Edge-based color constancy

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Abstract

- Proposed method
  - Edge-based color constancy
    - Color derivative distribution of images in the opponent color space
      - Ellipsoid-like shape
      - The long axis of the ellipsoid is constant regardless of illuminants
    - Gray-Edge hypothesis
      - The average of the reflectance differences in a scene is achromatic

Introduction

- Categories of color constancy
  - Representing an image by illuminant invariant descriptors
  - Color constancy methods
    - Representing images by invariant features for light sources
    - Correcting images for deviations from a canonical light sources
      - Gamut mapping algorithms
      - Probabilistic approaches
        - Low-level image features: Max-RGB, Gray-world, Shades of color constancy
      - Learning-based methods

Background

- Color image model
  - Assumption
    - Lambertian surface and a single light source
    - Image values or Intensity:

$$\mathrm{f} = \int e(\lambda)s(\lambda)\mathbf{c}(\lambda)\,d\lambda = \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

where $e(\lambda)$ is the light source, $s(\lambda)$ is the surface reflectance, and $\mathbf{c}(\lambda)$ is the camera sensitivity functions

    - Estimation of the light source color

$$\mathbf{e} = \int e(\lambda)\mathbf{c}(\lambda)\,d\lambda = \begin{bmatrix} R_e \\ G_e \\ B_e \end{bmatrix}$$

❑ Max RGB

- Assumption
  - Lambertian surface and a single light source
  - Reflectance $s(\lambda) = 1$ on the white patch
  - Image values or Intensity:

$$\max_{\boldsymbol{x}} \mathbf{f}(\boldsymbol{x}) = \int e(\lambda)\mathbf{c}(\lambda)\, d\lambda = \mathbf{e}$$

❑ Gray-world hypothesis

– Assumption

- Lambertian surface and a single light source
- The average reflectance in a scene is achromatic:

$$\frac{\int s(\lambda, \mathbf{x})\, d\mathbf{x}}{\int d\mathbf{x}} = g(\lambda) = k$$

- Estimation of the light source

$$\frac{\int \mathbf{f}(\mathbf{x})\, d\mathbf{x}}{\int d\mathbf{x}} = \frac{1}{\int d\mathbf{x}} \iint e(\lambda) s(\lambda, \mathbf{x}) \mathbf{c}(\lambda)\, d\lambda d\mathbf{x}$$

$$= \int e(\lambda)\mathbf{c}(\lambda) \left(\frac{\int s(\lambda, \mathbf{x})\, d\mathbf{x}}{\int d\mathbf{x}} \right) d\lambda = k \int e(\lambda)\mathbf{c}(\lambda)\, d\lambda = k\mathbf{e}$$

