Light, Color, and Surface Reflectance

Shida Beigpour
Overview

- Introduction
- Multi-illuminant Intrinsic Image Estimation
- Multi-illuminant Scene Datasets
- Multi-illuminant Color Constancy
- Conclusions
Introduction

Modeling scene optics plays a crucial role in scene understanding.

- Interreflection
- Specularities
- Colorcast
- Multi-illuminant
- Colored illuminant
- Colored shadows
Introduction

1. Automatic White Balance (AWB)

Original Image

Color corrected
Introduction

1. Automatic White Balance (AWB)
2. Changing the illuminant (Re-lighting)
Introduction

1. Automatic White Balance (AWB)
2. Changing the illuminant (Re-lighting)
3. Segmentation
Introduction

1. Automatic White Balance (AWB)
2. Changing the illuminant (Re-lighting)
3. Segmentation
4. Object Recoloring (physically plausible)
Introduction

1. Automatic White Balance (AWB)
2. Changing the illuminant (Re-lighting)
3. Segmentation
4. Object Recoloring
5. Photo forensics
Introduction

1. Automatic White Balance (AWB)
2. Changing the illuminant (Re-lighting)
3. Segmentation
4. Object Recoloring
5. Photo forensics
6. Shadow removal
7. ...

Original Image  Shadow removed
Introduction

Context:

- There are mainly two fields which investigate illumination and object modeling in computer vision:
  - Intrinsic image estimation
  - Color constancy
Introduction

Context:

- Many real-world scenes present complex reflectance under multiple-illuminants.
- Most existing methods limit their domain by making unrealistic assumptions.
Introduction

Context:

- Many real-world scenes present complex reflectance under multiple-illuminants.
- Most existing methods limit their domain by making unrealistic assumptions.
- Many fields in computer vision that rely on illuminant and reflectance models can strongly benefit from more realistic models:
  - Object classification methods which use color cues
  - Segmentation algorithms
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There are two main forms of reflectance: specular and diffuse.
Single-illuminant Object Reflectance Model

- **Lambertian Reflection Model**
  Models the interaction of light and matte (diffuse) object surfaces
  \[ f^c (\mathbf{x}) = m_b (\mathbf{x}) \int b (\lambda, \mathbf{x}) e (\lambda) \rho^c (\lambda) d\lambda \]

- **Dichromatic Reflection Model (DRM) [Shafer, JCRA 1985]**
  \[ f^c (\mathbf{x}) = m_b (\mathbf{x}) \int b (\lambda, \mathbf{x}) e (\lambda) \rho^c (\lambda) d\lambda + m_s (\mathbf{x}) \int i (\lambda) e (\lambda) \rho^c (\lambda) d\lambda \]
  \[ \omega \]
  Diffuse component
  Specular component
Multi-illuminant Object Reflectance Model

Image formation under multiple lights:

- Primary Light
- Secondary Light
- Surface Normal
- Specular Reflection
- Diffuse Reflection

Object Surface → Surface Particles → Object Image
Multi-illuminant Object Reflectance Model

We extend the DRM to account for multiple illuminants:

Multi-Illuminant Dichromatic Reflection (MIDR) model

Assumption: Single-colored object pre-segmented from its background.

\[
\text{DRM} \quad f = [m_b(x) \ m_s(x)] [L \ c \ I]^T = M \ C^T
\]

\[
\text{MIDR} \quad f = [M^1 \ldots M^n] [C^1 \ldots C^n]^T = \bar{M} \bar{C}^T
\]

As error metric we define Reconstruction error, the mean square error between the estimated model and the object pixels.

\[
E_r(f, \bar{M}, \bar{C}) = (f - \bar{M} \bar{C}^T)^T (f - \bar{M} \bar{C}^T)
\]

Multi-illuminant Object Reflectance Model

An example of modeling:

- Object is segmented from its background
Multi-illuminant Object Reflectance Model

