Conditional Random Fields for Dense Stereo Matching

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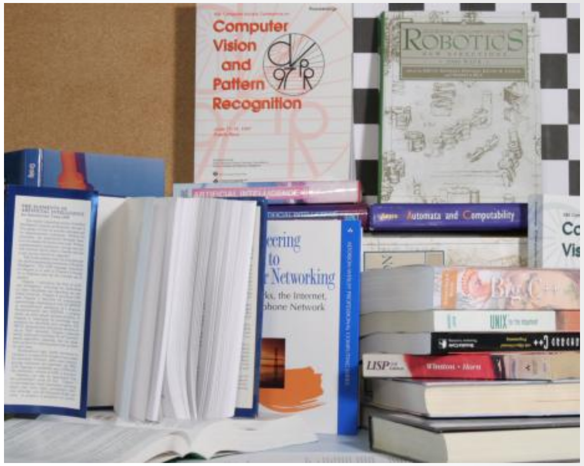
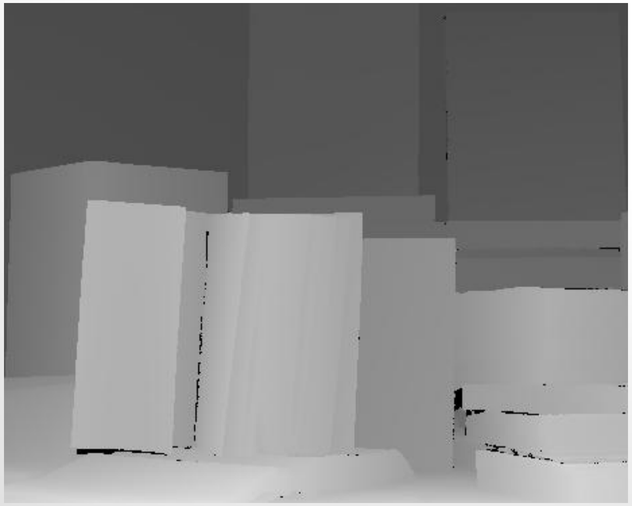
Stereo Correspondence Problem

Left Image



Right Image

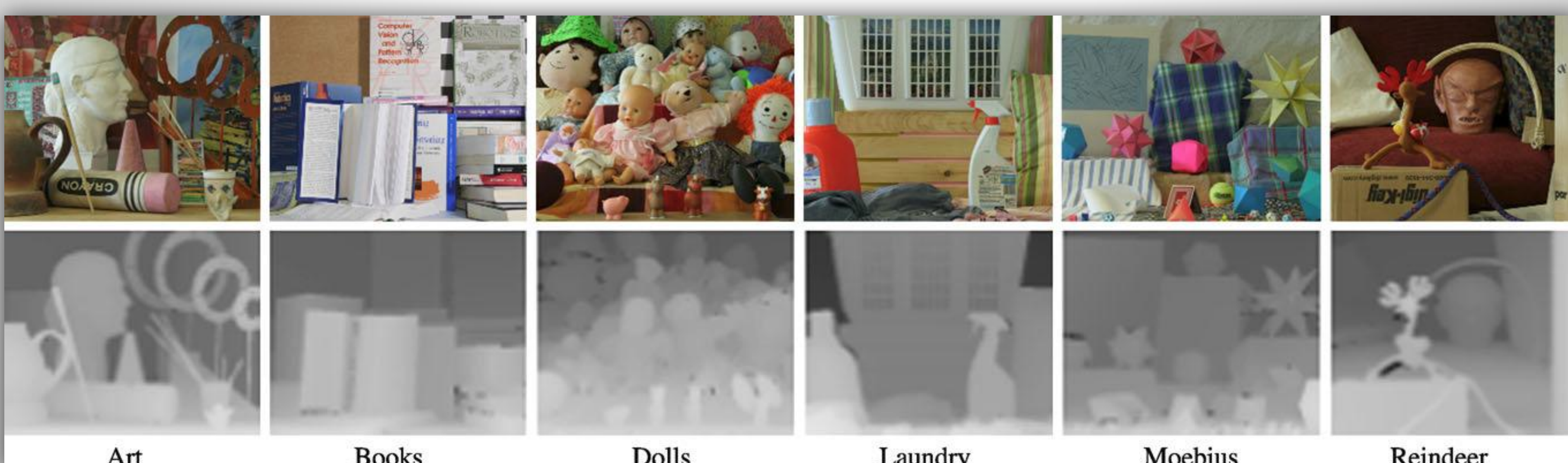


Depth Map

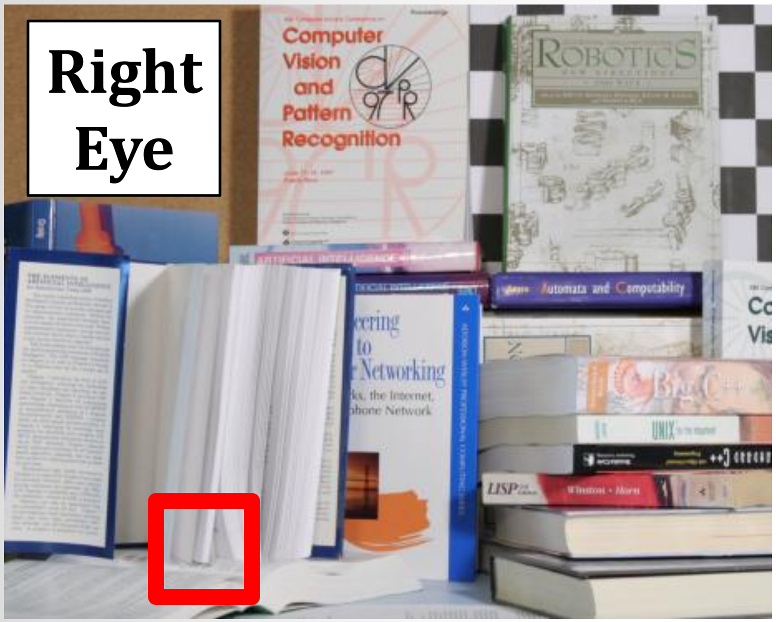
Darker colors indicate greater distance from the camera to the object.

Stereo Image Datasets

- Middlebury 2005 datasets
  - Accurate ground truth depth maps
  - Widely-used → easy to make comparisons



Local Matching



i

i

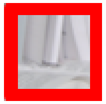
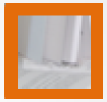
$i + x_i$

$i + x_i$

$i + x_i$

Find matching **disparity (x_i)** between individual pixels or patches of pixels in left and right images.

