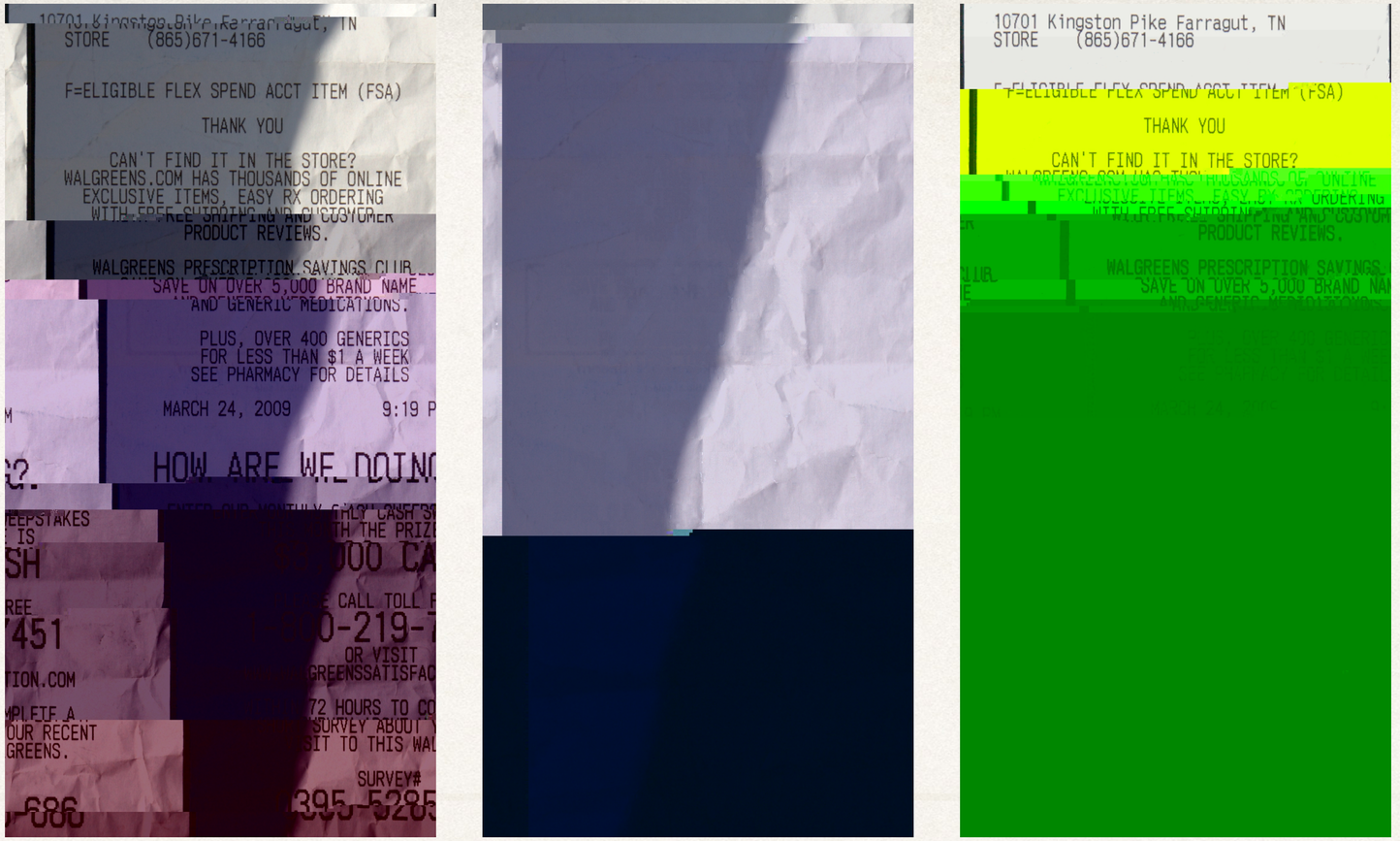


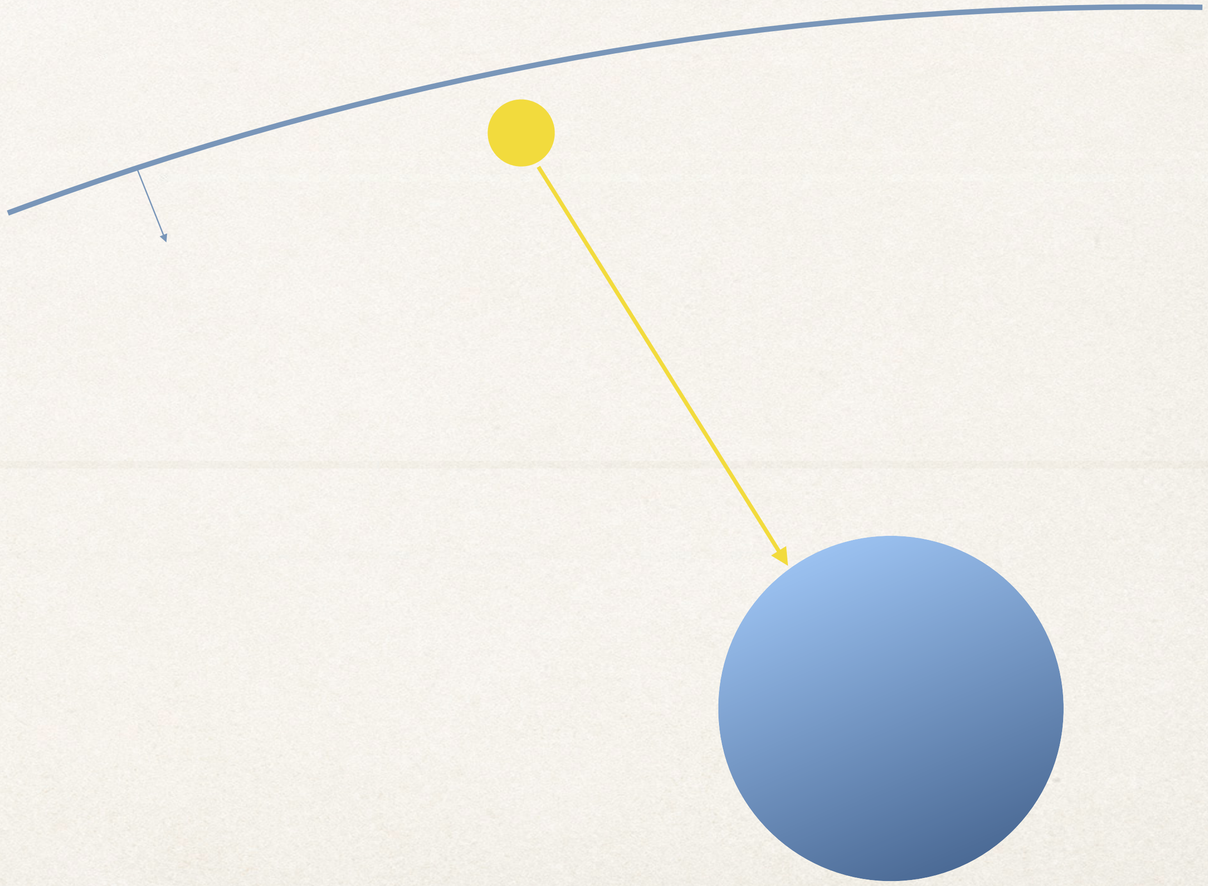

# Intrinsic Imaging: What have we learned?

*Bruce A. Maxwell*

Colby College, Tandent Vision Science

# What is an Image?

- Light
- Surfaces
- Geometry
- Reflected light
- Sensor



# Intrinsic Images

- Barrow and Tenenbaum 1976: intrinsic images make computer vision easier
- Intrinsic images are the components that create the reflected light




Original



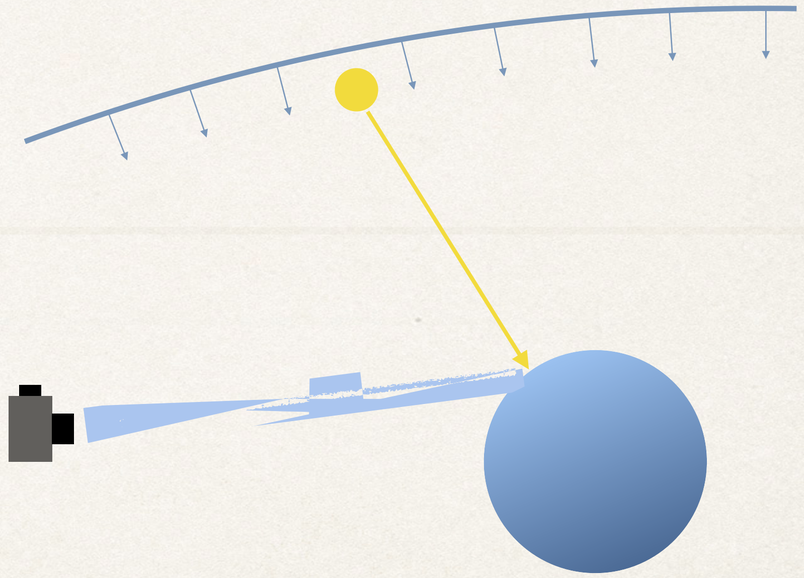
Illumination




Reflectance

# Bi-Illuminant Dichromatic Reflection Model

- BIDR model: two illuminants
- $R_b(L_a + L_d g_b)$ is a line in RGB space
  - Doesn't point at the origin
  - Each line has a different orientation
- Consider the log of the body reflection



# Log Space Chromaticity

- Illumination Spectral Direction defines the log space chromaticity plane
- Any lit-dark pair tells you the ISD

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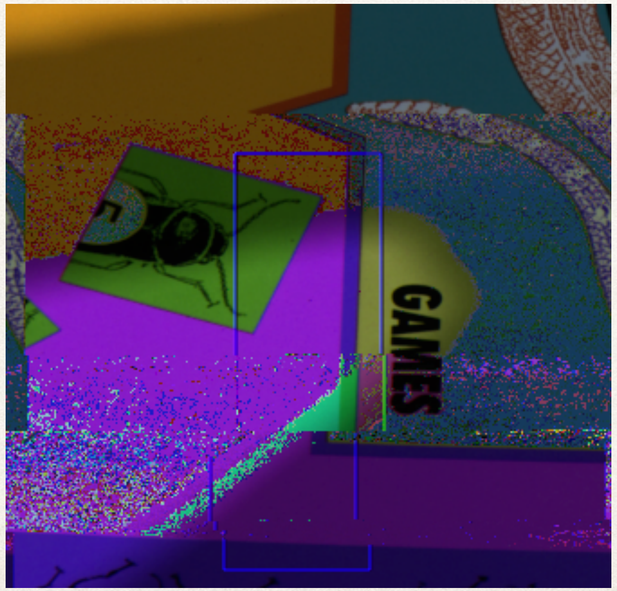

