# Recovering Intrinsic Images with a Global Sparsity Prior on Reflectance

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# Recovering Intrinsic Images

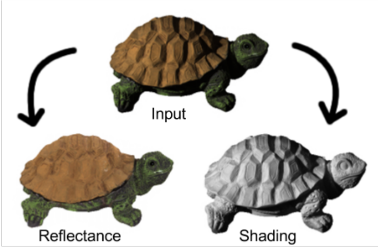



**Figure 1:** Separation of the input image into its material-dependent (reflectance, left hand side) and light-dependent properties (shading, on the right hand side).

## 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

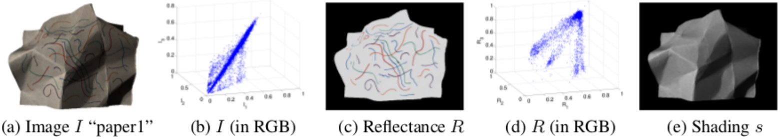



**Figure 2:** Global sparsity prior on Reflectance based on the properties shown in this figure. An image often contains only a few different basis colorlines (d). Assume basis colors as a mixture of Gaussians.

# 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

# 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

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

# 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 $g(I)$

- $\theta_g$ : threshold for gradient of the intensity image
- $\theta_c$ : 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

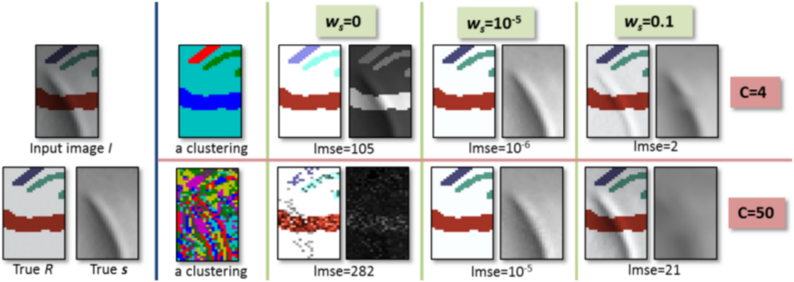



**Figure 3:** True decomposition is shown on the left hand side, the columns show the results for various settings for smoothness prior ($E_s$) and clusters regarding the Global Sparse Reflectance Prior ($E_{cl}$)

# 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 $\alpha$
  Use initialization of $r$ with K-means clustering. Use best from 5 restarts.
- updating r
- updating $\alpha$

# 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

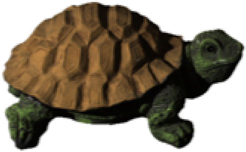
# Results

## 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

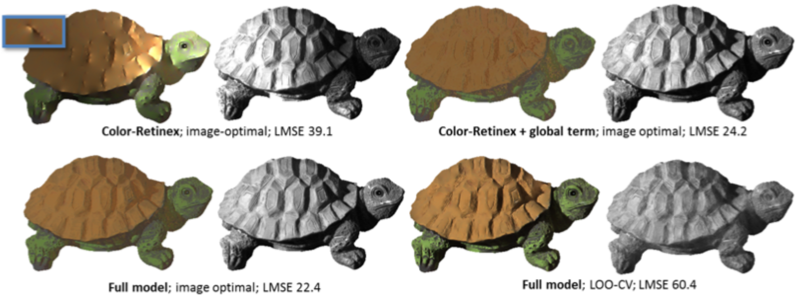



**Figure 5:** Various results for different methods and parameter settings

# 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?