Gradient Domain Manipulation Techniques in Vision and Graphics

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Course WebPage :
http://www.cfar.umd.edu/~aagrawal/ICCV2007Course/

Course: Gradient Domain Techniques

Course Web Page

Google "ICCV 2007 gradient course"

Course Evaluation

Previous Sections

- Gradient domain manipulation (images)
  - Section 2

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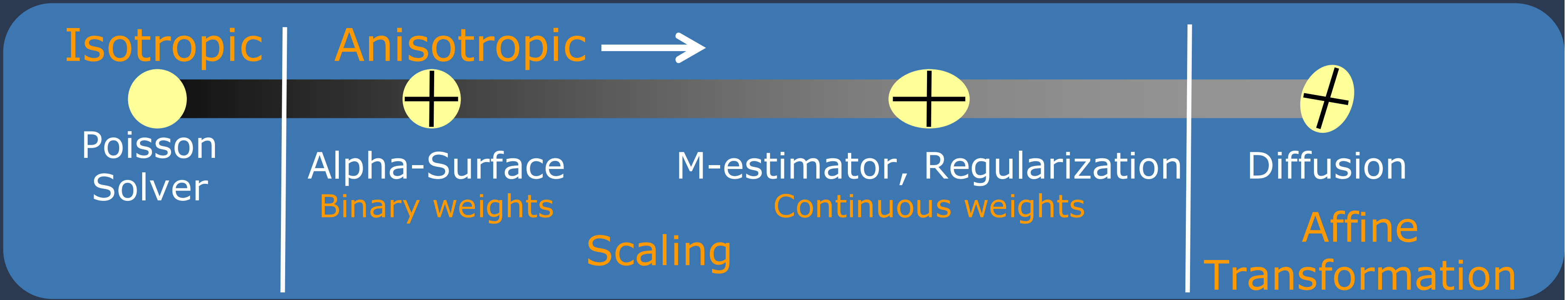
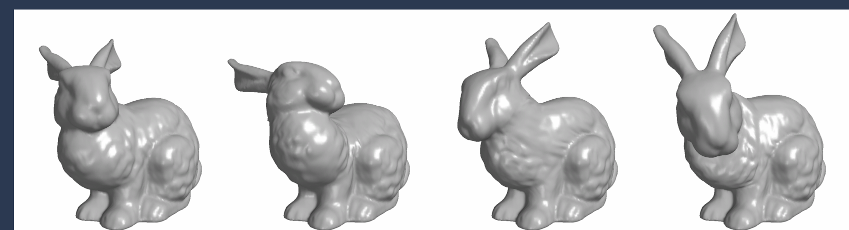
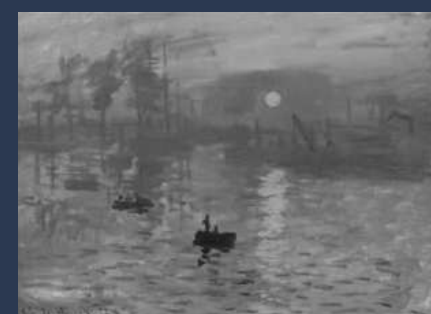
- Reconstruction from gradients
  - Section 3



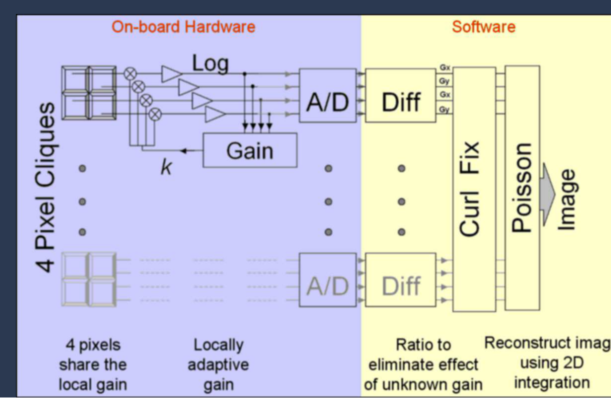
Advanced Topics

- Video Manipulations
  - Space-time gradients
- Mesh Deformations
  - 3D gradients





- Color2Gray
  - Large Neighborhood differences
- Gradient Camera
  - High dynamic range imaging
  - Gradient operations at sensor level



Seamless Video Editing

- Video A and B
  - Gradients (A_x, A_y, A_t) and (B_x, B_y, B_t)
- Modify gradient field
  - Combine gradients of A and B
- 3D Intergration
- Operators
  - Max contrast
  - Substitute
  - Threshold

Hongcheng Wang, Ramesh Raskar and Narendra Ahuja, Seamless Video Editing, International Conference on Pattern Recognition (ICPR), 2004