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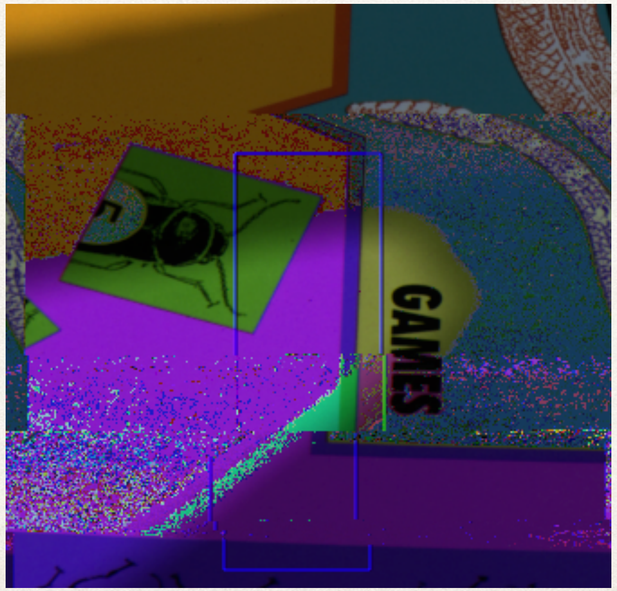


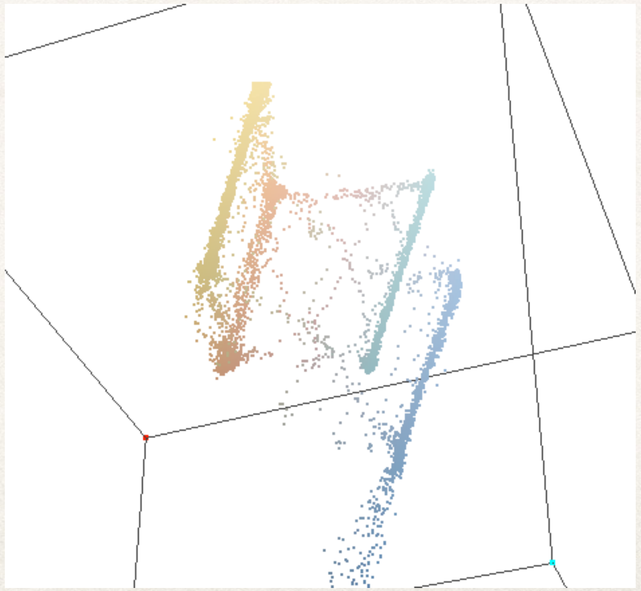

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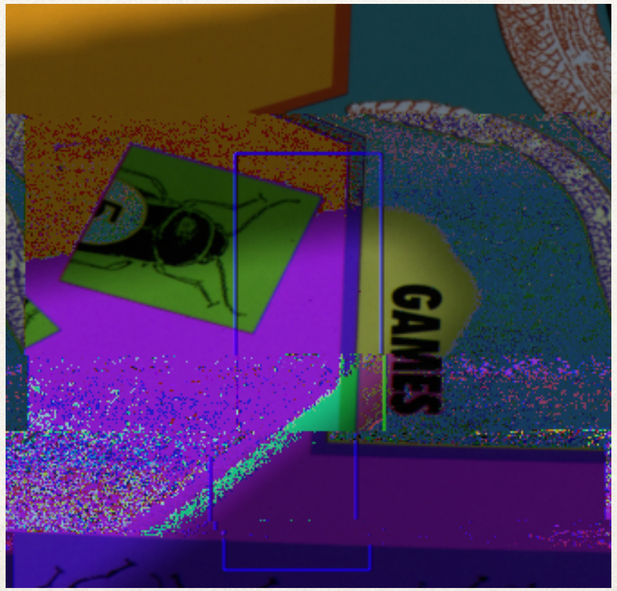


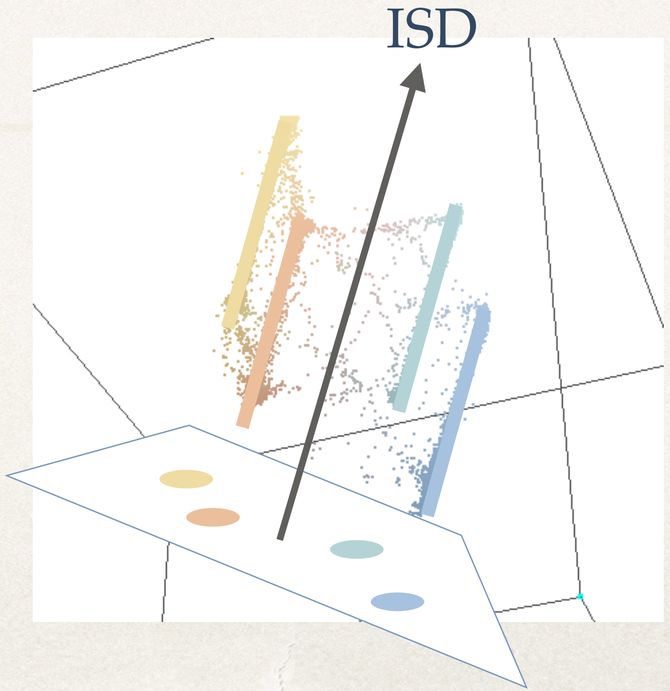

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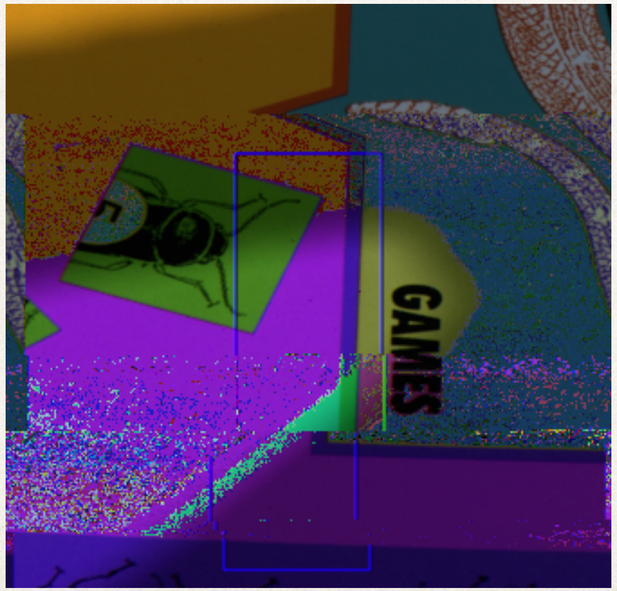
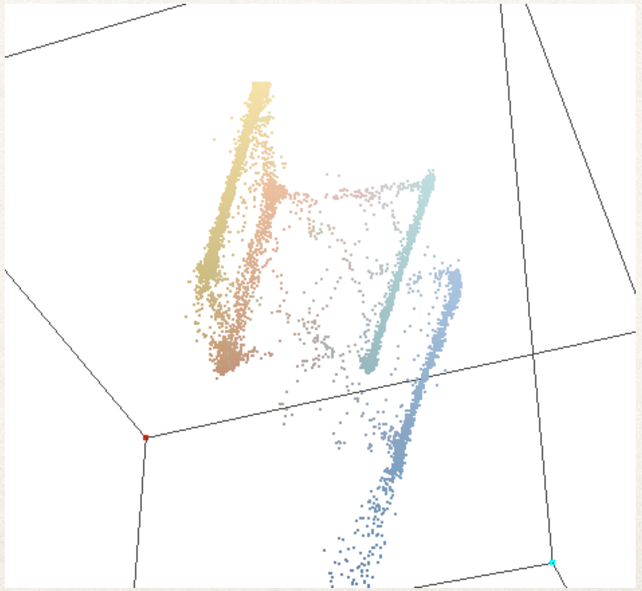
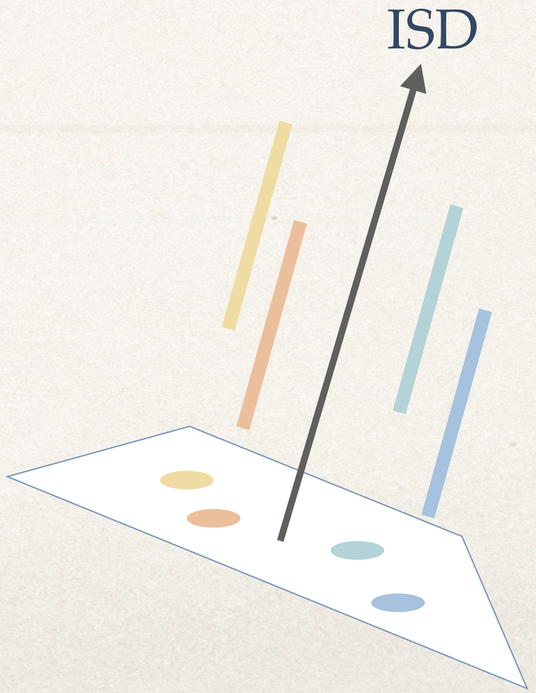




