Recovering Intrinsic Images with a Global Sparsity Prior on Reflectance

By: Gehler, Rother, Kiefel, Zhang and Scholkopf

Niels Backer   Iris Verweij

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Recovering Intrinsic Images

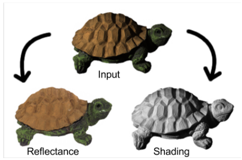

Figure 1: Separation of the input image into its material-dependent (reflectance, left hand side) and light-dependent properties (shading, on the right hand side).

Simplified Formula

$$I = s \cdot R$$

$I \in \mathcal{R}^3$, $R \in \mathcal{R}^3$, $s \in \mathcal{R}$

Each image pixel is the product of two components, scalar s represents shading and vector $\mathcal{R}$ for reflectance.

Probabilistic model for Estimation

3 Factors

1. Retinex-based method for reflectance
2. Smoothness prior on shading
3. Global sparsity prior on reflectance

Global Sparsity prior on Reflectance

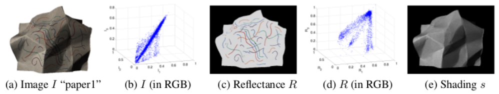

Figure 2: Global sparsity prior on Reflectance based on the properties shown in this figure. An image often contains only a few different basis colorlines (d). Assume basis colors as a mixture of Gaussians.

Outline

Lightness and Retinex theory

1971

Authors

Edwin H. Land, John J. McCann

Summary

- Seminal work on intrinsic image decomposition
- Theory based on biological cone receptors to separate reflectance from illumination (flux)
- Basic assumption: small image gradients more likely to be caused by shading, strong gradients by change in reflectance
- Later extended to 2D, color Retinex

Ground truth dataset and baseline evaluations for intrinsic image algorithms

2009

Authors

Roger Grosse, Micah K. Johnson, Edward H. Adelson, William T. Freeman

Summary

- Comparison paper on intrinsic image decomposition
- Provides a ground-truth data set (16 images) and evaluation standard
- Main difference between algorithms lies in estimation of log reflectance derivatives

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Intrinsic Image Decomposition with Non-Local Texture Cues

2008

Authors

Li Shen, Ping Tan, Stephen Lin

Summary

- Examine texture information to obtain non-local restraints on reflectance
- Extends Retinex algorithm with texture constraints to local derivative analysis
- Same intuition (sparse set of reflectances in scene), but different image representation (wavelet transform vs. RGB)

Intrinsic Images Decomposition Using a Local and Global Sparse Representation of Reflectance

2011

Authors

Li Shen, Chuohao Yeo

Summary

- Extends Retinex by clustering into super-pixels
- Neighbouring pixels usually have same reflectance if chromacity is similar
- Results in sparse representation of reflectance components
- Uses wavelets instead of RGB, and no joint probability model

Conditional Probability Distribution

Conditional Random Fields

$$p(\mathbf{s}, R|I) \propto exp(-E(\mathbf{s}, R|I))$$

Complexity Reduction

Assume delta-prior:

$$I_i^c = s_i R_i^c \text{ thus: } R_i = r_i \cdot \overrightarrow{R}_i$$
$$\text{with: } \overrightarrow{R}_i = I_i/||I_i|| \text{ and } s_i = ||I_i||/r_i$$

Model: MAP Energy Function

$$\min_{r_i, \alpha_i; i=1,\dots n} w_s E_s(\mathbf{r}) + w_s E_{ret}(\mathbf{r}) + w_{cl} E_{cl}(\mathbf{r}, \alpha)$$

Model: Shading Prior

$$E_s(r) = \sum_{i \sim j} (r_i^{-1}||I_i|| - r_j^{-1}||I_j||)^2$$

- Assume: Shading varies smoothly over image
- 4-connected pixel graph $\rightarrow$ neighbourhood relation
- Potential problem of multiple local minima: use restarts

Model: Gradient Consistency

Retinex based

"Disambiguate between edges that are due to shading variations from those that are caused by material reflectance changes"

$$E_{ret}(\mathbf{r}) = \sum_{i \sim j} (\log(r_i) - \log(r_j) - g_{ij}(I)(\log(||I_i||) - \log(||I_j||)))^2$$

