Color Constancy for Multiple Light Sources

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Arjan Gijsenij, Rui Lu, and Theo Gevers
Presented by Bong-Seok Choi

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

- Color constancy algorithm
  - Assumption about light source
    - Uniform spectral distribution of light source at scene
  - Drawback of this assumption
    - Violation in presence of multiple light source

- Proposed method
  - Color constancy for multiple light source
    - Applying color constancy locally to image patches
    - Local illuminant estimation
    - Applying local correction based on modified diagonal model
  - Applying proposed method
    - Considering chromatic difference between two illuminants
      - Chromatic difference more than 1°
Introduction

- Influencing different color of light source on object color
  - Introducing undesirable effect in digital image
    - Negative affect performance of computer vision
      - object recognition, tracking, surveillance

- Aim of color constancy
  - Correction to effect of illuminant color
    - Computing invariant features
    - Transforming input image
      - Removing effects color of light source (white balancing)
Color constancy algorithm

- Color constancy algorithms
  - Exploiting pixel value for estimate color of light
    - Based on low-level features
    - Gamut-based algorithm
    - Using knowledge acquired in learning phase
  - Edge based color constancy
    - Using edges and higher order statistics
- Assumption of color constancy algorithms
  - Illuminating spectrally uniform light source in scene
  - Case of violated this assumption
    - Indoor scenes
      » Affecting indoor and outdoor illumination
      » Interreflections
    - Outdoor scenes
      » Shadow region and nonshadow region
– Example scenes with multiple light sources

**Fig. 1.** Scenes with multiple different light sources
– Method of Retinex for color constancy
  • Basic assumption
    – Causing change reflectance properties by Abruptly change chromaticity
  • Using very large scale integration for real-time image processing
  • Using center/surround for practical image processing
  • Using MATLAB to standardize evaluation of retinex

– Other algorithm
  • Considering multiple light sources include physics-based methods
  • Biologically inspired model
    – Requiring manual intervention
Proposed method

- Color constancy under multiple light source
  - Methodology design criteria
    - Scenes containing multiple light sources
    - Work on single image
    - No human intervention
    - No prior knowledge or restrictions on spectral distribution of light source
  - Procedure of proposed method
    - Sampling
      - Grid based, key-point based, segmentation based sampling
    - Illumination estimation and combination
      - Applying to obtain illuminant estimate and combination
      - Two different approach of combination
        » Segmentation and clustering
    - Back-projection local illuminant estimation
    - Color correction
Color Constancy

- **Goal of computational color constancy**
  - Estimation of chromaticity of light source
  - Correction image to canonical illumination
    - Using diagonal model

- **Reflection model**
  - Image color $I = (I_R, I_G, I_B)^T$ for Lambertian surface

\[
I_c(x) = \int_{\omega} E(\lambda, x) S(\lambda, x) \rho_c(\lambda) d\lambda
\]  

where $c \in \{R, G, B\}$ and $E(\lambda, x), S(\lambda), \rho_c(\lambda, x)$ are illuminant spectrum, surface reflectance, and camera sensitivity.
– Computing color of light source
  • Given location \( x \)
    \[
    L(x) = \begin{pmatrix}
    L_R(x) \\
    L_G(x) \\
    L_B(x)
    \end{pmatrix} = \int_{\omega} E(\lambda, x) \rho(\lambda) d\lambda
    \]  

– Assumption of color constancy
  • Problem of estimating color of light source
    – Unknowing \( E(\lambda, x) \) and \( \rho(\lambda) = (\rho_R, \rho_G, \rho_B)^T \)
  • Assumption for computing color of light source
    – Considering statistical property of illuminant
    – Considering surface reflectance property
  • Assumption of most color constancy algorithms
    – Color of light source is uniform across scene
Illumination estimation

- Estimating illumination at one light source
  - Global estimate of light source
    \[
    \left( \int \left| \frac{\partial^n I_{c,\sigma}(x)}{\partial x} \right|^p dx \right)^{\frac{1}{p}} = kL_c^{n,p,\sigma}
    \]
  
  where $|\cdot|$ is Frobenius norm, $c = \{R, G, B\}$, $n$ is order of derivative, $p$ is Minkowski norm, and $I_{c,\sigma} = I_c \otimes G_\sigma$ is convolution of image with Gaussian filter with scale parameter $\sigma$