# Chromaticity v. Log Chromaticity

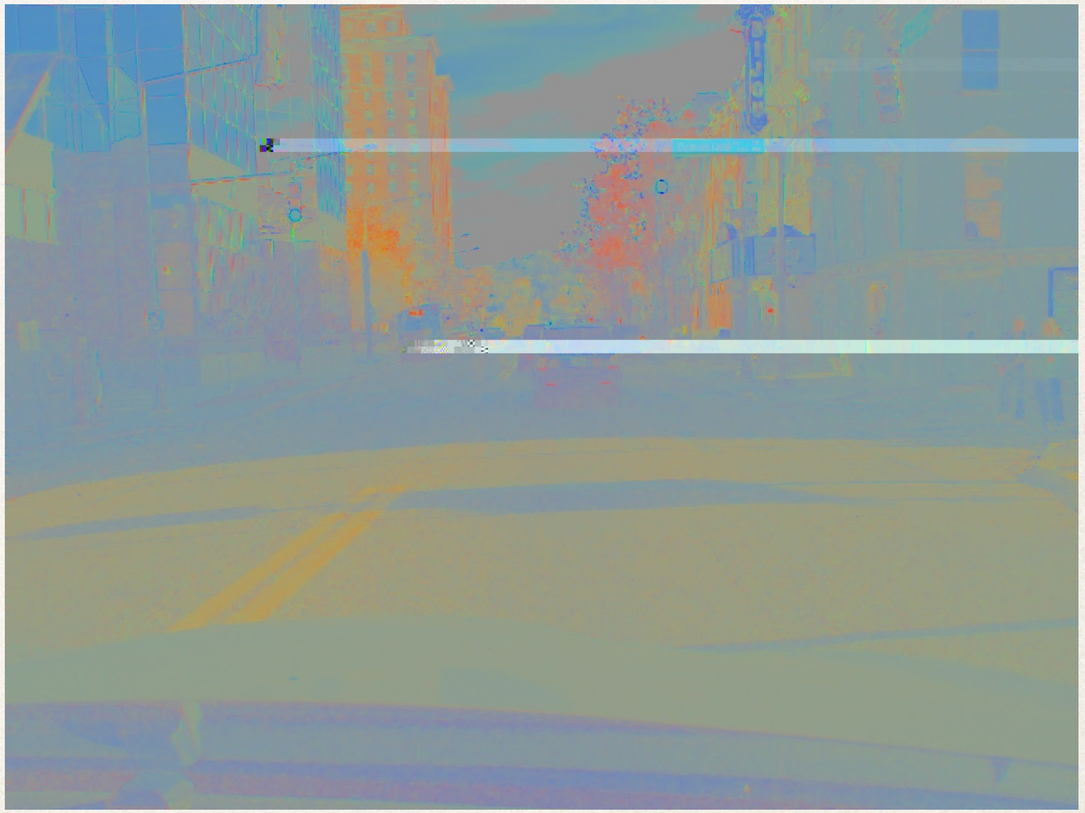



Original

# Chromaticity v. Log Chromaticity

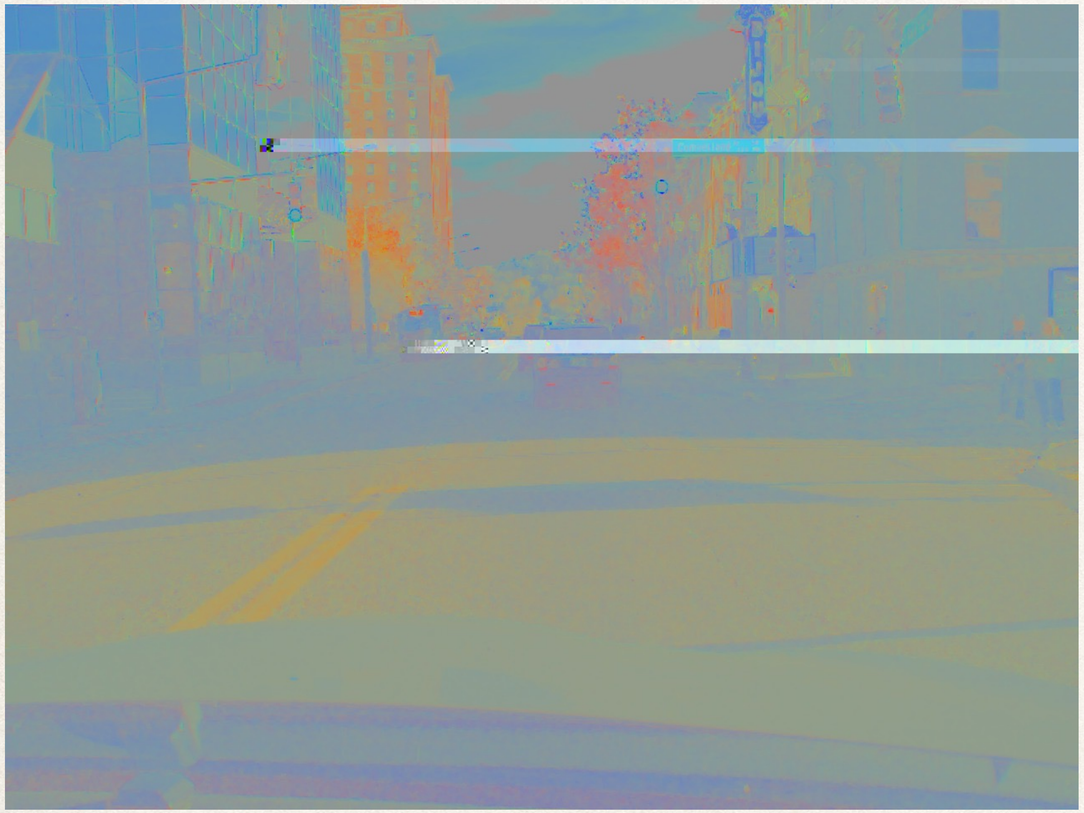



Original

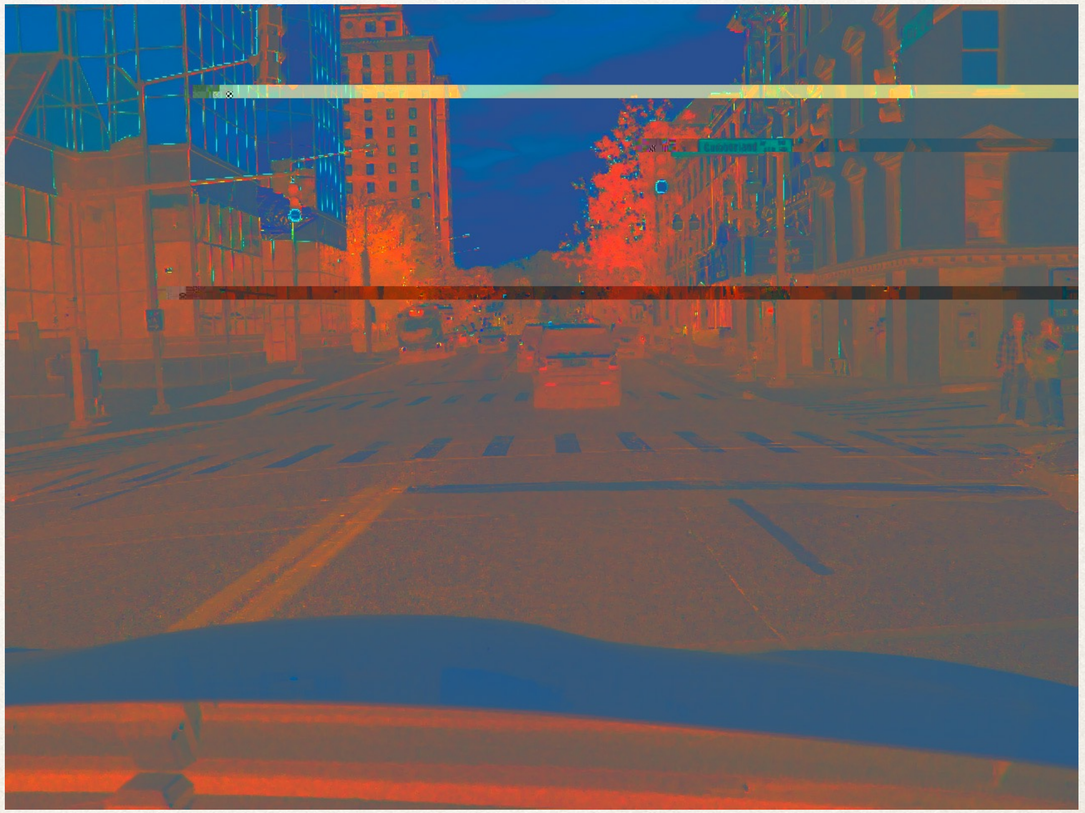


Standard Chromaticity

# Chromaticity v. Log Chromaticity



Standard Chromaticity



Log Chromaticity

# Symbolic Intrinsic Imaging

- **Phase 1: Classify image gradients and re-integrate the image**
- Land and McCann, Lightness and Retinex Theory, JOSA 1971
  - *Shafer, Using Color to Separate Reflection Components, CRA 1985*
  - *Klinker, Shafer, Kanade, A Physical Approach to Color Image Understanding, IJCV 1990*
- Weiss, Deriving intrinsic images from image sequences, ICCV 2001
- Tappen, Adelson, Freeman, Recovering Intrinsic Images from a Single Image, NeuroIPS 2002
- Finlayson, Drew, and Lu, Intrinsic Images by Entropy Minimization, ECCV 2004
- Chung et. al, Intrinsic Image Extraction from a Single Image, JISE 2009

# Symbolic Intrinsic Imaging

- **Phase 2: link pixels of the same material, assume smooth illumination, and solve a big linear system of equations**
- Bousseau, Paris, and Durand, User-assisted Intrinsic Images, SIGGRAPH 2009 (sort of)
- Tandent Vision Science, Lightbrush, demos at SIGGRAPH 2011, 2012
- Garces et. al., Intrinsic Images by Clustering, CGF 2012
- Zhao et. al., A Closed-Form Solution to Retinex with Non-local Texture Constraints, PAMI 2015

# Symbolic Intrinsic Imaging

- **Phase 3: apply lots of priors and execute a non-linear optimization**
- Gehler et. al, Recovering Intrinsic Images with a Global Sparsity Prior on Reflectance, NeuroIPS 2011
- Bell, Bala, and Snavely, Intrinsic Images in the Wild, SIGGRAPH 2014
- Chang et. al., Bayesian Nonparametric Intrinsic Image Decomposition, ECCV 2014
- Barron and Malik, Shape, Illumination, and Reflectance from Shading, PAMI 2015
- Meka et. al, Live Intrinsic Video, SIGGRAPH 2016

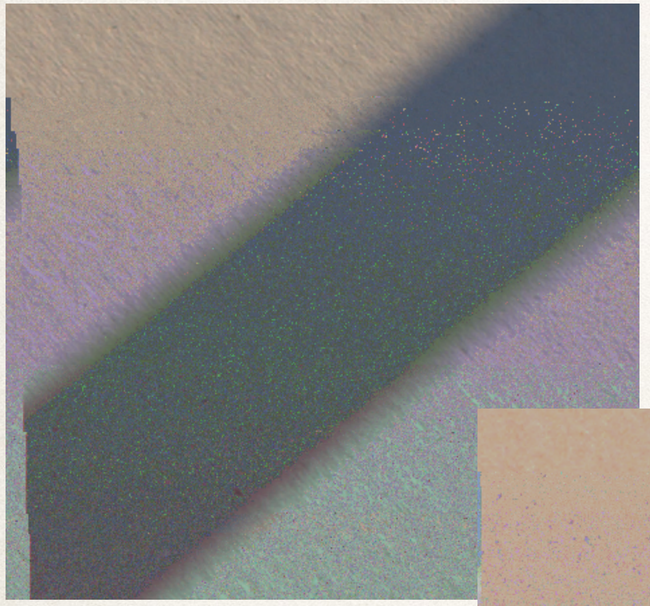
# Five guidelines for intrinsic imaging

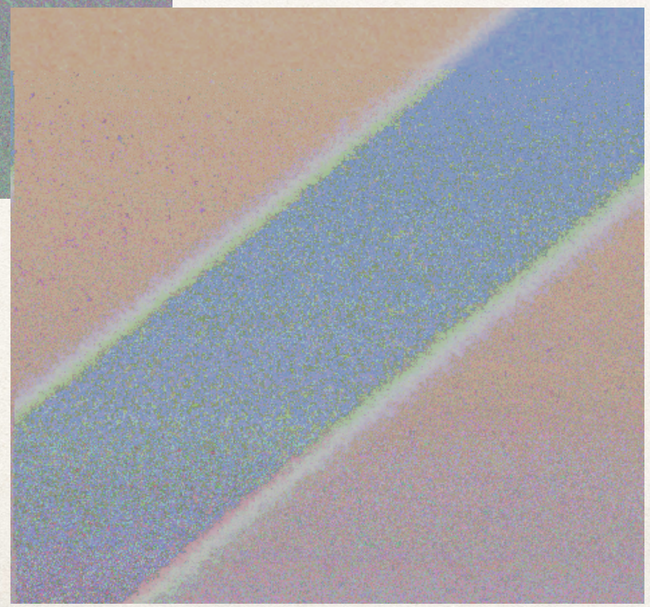
1. Illumination is colored; there are two primary colors
2. Reflectance is a simpler signal to estimate
3. Something has to link across strong, small, and sharp illumination boundaries
4. Solving linear equations is pretty fast and works for large images
5. A perfect segmentation by material type gets you most of the way there