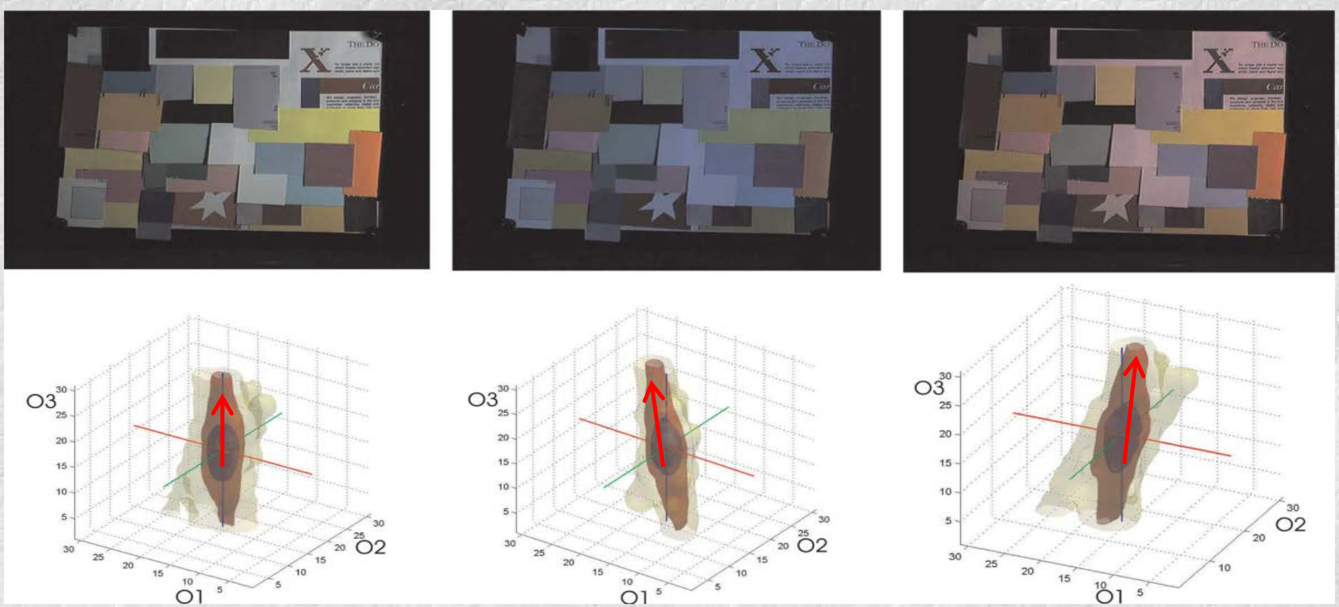
Shades of color constancy

- Assumption
  - Lambertian surface and a single light source
  - *p*th Minkowski norm of the reflectance in a scene is achromatic
  - Estimation of the light source

$$\left(\frac{\int \left(\mathbf{f}^{\sigma}(\mathbf{x})\right)^{p} d\mathbf{x}}{\int d\mathbf{x}}\right)^{1/p} = k\mathbf{e}$$

Proposed method

- ❑ Gray-edge hypothesis
  - – The color derivative distribution of images (Previous work)
    - A relatively regular, ellipsoid-like shape
    - Coincidence of directions between the long axis and the light source
      - − Coincidence directions between O_3 and the white light direction



Proposed method

– Assumption

- Lambertian surface and a single light source
- Coincidence directions between O_3 and the white light direction
  - The average of the reflectance differences in a scene is achromatic:

$$\frac{\int |\boldsymbol{s}_{\mathrm{x}}^{\sigma}(\lambda, \mathbf{x})| \quad d\mathbf{x}}{\int d\mathbf{x}} = g(\lambda) = k\mathbf{e}$$

- Estimation of the light source

$$\frac{\int |\mathbf{f}_{\mathbf{x}}(\mathbf{x})|\, d\mathbf{x}}{\int d\mathbf{x}} = \frac{1}{\int d\mathbf{x}} \iint e(\lambda) |s_{\mathbf{x}}(\lambda, \mathbf{x})| \mathbf{c}(\lambda)\, d\lambda d\mathbf{x}$$

$$= \int e(\lambda)\mathbf{c}(\lambda) \left(\frac{\int |s_{\mathbf{x}}(\lambda, \mathbf{x})|\, d\mathbf{x}}{\int d\mathbf{x}} \right) d\lambda = k \int e(\lambda)\mathbf{c}(\lambda)\, d\lambda = k\mathbf{e}$$

– General form of the proposed method

- Consideration of Gaussian filtering (denoising)
- Incorporation of Minkowski norm

$$\left(\frac{\int |\mathbf{f}_{\mathrm{x}}^{\sigma}(\mathbf{x})|^{p} d\mathbf{x}}{\int d\mathbf{x}}\right)^{1/p} = k\mathbf{e}$$

- High-order derivatives

$$\left(\frac{\int \left|\frac{\partial^{n}\mathbf{f}^{\sigma}(\mathbf{x})}{\partial\mathbf{x}^{n}}\right|^{p} d\mathbf{x}}{\int d\mathbf{x}}\right)^{1/p} = k\mathbf{e}^{n,p,\sigma}$$

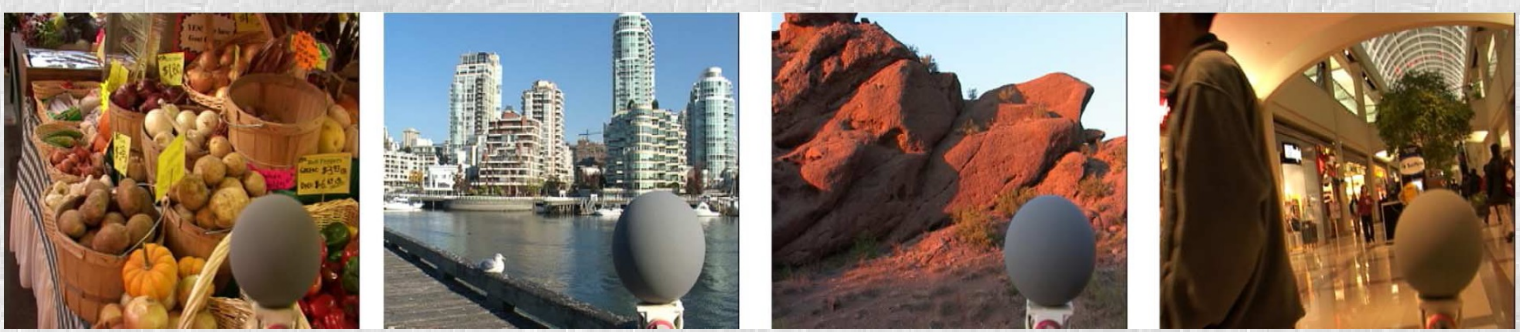
Table 1. Overview of the different illuminant estimations methods together with their hypotheses. Theses illuminant estimations are all instantiations of (17)