Local Matching Cost

Data Term: $U(x_i) = \Big|$  $-$  $\Big|$

- $U(x_i)$ measures the similarity of two patches between the left and right images.
  - Patches are similar → small value for $U(x_i)$
  - Patches are different → large value for $U(x_i)$
- Similarity measured in terms of absolute intensity difference

Smoothness

- Majority of an image is “smooth”
- Disparities for neighboring pixels should be similar

Let pixel ***i*** and pixel ***j*** be neighboring pixels. In most cases, they will have the same disparity.

$$x_i \approx x_j$$

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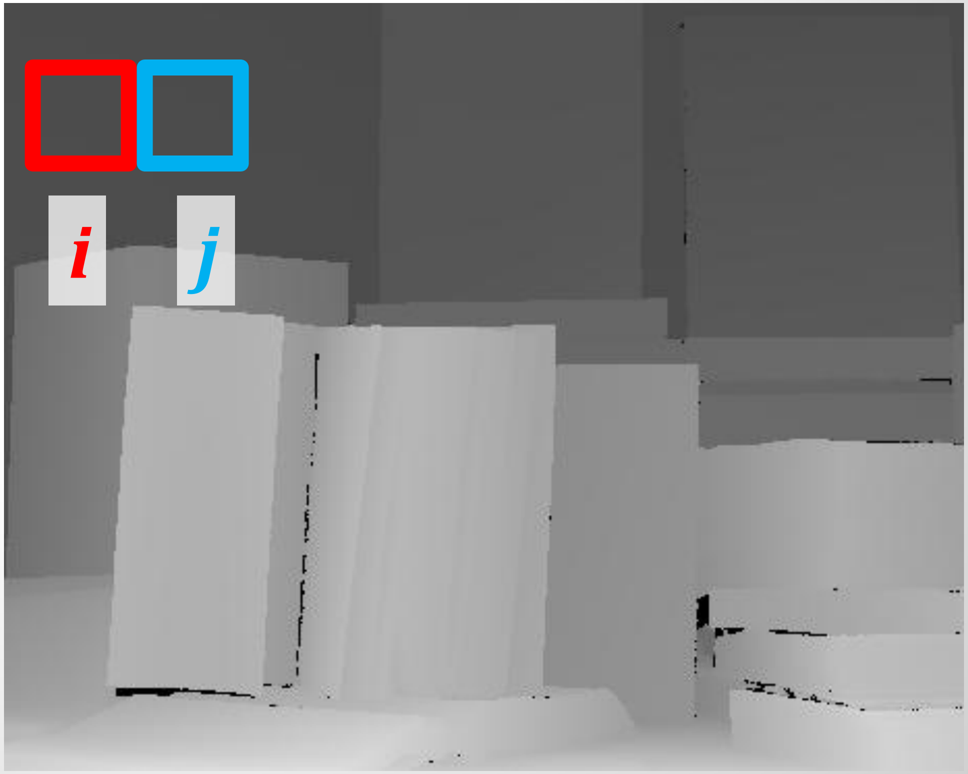
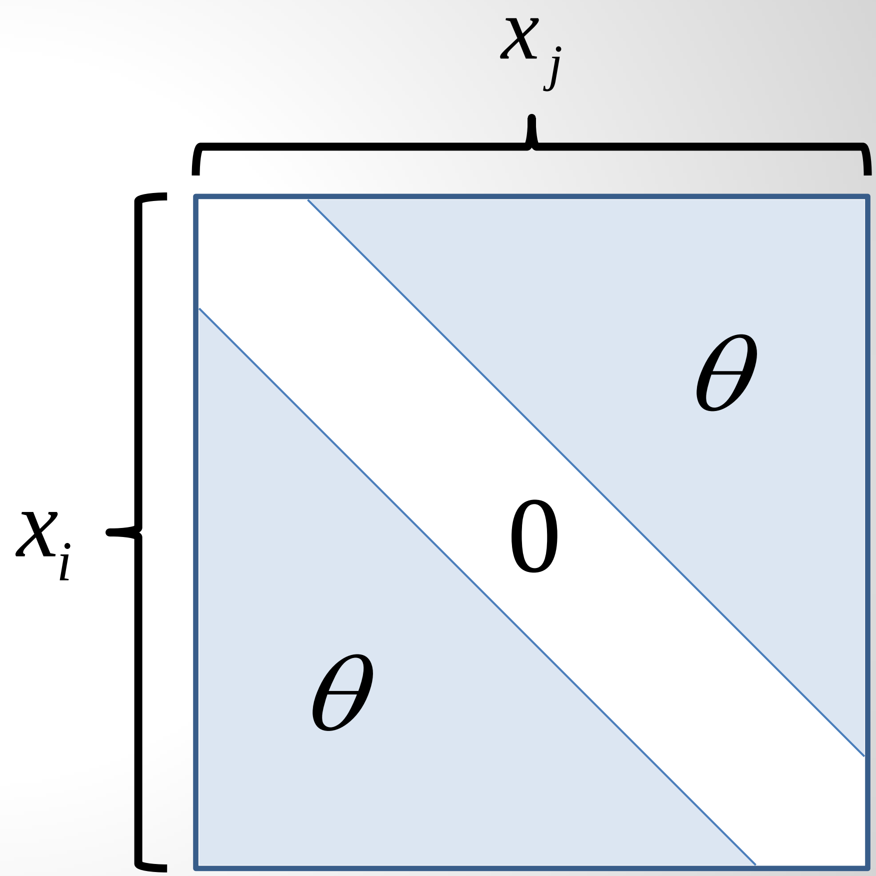


Smoothness Cost

Basic Smoothness Term

$$V(x_i, x_j) = \begin{cases} 0, & \text{if } x_i = x_j \\ \theta, & \text{if } x_i \neq x_j \end{cases}$$

- Penalize when the disparities between neighboring pixels *i* and *j* are different
- Known as <u>Potts Model</u>