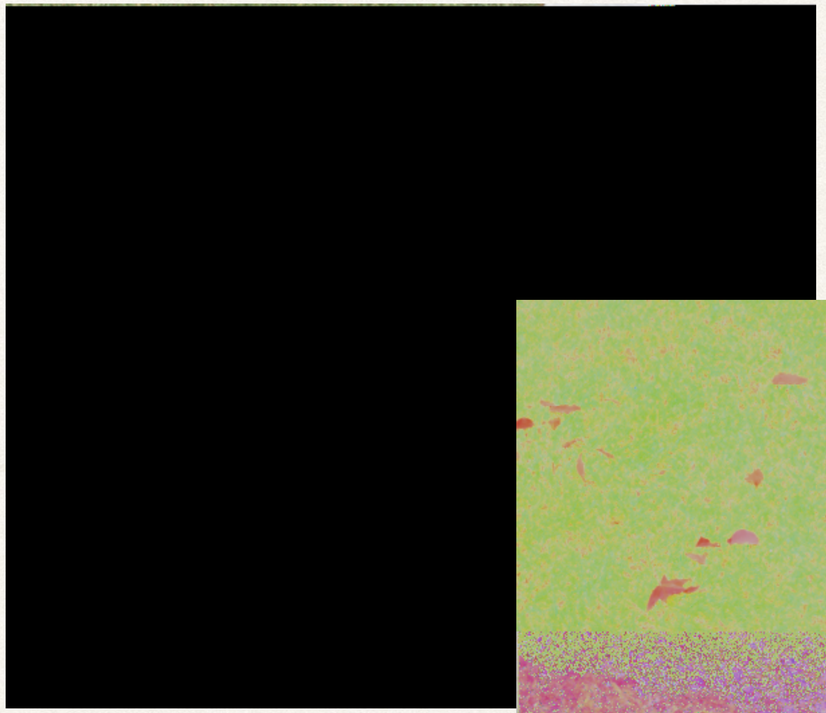
# Symbolic colored illumination

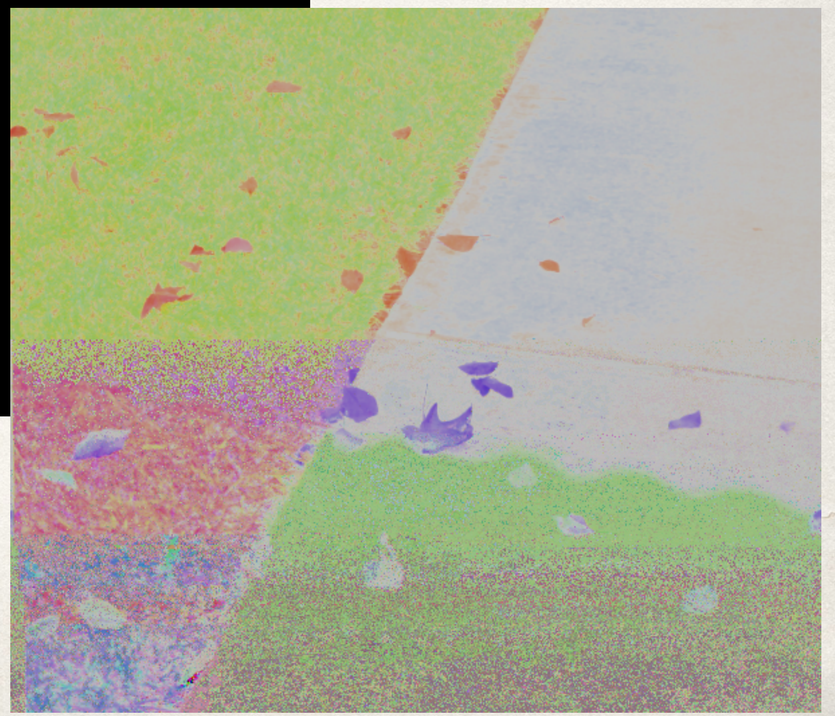
- Chung et. al., solve for RGB for both reflectance and illumination
- Bousseau et. al, extend their monochromatic method to RGB for illumination
- Lightbrush, solves explicitly for RGB for both reflectance and illumination
- Chang et. al, implement a global color shift, no results on outdoor images
- Barron and Malik, illumination is modeled as spherical harmonics, favors less saturation

