LEARNING ILLUMINANT ESTIMATION FROM OBJECT RECOGNITION

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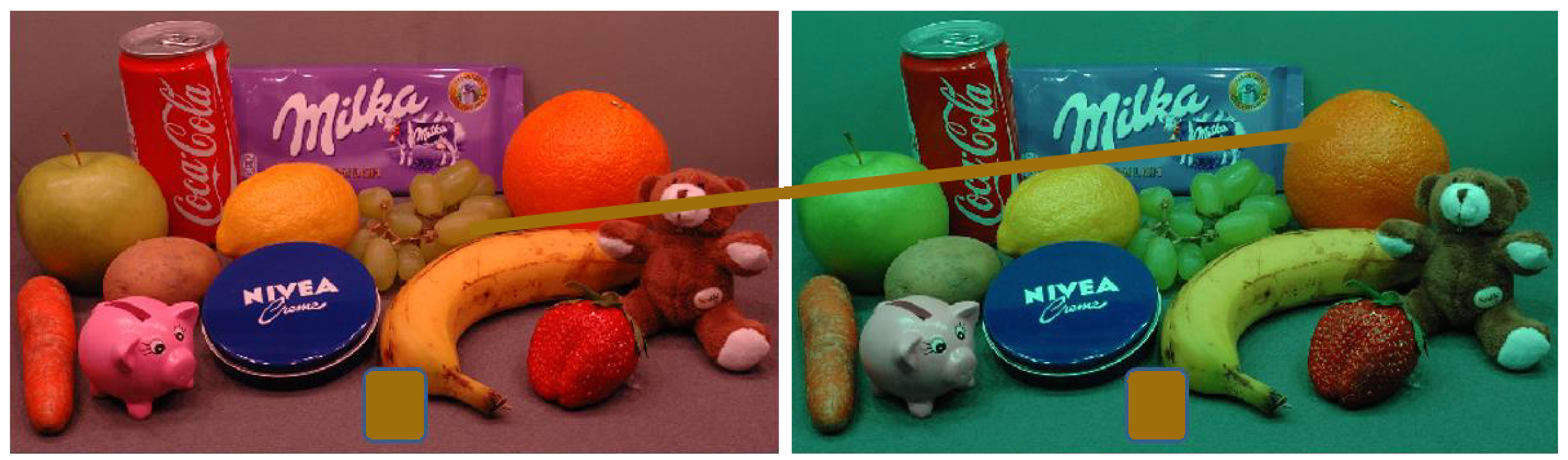
Abstract

Illuminant estimation consists in determining the chromatic properties of the light in the scene. Existing methods typically rely on explicit ground truth for training.
Based on the observation that human beings learn to distinguish colors under different illuminations without “ground truth illuminants”, we propose a **learning strategy** that relies only on object-class annotations as a proxy for illuminant estimation.