An example of algorithm performance:
- First the object is modeled just by the DRM.
- But in this case, the greenish inter-reflection is lost.
Multi-illuminant Object Reflectance Model

An example of algorithm performance:

- The reconstruction error provides a mask for which the secondary illuminant is dominant.
Multi-illuminant Object Reflectance Model

An example of algorithm performance:
- Using the illuminant mask, two models are generated.
Multi-illuminant Object Reflectance Model

An example of algorithm performance:

- The models and corresponding masks are iteratively refined until convergence.
Multi-illuminant Object Reflectance Model

An example of modeling:
- Decomposition

Object Image

1\textsuperscript{st} Body Reflectance

Object Color

Specular Reflectance

Primary Light

2\textsuperscript{nd} Body Reflectance

Secondary Light
Multi-illuminant Object Reflectance Model

Improving photo-fusion:

- Here the green mug is replaced by a purple mug.
- But now the greenish interreflection on the blue mug doesn’t match the scene.
Multi-illuminant Object Reflectance Model

Improving photo-fusion:

- The purple color from the mug is assigned as the secondary illuminant.
Multi-illuminant Object Reflectance Model

Improving photo-fusion:

- The mug is then constructed using the new color.
Multi-illuminant Object Reflectance Model

Improving photo-fusion:

- The greenish inter-reflection on the blue mug is transformed to purple.
Single-illuminant Object Reflectance Model

Recoloring a video

Original Video

Recolored Video
Multi-illuminant Object Reflectance Model

Next step:

- Multi-illuminant dataset with pixel-wise accurate ground-truth for the purpose of quantitative evaluation.

- Solving the model without the need of segmentation or assumptions on the illuminant.
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- Multi-illuminant Color Constancy
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Multi-illuminant Datasets

Observations:

- Existing dataset for reflectance and illuminant estimation are mostly limited to single-illuminant scenarios.
- In addition intrinsic image datasets mainly consist of single-object scenes.

We propose two multi-illuminant datasets:

- **Synthetic intrinsic image dataset**: Computer graphics generated dataset for intrinsic estimation benchmarking in complex scenes.
- **Multi-Illuminant Multi-Object (MIMO)**: Dataset for multi-illuminant color constancy benchmarking.
Synthetic intrinsic image dataset *

Our proposal is to use computer graphics generated data for this purpose:

- **3D-Modeling**: Blender

- **Photo-realistic rendering**: Yafaray

- **Multi-spectral images**:
  - Using 6-band color images instead of 3-band RGB to improve accuracy
  - We use recorded multi-spectral data for Munsell color patches for the surfaces along with the multi-spectral Planckian and non-Planckian lights.

Intrinsic Image datasets

We propose the use of synthetic data for intrinsic image estimation:

- Global lighting
- Photo-realism
Intrinsic Image datasets

We propose the use of synthetic data for intrinsic image estimation:

- Global lighting
- Photo-realism
- Accurate pixel-wise ground-truth
Intrinsic Image datasets

An example of benchmarking for three intrinsic image methods:

- Ground-truth reflectance
- Reflectance Estimation Results
- Gehler, NIPS 2011
- Barron ECCV 2012
- Serra, CVPR2012

White light

Colored light

Multi-illuminant
Multi-illuminant Datasets

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Color constancy datasets

Examples of some of the most popular single-illuminant color constancy datasets.

Ciurea & Funt

Barnard et. al.

Parraga et. al.

Gehler et. al.
Multi-Illuminant Multi-Object scene dataset (MIMO) *

We propose our multi-illuminant dataset  MIMO

- MIMO-Lab: Toy images captured under controlled lab conditions.

Multi-Illuminant Multi-Object scene dataset (MIMO)

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- MIMO-Lab: Toy images captured under controlled lab conditions.