# Illumination is colored

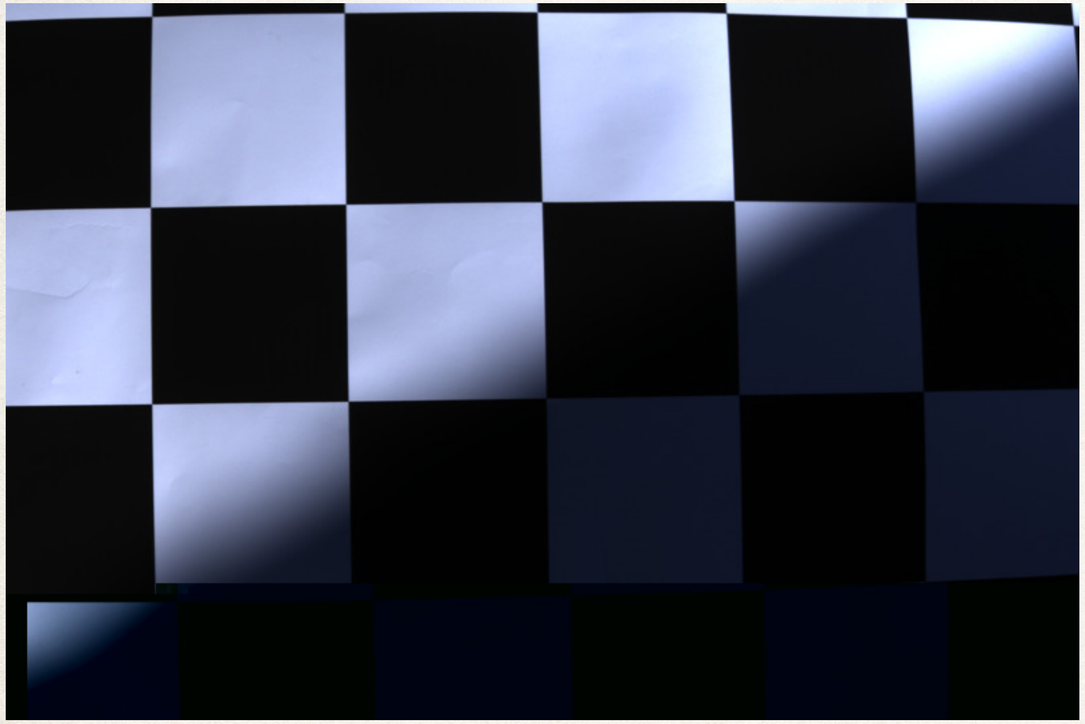




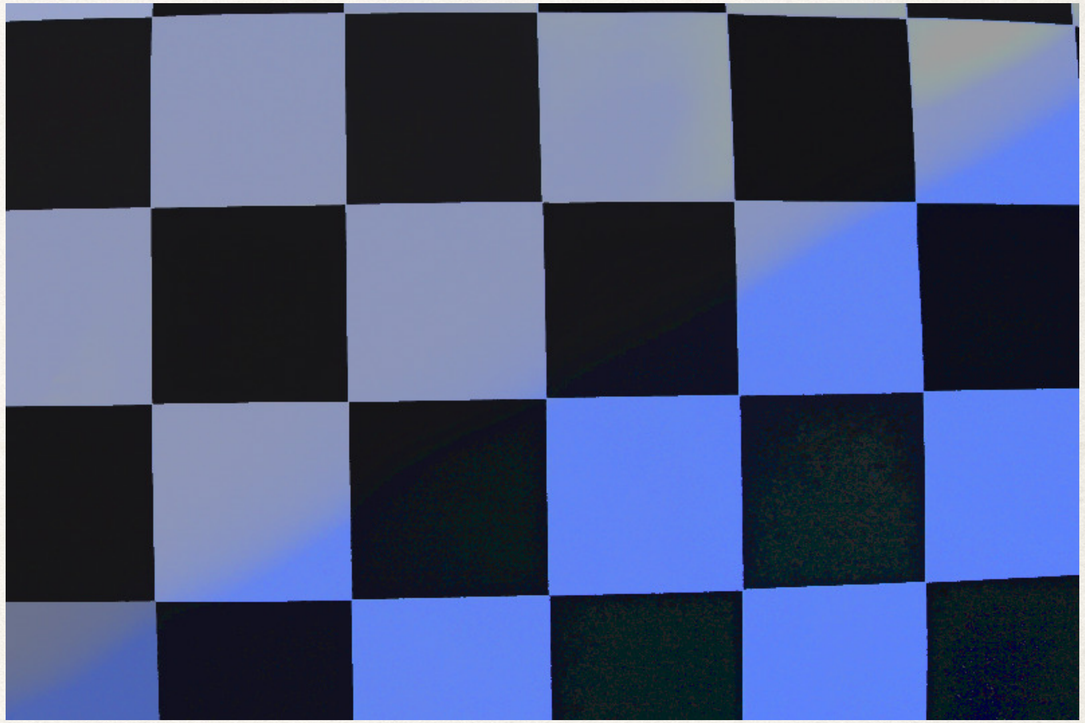




# Assuming grey illumination



Original

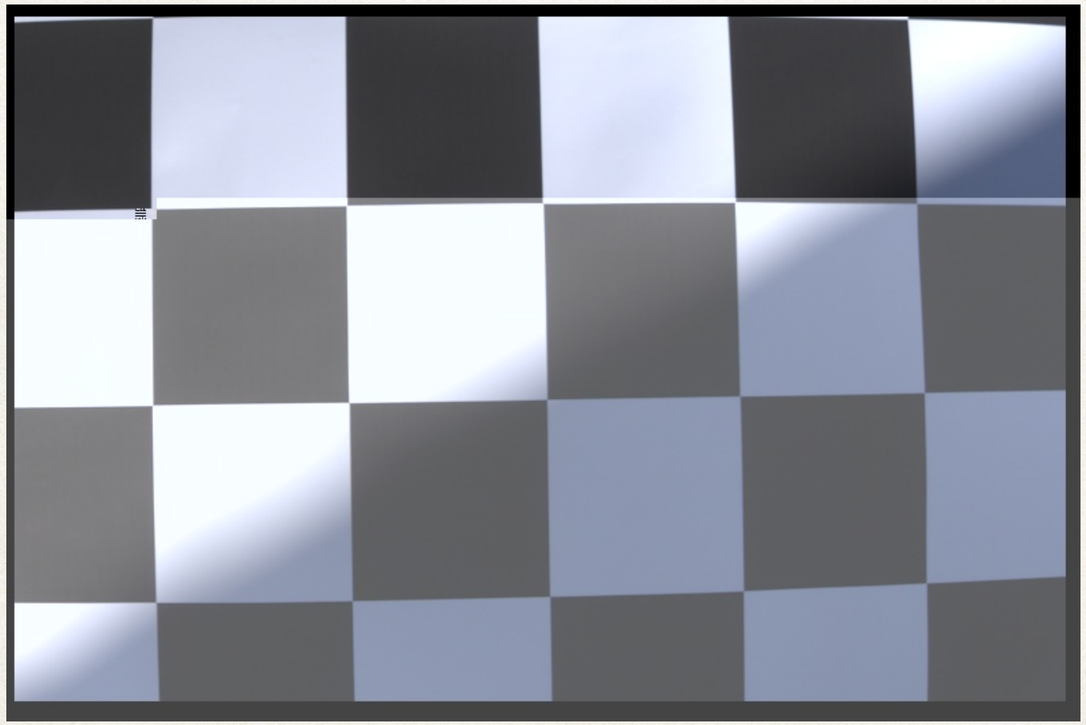


Reflectance

Bell et. al

# Assuming colored illumination

Barron and Malik



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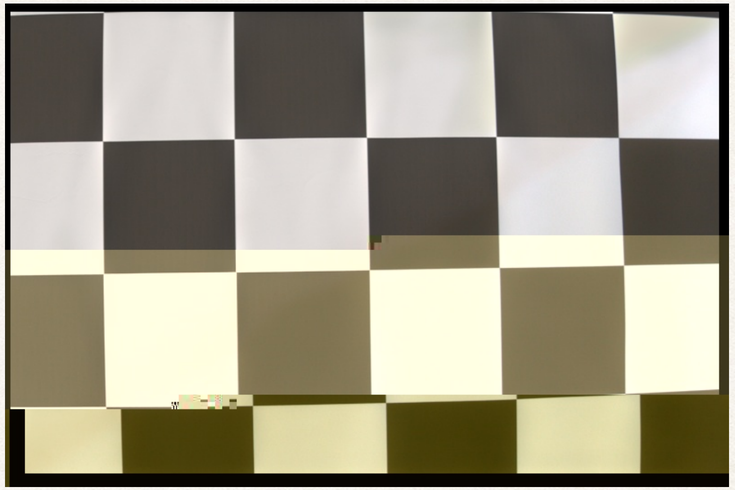
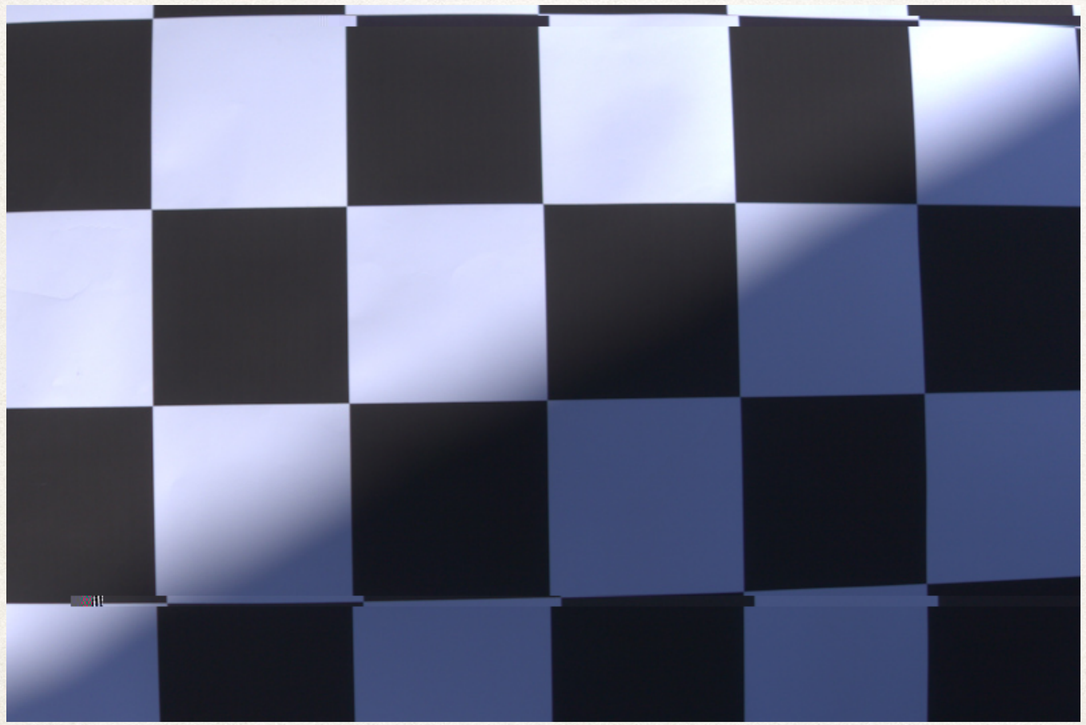


Reflectance



Illumination

# Lightbrush



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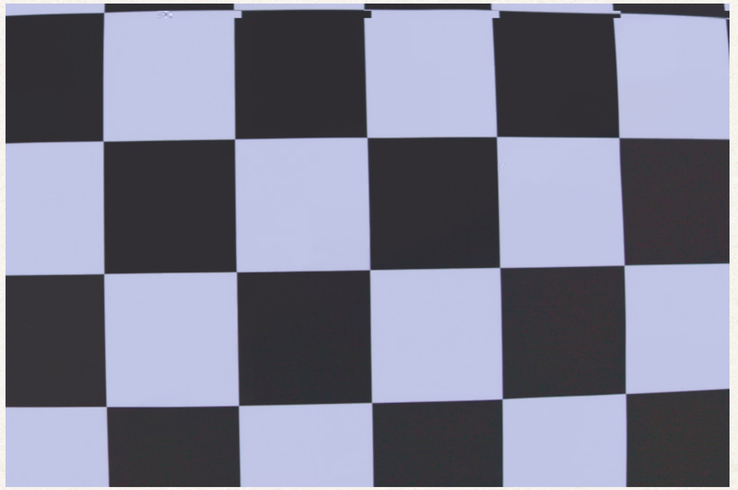
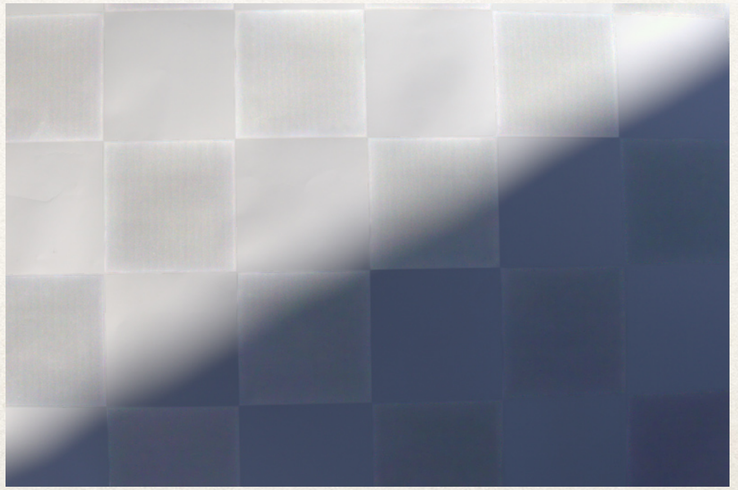


Reflectance



Illumination

# Symbolic Reflectance Estimators

- Chung: solve for R
- Lightbrush: solve for R
- Barron and Malik: estimate both R and L simultaneously
- Bell et. al: iteratively estimate both R and L

# Linking across shadows

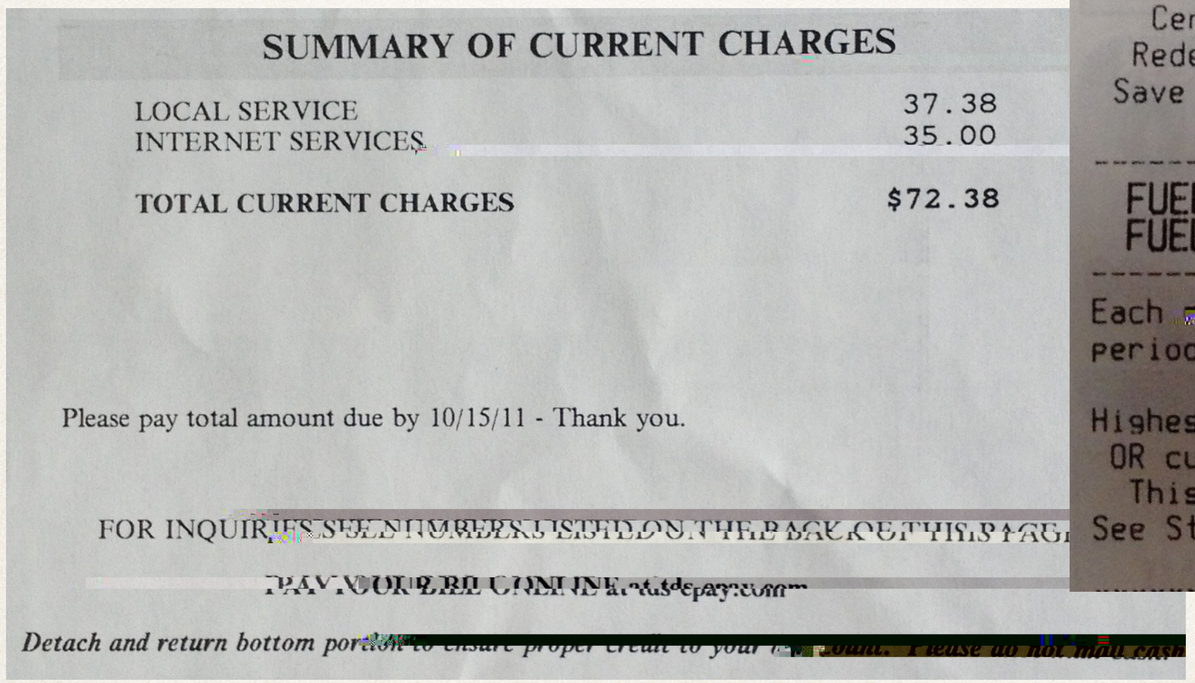
- Garces: chromaticity
- Zhao: chromaticity
- Bell: chromaticity
- Lightbrush: log space chromaticity