name	symbol	equation	hypothesis
Grey-World	$e^{0,1,0}$	$\left(\int \mathbf{f}(\mathbf{x})\, dx\right) = k\mathbf{e}$	the average reflectance in a scene is achromatic
max-RGB	$e^{0,\infty,0}$	$\left(\int \lvert\mathbf{f}(\mathbf{x})\rvert^{\infty} dx\right)^{\frac{1}{\infty}} = k\mathbf{e}$	the maximum reflectance in a scene is achromatic
Shades of Grey	$e^{0,p,0}$	$\left(\int \lvert\mathbf{f}(\mathbf{x})\rvert^{p} dx\right)^{\frac{1}{p}} = k\mathbf{e}$	the *p*th-Minkowsky norm of a scene is achromatic
General Grey-World	$e^{0,p,\sigma}$	$\left(\int \lvert\mathbf{f}^{\sigma}(\mathbf{x})\rvert^{p} dx\right)^{\frac{1}{p}} = k\mathbf{e}$	the *p*th-Minkowsky norm of a scene is achromatic after local smoothing
Grey-Edge	$e^{1,p,\sigma}$	$\left(\int \lvert\mathbf{f}^{\sigma}_{\mathbf{x}}(\mathbf{x})\rvert^{p} dx\right)^{\frac{1}{p}} = k\mathbf{e}$	the *p*th-Minkowsky norm of the image derivative in a scene is achromatic
Max-Edge	$e^{1,\infty,\sigma}$	$\left(\int \lvert\mathbf{f}^{\sigma}_{\mathbf{x}}(\mathbf{x})\rvert^{\infty} dx\right)^{\frac{1}{\infty}} = k\mathbf{e}$	the maximum reflectance difference in a scene is achromatic
2nd order Grey-Edge	$e^{2,p,\sigma}$	$\left(\int \lvert\mathbf{f}^{\sigma}_{\mathbf{xx}}(\mathbf{x})\rvert^{p} dx\right)^{\frac{1}{p}} = k\mathbf{e}$	the *p*th-Minkowsky norm of the second order derivative in a scene is achromatic

Experimental evaluation

- Evaluation by using angular error
  - Using two databases
    - Controlled indoor image set

    - Real-world image set



– Comparison measure

- Angular error:

$$\text{angular error} = \cos^{-1}(\hat{e}_l \cdot \hat{e}_e)$$

❑ Results

– Indoor image set

Table 2. Median angular error (degrees) on indoor image data set for various color constancy methods.

indoor set	symbol	median
Grey-World	$e^{0,1,0}$	7.0
Max-RGB	$e^{0,\infty,0}$	6.5
Shades of Grey	$e^{0,7,0}$	3.7
general Grey-World	$e^{0,11,1}$	3.2
Grey-Edge	$e^{1,7,4}$	3.2
2nd order Grey-Edge	$e^{2,7,5}$	2.7
Color by Correlation	-	3.2
Gamut Mapping	-	2.9
Neural Networks	-	7.8
GCIE Version 3, 11 lights	-	1.3
GCIE Version 3, 87 lights	-	2.6

Table 3. Parameter settings for which the performance remains within 10% of optimal performance as given in **Table 2**.

method	local scale	Minkowski norm
general Grey-World	$1 \leq \sigma \leq 5$	$8 \leq p \leq 18$
Grey-Edge	$3 \leq \sigma \leq 5$	$6 \leq p \leq 14$
2nd order Grey-Edge	$4 \leq \sigma \leq 7$	$5 \leq p \leq 11$