Using CRFs for Stereo

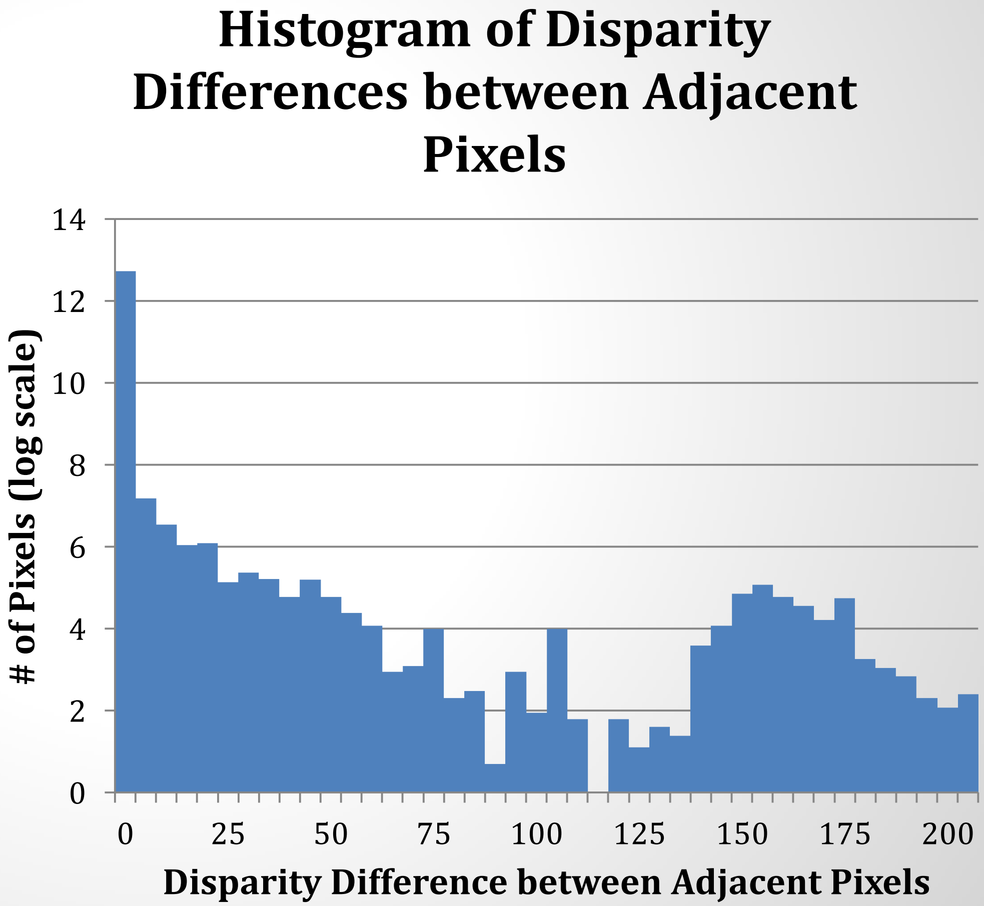
Basic Cost (Energy) Function

$$F(X) = \sum_{i} U(x_i) + \sum_{i\sim j} V(x_i, x_j)$$

- Combine local and smoothness costs into one function
- $F(X)$ = total cost for a certain configuration of disparities X
  - Goal = minimize $F(X)$
- Known as a Conditional Random Field (CRF)

Purpose of Smoothness Term

- Majority of an image is “smooth”
  - in most cases, penalize for disparity jumps
- Allow for disparity jumps at edges
  - Requires accurate edge detection



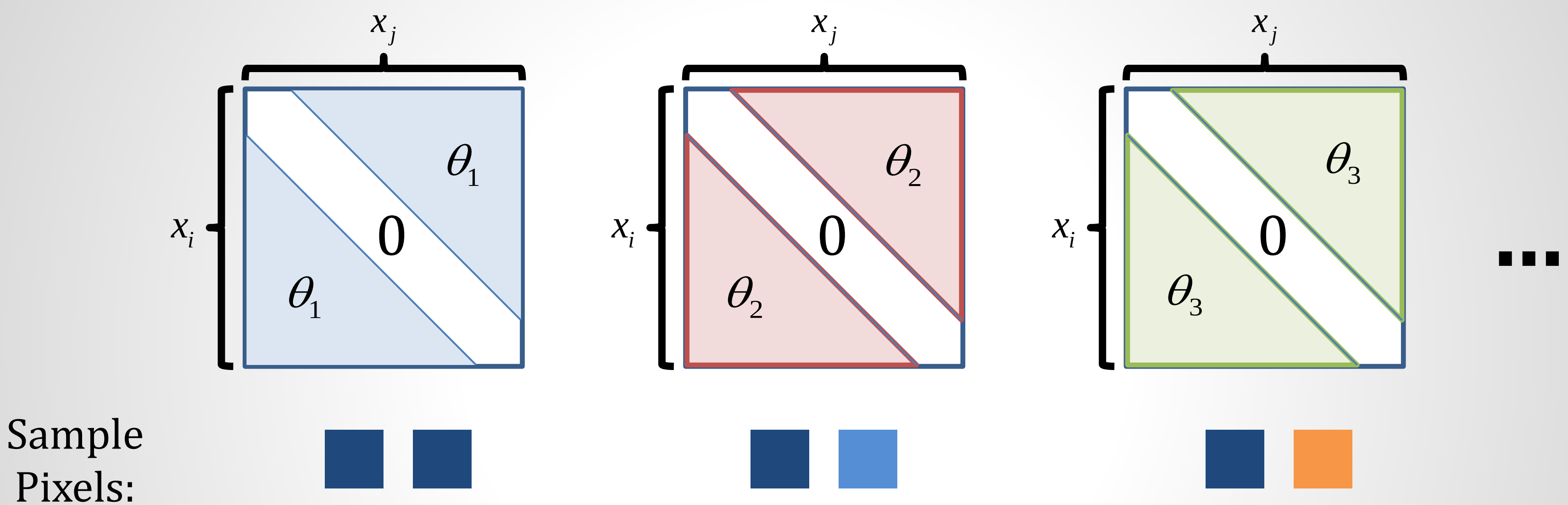
Smoothness Cost: Gradients

Gradient-Modulated Potts Model Smoothness Term

$$V(x_i, x_j) = \begin{cases} 0, & \text{if } x_i = x_j \\ \theta_z, & \text{if } x_i \neq x_j \text{ and } g_{ij} \in B_z \end{cases}$$

- Vary the cost based on color gradient g_{ij} between neighboring pixels using $z = 6$ discrete bins B_z
  - Color gradient (g_{ij}) = root mean square color difference between adjacent pixels
  - B_z = intervals on [0, 2, 4, 8, 12, 16, ∞]

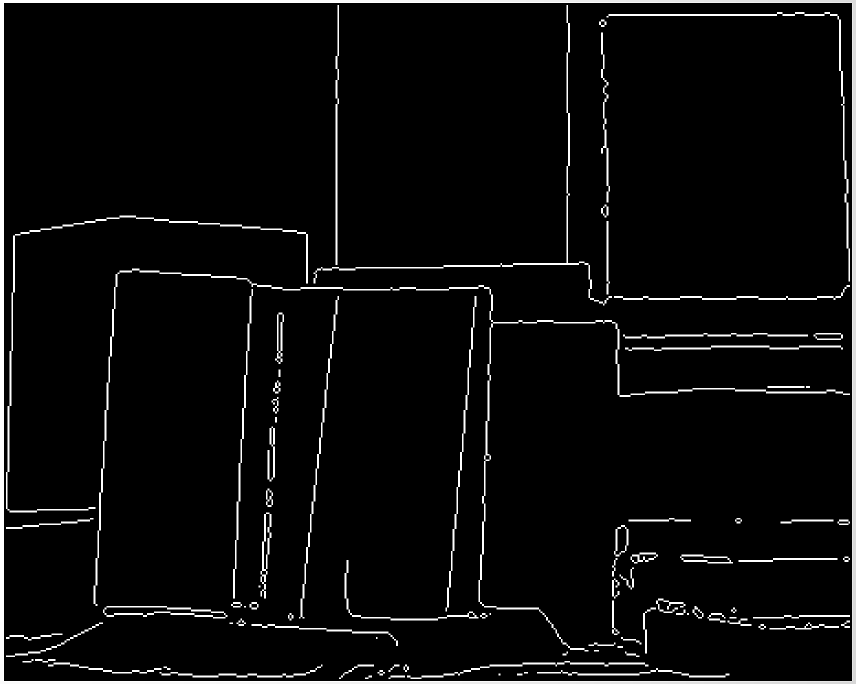
Gradient Bins



Bin (B_z)	1	2	3	...
Color Gradient (g_{ij})	[0, 2)	[2, 4)	[4, 8)	...
θ	$\theta_1 = 3.23$	$\theta_2 = 2.92$	$\theta_3 = 2.87$	...

