# Quasi-Unsupervised Color Constancy

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## The problem

Computational color constancy consists in correcting images to make them appear as if they were taken under a neutral illuminant

This problem is often tackled in two steps

- first the color of the illuminant is estimated
- then the estimate is used to correct the input image

Deep learning can be used for illuminant estimation. There are two main issues in doing this

- the datasets annotated with ground truth illuminants are orders of magnitude smaller ($\sim 10^3$) than those used for deep learning ($\sim 10^6$)
- learned models are specialized for images acquired with the same devices used to collect the training images

## The main idea

We propose a method for computational color constancy that we call *quasi-unsupervised* because

- it does not require any information about the illuminant in the scene
- it relies only on the weak assumption that training images have been approximately balanced

The method works as follows

- the input image is converted to grayscale and then equalized to make it independent on the color of the illuminant and on the acquisition device
- a Convolutional Neural Network (CNN) detects those pixels that were achromatic in the input RGB image
- the average of the detected pixels estimates the color of the illuminant
- the von Kries model is used to correct the input image

Thanks to its design the method allows

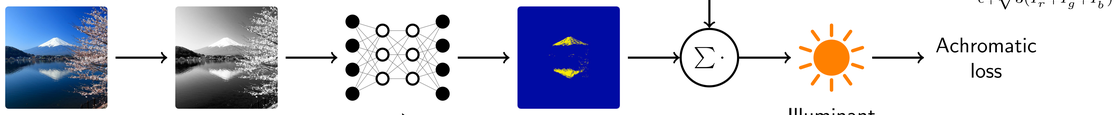
- to exploit a complex neural network architecture, without requiring a large training set of annotated images
- to leverage the large datasets used for image recognition and retrieval
- to apply the trained model to unbalanced images acquired with any camera without the need of any kind of adaptation

## Method

End to end quasi-unsupervised training

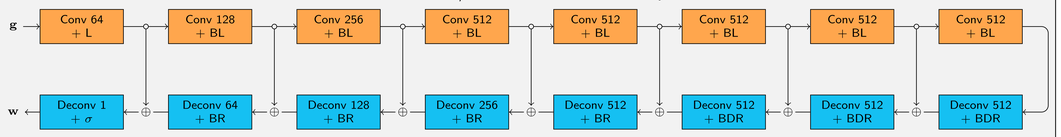
- the illuminant is estimated as the normalized weighted sum of the input pixels plus some Gaussian noise $\mathbf{n}$ (to favor large weights)
- the parameters of the CNN are optimized to minimize the *achromatic loss* without any ground truth illuminant

$$\mathcal{L}_A(\mathbf{I}) = 1 - \frac{I_r + I_g + I_b}{\epsilon + \sqrt{3(I_r^2 + I_g^2 + I_b^2)}}$$




$$\mathbf{I} = \frac{\mathbf{n} + \sum_{i=1}^{H} \sum_{j=1}^{W} \mathbf{x}_{ij} w_{ij}}{Z}$$

The CNN is an ecoder/decoder U-Net with skip connections




R → ReLU, L → leaky ReLU, B → batch norm., D → dropout, $\sigma$ → sigmoid, $\oplus$ → concatenation

## Experiments

Training on three large unannotated datasets, test on Color Checker (CC) and NUS

Angular errors

| Test set | Training set | Mean | Median | Max |
|---|---|---|---|---|
| CC | Ilsvrc12 | 3.46 | 2.23 | 21.17 |
| | Places365 | 3.60 | 2.45 | 21.47 |
| | Flickr100k | 3.59 | 2.25 | 20.04 |
| NUS | Ilsvrc12 | 3.00 | 2.27 | 19.16 |
| | Places365 | 3.07 | 2.20 | 17.12 |
| | Flickr100k | 2.98 | 2.16 | 15.86 |

Optional supervised fine tuning on test datasets (three-fold cross validation)

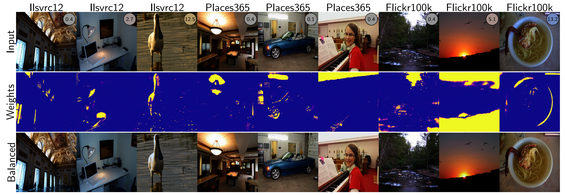
| Test set | Training set | Mean | Median | Max |
|---|---|---|---|---|
| CC | Ilsvrc12 | 2.91 (-0.55) | 1.98 (-0.25) | 19.9 (-1.2) |
| NUS | Ilsvrc12 | 1.97 (-1.03) | 1.41 (-0.86) | 20.5 (+1.6) |

Remarks

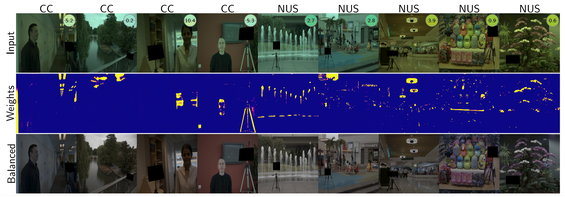
- results are almost independent on the training dataset
  → the hypothesis that training images are almost balanced is easily met in practice
- supervised fine tuning further decreases the angular error

## Examples

Training datasets

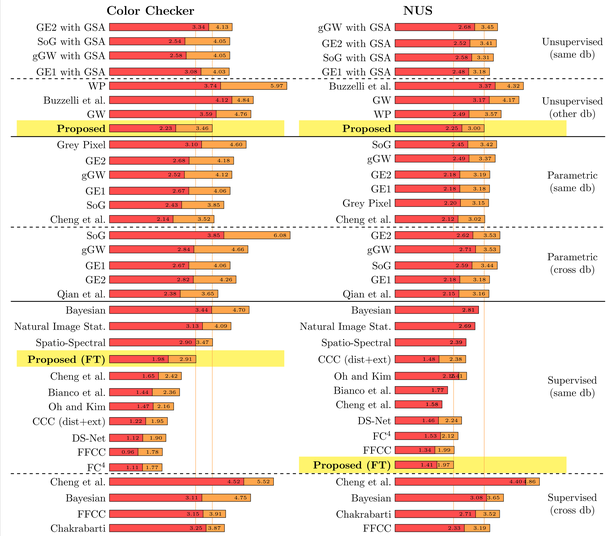



Test datasets




## Comparison with the state of the art

Median and mean angular errors




The proposed method

- outperforms all the purely unsupervised algorithms by a large margin
- outperforms all the supervised methods in the cross-dataset setting
- after fine tuning (FT), it rivals with the best supervised methods (best mean error and second best median on NUS)

## Conclusions

We presented a method for computational color constancy which exploits a deep convolutional neural network and leverages large unannotated datasets thanks to a quasi-unsupervised learning procedure

The method outperforms the other unsupervised methods being at the same time flexible enough to be supervisedly fine-tuned on a specific dataset reaching performance comparable with those of the best supervised methods

The source code and an interactive demo are available online at the address

claudio-unipv.github.io/quasi-unsupervised-cc/