Scene Illumination as an Indicator of Image Manipulation

June 28th, 2010

Christian Riess

Elli Angelopoulou

Pattern Recognition Lab (Computer Science 5)

University of Erlangen-Nuremberg

Subtopics in Image Forensics

- Verification of expected camera properties
  - Sensor noise
  - Lateral chromatic aberration
  - Bayer pattern

- Detection of output image artifacts
  - JPEG compression inconsistencies
  - Copy-move artifacts
  - Resampling artifacts

Images from [1].

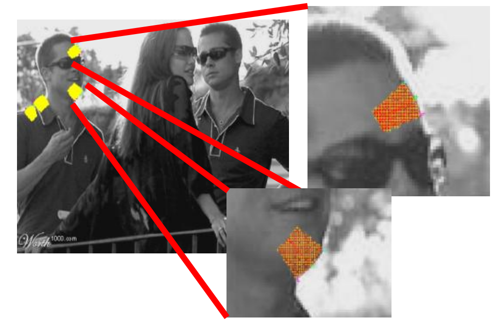
- Verification of scene properties
  - Lighting direction
  - Specularity distribution

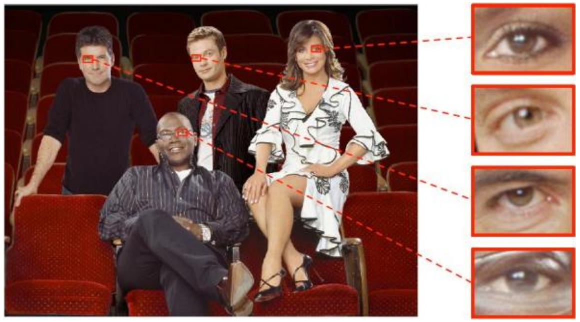
Images from [2].

[1] B. Mahdian and S. Saic: "Detection of Copy-Move Forgery using a Method Based on Blur Moment Invariants", Forens. Sc. Int. (2) 2007, pp. 180-189.

[2] M. Johnson and H. Farid: "Exposing Digital Forgeries in Complex Lighting Environments", Inf. Forens. and Sec. (2) 2007, pp. 450-461.

Related Work on Scene Analysis





- Johnson/Farid
  - Illumination direction of objects
  - Position of light sources from reflections in the eye
- Lalonde/Efros, Cao et al.: Color consistency

- Yu et al.: Specularities for recapturing detection

Scene Analysis in Image Forensics

Contest Submission Docma-Award © DOCMA 2009

Scene Illumination and Image Manipulation

In this work, we present a method for **locally** estimating the **color of the illuminant** from a single image, and apply these estimates in **image forensics**.

Prior Work on Color Constancy

- Color constancy: create an image, where the object representation is independent of the illumination color.
- Under some assumptions this is equivalent to estimating the illuminant color

- Well-known illuminant estimation / color constancy methods:
  - Gray world, maxRGB: baseline methods
  - Gamut mapping: machine learning
  - Gray edge-* methods: machine learning + constrained variants
  - Color by correlation: physics-based, hard constraints
  - Inverse-intensity chromaticity: physics-based + specularity segmentation

our starting point

Physics-based Reflectance Model

- Intensities: Sum of diffuse and specular components

$$I_c = m_d(\mathbf{x})\Lambda_c(\mathbf{x}) + m_s(\mathbf{x})\Gamma_c$$

$m_s(\mathbf{x})$	Specular geometry
$m_d(\mathbf{x})$	Diffuse geometry
$\Lambda_c(\mathbf{x}) = B_c(\mathbf{x}) / \sum_i B_i(\mathbf{x})$	Diffuse chromaticity
$\Gamma_c = G_c / \sum_i G_i$	Specular chromaticity
G_c, $B_c(\mathbf{x})$	Diffuse and specular camera response
$i \in \{R, G, B\}$	Color bands

Inverse-Intensity Chromaticity Space

- $I_c = m_d(\mathbf{x})\Lambda_c(\mathbf{x}) + m_s(\mathbf{x})\Gamma_c$ can be reformulated [1]:

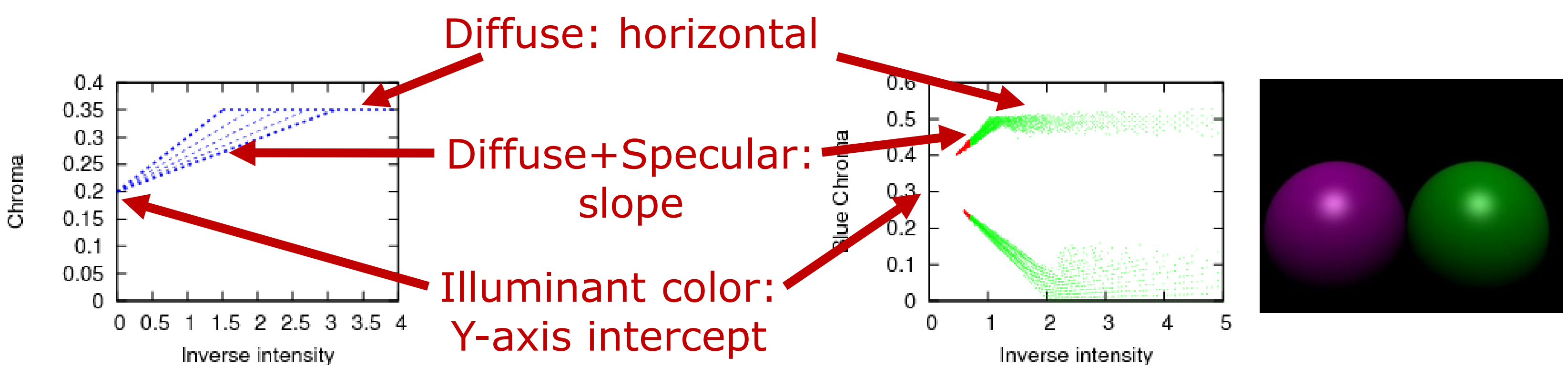
$$\sigma_c(\mathbf{x}) = p_c(\mathbf{x})\frac{1}{\sum_i I_i(\mathbf{x})} + \Gamma_c$$

$\sigma_c(\mathbf{x})$ Pixel chromaticity

$p_c(\mathbf{x})$ "mostly geometry"

$$y \quad = \quad m \quad \cdot \quad x \qquad + t$$

is a line equation with slope $p_c(\mathbf{x})$ and intercept Γ_c .

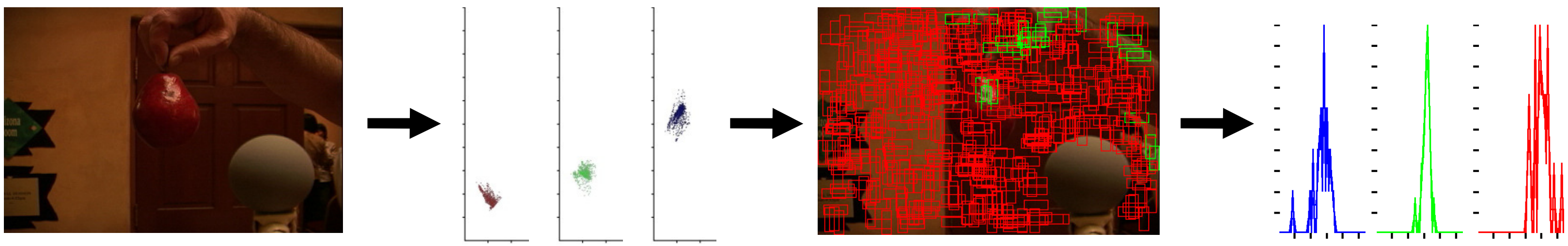


[1] R. Tan, K. Nishino, K. Ikeuchi: Color Constancy through Inverse-Intensity Chromaticity Space. Journal of the Optical Society of America A. 21(2004) 321-334.

Illuminant Estimation – Our Version

- This can be extended to real-world images [1]
  - Draw local samples
  - Project them in IIC-space
  - Discard samples that fail some consistency checks
  - Let the rest vote for an illuminant

Ensure minimum slope & elongation



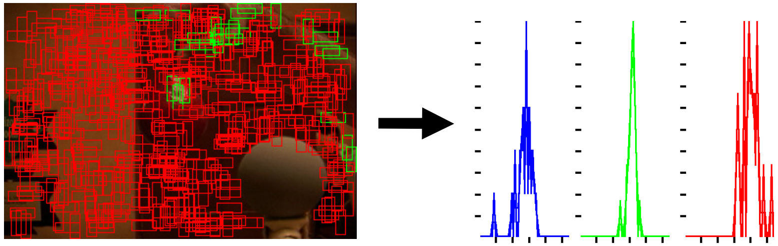
- Best-performing physics-based method on Ciurea/Funt benchmark database [2].

[1] C. Riess, E. Eibenberger, E. Angelopoulou: Illuminant Estimation by Voting, Technical Report, 2009.
[2] F. Ciurea, B. Funt: A Large Image Database for Color Constancy Research. Color Imaging Conference. (2003) 160-164.

Illuminant Estimation – Our Version

- This can be extended to real-world images [1]
  - Draw local samples
  - Project them in IIC-space
  - Discard samples that fail some consistency checks
  - Let the rest vote for an illuminant

Ensure minimum slope & elongation



ethod on Ciurea/Funt

stimation by Voting, Technical Report, 2009.
onstancy Research. Color Imaging Conference.