Edge Detection

- Color gradient is not a true edge detector
- Separate parameters for non-edge vs. edge pixels
- Combine color gradient feature with **Canny edge detection** feature → produces more accurate results



Problems with the Potts Model

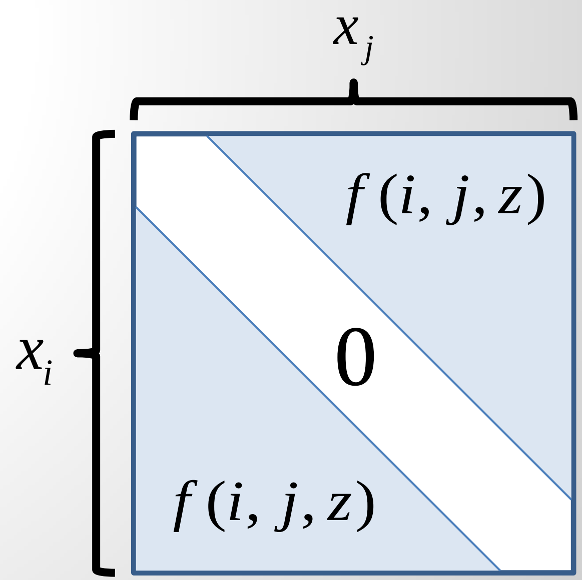
- Uses discrete costs
- Uses simple binary approach to account for differences in disparity between neighboring pixels
  - Only considers $x_i = x_j$ or $x_i \neq x_j$
  - Fails to factor in $x_i - x_j$

Smoothness Cost: Log Model

Disparity Difference and Gradient-Modulated Log Model

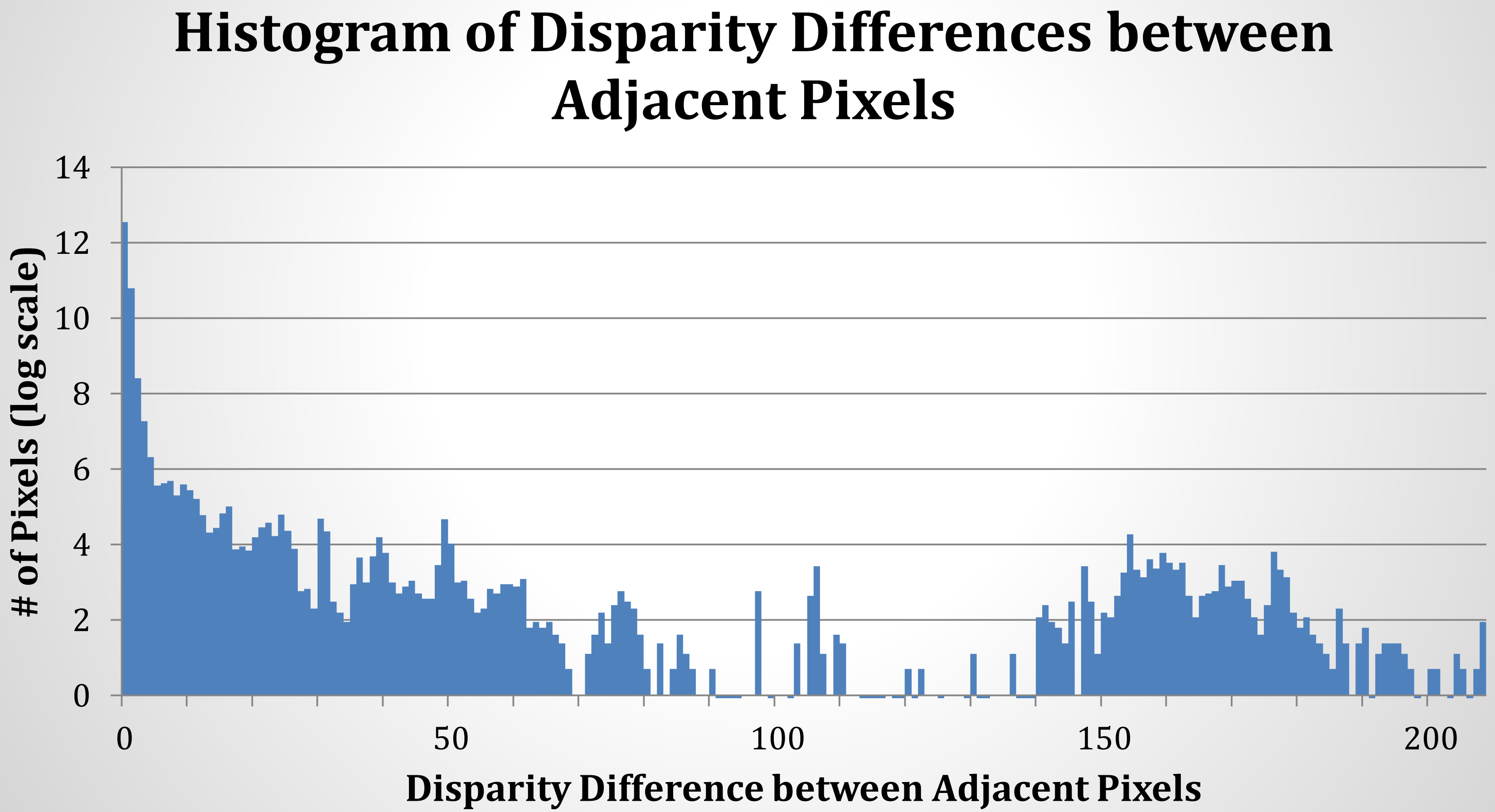
$$V(x_i, x_j) = \begin{cases} 0, & \text{if } x_i = x_j \\ f(i, j, z), & \text{if } x_i \neq x_j \text{ and } g_{ij} \in B_z \end{cases}$$