- Derivative (3) by characteristics of gaussian filter
  \[
  \frac{\partial^{a+b} I_{c,\sigma}}{\partial x^a y^b} = I_c \ast \frac{\partial^{a+b} G_\sigma}{\partial x^a \partial y^b}
  \]
  where $\ast$ denotes convolution and $a + b = n$
– Color constancy algorithm
  • Pixel based color constancy algorithms \((n = 0)\)
    – Gray-world algorithm
      » \(n = 0\), Minkowski norm \(p = 1\), smoothing parameter \(\sigma = 0\); \(L^{0,1,0}\)
    – White patch algorithm
      » \(n = 0\), Minkowski norm \(p = \infty\), smoothing parameter \(\sigma = 0\); \(L^{0,\infty,0}\)
    – Specific instantiation of General gray world algorithm
      » \(n = 0\), Minkowski norm \(p = 8\), smoothing parameter \(\sigma = 1\); \(L^{0,8,1}\)
  • Higher order color constancy methods
    – First order gray-edge \(L^{1,1,1}\)
    – 2\(^{nd}\) order gray-edge \(L^{2,1,1}\)
Correction

- Aim to transform input image
- Using diagonal model or von Kries model

\[ I^c = \Lambda^{u,c} I^u \]  \hspace{1cm} (5)

where \( I^u \) is image taken under unknown light source while \( I^c \) is image transformed, \( \Lambda^{u,c} \) is mapping diagonal matrix

- Mapping diagonal matrix \( \Lambda^{u,c} \)

\[
\Lambda^{u,c} = \begin{pmatrix}
\alpha & 0 & 0 \\
0 & \beta & 0 \\
0 & 0 & \gamma
\end{pmatrix} = \begin{pmatrix}
\frac{L_R^c}{L_R^u} & 0 & 0 \\
0 & \frac{L_G^c}{L_G^u} & 0 \\
0 & 0 & \frac{L_B^c}{L_B^u}
\end{pmatrix}
\]  \hspace{1cm} (6)

where \( L^u \) is unknown light source, \( L^c \) is canonical light source
Color Constancy for Multiple Light source

- Color constancy for multiple light source
  - Extending traditional method to estimate N different light source
  - Outline of proposed method process
    - Step 1. Sampling of image patches
      - Grid-based sampling
      - Keypoint-based sampling
      - Segmentation-based sampling
    - Step 2. Patch-based illuminant estimation
    - Step 3. Combination of estimates
    - Step 4. Back-projection of clusters
    - Step 5. Color correction
Fig. 1. Illustration of the proposed methodology. The input image, recorded under two different illuminants.
Proposed framework

- Sampling of image patches
  - Sampling patches $P$ from image
    - Using uniform color of light source with each patch
  - Way to sampling strategies
    - Segmentation sampling
      » Naturally result image between boundary and light source
    - Grid based sampling
      » Containing varied information
    - Key-point sampling
      » Specifically locating around edge and junctions
      » Using Harris detector
- Patch-based illuminant estimation
  - Spectrally uniform at each patches illuminant
    - Estimating local illuminant
      » Applying traditional color constancy method each patch

- Combination of estimates
  - Drawback of patch based sampling
    - Lack of information to estimate light source
    - Introducing estimation error
  - Overcome this lack of information
    - Taking patches from part of image with illuminated same light source
      » Grouping clustering algorithms
    - Combining same patches to form larger patch
- Back-projection of clusters
  - Illuminant classification
    - Back-projected onto original image to identify locations in image
    - Assigning to one of estimated light source every pixel
  - After back-projection
    - Estimating illuminant by pixelwise
- Color correction
  - Using pixelwise estimation
  - Using diagonal model or von kries model
Light source estimators
- Estimating illuminant
  - Using standard color constancy algorithm at each patch
  - Every estimation to normalized for intensity

\[
\begin{align*}
    r &= R / (R + G + B) \\
    g &= G / (R + G + B)
\end{align*}
\]  