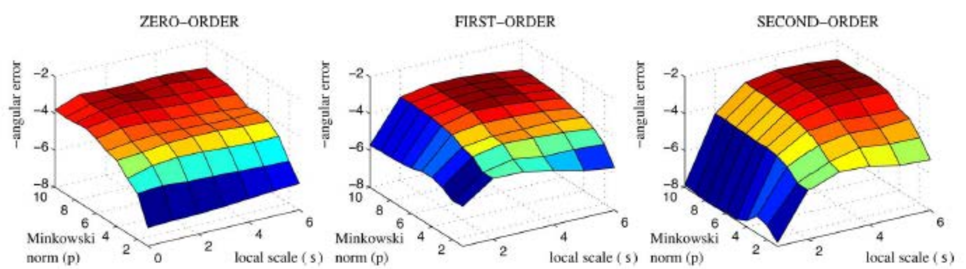
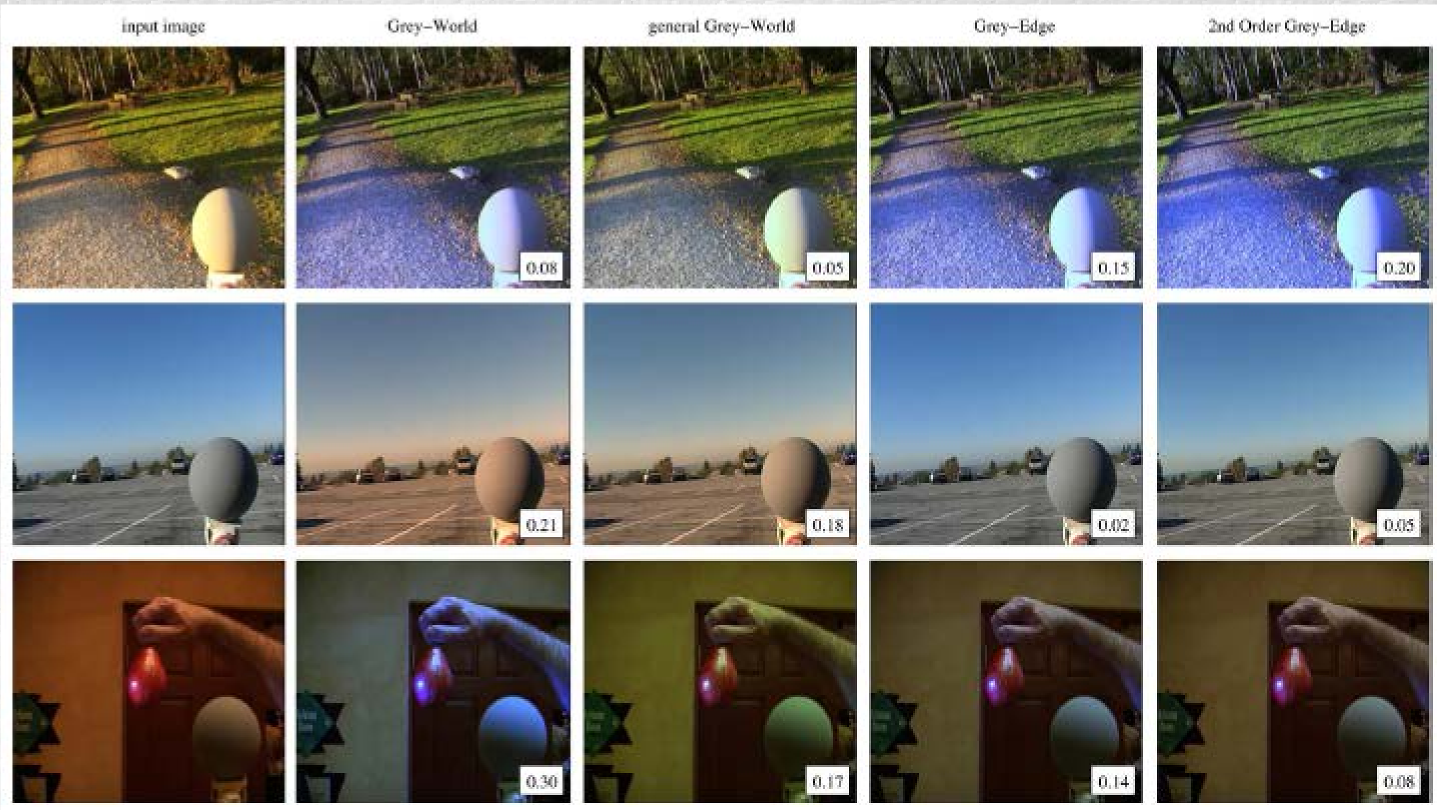


Fig. 3. Median angular error of the general gray-world, first-order, and second-order gray-edge method as a function of the Minkowski norm and local smoothing. The angular error axis is inverted for visualization purposes

Real-World set	symbol	median
Grey-World	$e^{0,1,0}$	7.3
Max-RGB	$e^{0,\infty,0}$	6.7
general Grey-World	$e^{0,13,2}$	4.7
Grey-Edge	$e^{1,1,6}$	4.1
2nd order Grey-Edge	$e^{2,1,5}$	4.3

– Real-world data set

Fig. 3. Color constancy results of gray-world, general gray-world, gray-edge, and second-order gray-edge on real-world data set. The angular error is indicated in the right bottom corner. **The first row** depicts a failure of the edge-based approaches, whereas the gray-world methods give acceptable results. **The second and third rows** show examples where the gray-world methods fail and the gray-edge methods obtain superior results.



Conclusion

- Discussion
  - Improvement and Advantages
    - Introduction of the higher order structure of images
    - Better results than those obtained with the gray-world method for real-world images
  - Disadvantages
    - The optimal parameter setting vary for the different data sets