- MIMO-Realworld: Indoor/outdoor images of some real-world scenes.
Multi-Illuminant Multi-Object scene dataset (MIMO)

We propose our multi-illuminant dataset MIMO

- **MIMO-Lab**: Toy images captured under controlled lab conditions.
- **MIMO-Realworld**: Indoor/outdoor images of some real-world scenes.
Multi-Iluminant Multi-Object scene dataset (MIMO)

Ground-truth calculation:

- We use the linearity of the images and illuminants:

\[
\mathbf{f}_{ab} = \mathbf{f}_a + \mathbf{f}_b
\]

- DS Image
- Image of Illuminant a \((\mathbf{f}_a)\)
- Both Illuminants \((\mathbf{f}_{ab})\)
- Image of Illuminant b \((\mathbf{f}_b)\)

Macbeth color checker
Multi-Illuminant Multi-Object scene dataset (MIMO)

Ground-truth calculation:

- The ratio of each illuminant in the green channel:
  \[ r_{a,g} = \frac{f_{a,g}}{f_{a,g} + f_{b,g}} \]

- Using this ratio, we can calculate the illuminant at each pixel of the multi-illuminant image \( (i_{ab}) \) by a linear interpolation:
  \[ i_{ab} = r_{a,g} \cdot a + (1 - r_{a,g})b \]

The per pixel \( r_{a,g} \) ratio

Illuminant Chroma Map (ground-truth)
Multi-Illuminant Multi-Object scene dataset (MIMO)

Examples from the MIMO-lab dataset:
Multi-Illuminant Multi-Object scene DS: Expanding the framework

Examples from our new Multi-illuminant dataset in Norway:

- 6 scenes, 5 illumination conditions : 30 images

Blue, Orange, and ceiling lamp

Scene with Macbeth Checkered

Multi-Iluminant Multi-Object scene DS: Expanding the framework

For each multi-illuminant scene we require the images of each light separately:
In the color-coded ratio image, Red, Green and Blue stand for Orange (from left), Ceiling lamp (from top), and Blue (from right).
Multi-Illuminant scene datasets

Conclusion:

- We introduced a synthetic dataset for intrinsic image estimation for multiple illuminants and complex scenes.
- We created the first multi-illuminant complex scene dataset with pixel-wise ground-truth accuracy.

Next step:

- We use our multi-illuminant scene dataset for multi-illuminant color constancy.
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Color constancy

Can you guess the color of the woman’s top?
Color constancy

Can you guess the color of the woman’s top?
Computation Color Constancy

Color constancy algorithm mainly consist of two steps:

- Estimation of chromaticity of light source
  - Statistical methods

\[
\left( \int \left| \frac{\partial^n (f(c))}{\partial x^n} \right|^m dx \right)^{\frac{1}{m}} = k(e^c)^{n,m,\sigma}
\]

using the Minkowski framework:

- **Gray-world** \((e^{0,1,0})\): The average reflectance is the illuminant color.
- **Max-RGB** \((e^{0,\infty,0})\): The maximum reflectance is the illuminant color.
- **Gray-edge** \((e^{1,m,\sigma})\): The average reflectance differences is the illuminant color.
- **Second-order gray-edge** \((e^{2,m,\sigma})\)

\[\text{Minkowski norm}\]
Color constancy algorithm mainly consists of two steps:

- Estimation of chromaticity of light source
  - Statistical methods
  - Physics-based methods

  - Using R. Tan et al. 2004, Inverse-Intensity Chromaticity (IIC) space for color constancy:
    1. Detection of possible specular regions
    2. Illuminant estimation in the detected regions.

Using the linear relation between chromaticity and inverse intensity in the image:

\[ \sigma_c = p \left( \frac{1}{\sum I_i} + \Gamma_c \right) \]

\[ p = m_b(\Lambda_c - \Gamma_c) \]
Computation Color Constancy

Color constancy algorithm mainly consist of two steps:

- **Estimation of chromaticity of light source**
  - Statistical methods
  - Physics-based methods
  - Gamut-mapping
  - Learning methods

- **Image color correction to canonical illumination**
  - von Kries model
  - Diagonal-offset model
  - ...

