Decoupling Semantic Context and Color Correlation with Multi-task Cross Branch Regularization

IEEE ICME 2019
July 8-12, 2019
Shanghai, China

Vishal Keshav, Tejpratap G.V.S.L
Samsung Research Institute Bengaluru, India

Introduction

Problem statement: Color constancy

$$I_{xy}^{rgb} = W_{xy}^{rgb} \times L^{rgb}$$

where **I** is the illuminated image. **W** is the white balanced image. **L** is the global illumination common across spatial region.

- Illumination estimation is an under constrained problem.
- Suppressing ambiguous image regions is challenging [1].
- Accurate methods are runtime inefficient.

Assumptions

- Cross-channel correlation captures statistical properties relevant for estimating illumination independently and identically across the pixels in all channels.
- Local patches captures the semantic properties in an image present across spatial domain without depending on color information.

Approach

- Model illumination with IID assumption

$$P(L_{x,y}|I_{x,y})$$

- Capture relevant spatial regions with rich semantic value to disambiguate the ambiguous regions.
- Ensemble the estimated illumination from unambiguous portions and aggregate them for global illumination estimation.

Method

- End-to-end trainable dual branch architecture for extracting color and semantic information independently.
- Point-wise convolution for capturing per pixel cross-channel correlation.
- Depth-wise convolution for computing the confidence maps for each channel in the image.
- Channel-wise weighted pooling to ensemble the estimated illumination with respective confidence weight maps.
- Soft parameter sharing across the branches to improve generalization accuracy.