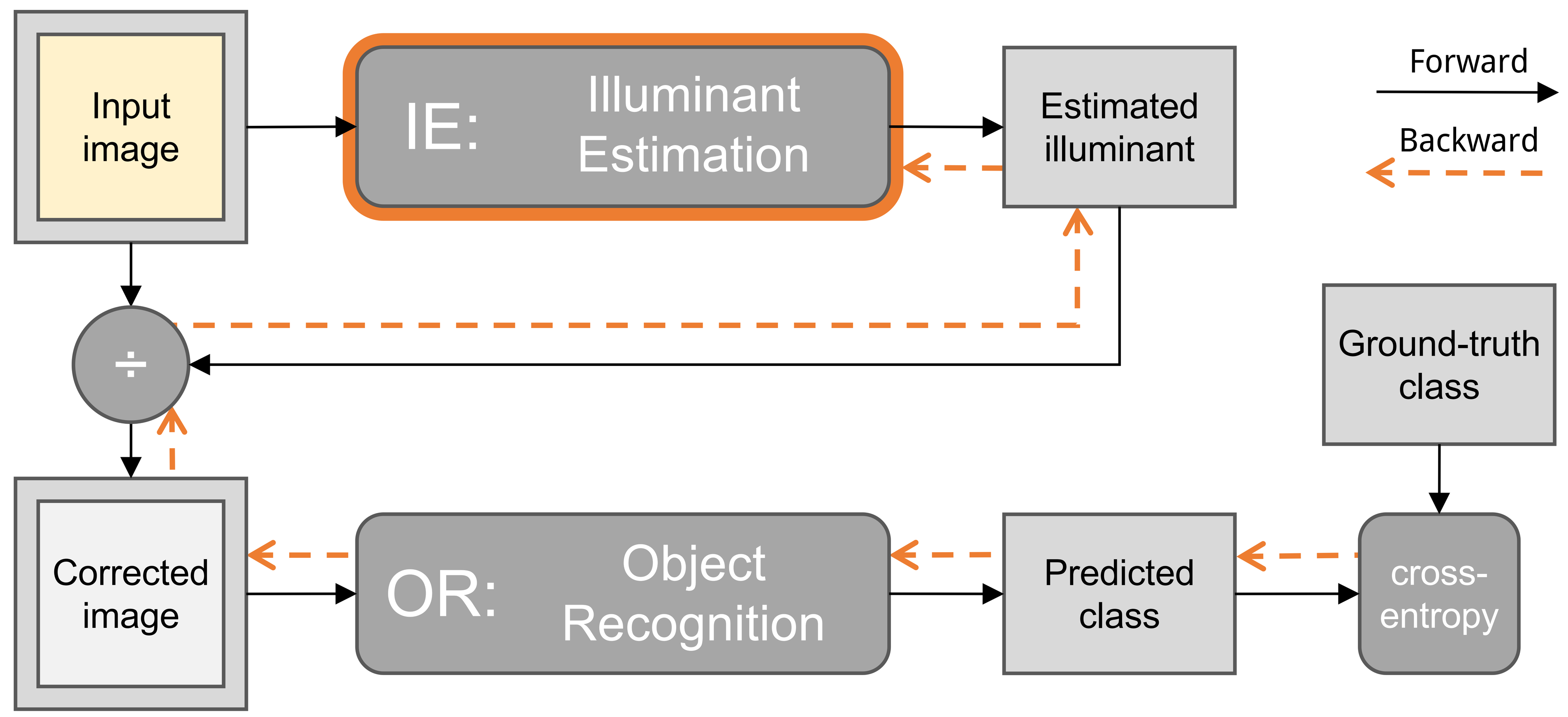


Color constancy: people can tell the color of items despite the different illuminations.

Training on VegFru [1]

Our training requires a classification task where color is a discriminating feature. We use the vegetables subset from the VegFru [1] dataset: more than 90000 images belonging to 200 vegetable classes.

Proposed learning strategy



- Illuminant Estimation trained with the objective of optimizing Object Recognition
- Required training annotations are object classes, instead of illuminants
- At inference time only the trained Illuminant Estimation module is needed

To properly drive the training process:

1. We pre-train O.R. alone on the chosen auxiliary task.
2. We attach I.E. and train the whole system end-to-end. Gradients flow through OR, but we update only I.E.

