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Computational Color Constancy using Graph Convolutional Networks

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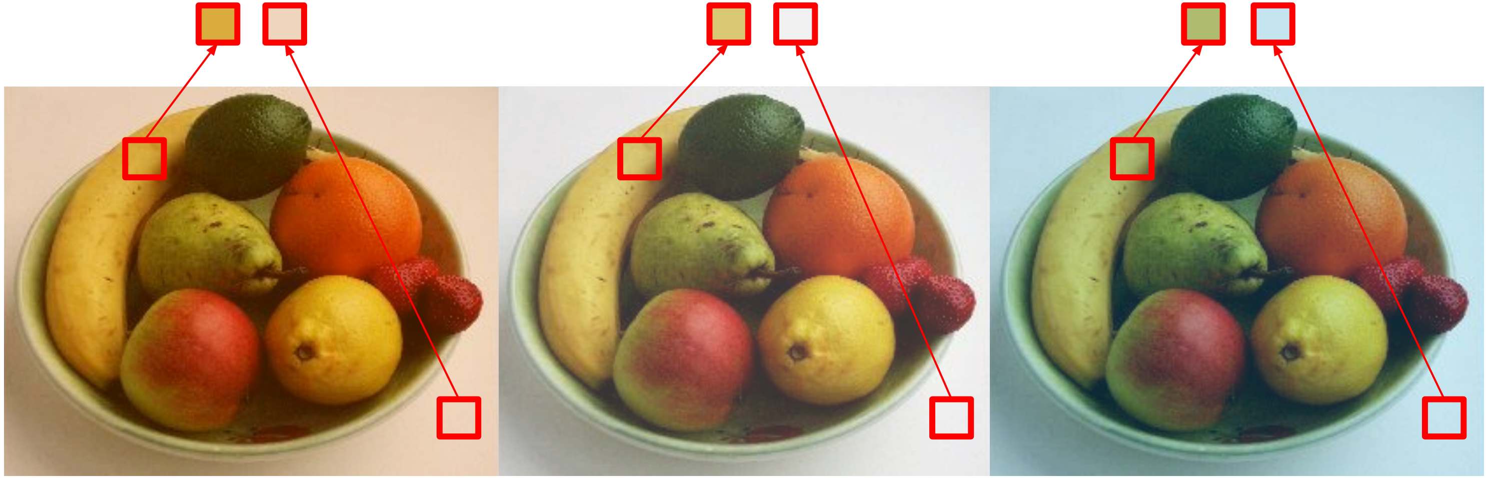
What is computational color constancy?

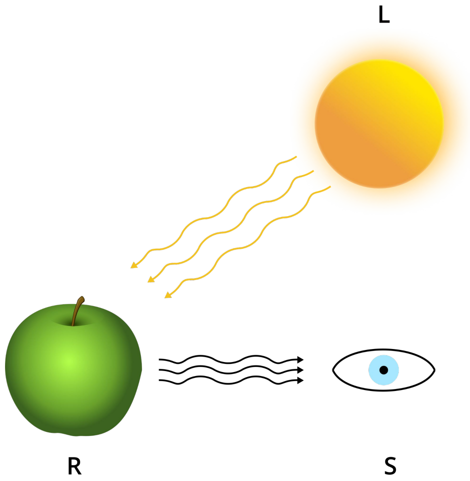
Color constancy is the ability of the human vision system of adapting to different illuminations



Computational color constancy is the attempt to achieve the same result in computer vision

What is computational color constancy?

Considering the simplest image formation model:



$$I = (L \odot R) * S$$

Where:

I = obtained image

L = illumination of the scene

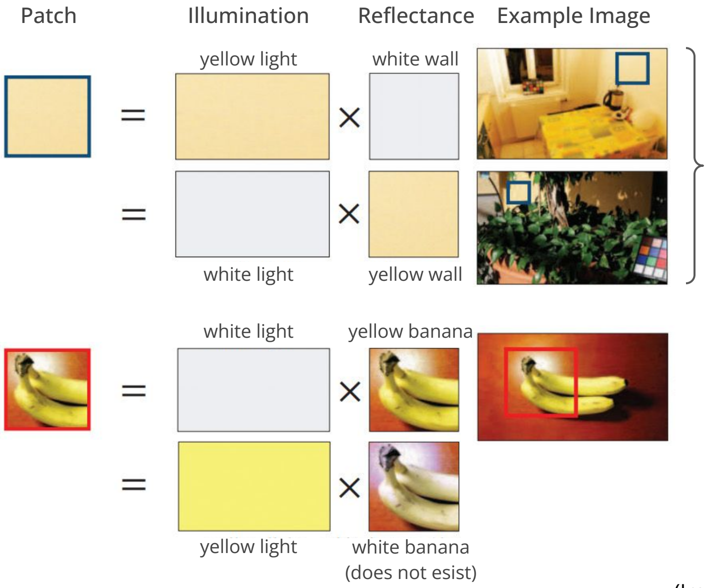
R = reflectance of the object in the scene

S = sensor

Computational color constancy is achieved by estimating L from I.
This is, by definition, an ill-posed problem.

What is computational color constancy?

The illuminant can be estimated by considering the context of the scene



Both plausible, which one is correct?

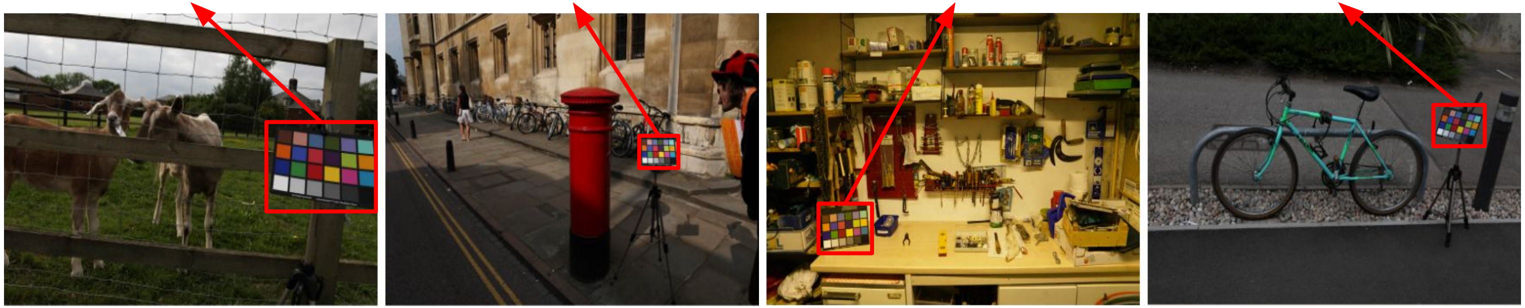
Reflectance is probably yellow → illuminant is white

(Image taken from [1])

[1] Hu, Y., Wang, B., & Lin, S. (2017). Fc4: Fully convolutional color constancy with confidence-weighted pooling. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4085-4094).

What is computational color constancy?

Datasets are usually generated by having a colorimetrically characterized target (e.g. ColorChecker) in the scene.
The groundtruth is an RGB triplet computed by looking at the target



(Images from Shi-Gehler dataset [2][3])

[2] Gehler, P. V., Rother, C., Blake, A., Minka, T., & Sharp, T. (2008, June). Bayesian color constancy revisited. In 2008 IEEE Conference on Computer Vision and Pattern Recognition (pp. 1-8). IEEE.
[3] Hemrit, G., Finlayson, G. D., Gijsenij, A., Gehler, P., Bianco, S., Funt, B., ... & Shi, L. (2018). Rehabilitating the colorchecker dataset for illuminant estimation. arXiv preprint arXiv:1805.12262.

Experiments

Research question:

Can we treat images as graphs and achieve computational color constancy using graph neural networks? How does this perform in comparison with other approaches?