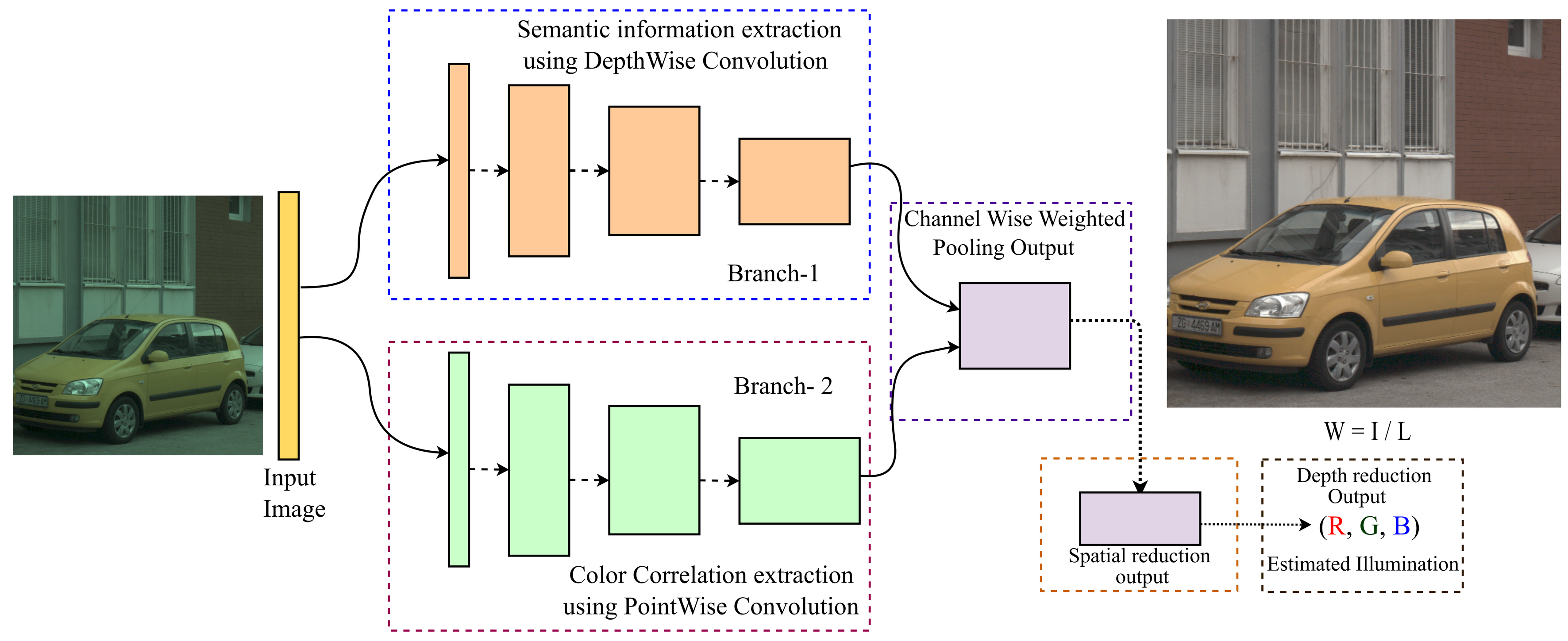
References

[1] Yuanming Hu, Baoyuan Wang, and Stephen Lin, Fc4: Fully convolutional color constancy with confidence-weighted pooling, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR17), 2017

[2] Dongliang Cheng, Dilip K Prasad, and Michael S Brown, Illuminant estimation for color constancy: why spatial-domain methods work and the role of the color distribution, JOSA A, vol. 31, no. 5, 2014

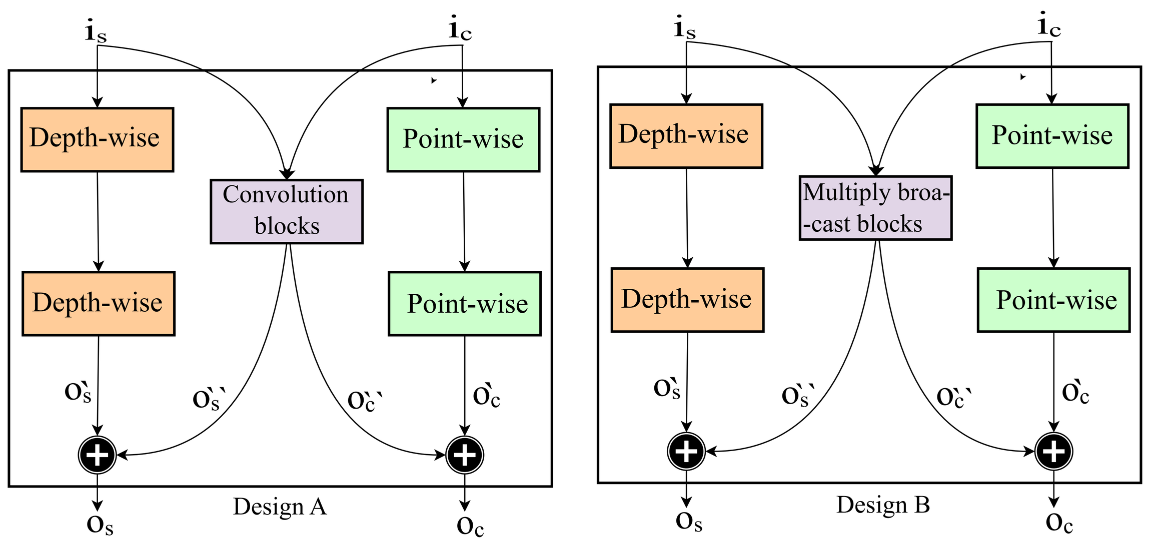
[3] Nikola Banic and Sven Loncaric, Unsupervised learning for color constancy, in VISIGRAPP, 2018

Method (Baseline Architecture)