Multi-illuminant Color Constancy

Motivation:

- Single-illuminant color constancy methods are not capable of modeling the complexity of illumination in the real-world scenarios.
- The assumption of uniform illumination made by the single-illuminant methods is unrealistic.

Objective:

- The goal of Multi-illuminant Color Constancy is to provide accurate pixel-wise illuminant estimates.
Multi-illuminant Color Constancy

Multi-Illuminant Random Field (MIRF) method *:
Image is divided to patches using grid and illuminant is estimated locally.

- **Unary potentials:**
  - Statistical estimation
  - Physics-based estimation
- **Pair-wise potentials**

\[
E(\tilde{x}|\mathcal{F}) = \sum_{i \in \mathcal{V}} \phi(x_i|\mathcal{F}_i) + \theta_p \sum_{(i,j) \in \mathcal{E}} \psi((x_i, x_j)|(\mathcal{F}_i, \mathcal{F}_j))
\]

Multi-illuminant Color Constancy

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Multi-illuminant Color Constancy

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\]

Multi-illuminant Color Constancy

Multi-Illuminant Random Field (MIRF) method:
Image is divided to patches using grid and illuminant is estimated locally.

- **Unary potentials:**
  - **Error metric:**
    The “angular error” is the angle between any two color vectors \((i_1 \text{ and } i_2)\) in RGB space.

\[
\varphi(i_1, i_2) = \arccos \left( (i_1)^T i_2 \right)
\]

We use the angular error between the label and estimate to define the energy of a graph labeling.
Multi-illuminant Color Constancy

Multi-Illuminant Random Field (MIRF) method:
Image is divided to patches using grid and illuminant is estimated locally.

- **Unary potentials:**
  - **Statistical estimation**

  \[ f_j = (f_{R,j}, f_{G,j}, f_{B,j}) \] is the j-th pixel and \( P = \{p_1, p_2, \ldots, p_N\} \) are the patches then the local illuminant color for the \( i \)-th patch \( p_i \) using Minkowski norm is:

  \[
  i_{i,m}^{n,m} \approx m \left( \sum_{j \in p_i} \left| \frac{\partial^n f_{\sigma GW}^j}{\partial x^n} \right|^m \right)
  \]

  Therefore we can write the unary potential as:

  \[
  \varphi_s(x_i | F_i) = (w_i)^q \rho_{\sigma_T} \left( \varphi \left( i_i, x_i \right) \right)
  \]

  **Local estimate**
  **Patch label**
  **Error function**
Multi-illuminant Color Constancy

Multi-Illuminant Random Field (MIRF) method:
Image is divided to patches using grid and illuminant is estimated locally.

- **Unary potentials:**
  - **Physics-based estimation**
    Therefore:

    \[
    \phi^p(x_i \mid F_{i^p}) = w^{i^p} \rho_{\sigma_r}(\varphi(i_{i^p}, x_i))
    \]

    where the binary weighting \(w\) is defined using sum of the intensity for possible specular pixels (\(s_{sp}\)) and a threshold (\(t_{sp}\))

\[
w = \begin{cases} 
1 & \text{if } s_{sp} \geq t_{sp} \\
0 & \text{otherwise} 
\end{cases}
\]

Lehmann and Palm JOSA 2001
Multi-illuminant Color Constancy

Multi-Illuminant Random Field (MIRF) method:
Image is divided to patches using grid and illuminant is estimated locally.

- **Unary potentials:**
  - **Defining labels:**
    The labels are centers of the clustered formed by the patch-wise local illuminant estimates in RGB space.

To improve the performance highly saturated values are discarded:

Label set $L = \left\{ \forall i \left| \phi(l_i, i_w) < \phi_d \right\} \right.$

Each label

White light $i_w = \frac{1}{\sqrt{3}} (1,1,1)^T$

- Statistical estimates
- K-means
- Physics-based estimates
- Label-set
Multi-illuminant Color Constancy

Multi-Illuminant Random Field (MIRF) method:
Image is divided to patches using grid and illuminant is estimated locally.