$$f(i, j, z) = \theta_{a,z} \ln\left(1 + e^{\theta_{b,z}}(x_i - x_j)\right)$$

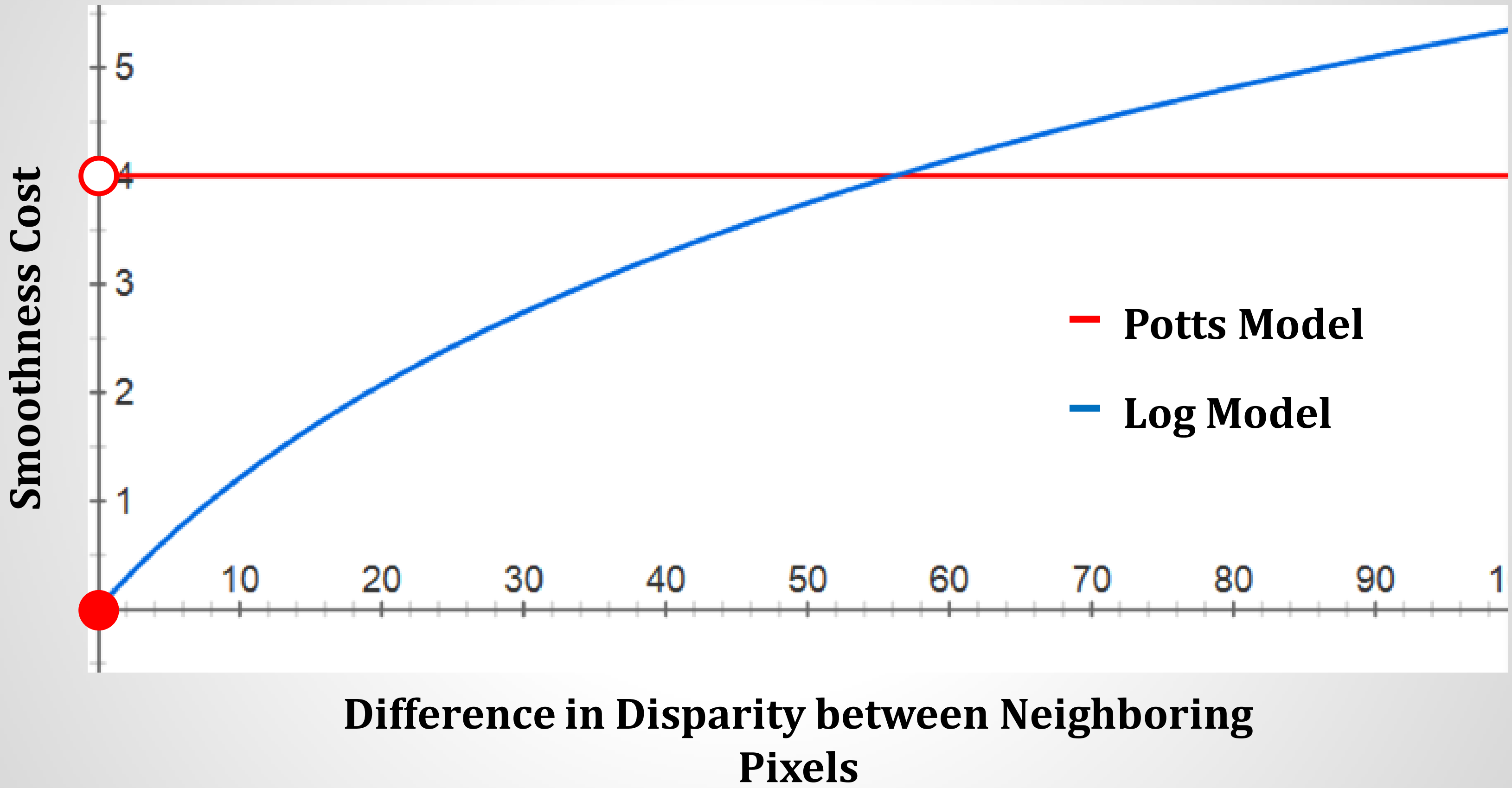


- Cost for difference in disparity modeled logarithmically
- Takes 2 parameters (θ_a and θ_b) per gradient bin
  - Twice as many as Potts Model

Why Log Model



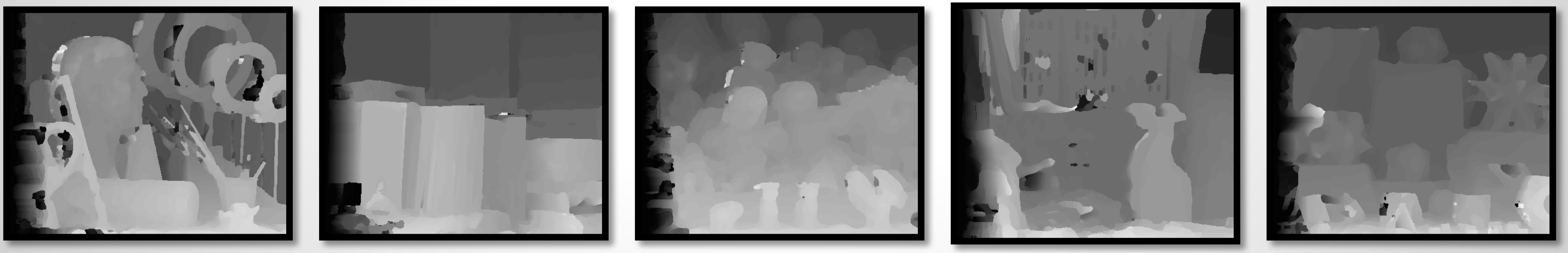
Why Log Model



Disclaimer: The equations used in graph above are $y=3*\ln(1+e^{-3}x)$ and $y=4$. These values are for demonstration purposes only. They were not actually used in the research.