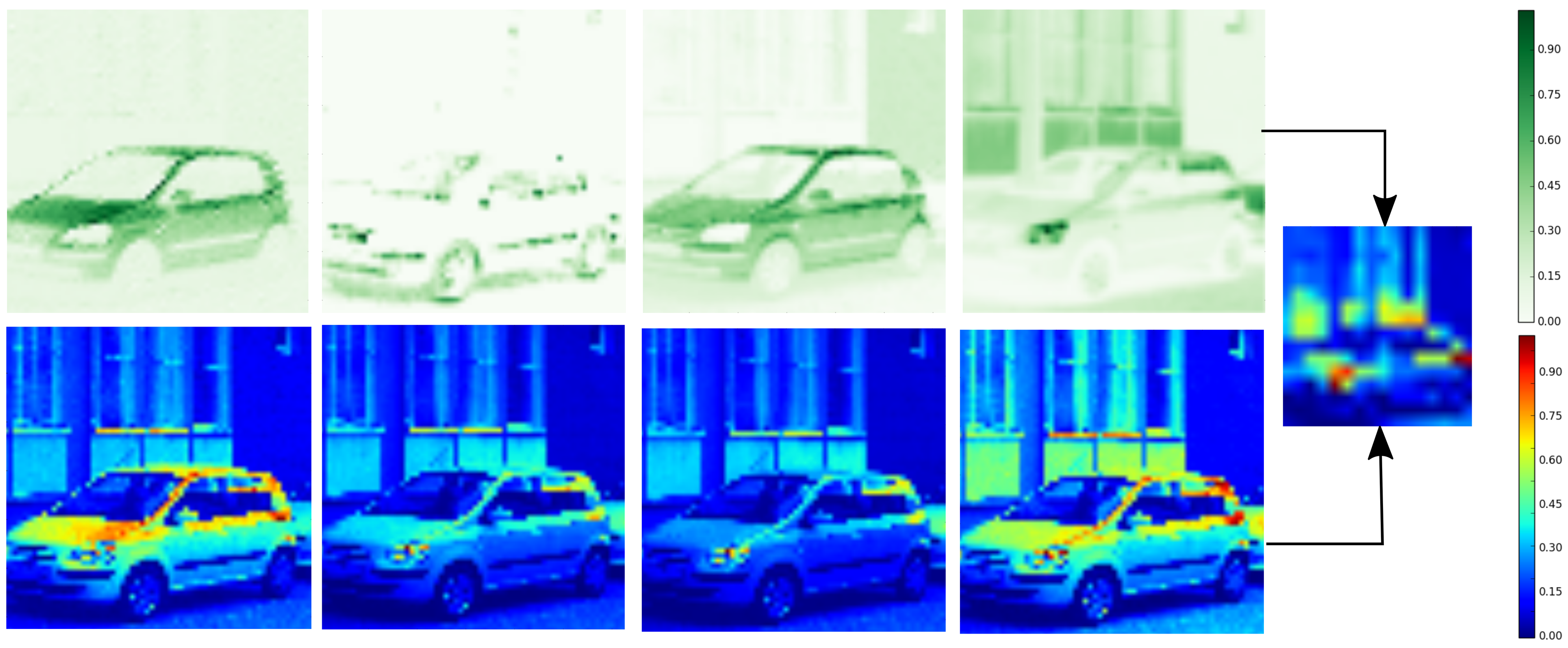
Dual branch architecture for color constancy depicting respective output tensors of each layer.

Method (Regularizing Micro-blocks)