- Representing illuminant each patch by 1 x 2 vector
- Illuminant estimation result
  » White-light source (r=g=1/3)
- Overlapping light source
  - Underlying assumption of proposed framework
    - Different light sources are locally constant
  - Drawback of this assumption
    - Linear mixture of two light sources
      - True light source at location in between two light sources
      - Introducing quantitative and qualitative errors
  - Overcome this problem
    - Filtering of back-projected clusters
      - Smooth transition from one light source to another
    - Similarity between estimated illuminant of patch and j illuminant

\[
d' _j (x) = \frac{\sum_x d_j(x)}{d_j(x)}
\]

(8)

where \(d_j(x)\) denote chromatic distance of estimated illuminant of patch located at spatial coordinate \(x\) in image to \(j\)th illuminant
• Mask map $m_j(x)$
  - Indicating estimated probability of $j$ th illuminant
  - Definition as ratio of $d'_j(x)$ to sum of distances to all illuminant

$$m_j(x) = \frac{d'_j(x)}{\sum_{k=1}^{N} d'_k(x)}$$  (9)
Image correction

- Estimating illumination for each pixel

\[
L_e(x) = \sum_{i=1}^{N} L_{e,i} m_i(x)
\]  

(10)

where \( L_e \) is the illuminant estimation over the scene, \( L_{e,i} \) is estimation for \( i \) th illumination, and \( m_i(x) \) is the contribution of \( i \) th light-source estimation to pixel \( x \)
Fig. 3. Example of light mask maps. (a) There are two light sources in the synthetic image. The illumination for each pixel is present in (b). (c)–(d) Illuminant mask maps: The contribution each light source makes to the light mixture in which white means a big ratio, whereas dark, a small ratio.
Experiments

- Performance measurement
  - Using two performance measurement
    - Evaluating Clustering performance
      - Using misclassification rate
        \[ \eta = \frac{1}{T} \sum_{i=1}^{N} S_i \]  
        where \( S_i \) is the number of misclassified pixels illuminated by the \( i \)th light source, whereas \( T \) is the total number of pixels in the image
    - Evaluating performance of color constancy algorithm
      - Using angular error
        \[ \varepsilon(x) = \cos^{-1} \left( \hat{L}_i(x) \cdot \hat{L}_e(x) \right) \]  
        (12)
  - Statistical significance
    - Evaluation of summarizing statistic
Hyperspectral data

- Using hyperspectral data taken by foster et al.
  - Consist of mixture of rural and urban scenes
  - Illumination by two different light sources
  - Using randomly selected image from set of 81 illuminant spectra
    - Using 1437 images
    - Containing wide variety of combinations of light sources
      » Ranging from 0 to roughly 40

**Fig. 4.** Example images: The first image is the original hyperspectral image, whereas the others are generated using two light sources on the original image. Note that all experiments are performed on linear images; gamma correction is applied only for improved visualization.
<table>
<thead>
<tr>
<th>Method</th>
<th>Median</th>
<th>Method</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Do Nothing (DN)</td>
<td>26.3°</td>
<td>general Grey-World (gGW)</td>
<td>11.5°</td>
</tr>
<tr>
<td>Grey-World (GW)</td>
<td>14.0°</td>
<td>1\textsuperscript{st}-order Grey-Edge (GE-1)</td>
<td>16.8°</td>
</tr>
<tr>
<td>White-Patch (WP)</td>
<td>12.5°</td>
<td>2\textsuperscript{nd}-order Grey-Edge (GE-2)</td>
<td>16.7°</td>
</tr>
<tr>
<td>LSAC Retinex</td>
<td>10.5°</td>
<td>LSAC Retinex</td>
<td>10.2°</td>
</tr>
<tr>
<td>Exponential filter (Impl. from [14])</td>
<td>11.7°</td>
<td>(Impl. from [34])</td>
<td>9.9°</td>
</tr>
<tr>
<td>Proposed: grid-based sampling, then clustering (k-means, (k = 2))</td>
<td>GW</td>
<td>Proposed: grid-based sampling, then clustering (k-means, (k = 2))</td>
<td>GW</td>
</tr>
<tr>
<td>Proposed: grid-based sampling, then segmentation (mean-shift)</td>
<td>WP</td>
<td>Proposed: segmentation-based sampling then clustering (k-means, (k = 2))</td>
<td>WP</td>
</tr>
<tr>
<td>Proposed: grid-based sampling, then clustering (k-means, (k = 2))</td>
<td>GWW</td>
<td>Proposed: segmentation-based sampling then clustering (k-means, (k = 2))</td>
<td>GWW</td>
</tr>
<tr>
<td>GE-1</td>
<td>15.4° (-8%)</td>
<td>GE-1</td>
<td>15.9° (-5%)</td>
</tr>
<tr>
<td>GE-2</td>
<td>15.0° (-10%)</td>
<td>GE-2</td>
<td>15.4° (-8%)</td>
</tr>
<tr>
<td>Proposed: grid-based sampling, then segmentation (mean-shift)</td>
<td>GW</td>
<td>Proposed: grid-based sampling, then segmentation (mean-shift)</td>
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<tr>
<td>Proposed: grid-based sampling, then segmentation (mean-shift)</td>
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<td>GWW</td>
</tr>
<tr>
<td>GE-1</td>
<td>16.8° (-0%)</td>
<td>GE-1</td>
<td>13.0° (-23%)</td>
</tr>
<tr>
<td>GE-2</td>
<td>16.1° (-4%)</td>
<td>GE-2</td>
<td>15.4° (-8%)</td>
</tr>
</tbody>
</table>

