Color Constancy Using Natural Statistics and Scene Semantics

Arjan Gijsenij and Theo Gevers

Presented by Ji-Hoon Yoo

School of Electrical Engineering and Computer Science
Kyungpook National Univ.
Abstract

◆ Proposed method
  – Identifying the most important characteristics of color images
    • Use of natural image statistics
      – Application of Weibull parameterization
        » Relating image attributes
      – Use of MoG-classifier
        » Learning correlations and weighting between the Weibull-parameters and the image attributes
Introduction

◆ Color constancy
  - Perceiving same color of an object despite large difference of illumination
  - Color constancy algorithms
    • Use of low-level image features
      – Applying retinex theory
        » White-patch algorithm
        » Gray-world algorithm
        » Shade-of-gray algorithm
        » Gray-edge algorithm
• Use of image information
  – Gamut mapping algorithm
    » Color-by-correlation
    » Gamut-constrained illuminant estimation
    » Derivative-based gamut mapping
  – Other approaches
    » Probabilistic methods
    » Methods based on genetic algorithms
– Assumption

• Application of constrained gamuts
  – Observation of limited number of image colors
    » Taking image under a specific illuminant

• Use of distribution of colors
  – White-patch
  – Gray-world
  – Gray-edge
– Proposed method
  • The most appropriate color constancy algorithm for an image
    – Based on statistical contents of the image
    – Application of Weibull-parameterization
      » Expressing image characteristics
    – Use of Weibull-distribution
      » Supporting choice of a proper set of different color constancy methods
Color constancy

◆ Reflection model
  – Assumption
    • Using one light source and the observed color of the light source
    – Illuminating a scene
  – Image values $\mathbf{f} = (f_R, f_G, f_B)^T$ for a Lambertian surface

$$f_c = m(x) \int_\omega I(\lambda) \rho_c(\lambda) S(x, \lambda) d\lambda$$

(1)

where $I(\lambda)$ is color of the light source, $S(x, \lambda)$ is surface reflectance, $\rho(\lambda) = (\rho_R(\lambda), \rho_G(\lambda), \rho_B(\lambda))^T$ is camera sensitivity function, $\lambda$ is wavelength, $x$ is spatial coordinate, $\omega$ is the visible spectrum, $m(x)$ is Lambertian shading, $c \in \{R, G, B\}$. 
– Estimating color of the light source \( e \)

\[
e = \begin{pmatrix} e_R \\ e_G \\ e_B \end{pmatrix} = \int_{\omega} I(\lambda) \rho(\lambda) d\lambda
\]

(2)

• Problem
  – Unknown \( I(\lambda) \), unknown \( \rho(\lambda) \)

– Simplification of assumption

• Restricted gamuts
  – Limited number of image colors

• Distribution of colors
  – Presentation on image

• Set of possible light sources
◆ Illuminant estimation

– Two well-established algorithms

• Division by Minkowski-norm

\[ L_c(p) = \left( \int f_c^p(x)dx \right)^{\frac{1}{p}} = k e_c \]  

(3)

where \( p \) is Minkowski-norm, \( c = \{R,G,B\} \), \( k \) is a multiplicative constant chosen such that illuminant color \( e = (e_R, e_G, e_B)^T \) has unit length.

– Gray-world algorithm

\( p = 1 \)

– White-patch algorithm

\( p = \infty \)
• Incorporation of higher order image statistics

\[
\left( \int \left| \frac{\partial^n f_{c,\sigma}(x)}{\partial x^n} \right|^p dx \right)^{\frac{1}{p}} = k e_{n,p,\sigma}^c
\]  

(4)

where \(|\cdot|\) indicates the Frobenius norm, \(c = \{R,G,B\}\), \(n\) is the order of the derivative, and \(p\) is the Minkowski-norm.