# A Material Segmentation Goes a Long Way

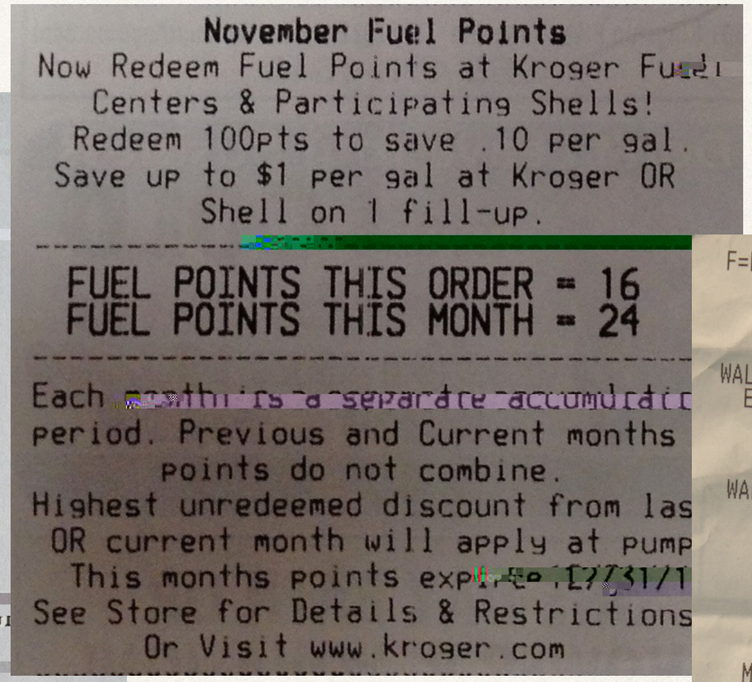
- Filtering/Segmentation as the basis for intrinsic imaging
  - Bi, Han, and Yu, An L1 Image Transform for Edge-Preserving Smoothing and Scene-Level Intrinsic Decomposition, SIGGRAPH 2015
  - Tandent OCR System

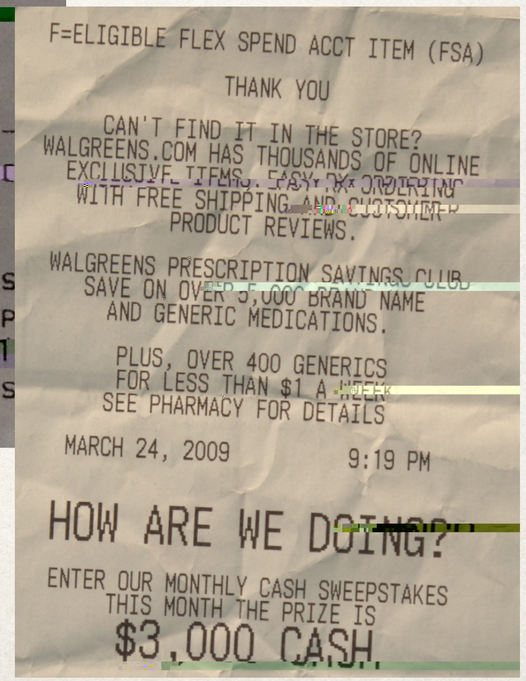
# Optical Character Recognition

Primarily a single background




Shadows show penumbra / umbra




In-focus text has sharp edges

# Umbra and Penumbra

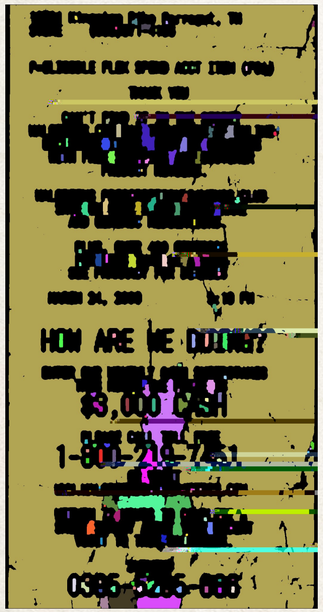
- OCR situation: camera fairly close, things casting shadows further away
- Magnitude of the gradient is not discriminative
- Magnitude of the second derivative can be discriminative
- Second derivative is low in a penumbra, high on text boundaries
- Looking for soft entry into and exit from the penumbra

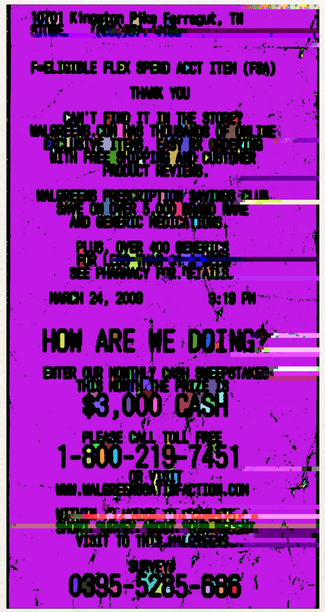
# Filters in Log Space

- Interesting features are ratios, not differences
- Two materials in the same illumination condition will have the same ratio under any reasonable illuminant
- Working in linear space, there is no single threshold to differentiate sharp edges from soft edges
- All second derivative filters are applied to log images

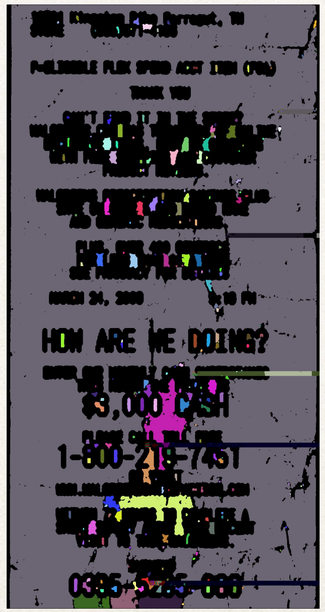
# Second Derivative Regions

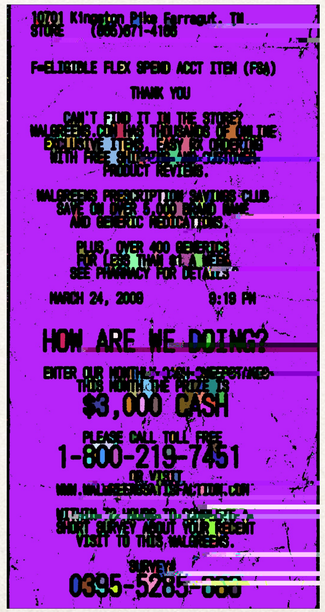
- Apply second derivative filters at different scales
- Grow regions that don't cross high second derivative responses
- Merge regions that have significant overlap

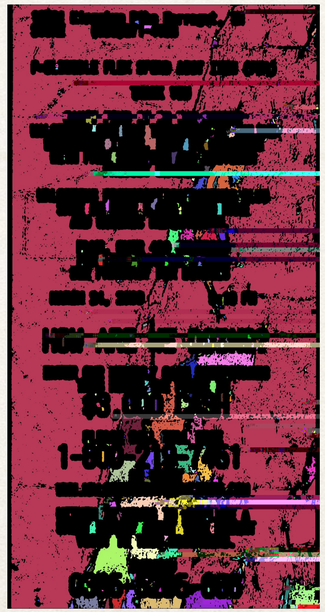

DOG 1

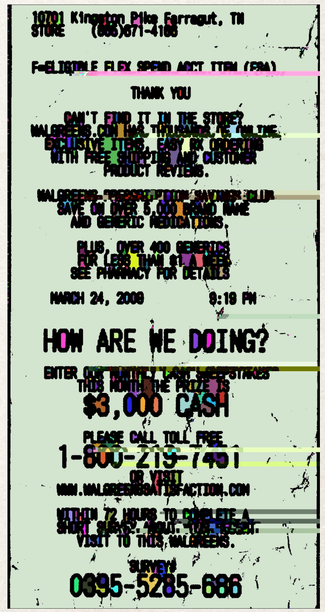

DOG 2


DOG 3


DOG 4

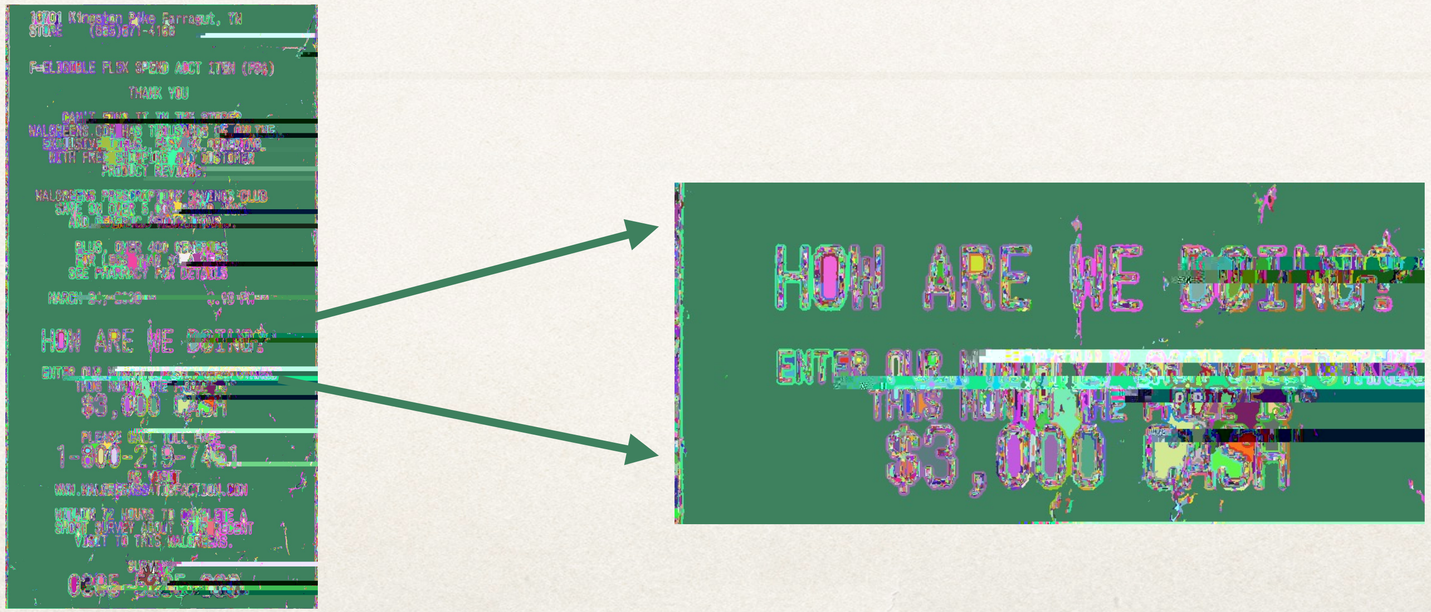

DOG 5


DOG 6


Merged

# Superpixels

- For the remaining pixels, group into superpixels
- Region grow using starting seeds of 2x2
- Region grow using starting seeds of 1x1