ulation

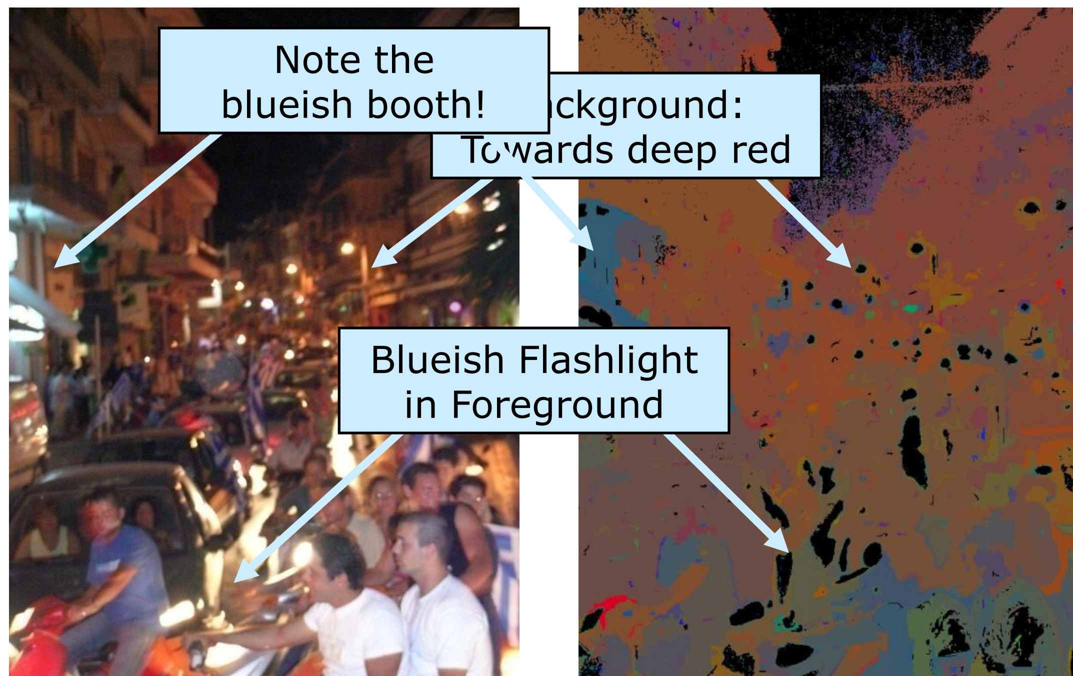
Underlying Assumptions

- Dielectric surfaces: Non-metallic, non-fluorescent, …
- Neutral interface assumption (NIA): Color if specularities equals color of the illuminant
- Linear camera response, i.e. compensate gamma
- Objects
  - Curved
  - Directly lit
  - Not fully diffuse

Local Patches: Evident Consequence

- Perform the voting on parts of the image
  - This leads to a what we call „Illuminant Map“ of the scene
  - Influences of multiple illuminants depend on the scene geometry

  - Handling of multiple illuminants is a barely explored research problem (see e.g. [1])



[1] E. Hsu, T. Mertens, S. Paris, S. Avidan, F. Durand: Light Mixture Estimation for Spatially Varying White Balance. ACM Transactions on Graphics 27 (2008) 70:1-70-7

Illumination Color: Indicator of Manipulation

- Proposed method
  - Estimate illuminant colors locally
  - Create the **illuminant map**
  - Let user select a region with estimates of the dominant illuminants
  - Create a grayscale image where the shading of the pixels is

$$I_d(\mathbf{x}) = (\Gamma_I(\mathbf{x}) - I_1) \circ (I_2 - I_1))$$

    i.e. the „membership" to an illuminant
  - Call this output **distance map**

$\Gamma_I(\mathbf{x})$ Local estimate

I_1 Est. Dom. Illum 1

I_2 Est. Dom. Illum 2

Image

Illuminant map

Distance map

Ground Truth Results Illuminant Estimation

- Competitive results on two standard ground-truth datasets [1,2]

- Error measure:
  - Angular error

$$e = \cos^{-1}\left(\frac{\Gamma_l \cdot \Gamma_e}{\|\Gamma_l\| \|\Gamma_e\|}\right)$$

  - median over test set

Method	Median e
Gamut mapping	**3.1°**
Gray-World	8.8°
White-patch	5.0°
Color-by-Corr.	8.6°
Proposed method	4.4°

[1]

Method	Median e
Gamut with offset-model	5.7°
Gray-World	7.0°
White-Patch	6.7°
Color-by-Correlation	6.5°
1st-order Gray-Edge	5.2°
2nd –order Gray-Edge	5.4°
Tan et al.	5.6°
Proposed method	**4.4°**

[2]

[1] K. Barnard, L. Martin, B. Funt and A. Coath: A dataset for Color Research. Color Research and Application (3) 2002, pp. 147-151.
[2] F. Ciurea, B. Funt: A Large Image Database for Color Constancy Research. Color Imaging Conference 2003, pp. 160-164.

Why a Physics-based Method?

- Illuminant color estimation from a single image is **underconstrained**
- Therefore, every method **fails** under certain conditions
- Machine-learning caused failures are sometimes counter-intuitive

- Using a physics-based model increases the chances that an educated user can **explain the failures**

An Introductory Example

Christian Riess

A Complex Example

Another Example

Conclusions

- The goal of our work is to perform **forensics analysis** on top of the **physics** of the shown scene.

- We presented a method for estimating the **illuminant color** locally.
- This information can be exploited for assessing the **illumination consistency**.

- Future work: a **metric** for the inconsistency of illumination

- Source Code at http://www5.informatik.uni-erlangen.de/code