• Expression of derivatives
  
  – Convolution of the image with the derivative of a Gaussian filter with scale parameter \(\sigma\)

\[
\frac{\partial^{s+t} f_{c,\sigma}}{\partial x^s \partial y^t} = f_c * \frac{\partial^{s+t} G_\sigma}{\partial x^s \partial y^t}
\]  

(5)

where \(*\) denotes the convolution and \(s + t = n\).
• Generating color constancy algorithms
  – Based on zeroth-order statistics of three algorithm
    » $e^{0,1,0} (\equiv L(1))$: gray-world algorithm
    » $e^{0,\infty,0} (\equiv L(\infty))$: white-patch algorithm
    » $e^{0,p,\sigma}$: general gray-world algorithm
  – Extension color constancy algorithms
    » $e^{1,p,\sigma}$: the first-order gray-edge
    » $e^{2,p,\sigma}$: the second-order gray-edge
Diagonal model

- Transforming colors of input image
  - Taking image from unknown light source to canonical illuminant
    \[ f_t = D_{u,t} f_u \]  
    where \( f_u \) is image taken under an unknown light source, \( f_t \) is same image transformed, \( D_{u,t} \) is a diagonal matrix.
  - Use of diagonal matrix \( D_{u,t} \)

\[
\begin{pmatrix}
R_c \\
G_c \\
B_c
\end{pmatrix} =
\begin{pmatrix}
d_1 & 0 & 0 \\
0 & d_2 & 0 \\
0 & 0 & d_3
\end{pmatrix}
\begin{pmatrix}
R_u \\
G_u \\
B_u
\end{pmatrix}
\]
Natural image statistics and scene semantics

◆ Spatial image structure
  – Visible identification cues
    • Determining image from scene type
  – Scene classification
    • Modeling distribution of edge responses
      – Use of Weibull distribution

\[
\omega(x) = C \exp\left( -\frac{1}{\gamma} \left| \frac{x}{\beta} \right|^{\gamma} \right)
\]

(8)

where \( x \) is the edge responses in single-color channel to the Gaussian derivative filter, \( C \) is a normalization constant, \( \beta > 0 \) is the scale parameter of the distribution, and \( \gamma > 0 \) is the shape parameter.
– Examples of images
  » Consisting edge distribution of images

**Fig. 1.** Examples of images that can be considered to be characteristic of the corresponding color constancy algorithms. Below each image, the distribution of edges in the intensity channel is plotted.
Combination of illuminant estimation method

◆ Color constancy using standard fusion
  – Generating a new estimate of the illuminant
  – Based on weighting the output of the used color constancy algorithms
    • Using the weighted average of the estimated illuminant
      \[\bar{e} = \sum_{i=1}^{n} \omega_i e_i\]  
      where \(\sum_{i=1}^{n} \omega_i = 1\).
    • Combining a statistics-based method with a physics-based method
Color constancy using natural image statistics

- Novel algorithm
  - Combining the estimates of color constancy algorithms into single
    - $M$ : combining set of algorithms
      - $M_i$ : algorithm $i$
    - $\varepsilon_i(j)$ : accuracy of the estimate
      - Algorithm $i$ on image $j$
  
- Procedure
  - First, computing image statistics $\omega \in \mathbb{R}^{p \times q}$ of all images
    - $p$ : number of features
    - $q$ : number of images
    - $\omega_{ij}$ : $i$ th feature on the $j$ th image
    - Omitting $i$ for simplicity
– Then, labeling all images in training set
  » Derivation of label \( y_j \)
  \[
  y_j = \arg \min_i \{ \varepsilon_i(j) \}
  \] (10)

– Application of MoG-classifier on the training data
  \[
  p(\omega_j|y_j) = \sum_{m=1}^{k} \alpha_m G(\omega_j, \mu_m, \sum_m)
  \] (11)
  where \( \alpha_m \) are the positive weights of the Gaussian components (with mean and variance defined as \( \mu_m \) and \( \sum_m \), respectively) such that \( \sum_{m=1}^{k} \alpha_m = 1 \).