# A Big Linear System

- Assume constant illumination across region boundaries
- Change between adjacent pixels in different regions is reflectance only
- Relative constraints have the form: $i_j - i_k = r_0 - r_1$
- One region must be constrained to an arbitrary value

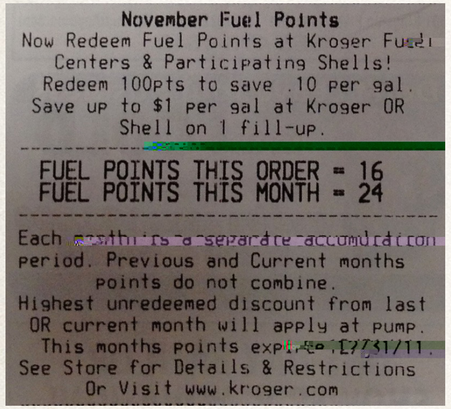
$$\begin{bmatrix} i_j - i_k \\ i_l - i_m \\ \cdots \\ i_n - i_o \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & -1 & 0 & \cdots & 0 \\ 1 & 0 & -1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & 0 & 0 & \cdots & -1 \\ 1 & 0 & 0 & \cdots & 0 \end{bmatrix} \begin{bmatrix} r_0 \\ r_1 \\ r_2 \\ \cdots \\ r_{N-1} \end{bmatrix}$$

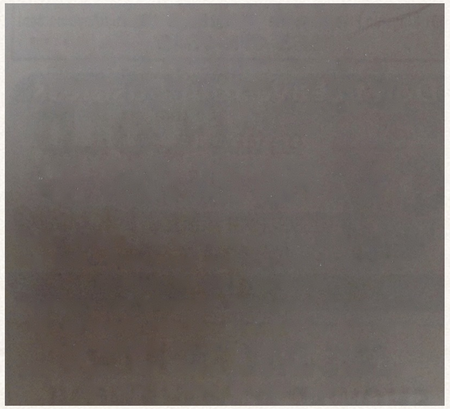


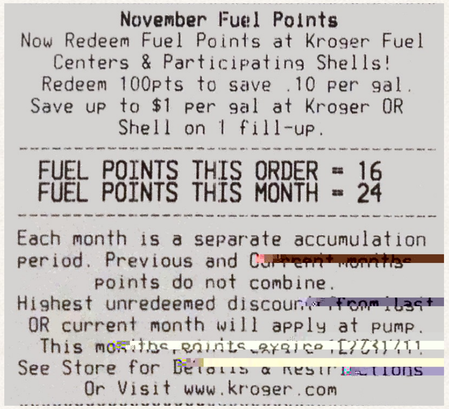



# Results

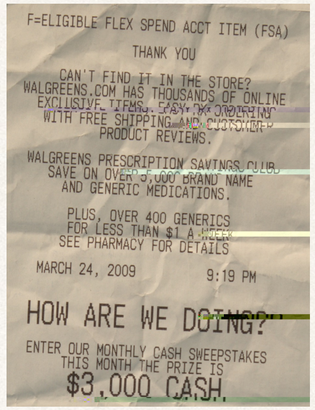
## Level 1

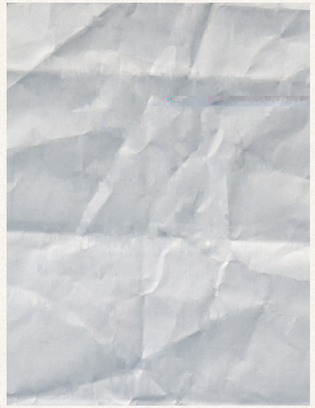


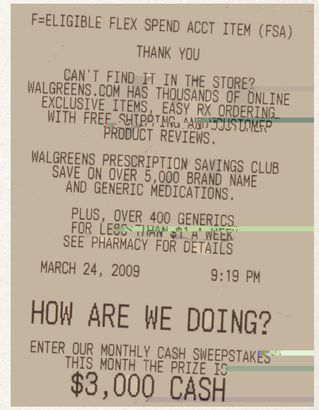





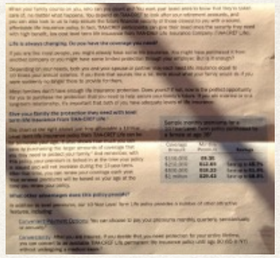

## Level 2



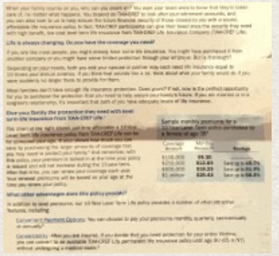





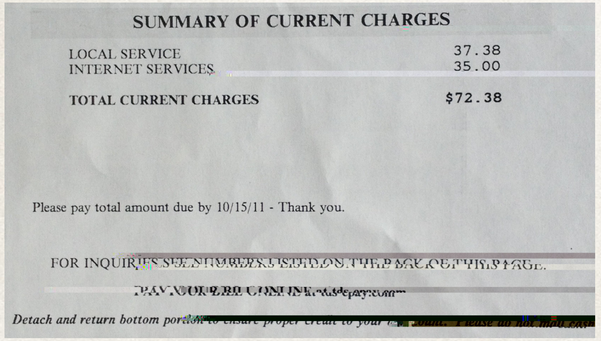

## Level 3

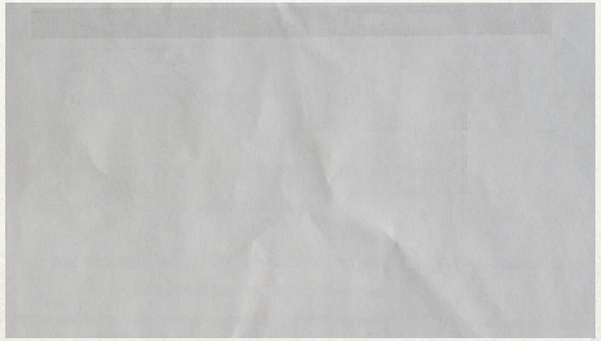


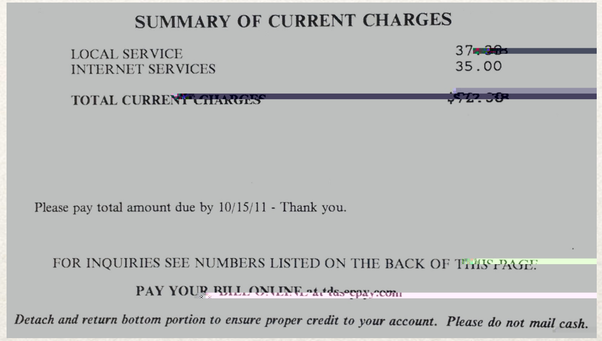




## Level 0





# Deep Network Intrinsics

- **Phase 1: is it possible?**
- Narihira, Maire, and Yu, Direct Intrinsics: Learning Albedo-Shading Decomposition by Convolutional Regression", ICCV 2015
- Shi, Dong, Su, and Yu, Learning Non-Lambertian Object Intrinsics across ShapeNet Categories, CVPR 2017
- Fan, et. al, "Revisiting Deep Intrinsic Image Decompositions", CVPR 2018

# Deep Network Intrinsics

- **Phase 2: Unsupervised or Weakly Supervised Learning**
- Janner et. al., Self-Supervised Intrinsic Image Decomposition, NeuroIPS 2017
- Li and Snavely, Learning Intrinsic Image Decomposition from Watching the World, CVPR 2018
- Ma et. al, Single Image Intrinsic Decomposition without a Single Intrinsic Image, ECCV 2018

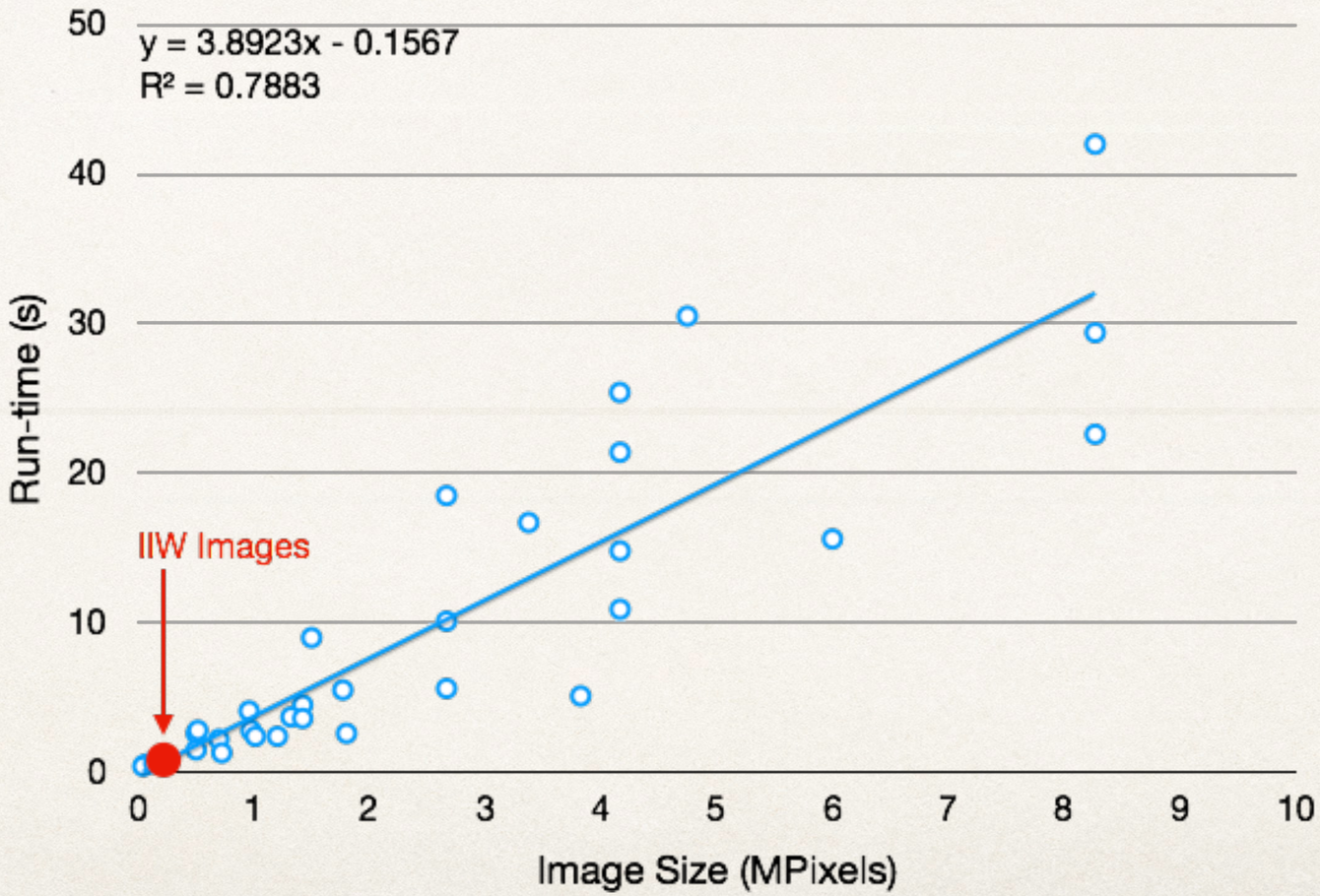
# Deep Network Intrinsics

- **Phase 3: Joint Learning and Multi-Stage Networks**
- Shelhamer, Barron, and Darrell, Scene Intrinsics and Depth from a Single Image, ICCV 2015
- Shi, Dong, Su, and Yu, Learning Non-Lambertian Object Intrinsics across ShapeNet Categories, CVPR 2017
- Baslamisli et al, Joint Learning of Intrinsic Images and Semantic Segmentation, ECCV 2018
- Saini and Narayanan, Semantic Priors for Intrinsic Image Decomposition, BMVC 2018