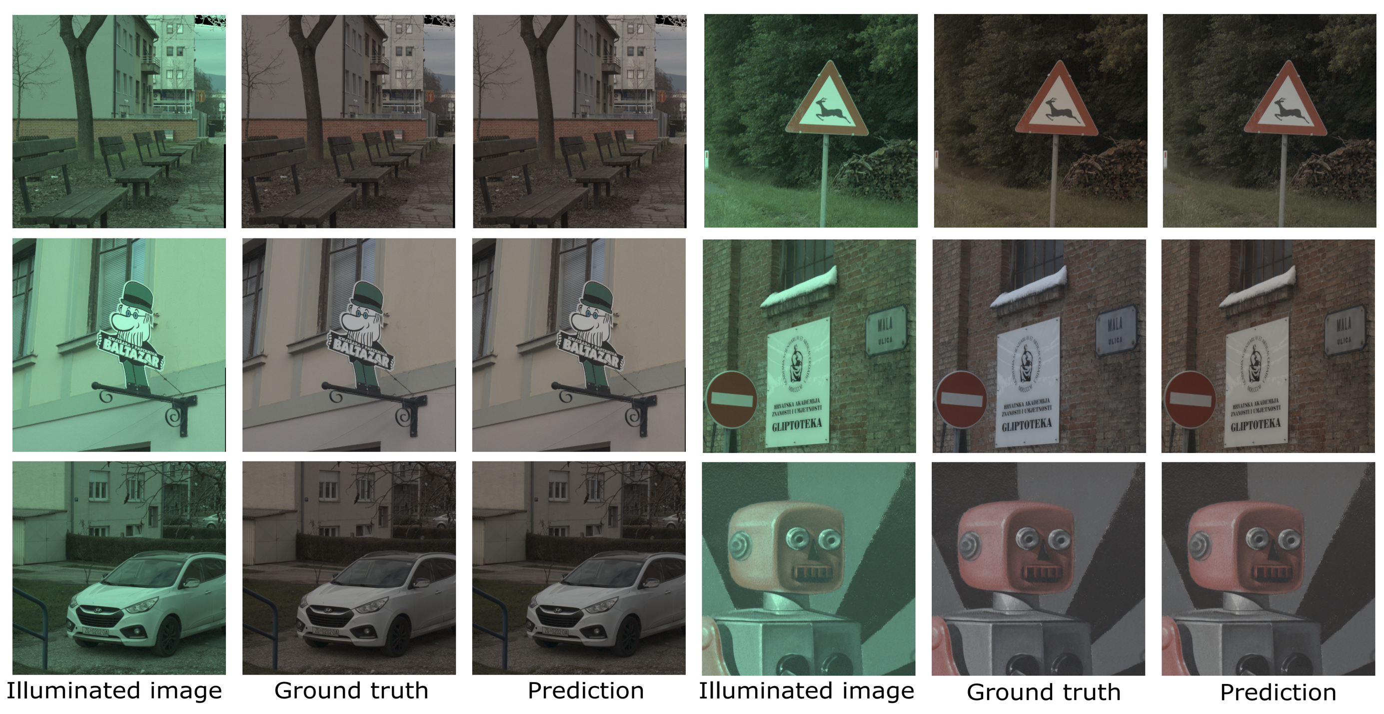


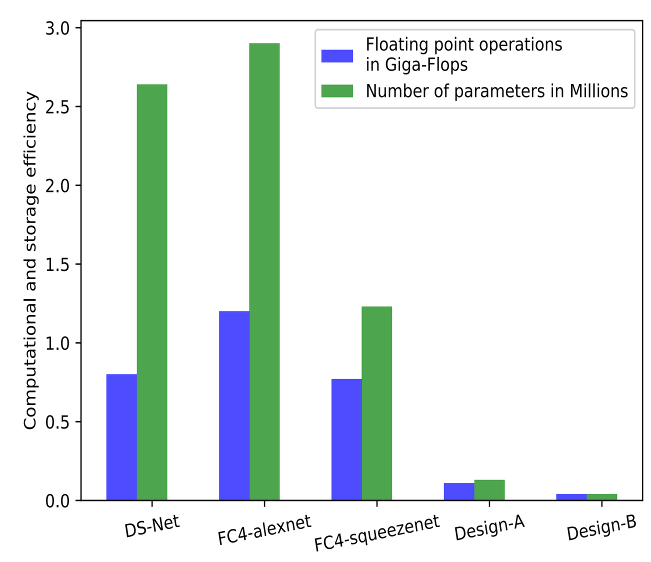
The two design variants of micro-block architecture for soft parameter sharing over baseline method. Non-linearization and pooling layers are not shown for a better depiction.

Experimental Results



Semi-dense semantic and illumination feature maps from the respective branches.





Comparision results of computational complexity of different color constancy methods

Results on NUS-8 [2] dataset

Models	Mean	Tri mean	Best 25%	Worst 25%	Params	Flops
Gray-world	4.14	3.39	0.9	9	–	–
DS-Net	2.24	1.68	0.48	5.28	2.64	0.031*
FC4-alex	2.12	1.67	0.48	4.78	2.9	1.2
FC4-squeeze	2.23	1.72	0.47	5.15	1.23	0.77
Design A	**2.102**	**1.72**	0.576	**4.469**	**0.13**	**0.11**
Design B	2.442	1.956	0.67	5.283	**0.04**	**0.04**

Results on Cube[3] dataset

Models	Mean	Tri-mean	Best 25%	Worst 25%
Gray-world	3.75	3.15	0.69	8.18
Color Tiger	2.94	2.66	0.61	5.88
Restricted Color Tiger	1.64	1.05	0.24	4.37
Baseline	1.701	1.276	0.345	**4.003**
Design A	**1.616**	1.242	**0.318**	**3.76**