Computational Photography and Video:

Intrinsic Images

Prof. Marc Pollefeys
Dr. Gabriel Brostow
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Example Problem:
Background Normalization

Sonnet for Lena

O dear Lena, your beauty is so vast
It is hard sometimes to describe it fast.
I thought the entire world I would impress
If only your portrait I could compress.
Alas! First when I tried to use VQ
I found that your cheeks belong to only you.
Your silky hair contains a thousand lines
Hard to match with sums of discrete cosines.
And for your lips, sensual and tactual
Thirteen Crays found not the proper fractal.
And while these setbacks are all quite severe
I might have fixed them with hacks here or there
But when filters took sparkle from your eyes
I said, ‘Damn all this. I’ll just digitize.’

Thomas Colthurst
When taking a picture, what color is a (Lambertian) surface?
Region lit by skylight only

Region lit by sunlight and skylight
What great things could we do if we could easily find shadows?
An Intrinsic Image

• What effect is the lighting having, irrespective of surface materials?

• What is the surface reflectance, irrespective of lighting?
Pursuit of Intrinsic Images (1)

- Lightness and Retinex Theory
  - Land & McCann ’71

- Recovering Intrinsic Scene Characteristics From Images
  - Barrow & Tenenbaum ‘78
Pursuit of Intrinsic Images (2)

• Painted Polyhedra - ICCV’93

• Image Sequences - ICCV’01

• Single Image - NIPS’03

• Entropy Minimization - ECCV’04
Pursuit of Intrinsic Images (2)

- Painted Polyhedra - ICCV’93  (Generative)
- Image Sequences - ICCV’01  (Discriminative)
- Single Image - NIPS’03  (Discriminative)
- Entropy Minimization - ECCV’04  (Generative)
Painted Polyhedra

- Recovering Reflectance and Illumination in a World of Painted Polyhedra
  - Sinha & Adelson, ICCV’93
Not All Edges are Equal
Local Edges are a Hint?

Zig-zag

Stairs and Stripes
Edge Junctions are Useful

(a)

(b)
Junction Catalog

‘Y’, ‘arrow,’ and ‘psi’ junctions

‘T’ junctions
Examples

Reflectance edges

Illumination edges
Examples

Reflectance edges  Illumination edges
Examples

Reflectance edges

Illumination edges
Examples

Reflectance edges

Illumination edges
Examples
Junction Analysis of the ‘Impossible’ Object
Counter-Example

(a) 

(b)
Consistency Check
Global Measures of ‘Correctness’

• Low variance of angles

• Planarity of faces

• Overall compactness

• Consistency with light source
Global Measures of ‘Correctness’

• Low variance of angles

• Planarity of faces

• Overall compactness

• Consistency with light source
Possibility of Consistent Lighting
Global Analysis
Confirms Local Analysis
Global Analysis

Trumps Local Analysis

(a)  

(b)

(c)

(d)
Image Sequences

- Deriving Intrinsic Images from Image Sequences
  - Weiss ICCV’01

- For static objects, **multiple frames**
Problem Formulation

Given a sequence of T images \( \{I(x,y,t)\}_{t=1}^{T} \) in which reflectance is constant over time and only the illumination changes, can we solve for a single reflectance image and T Illumination images \( \{L(x,y,t)\}_{t=1}^{T} \)?

\[ I(x,y) = L(x,y)R(x,y) \]

\[ \{I(x,y,t)\}_{t=1}^{T} = \{L(x,y,t)\}_{t=1}^{T}R(x,y) \]

Still completely ill-posed: at every pixel there are T equations and T+1 unknowns.
• Prior based on intuition:
  – derivative-like filter outputs of $L$ tend to be sparse

\[
\begin{align*}
\{I(x,y,t)\}_{t=1}^T &= \{L(x,y,t)\}_{t=1}^T R(x,y) \\
\text{(move to log-space)}
\end{align*}
\]

\[
i(x,y,t) = r(x,y) + l(x,y,t)
\]

\[
o_n(x,y,t) = i(x,y,t) * f_n
\]

\[
f_n = \text{one of } N \text{ filters like } 1 \begin{bmatrix} 1 & -1 \end{bmatrix}
\]
\\hat{r}_n = \text{median}_t(o_n(x, y, t))

\[ o_n(x, y, t) = i(x, y, t) * f_n \]

- Variety of responses has Laplacian-shaped distribution
Toy Example

frame 1

horiz filter

vertical filter

frame 2

horiz filter

vertical filter

frame 3

horiz filter

vertical filter

reflectance image

median horiz

median vertical
Example Result 1

- Einstein image is translated diagonally
  4 pixels per frame
Example Result 2

- 64 images with variable lighting from Yale Face Database
III
Single Image

- Recovering Intrinsic Images from a Single Image
  - Tappen, Freeman, Adelson
  - NIPS’03 & PAMI’05
Assumption

• Each derivative is caused either by Shading or Reflectance
• Reduces to a binary classification problem
Classifying Derivatives

- 4 Basic phases:
  1. Compute image derivatives
  2. Classify each derivative as caused by shading or reflectance
  3. Invert derivatives classified as shading to find shading images
  4. Reflectance image is found the same way
Classification

1. Color information
   - changes due to shading should affect R,G and B proportionally
     \[ C_1 = \alpha \cdot C_2 \]

   If \( C_1 \neq \alpha \cdot C_2 \) the changes are caused by reflectance
Color Information - examples

Black on white may be interpreted as intensity change.