Results

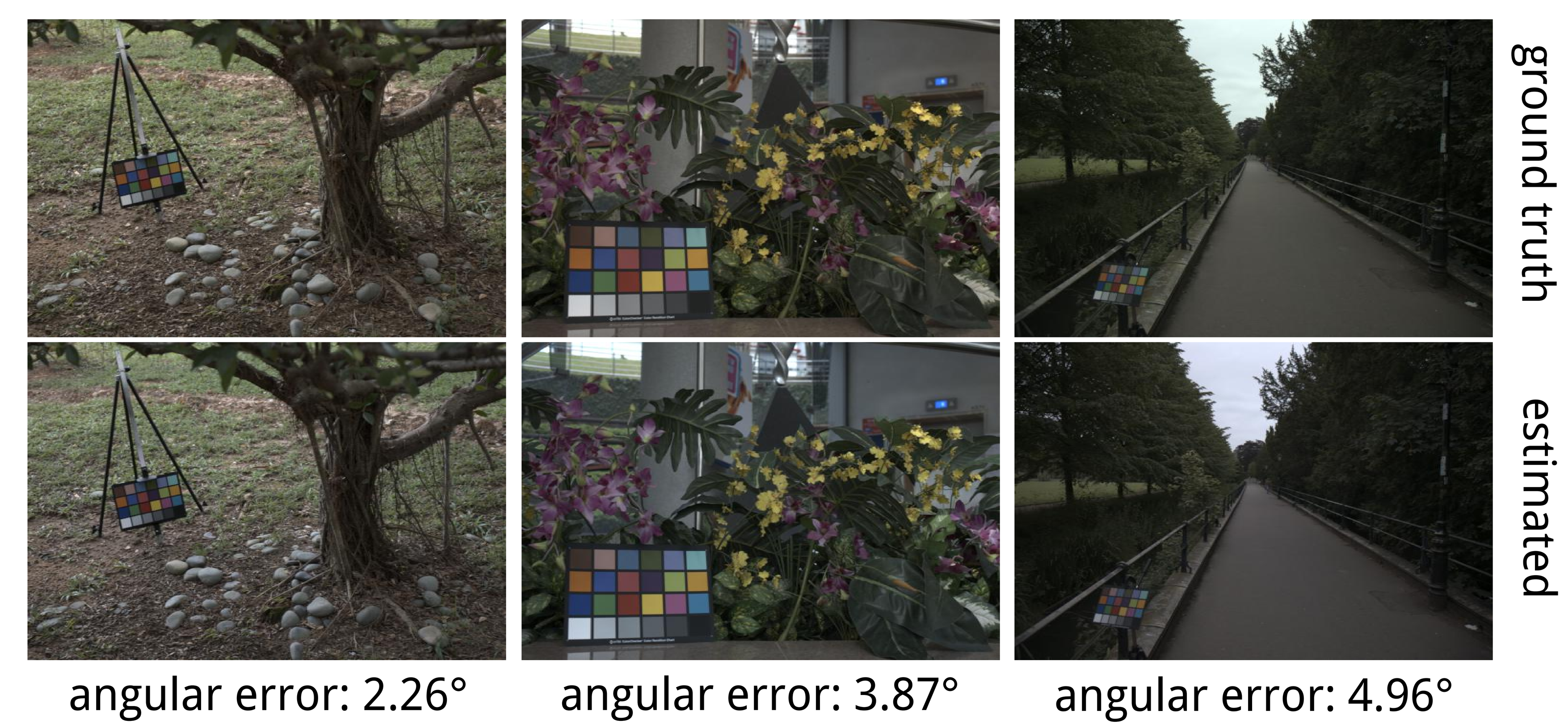
	Method	Shi-Gehler [2] Mean	Shi-Gehler [2] Max	NUS [3] Mean	NUS [3] Max
Baselines	Unchanged	13.62°	13.55°	19.50°	25.83°
	Greyworld	7.35°	6.70°	4.59°	22.61°
	Regression	5.96°	5.31°	5.19°	22.07°
Parametric	Akbarinia et al. ('17)	3.8 °	2.4 °	-	-
	Cheng et al. ('14)	3.52°	2.14°	3.02°	17.24°
	Funt et al. ('12)	3.2 °	2.3 °	-	-
Learned (cross-dataset)	**Ours (global norm.)**	4.84°	4.12°	4.88°	18.70°
	Ours (channel norm.)	5.48°	4.81°	4.32°	22.36°
	Joze et al. ('14)	6.5 °	5.1 °	-	-
	Gao et al. ('15)	5.03°	3.39°	-	-
	Lou et al. ('15)	4.7 °	3.3 °	-	-
Learned (in-dataset)	Chakrabarti et al. ('12)	3.59°	2.96°	3.04°	15.38°
	Bianco et al. ('15)	2.63°	1.98°	-	-
	Oh et al. ('17)	2.16°	1.47°	2.41°	-

Diagonal illuminant model:

$$\begin{bmatrix}R_{\text{out}}\\G_{\text{out}}\\B_{\text{out}}\end{bmatrix} = \begin{bmatrix}1/\rho^e_R & 0 & 0\\ 0 & 1/\rho^e_G & 0\\ 0 & 0 & 1/\rho^e_B\end{bmatrix}\cdot\begin{bmatrix}R_{\text{in}}\\G_{\text{in}}\\B_{\text{in}}\end{bmatrix}$$

Angular recovery error:

$$err = \arccos\left(\frac{\rho^{e\mathrm{T}}\rho^r}{||\rho^e||\,||\rho^r||}\right)$$



References

[1] Hou, S., Feng, Y., and Wang, Z. “Vegfru: A domain-specific dataset for fine-grained visual categorization”. In Computer Vision (ICCV), 2017 IEEE International Conference on (pp. 541-549) IEEE. (2017)

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