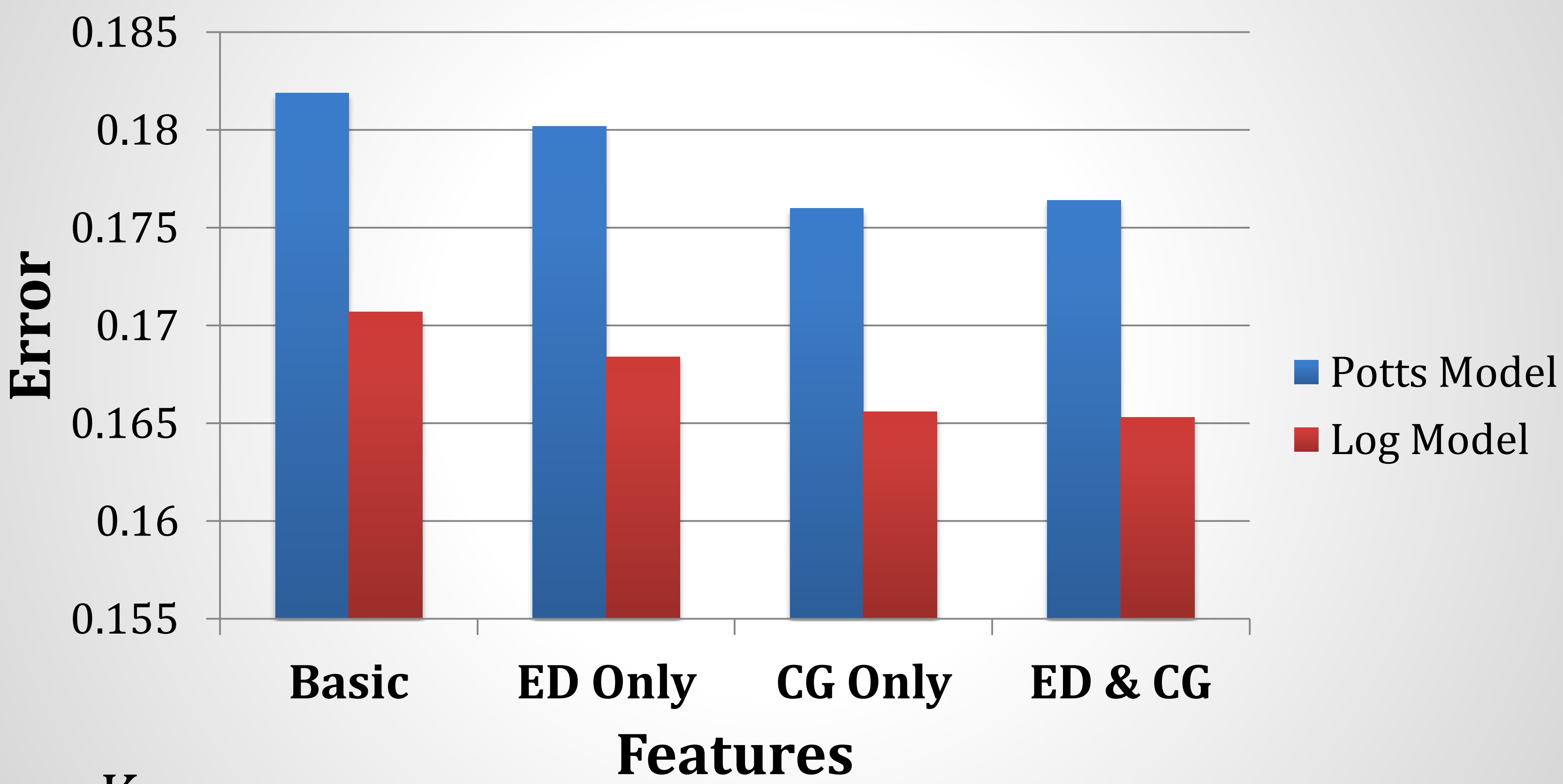
Solving Parameters: Machine Learning

- What is Machine Learning?
- 5 “Training” Datasets from Middlebury
- JGMT Toolbox for MATALB



<u>Note:</u> 1. Images above are from the log model with edge detection but no gradient bins. 2. Training was done using Justin's Graphical Models / Conditional Random Field Toolbox (JGMT), which can be found online here: http://users.cecs.anu.edu.au/~jdomke/JGMT/

Results Summary



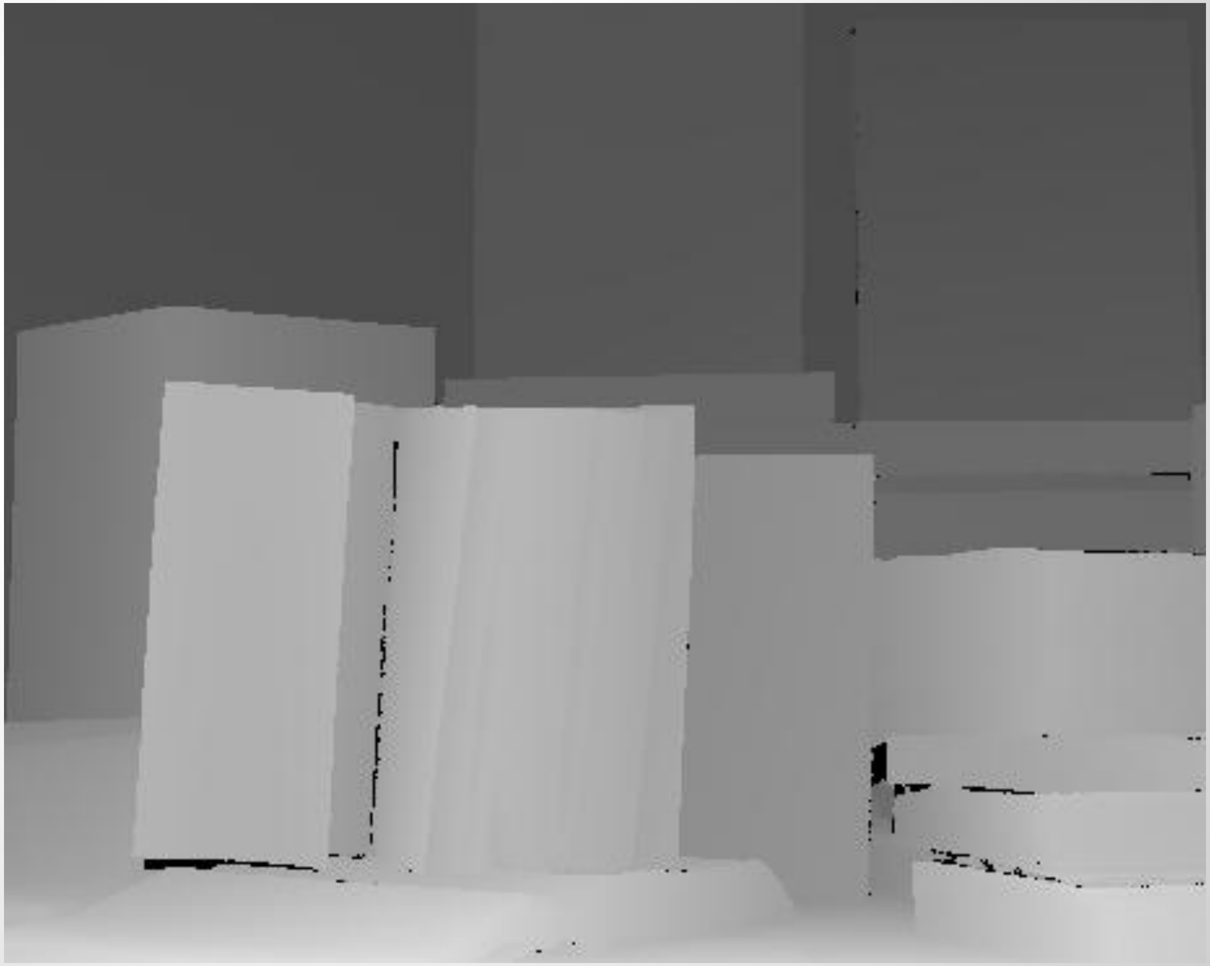
Key:

- ED = Canny **E**dge **D**etection
- EG = **C**olor **G**radients

Potts vs. Log: An Example

Ground Truth

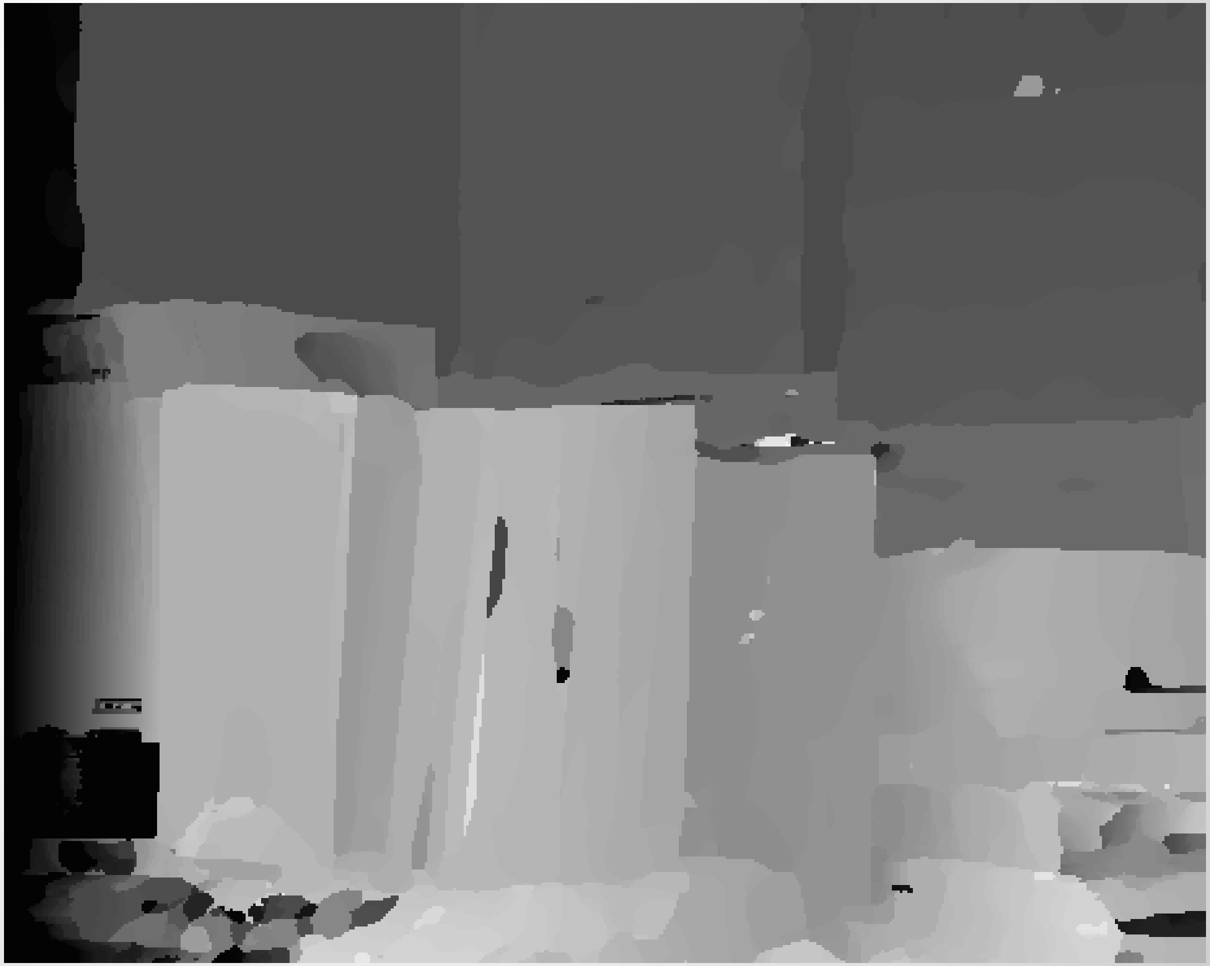
What the depth map should look like.