Resulting in misclassification
Classification

1. Color information
   - changes due to shading should affect R, G and B proportionally
     \[ C_1 = \alpha \cdot C_2 \]

   If \( C_1 \neq \alpha \cdot C_2 \) the changes are caused by reflectance.
Classification

1. Color information
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   \[ C_1 = \alpha \cdot C_2 \]

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2. Statistical regularities of surfaces
GrayScale Information - examples

Misclassification of the cheeks – due to weak gradients
Combing Information (Assuming Statistical Indep.)
Handling Ambiguities

- Ambiguities - for example – center of the mouth

Shading example  Input image  Reflectance example
Handling Ambiguities

- Derivatives that lie on the same contour should have the same classification.

- The mouth corners are well classified as reflectance.

→ Propagate evidence from conclusive areas to ambiguous ones using MRF.
Final Results

[Diagram showing two images: one with a happy face and another with a sad face.]

Unpropagated
Final Results
Final Results
Final Results
Entropy Minimization

• Intrinsic Images by Entropy Minimization
  – Finlayson, Drew, Lu, ECCV’04
Sensor Response at a Pixel

\[ p_k = \int \lambda R(\lambda) L(\lambda) S_k(\lambda) d\lambda \]

**R** = Reflectance

**L** = Illumination

**S** = Sensor Sensitivity
Best When Sensors are Narrow Band
Best When Sensors are Narrow Band

\[ S_k(\lambda) = \delta(\lambda - \lambda_k) \]

\[ k \in \{R, G, B\} \]
Just Reflectance & Illumination

\[ p_k = \int_{\lambda} R(\lambda) L(\lambda) S_k(\lambda) d\lambda \]

\[ p_k = \int_{\lambda} R(\lambda) L(\lambda) \delta(\lambda - \lambda_k) d\lambda \]

\[ p_k = R(\lambda_k) L(\lambda_k) \]
Chromaticity for 7 Surfaces for 10 Illuminants
Macbeth Chart Under Changing Illumination
Entropy Minimization

Correct Projection

Incorrect Projection
More “spread-out” distribution would produce a larger entropy, hence the projection direction that produces the minimum entropy is the correct projection direction.
Sweep Angle of Projection
Limitations of Shadow Removal

- Only Hard shadows can be removed
- No overlapping of object and shadow boundaries
- Planckian light sources
- Narrow band cameras are idealized
- Reconstruction methods are texture-dumb
Discussion...
Assumptions for Both Entropy Min. & Image Seq.

• Each edge can be a shadow border OR a change in the reflectance image

• Remove the shadow edges and get the reflectance image
  – Both algorithms use the same reconstruction method

• In real life there are soft shadow and vague shadow edges.
  – In many cases there will be mixed edges so the separation cannot be easily done

• The second algorithm is more sensitive because it has less redundancy (one image only!)
Modern Intrinsic Images Refs

- Recovering Reflectance and Illumination in a World of Painted Polyhedra
  - Sinha & Adelson ICCV’93
- Deriving Intrinsic Images from Image Sequences
  - Weiss ICCV’01
- Recovering Intrinsic Images from a Single Image
  - Tappen, Freeman, Adelson NIPS’03
- Intrinsic Images by Entropy Minimization
  - Finlayson, Drew, Lu, ECCV’04
Planck’s Law defines the energy emission rate of a blackbody illuminator, in unit of \textit{watts per square meter per wavelength interval}, as a function of wavelength $\lambda$ (in meters) and temperature $T$ (in degrees Kelvin).

$$P_r(\lambda) = c_1 \lambda^{-5} \left( \frac{c_2}{e^{\lambda T}} - 1 \right)^{-1}$$

Where $c_1 = 3.74183 \times 10^{-16} \text{Wm}^2$ and $c_1 = 1.4388 \times 10^{-2} \text{mK}$ are constants.

**Spectral power:**

$$E(\lambda) = I \times P_r = I c_1 \lambda^{-5} \left( \frac{c_2}{e^{\lambda T}} - 1 \right)^{-1} \approx I c_1 \lambda^{-5} e^{-\frac{c_2}{\lambda T}}; \quad I \text{ is the illumination intensity}$$
Calibration results

Nikon CoolPix 995

Nikon D-100