– Application of learned MoG-classifier on the test data
– Assigning current image \( j \) th algorithm
• Computing Weibull-parameters for each $R$, $G$, and $B$ channel separately
  – Problem
    » Highly correlated color channels
  – Transformation image to a decorrelated color space
    » Use of opponent color space

$$O_1 = \frac{R - G}{\sqrt{2}}$$ (12)

$$O_2 = \frac{R + G - 2B}{\sqrt{6}}$$ (13)

$$O_3 = \frac{R + G + B}{\sqrt{3}}$$ (14)
– Example of output of three algorithms

**Fig. 2.** A scatter plot of the $\beta$ and $\gamma$ of the gradient in the $O_3$-channel. Each point represents the Weibull-parameters of one image. The parameters of more than 11,000 images (the real-world set by Ciurea and Funt) are plotted.
Color constancy using scene semantics

- Use of scene semantics
  - Finding a category-specific combination of color constancy algorithms
    - Selection of the most appropriate color constancy algorithm
      - Corresponding Weibull-parameters
        » Dividing images into categories
Fig. 3. Scatter plots of the Weibull-parameters based on $O_3$ derived from images coming from several categories, overlayed on the Weibull-parameters of the images that are in the real-world set.
Experiments

◆ Data set

– Training data set
  • Based on spectral reflectance data
    – Combining surface and illuminant spectra into R, G, B-values
      » Creating Mondiran-like images from generated pixel colors

– Test data set
  • Color constancy data set of Ciurea and Funt
    – Presentation over 11,000 images
    – Providing ground truth of the illuminant color
Fig. 4. Examples of images that are in the two data sets that are used in this paper. The first data set consists of images that are generated using surface reflectance spectra combined with illuminant spectra. The second data set consists of real-world images.
Performance measure

- Using angular error $\varepsilon$
  
  - Measuring difference of the estimated illuminant $e_e$ and color of the light source $e_l$
    
    $$
    \varepsilon = \cos^{-1}\left(\frac{e_l \cdot e_e}{\|e_l\| \cdot \|e_e\|}\right)
    $$
  
  where $e_l \cdot e_e$ is the dot product of the two vectors and $\|\cdot\|$ indicates the euclidean norm.

  - Applying median angular error
    
    - Summarizing statistic
– Results of various algorithms
  • Application of images in second data set

Fig. 7. Examples of images that are in the data set used for evaluation in Section 5 and results of some color constancy algorithms. The corresponding angular errors are shown in the lower right corner of the images.
Fig. 7. Examples of images that are in the data set used for evaluation in Section 5 and results of some color constancy algorithms. The corresponding angular errors are shown in the lower right corner of the images.
Color constancy algorithms

– Result of several algorithms

Table 1. Median angular errors for several (single) algorithms on the complete data set of 11,346 images.

<table>
<thead>
<tr>
<th>Method</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Do nothing (i.e. without color constancy)</td>
<td>6.7°</td>
</tr>
<tr>
<td>Grey-World (ε^{0,1,0})</td>
<td>7.0°</td>
</tr>
<tr>
<td>White-Patch (ε^{0,\infty,0})</td>
<td>5.3°</td>
</tr>
<tr>
<td>General Grey-World (ε^{0,13,2})</td>
<td>5.5°</td>
</tr>
<tr>
<td>1\textsuperscript{st}-order Grey-Edge (ε^{1,1,6})</td>
<td>5.2°</td>
</tr>
<tr>
<td>2\textsuperscript{nd}-order Grey-Edge (ε^{2,1,5})</td>
<td>5.2°</td>
</tr>
<tr>
<td>Best 0\textsuperscript{th}-order algorithm: ε^{0,9,0}</td>
<td>5.3°</td>
</tr>
<tr>
<td>Best 1\textsuperscript{st}-order algorithm: ε^{1,1,1}</td>
<td>4.6°</td>
</tr>
<tr>
<td>Best 2\textsuperscript{nd}-order algorithm: ε^{2,1,2}</td>
<td>4.9°</td>
</tr>
<tr>
<td>Gamut mapping</td>
<td></td>
</tr>
<tr>
<td>- trained on: Mondrian data</td>
<td>5.5°</td>
</tr>
<tr>
<td>- trained on: real-world data</td>
<td>4.8°</td>
</tr>
</tbody>
</table>
Color constancy using standard fusion