Potts vs. Log: An Example

<u>Potts Model</u>
w/ ED + CG

Error:
0.18425



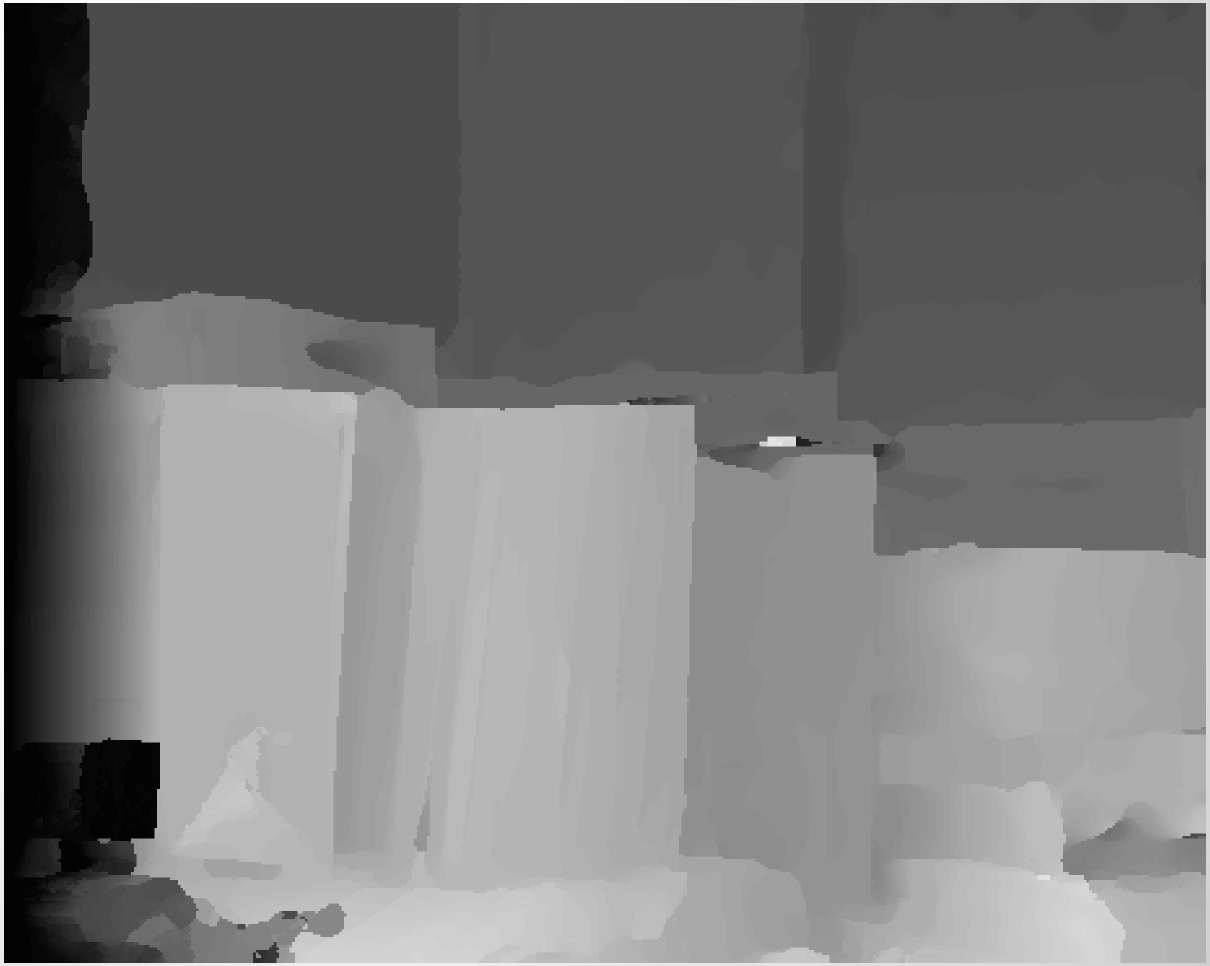
Potts vs. Log: An Example

Log. Model

w/ ED + CG

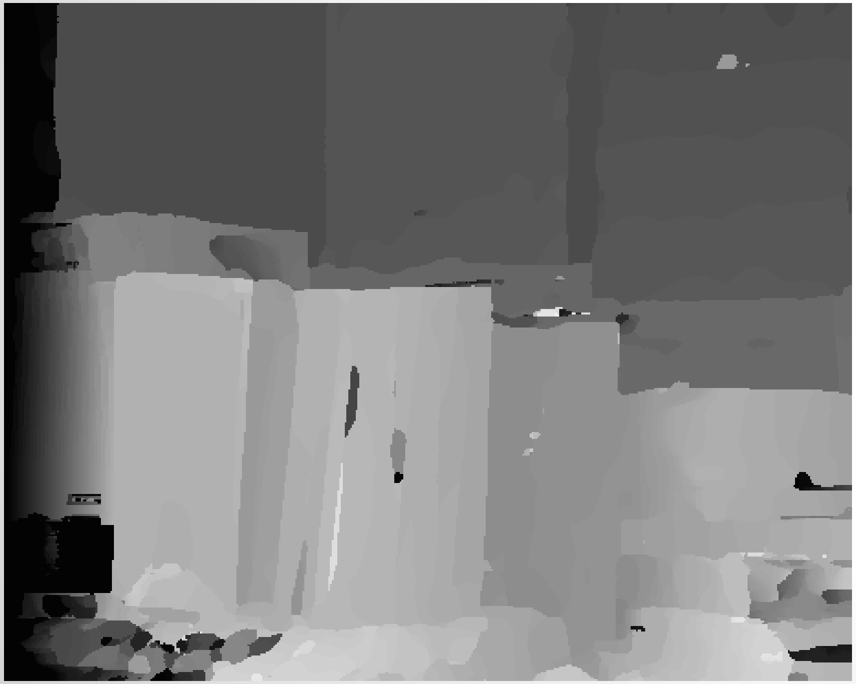
Error:

0.17602

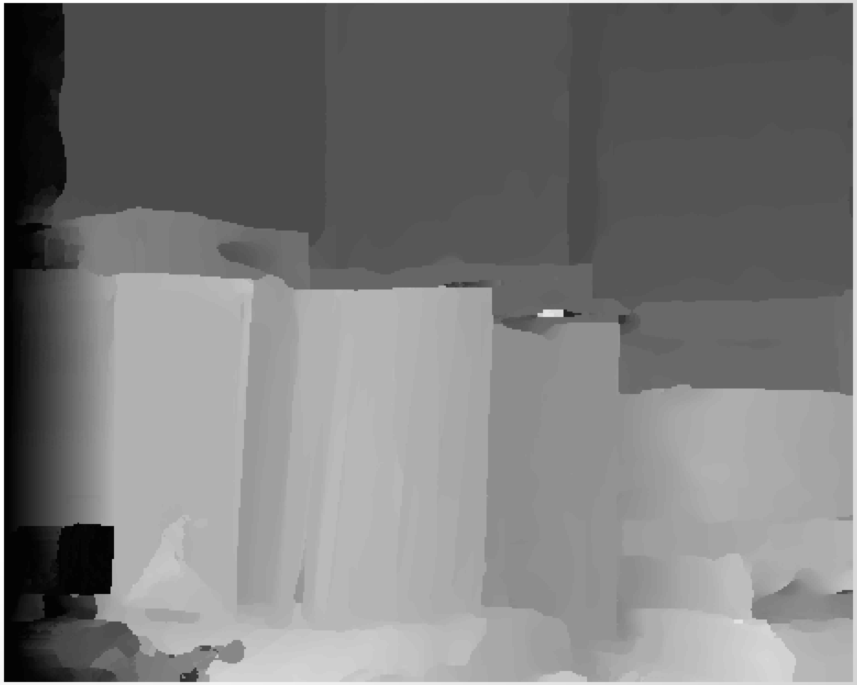


Potts vs. Log: An Example

Potts Model



Log Model



Number of Parameters

	# of Local Matching Parameters	# of Smoothness Parameters
Potts Model	1	1
Potts Model + ED	1	2
Potts Model + CG	1	6
Potts Model + ED + CG	1	12
Log Model	1	2
Log Model + ED	1	4
Log Model + CG	1	12
Log Model + ED + CG	1	24

Key:

- ED = Canny **E**dge **D**etection
- EG = **C**olor **G**radients

Normalized Results

2 Parameters

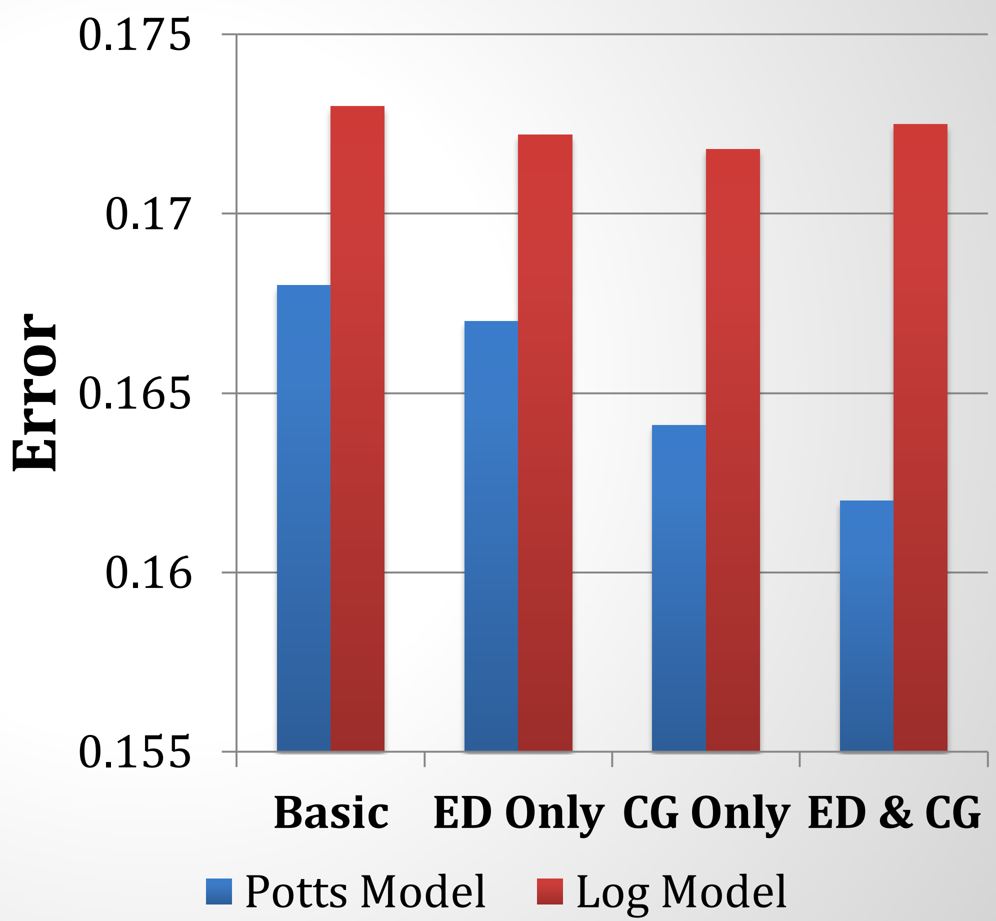
- Potts Model w/ ED
  - Error: 0.1802
- Basic Log Model
  - Error: **0.1707**
- Improvement: 5.3%

12 Parameters

- Potts Model w/ ED and CG
  - Error: 0.1764
- Log Model w/ CG
  - Error: **0.1656**
- Improvement: 6.1%

Testing on a Different Set

- Potts Model actually does better here
- Suggests that log model may be over-fitting the data
  - Solution: train on more datasets



Conclusions + Future Work

- Logarithmic Model is able to assign more accurate smoothness costs than a Potts Model
- Future work
  - Train model on more data to avoid over-fitting
  - Try different models

THANK YOU!