**Table. 1.** Performance of color constancy algorithms computed for hyperspectral data set
Fig. 5. Relationship between patch size and the algorithm performance. (From left to right) performance of gray world (GW), white patch (WP), general gray world (GGW), first gray edge (GE-1), and second gray edge (GE-2). Note that, in this experiment, In each graph, horizontal axis is the patch size, whereas the vertical axis is the median angular error. (Red line) performance assuming only one light source is present (while in fact there are two).
Fig. 6. Influence of illuminant differentiation. (Top row) influence of the chromatic difference between the light sources for clustering. (Bottom row) influence on the color constancy performance. No postprocessing is done in the experiment. Note that the blue lines are obtained by averaging over points with similar illumination difference and is superimposed to illustrate the trend.
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<th>Median</th>
<th>Method</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grey-World (GW)</td>
<td>8.9°</td>
<td>Proposed methodology using GW</td>
<td>8.1°(-9%)</td>
</tr>
<tr>
<td>White-Patch (WP)</td>
<td>7.9°</td>
<td>Proposed methodology using WP</td>
<td>8.4°(+6%)</td>
</tr>
<tr>
<td>general Grey-World (gGW)</td>
<td>5.5°</td>
<td>Proposed methodology using gGW</td>
<td>8.1°(+47%)</td>
</tr>
<tr>
<td>1&lt;sup&gt;st&lt;/sup&gt;-order Grey-Edge (GE-1)</td>
<td>15.1°</td>
<td>Proposed methodology using GE-1</td>
<td>15.0°(-1%)</td>
</tr>
<tr>
<td>2&lt;sup&gt;nd&lt;/sup&gt;-order Grey-Edge (GE-2)</td>
<td>14.9°</td>
<td>Proposed methodology using GE-2</td>
<td>14.8°(-1%)</td>
</tr>
</tbody>
</table>

**Table. 2.** Performance of color constancy algorithms computed for hyperspectral data set
Fig. 7. Examples of the real-world data set. (Upper row) The natural scenes and (bottom row) images captured in laboratory settings. Note that all experiments are performed on linear images; gamma correction is applied only for improved visualization.
Table 3. Performance of color constancy algorithms for real-world images. Performance on images under laboratory setting are shown in table (A), and performance on natural scenes are shown in table (B).
Fig. 8. Results of color constancy on some real-world images, (a) The original image. (b)–(c) The result of global correction with one of the two illuminants that are present. (d) The result of global correction with the gray-world algorithm and (e) the result of local correction with the proposed method (using gray world). Note that all experiments are performed on linear images; gamma correction is applied only for improved visualization.
Discussion

- Proposed method
  - Color constancy for multiple light sources
    - Proposing novel color constancy framework
    - Extending existing methods to more realistic scenarios
    - Patch based illuminant estimation
      - Sampling patches, estimation and combination, back-projection