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 source
      - 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:
      \[
      f = \int e(\lambda)s(\lambda)c(\lambda) \, d\lambda = \begin{bmatrix} R \\ G \\ B \end{bmatrix}
      \]
      where \( e(\lambda) \) is the light source, \( s(\lambda) \) is the surface reflectance, and \( c(\lambda) \) is the camera sensitivity functions
    - Estimation of the light source color
      \[
      e = \int e(\lambda)c(\lambda) \, d\lambda = \begin{bmatrix} R_e \\ G_e \\ B_e \end{bmatrix}
      \]
Max RGB

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

$$\max_x f(x) = \int e(\lambda)c(\lambda) \, d\lambda = e$$
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

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

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

\[
\left( \frac{\int (f^\sigma(x))^p \, dx}{\int dx} \right)^{1/p} = ke
\]
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:

\[
\frac{\int |s_x^g(\lambda, x)| \, dx}{\int dx} = g(\lambda) = ke
\]

- Estimation of the light source

\[
\frac{\int |f_x(x)| \, dx}{\int dx} = \frac{1}{\int dx} \int \int e(\lambda) |s_x(\lambda, x)| c(\lambda) \, d\lambda \, dx
\]

\[
= \int e(\lambda) c(\lambda) \left(\frac{\int |s_x(\lambda, x)| \, dx}{\int dx}\right) \, d\lambda = k \int e(\lambda) c(\lambda) \, d\lambda = ke
\]
- General form of the proposed method
  
  - Consideration of Gaussian filtering (denoising)
  - Incorporation of Minkowski norm

\[
\left( \frac{\int |f_x^\sigma(x)|^p \, dx}{\int \, dx} \right)^{1/p} = ke
\]

- High-order derivatives

\[
\left( \frac{\int \left| \frac{\partial^n f^\sigma(x)}{\partial x^n} \right|^p \, dx}{\int \, dx} \right)^{1/p} = ke^{n,p,\sigma}
\]
**Table 1.** Overview of the different illuminant estimations methods together with their hypotheses. Theses illuminant estimations are all instantiations of (17)

<table>
<thead>
<tr>
<th>name</th>
<th>symbol</th>
<th>equation</th>
<th>hypothesis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grey-World</td>
<td>$e^{0,1,0}$</td>
<td>$(\int f(x) , dx) = k_\varepsilon$</td>
<td>the average reflectance in a scene is achromatic</td>
</tr>
<tr>
<td>max-RGB</td>
<td>$e^{0,\infty,0}$</td>
<td>$(\int</td>
<td>f(x)</td>
</tr>
<tr>
<td>Shades of Grey</td>
<td>$e^{0,p,0}$</td>
<td>$(\int</td>
<td>f(x)</td>
</tr>
<tr>
<td>General Grey-World</td>
<td>$e^{0,p,\sigma}$</td>
<td>$(\int</td>
<td>f^\sigma(x)</td>
</tr>
<tr>
<td>Grey-Edge</td>
<td>$e^{1,p,\sigma}$</td>
<td>$(\int</td>
<td>f^\sigma_x(x)</td>
</tr>
<tr>
<td>Max-Edge</td>
<td>$e^{1,\infty,\sigma}$</td>
<td>$(\int</td>
<td>f^\sigma_{xx}(x)</td>
</tr>
<tr>
<td>2nd order Grey-Edge</td>
<td>$e^{2,p,\sigma}$</td>
<td>$(\int</td>
<td>f^\sigma_{xx}(x)</td>
</tr>
</tbody>
</table>
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.

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

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

<table>
<thead>
<tr>
<th>method</th>
<th>local scale</th>
<th>Minkowski norm</th>
</tr>
</thead>
<tbody>
<tr>
<td>general Grey-World</td>
<td>$1 \leq \sigma \leq 5$</td>
<td>$8 \leq p \leq 18$</td>
</tr>
<tr>
<td>Grey-Edge</td>
<td>$3 \leq \sigma \leq 5$</td>
<td>$6 \leq p \leq 14$</td>
</tr>
<tr>
<td>2nd order Grey-Edge</td>
<td>$4 \leq \sigma \leq 7$</td>
<td>$5 \leq p \leq 11$</td>
</tr>
</tbody>
</table>

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 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