Experiments outline:

- Train a Convolutional Neural Network as a baseline
- Convert images into graphs using different connectivities
- Train a Graph Convolutional Network on the graphs

Experiments - Baseline CNN

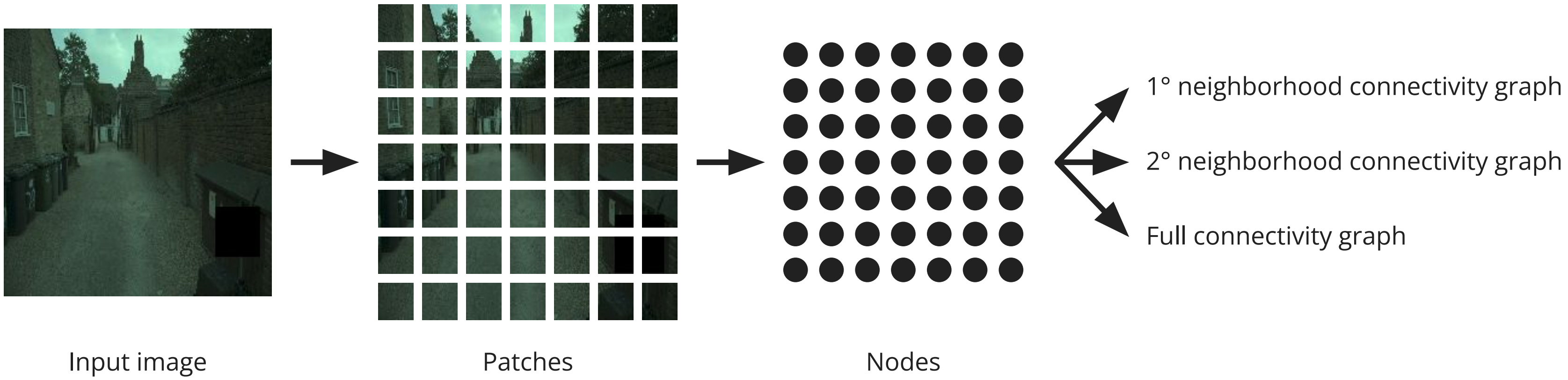
As a baseline, a simple Convolutional Neural Network (i.e., AlexNet [4][5]) is trained from scratch on Shi-Gehler dataset [2][3].
The final layer of the network is adapted to the task and returns a vector of 3 values.

Input size: (3x224x224)
Model architecture:
Conv+ReLU(3, 64, 11, 4, 2) → MaxPooling(3, 2) → Conv+ReLU(64, 192, 5, 2) → MaxPooling(3, 2) → Conv+ReLU(192, 384, 3, 1) → Conv+ReLU(384, 256, 3, 1) → Conv+ReLU(256, 256, 3, 1) → MaxPooling(3, 2) → AvgPooling(6, 6) → FC+ReLU(9216, 4096) → FC+ReLU(4096, 4096) → FC+ReLU(4096, 3)
Optimizer: Adam (l.r. 1e-5)
Early stopping: 10 epochs

[4] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 25.
[5] Krizhevsky, A. (2014). One weird trick for parallelizing convolutional neural networks. arXiv preprint arXiv:1404.5997.

Experiments - Graphs from images patches

Graphs are generated from images by splitting them into 16x16 patches and treating each patch as a node.
Node features are obtained by computing statistics from the corresponding patch.
Three connectivity schemes are followed: 1° neighborhood, 2° neighborhood, full connectivity



Node features: [relative_x, relative_y, relative_size, $mean_{\{RGB\}}$, $std_{\{RGB\}}$, $perc_{[10\text{-}90],\{R,G,B\}}$]

Experiments - Graph Convolutional Network

A **Graph Convolutional Network** featuring **Kipf's operator** [6] is trained **from scratch** on the graphs generated from Shi-Gehler dataset [2][3].

Number of nodes: 196
Number of features per node: 36
Number of edges: 702 (single connectivity), 1950 (double connectivity), 5520 (full connectivity)
Model architecture:
GCN+ReLU(36, 64) → GCN+ReLU(64, 64) → GCN+ReLU(64, 64) → GlobalMeanPooling → FC(64, 3)
Optimizer: Adam (l.r. 1e-5)
Early stopping: 10 epochs

[6] Kipf, T. N., & Welling, M. (2016). Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907.

