface for a specific coordinate ρ(x, y) is dependent on three factors: illuminant spectral power distribution I(x, y, λ), the surface spectral reflectance S(x, y, λ) and the sensor spectral sensitivities C(λ) where lambda represents the wavelength.

The paper implores statistic based and learning based algorithms. Van de Weijer et al. [1] propose a statistical approach to calculate illuminant I(n,p,σ) where n is the order of derivative, p is the Minkowski norm and σ is the parameter scale. Different values for σ, p, n refer to different estimation algorithms, for example The Gray world algorithm [2] the setting becomes (n,p,σ)=(0,1,0).

Weibull [3] parametrization has a maximum likelihood classifier based on mixture of Gaussians to select the best performing color constancy method for a certain image.

Methods:

Given a color image, it is divided into 32x32 sized non-overlapping patches, perform histogram normalization and fed into the architecture. Contrast normalization is needed to ensure the model is robust to various lightning conditions.

We have referred to code from a previous implementation to the same paper [github]. The original code from github and the paper mentions is trained on Shi-Gehler dataset that consists of color-casted HDR images and corresponding. These images were preprocessed in a higher dynamic range and is linear.

We attempt to train the model using Cheng et al [4] paper. The two datasets used are the Nikon D40 NEF format and Nikon D5200 PNG format. The error metric matches the one proposed in the Bianco paper suggested by Hordley and Finlayson [5].

Results:

As mentioned, we use two different datasets, and the results are as follows:

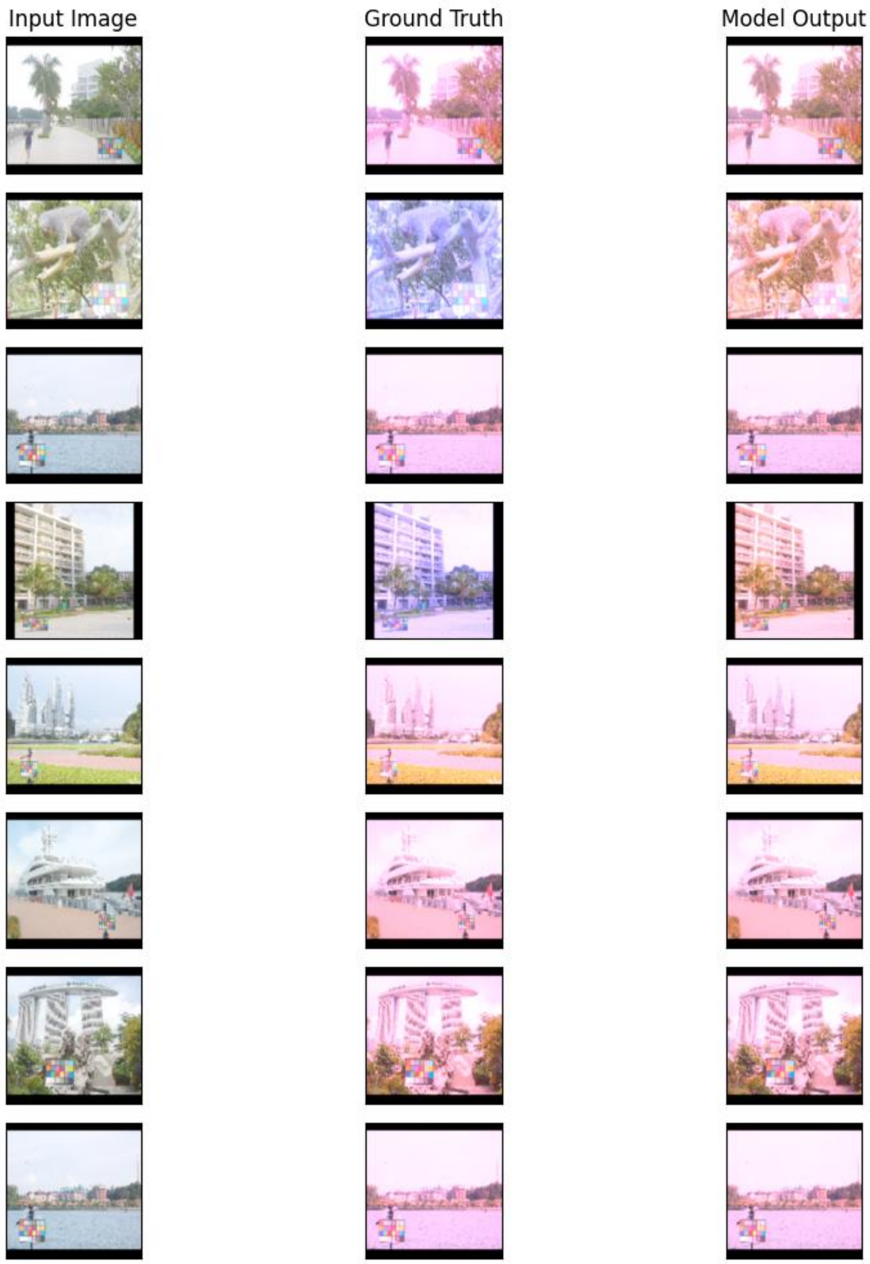

Fig A: Nikon D40 results

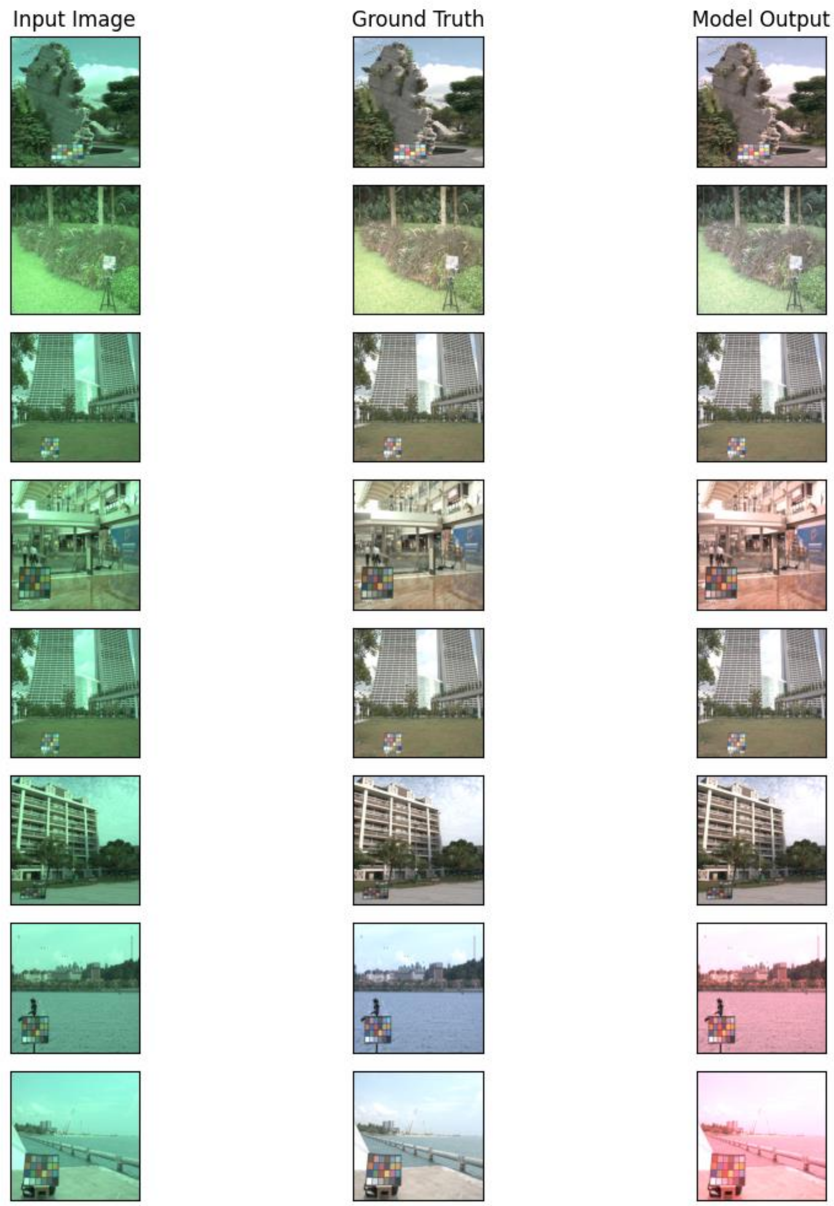

Fig B: Nikon D5200

Figure A shows the result when the CNN architecture is trained on Nikon D40 images. Results from the dataset Nikon D5200 (Figure B) seem better which could be due to various reasons such as the image quality, allowing the 32x32 patch size to contain more information and help the model learn better.

Bianco et al provided a detailed experimentation where they chose the best parameter to work and hence for this different dataset, a different patch size, kernel size or number of filters may help.

Reflection and acknowledgements:

The paper did help push neural networks implementation by using deep learning and is cited 100+ times. Even with a simple architecture it seems to work better than statistical methods. The correct parameters however seem data dependent and are not generalized enough. We would like to acknowledge the paper by Cheng et al, they used 6 different cameras to create it and prove their approach.
The model seems to work much better on the Nikon D5200 PNG dataset than Nikon D40 NEF dataset. As far as we can tell, it is due to the shape of the images. The D5200 image is the shape of 2010 x 3018 x 3, and the D40 image is the shape of 120 x 160 x 3. Therefore more 32 x 32 patches can be generated from the D5200 images, and a more accurate estimate can be obtained. There can be other factors impacting the output, we will investigate it more in the future.

References:

[1] J. van de Weijer, T. Gevers, and A. Gijsenij. Edge-based color constancy. *IEEE Transactions on Image Processing*, 16(9):2207–2214, 2007.

[2] G. Buchsbaum. A spacial processor model for object color perception. J. Franklin Inst., 310:1–26, 1980.

[3] A. Gijsenij and T. Gevers. Color constancy using natural image statistics and scene semantics. IEEE Transactions on Pattern Analysis and Machine Intelligence, 4(33):687–698, 2011.

[4] https://cvil.eecs.yorku.ca/projects/public_html/illuminant/illuminant.html

[5] S. Hordley and G. Finlayson. Re-evaluating color constancy algorithms. Proc. of the 17th International Conference on Pattern Recognition, pages 76–79, 2004.