Statistical estimates by Gray-word
Multi-illuminant Color Constancy

Multi-Illuminant Random Field (MIRF) method:
Image is divided to patches using grid and illuminant is estimated locally.

Statistical estimates by Gray-word

Results of the energy minimization
Multi-Illuminant Random Field (MIRF)

Experiment results:

- We compare our method with the single-illuminant and the method of Gijsenij et al.
- We use the median angular error over each set as our measure.

MIMO-Lab (58 images):

<table>
<thead>
<tr>
<th>Method</th>
<th>Single-light</th>
<th>Gijsenij et.al.</th>
<th>MIRF</th>
</tr>
</thead>
<tbody>
<tr>
<td>DN</td>
<td>10.5°</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>GW</td>
<td>2.9°</td>
<td>5.9°</td>
<td>2.8° (-3%)</td>
</tr>
<tr>
<td>WP</td>
<td>7.6°</td>
<td>4.2°</td>
<td>2.8° (-33%)</td>
</tr>
<tr>
<td>GE-1</td>
<td>2.8°</td>
<td>4.2°</td>
<td>2.6° (-7%)</td>
</tr>
<tr>
<td>GE-2</td>
<td>2.9°</td>
<td>5.7°</td>
<td>2.6° (-10%)</td>
</tr>
<tr>
<td>IEBV</td>
<td>8.3°</td>
<td>N/A</td>
<td>3.0° (-64%)</td>
</tr>
</tbody>
</table>
Multi-Illuminant Random Field (MIRF)

Experiment results:

- We compare our method with the single-illuminant and the method of Gijsenij et. al.
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Gijsenij-outdoor (9 images):

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<td>N/A</td>
</tr>
<tr>
<td>GW</td>
<td>13.8°</td>
<td>13.8°</td>
<td>10.1° (-27%)</td>
</tr>
<tr>
<td>WP</td>
<td>11.3°</td>
<td>8.4°</td>
<td>6.4° (-24%)</td>
</tr>
<tr>
<td>GE-1</td>
<td>10.1°</td>
<td>7.6°</td>
<td>4.7° (-38%)</td>
</tr>
<tr>
<td>GE-2</td>
<td>8.5°</td>
<td>7.4°</td>
<td>5.0° (-32%)</td>
</tr>
<tr>
<td>IEBV</td>
<td>7.3°</td>
<td>N/A</td>
<td>7.3°</td>
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## Multi-Illuminant Random Field (MIRF)

### Experiment results: Qualitative evaluation

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<tbody>
<tr>
<td><strong>White-balance</strong></td>
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<tr>
<td><strong>Single illuminant</strong></td>
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<tr>
<td><strong>Gijsenij White-balance</strong></td>
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</tbody>
</table>

- Original Image
- Ground-truth White-balance Image
- Single illuminant White-balance Image
- Gijsenij White-balance Image
- Our method’s White-balance Image

### Values

- Original: 3.1, 2.9, 10.6, 6.8
- Ground-truth: 2.0, 2.6, 6.6, 10.6
- Single illuminant: 2.7, 2.9, 6.6, 10.6
- Gijsenij: 2.7, 2.9, 6.6, 10.6
- Our method: 2.0, 2.6, 6.6, 10.6
Conclusions

- We proposed an intrinsic image estimation framework for single-colored objects in multi-illuminant scenarios (applied to object recoloring and color transfer).

- We created two multi-illuminant scene datasets:
  - Synthetic intrinsic image dataset: Computer graphics generated dataset for intrinsic estimation benchmarking in complex scenes.

- We proposed a CRF-based color constancy method for multi-illuminant scenes. State-of-the-art results are obtained on 3 datasets.
Thanks for your attention!
Publications