Results

Color constancy methods are usually evaluated in terms of angular error between the estimated illuminant and the groundtruth illuminant [7]:

$$AE = \arccos(ILL_{EST}, ILL_{GT})$$

Method	Mean	Median	Trimean	Best-25%	Worst-25%
AlexNet	$3.46_{(1)}$	$2.74_{(1)}$	$2.91_{(1)}$	$1.37_{(1)}$	$11.82_{(4)}$
GCN single connectivity	$3.82_{(4)}$	$3.59_{(4)}$	$3.64_{(4)}$	$1.68_{(4)}$	$5.71_{(3)}$
GCN double connectivity	$3.59_{(3)}$	$3.42_{(3)}$	$3.37_{(2)}$	$1.66_{(3)}$	$4.98_{(1)}$
GCN full connectivity	$3.57_{(2)}$	$3.27_{(2)}$	$3.37_{(2)}$	$1.62_{(2)}$	$5.33_{(2)}$

(Angular Error on the test set, the lower the better for all the values)

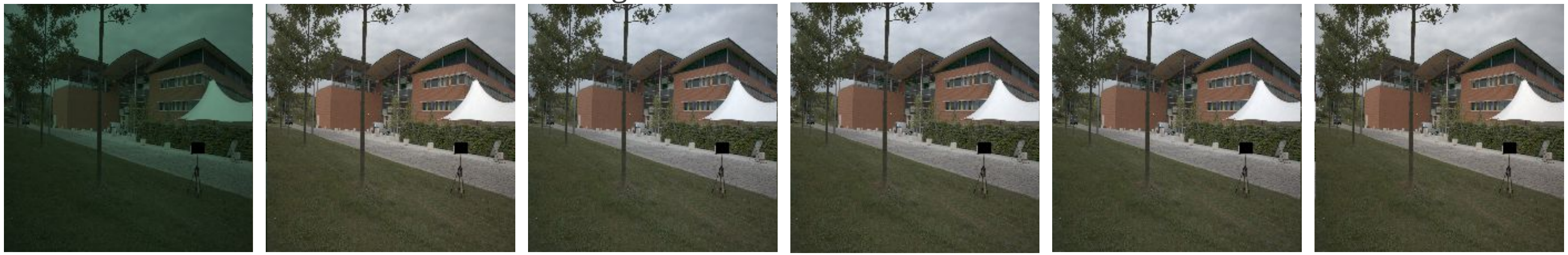
[7] Hordley, S. D., & Finlayson, G. D. (2004, August). Re-evaluating colour constancy algorithms. In Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004. (Vol. 1, pp. 76-79). IEEE.

Results

INPUT	AlexNet	GCN single conn.	GCN double conn.	GCN full conn.	GT

	AE: 5.5°	AE: 6.68°	AE: 5.62°	AE: 5.59	

INPUT	AlexNet	GCN single conn.	GCN double conn.	GCN full conn.	GT



	AE: 0.32	AE: 2.53°	AE: 1.71°	AE: 1.47°	

Ablation study - Positional features

To **verify** the **importance of positional information**, the GCN experiments are repeated removing the corresponding features from nodes:

Node features: [~~relative_x, relative_y~~, relative_size, mean$_{\{RGB\}}$, std$_{\{RGB\}}$, perc$_{[10\text{-}90],\{R,G,B\}}$]

Method	Pos. inf.	Mean	Median	Trimean	Best-25%	Worst-25%
GCN single connectivity	✓	3.82	3.59	3.64	1.68	5.71
	✕	**3.55**	**3.52**	**3.37**	**1.47**	**4.99**
GCN double connectivity	✓	3.59	**3.42**	3.37	1.66	4.98
	✕	**3.51**	3.46	**3.26**	**1.26**	**4.87**
GCN full connectivity	✓	3.57	**3.27**	3.37	1.62	5.33
	✕	**3.52**	3.41	**3.35**	**1.49**	**5.07**

(Angular Error on the test set, the lower the better for all the values)

Final considerations

Considering the obtained results, some considerations can be made:

- The **GCN** based approach **does not perform better than the CNN**, **but** it **achieves comparable results** and is more stable.
- **Double connectivity and total connectivity** achieve **slightly better** results **than single connectivity**.
- Providing **positional information** to the GCN **does not improve the performances**.

Is the spatial arrangement of local information irrelevant for the task?

Thank you

For your attention

References

[1] Hu, Y., Wang, B., & Lin, S. (2017). Fc4: Fully convolutional color constancy with confidence-weighted pooling. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4085-4094).

[2] Gehler, P. V., Rother, C., Blake, A., Minka, T., & Sharp, T. (2008, June). Bayesian color constancy revisited. In 2008 IEEE Conference on Computer Vision and Pattern Recognition (pp. 1-8). IEEE.

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