# What are the networks learning?

- U-net architectures are showing the best and sharpest results
  - Most outputs tend to be blurry
- Unsupervised learning results look a lot like Barron and Malik
- Joint learning tasks are producing better results
  - Segmentations
  - Specular reflection removal
- Networks that produce greyscale illumination fail the same way as symbolic networks that do the same

# What is fast?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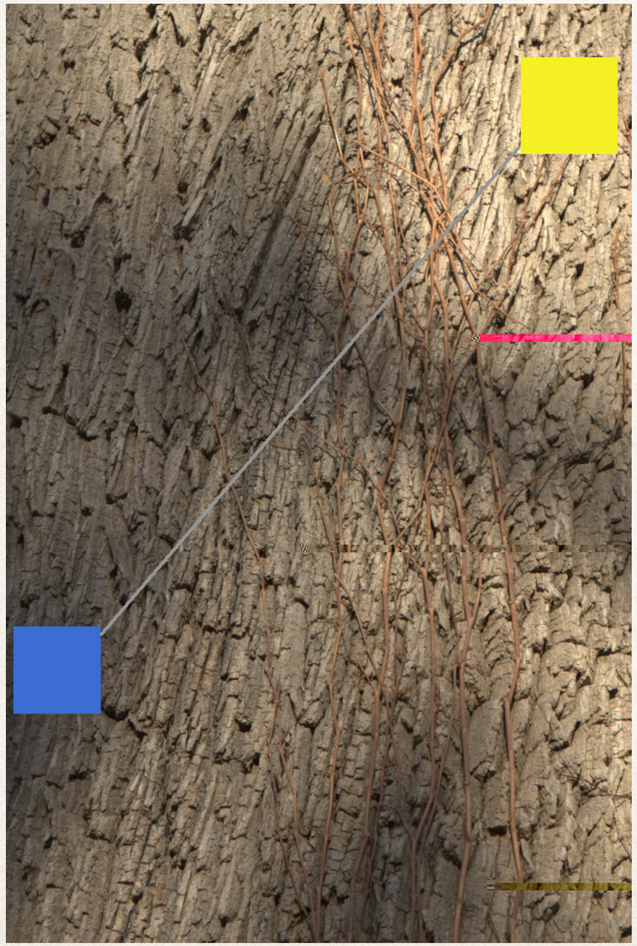
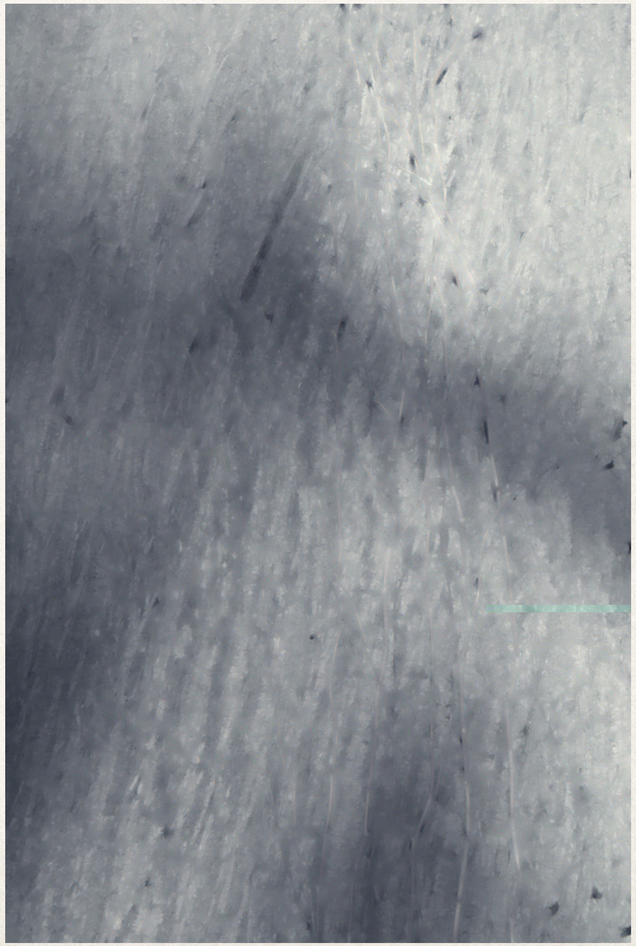
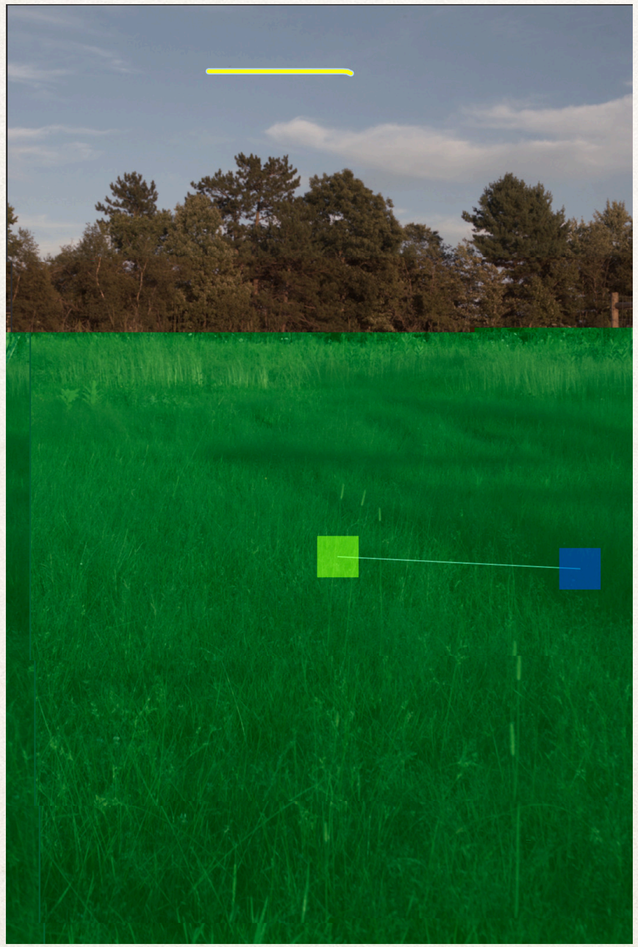
R² = 0.7883
Run-time (s)
Image Size (MPixels)
IIW Images
0
10
20
30
40
50
0
1
2
3
4
5
6
7
8
9
10

# What is state of the art?





# What is state of the art?







# What is state of the art?







# Image Editing



# Image Editing





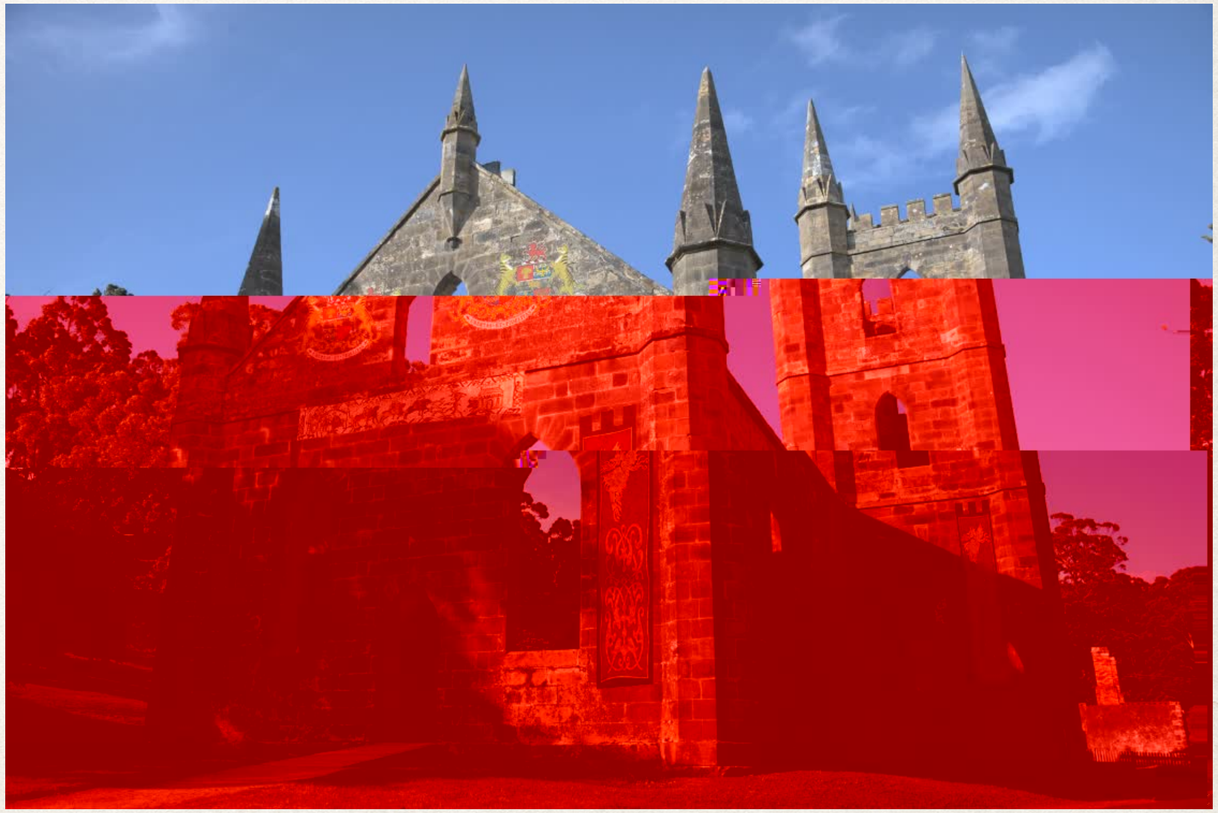

# Image Editing





# Image Editing





# Questions?