Classification function $g(I)$

- θ_g : threshold for gradient of the intensity image
- θ_c : threshold for gradient of the chromaticity change
- $g_{ij}(I) = 1 \rightarrow$ "reflectance edge"

Model: Global Sparse Reflectance Prior (GSRP)

"...include a term that acts as a global potential on reflectance and favors decomposition into clusters..."

$$E_{cl}(\mathbf{r}, \alpha) = \sum_{i=1}^{n} ||r_i \overrightarrow{R}_i - \tilde{R}_{\alpha_i}||^2$$

Global potential

- C different reflectance clusters, $\tilde{R}_c, c \in \{1, ..., C\}$
- r_i has cluster membership: $\alpha_i \in \{1, ..., C\}$
- Cluster means depend on assignment of all pixels in image

Model: Shading and GSRP

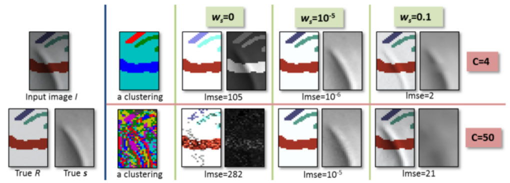

Figure 3: True decomposition is shown on the left hand side, the columns show the results for various settings for smoothness prior (E_s) and clusters regarding the Global Sparse Reflectance Prior (E_{cl})

Model: Optimization

Coordinate Descent

- Initialization of r
  Output has a fix range ($0 \geq R_i^c, s_i \geq 1$ for all c, i)
- Initialization of α
  Use initialization of r with K-means clustering. Use best from 5 restarts.
- updating r
- updating α

Experiments

Data and Error metric

- 16 images with ground truth information
- Evaluated using Local Mean Squared Error (LMSE) and average rank

Parameter estimation

- 5 free parameters: $w_{cl}, w_s, w_r, \theta_c, \theta_g$
- Leave-One-Out estimate (LOO-CV) using median error
- Both global optimal and image-optimal settings evaluated

Results

Comparing component influences

comment	E_s	E_{cl}	E_{ret}	LOO-CV	best single	image opt.
Color Retinex	-	-	✓	29.5	29.5	25.5
no edge information	✓	✓	-	30.0	30.6	18.2
Col-Ret+ global term	-	✓	✓	27.2	24.4	18.1
full model	✓	✓	✓	27.4	24.4	16.1

Figure 4: LMSE results of different component combinations

Results
Compared to other methods

	LOO-CV	rank	best single	im. opt.
TAP05 [17]	56*	-	-	-
TAP06 [16]	39*	-	-	-
SHE [14]$^{+}$	n/a	n/a	56.2	n/a
SHE [15]$^{\times}$	n/a	n/a	(20.4)	-
BAS [7]	72.6	5.1	60.3	36.6
Gray-Ret [7]	40.7	4.9	40.7	28.9
Col-Ret	29.5	3.7	29.5	25.5
full model	27.4	3.0	24.4	16.1
Weiss [19]	21.5	2.7	21.5	21.5
Weiss+Ret [7]	16.4	1.7	16.4	15.0

Result Visualization
Input

Input; Turtle

Ground truth

Result Visualization
Output

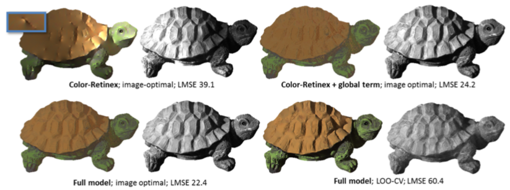

Figure 5: Various results for different methods and parameter settings

Result Visualization
Input

Figure 6: Another input example

Result Visualization
Output

Figure 7: Results of the teabag image

Follow up Research

By Authors

- Intrinsic Video (Kong, Black and Gehler)(2014)
- Reflectance Adaptive Filtering Improves Intrinsic Image Estimation (Nestmeyer & Gehler)(2016)

Cited

- Papers which focus on perfecting the priors
- Papers which enhance the current technique with multiple view points

Summary

Conclusion

- Main Contribution: Global Sparsity Prior on Reflectance
- The combination of the 3 priors yields good and accurate results
- Adjusting parameter settings to dataset

Summary

Discussion

- Small Dataset
- Experiments with real-world images is missing
- Little information on parameter settings

Questions?