– Comparison to baseline algorithm

Table 2. The performance of several different methods to combine the output of single-color constancy methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline (e^{1,1,1})</td>
<td>4.6°</td>
</tr>
<tr>
<td>Simple average</td>
<td>5.0° (±8.7%)</td>
</tr>
<tr>
<td>Weighted average</td>
<td>4.6° (±0%)</td>
</tr>
<tr>
<td>Proposed: NIS</td>
<td>4.2° (−8.7%)</td>
</tr>
<tr>
<td>Proposed: NIS - cross-validation</td>
<td>3.7° (−19.6%)</td>
</tr>
</tbody>
</table>

The color constancy methods used include one zeroth-order method (General Gray-World \(e^{0.5,1}\)), one first-order method (Gray-Edge \(e^{1.1,2}\)), and one second-order method (second-order Gray-Edge \(e^{2.1,1}\)).

The entry NIS-Mondrian denotes the proposed algorithm trained on the independent Mondrian data set and tested on the real-world data set, and the entry NIS real world denotes the proposed algorithm evaluated using cross validation on the real-world data set.
– Angular errors of all methods

Fig. 5. Median angular errors for all the methods plotted with a 95 percent confidence interval.
Color constancy using natural image statistics

– SNR performance analysis

• Average difference between two consecutive patches $a_i$ and $a_j$

$$SNR = \frac{a_i - a_j}{\sigma_{\text{noise}}}$$  \hspace{1cm} (16)

where $\sigma_{\text{noise}}$ is kept fixed.
• Sensitivities of three algorithms with SNR

Fig. 6. Experiment monitoring the sensitivity of the different color constancy algorithms to the signal-to-noise ratio.
◆ Color constancy use scene semantics
  – Evaluating scene semantics on real-world data set
    • Scene semantics methods
      – Comparison with natural image statistics methods

Table 3. Median angular error for several different methods on images from four categories.

<table>
<thead>
<tr>
<th>Scene</th>
<th>Entire image (NIS-Mondrian)</th>
<th>Proposed: Scene Semantics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open Country</td>
<td>5.5°</td>
<td>6.7°</td>
</tr>
<tr>
<td>Street</td>
<td>2.7°</td>
<td>3.4°</td>
</tr>
<tr>
<td>Indoor</td>
<td>5.1°</td>
<td>5.5°</td>
</tr>
<tr>
<td>Forest</td>
<td>5.6°</td>
<td>5.5°</td>
</tr>
</tbody>
</table>
Discussion

◆ Performance of color constancy methods
  – Three basic indicators of method based pixel and edge information
    • Image features
      – Use of derivatives
        » Providing more stable gamuts than pixel values
    • Number of features
      – Determining a variety of different edges in an image
    • SNR
      – Low SNR
        » Performing pixel-based method
      – High SNR
        » Performing higher order methods
- Three basic indicators of methods based Weibull parameters
  - Image features $\gamma$
    - Relation with amount of texture
  - Number of feature $\gamma$
    - Relation with number of edge
  - SNR $\beta$
Conclusion

◆ Use of Weibull parameterization
  – Identifying the most important characteristics of color images
  – Relation with three basic indicators
    • Number of image
    • Amount of texture
    • SNR
◆ Use of MoG-classifier

- Learning correlation
  - Weibull-parameters
    - Texture, contrast
  - Image attributes
    - Number of edges
    - Amount of texture
    - SNR

- Output of classifier
  - Selection of the best performing color constancy method for certain image