3D Poisson Solver

$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} + \frac{\partial^2 I}{\partial t^2}$$

$$\nabla \bullet G = \frac{\partial G_x}{\partial x} + \frac{\partial G_y}{\partial y} + \frac{\partial G_t}{\partial t}$$

$$\nabla^2 I = \nabla \bullet G$$

Modified gradient field

Operations

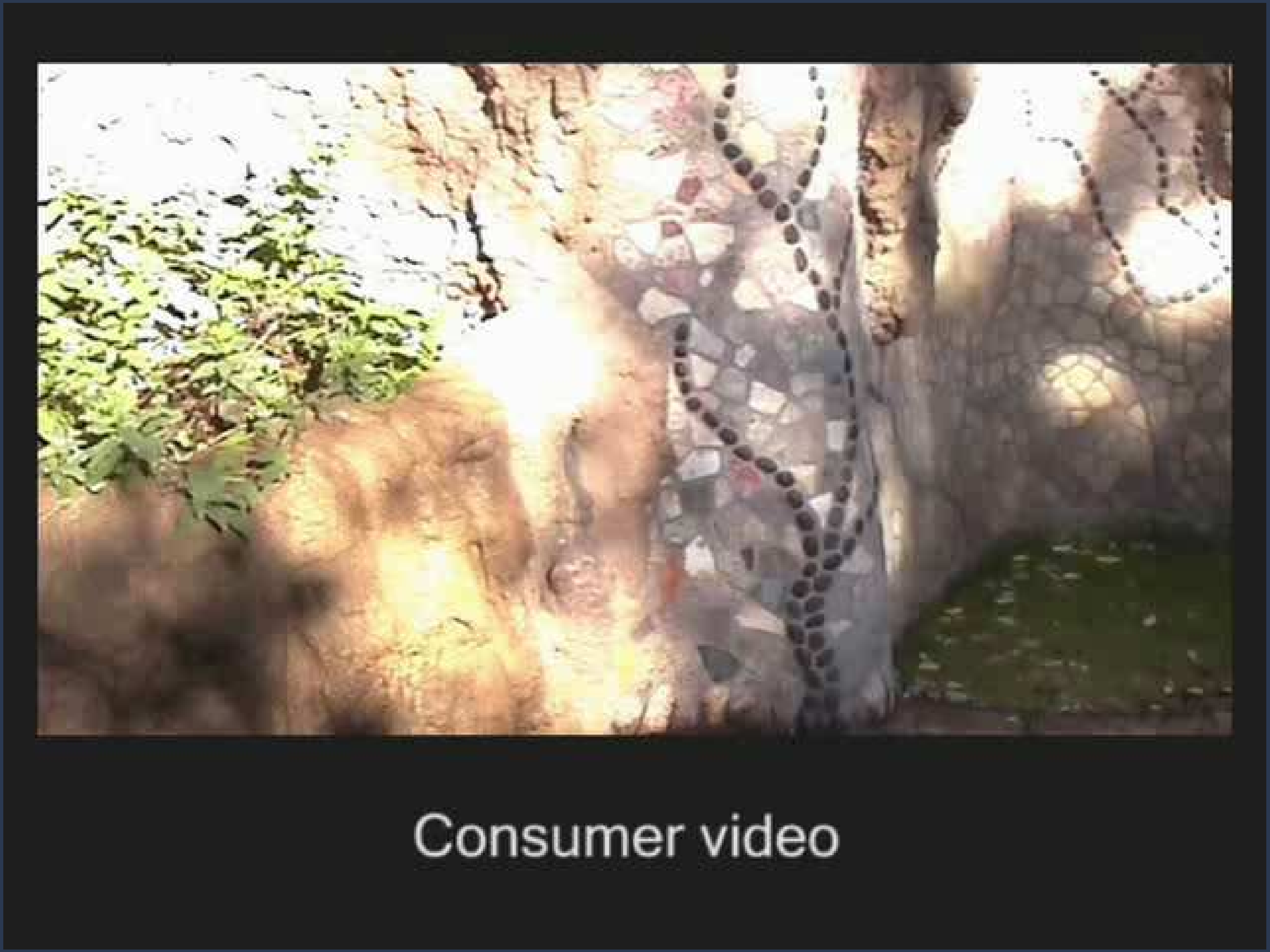
- Max operation

Clock sequence

Fish sequence

Importing Temporal Changes

Video Enhancement using Photographs



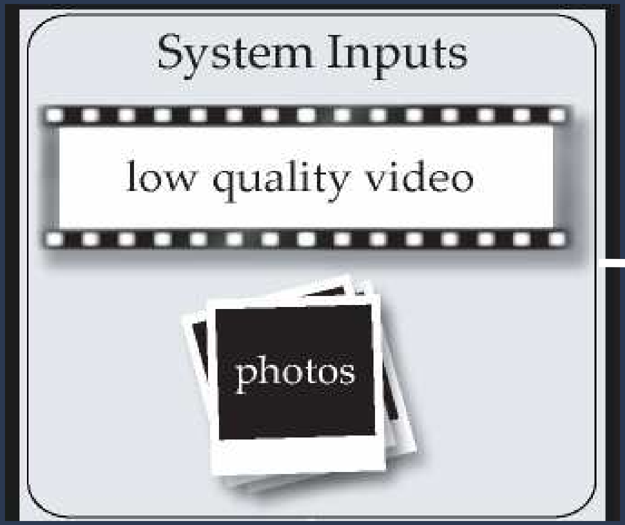
Pravin Bhat, C. Lawrence Zitnick, Noah Snavely, Aseem Agarwala, Maneesh Agrawala, Brian Curless, Michael Cohen, Sing Bing Kang, “Using Photographs to Enhance Videos of a Static Scene”, EGSR 2007

Consumer Photographs

Pravin Bhat, C. Lawrence Zitnick, Noah Snavely, Aseem Agarwala, Maneesh Agrawala, Brian Curless, Michael Cohen, Sing Bing Kang, “Using Photographs to Enhance Videos of a Static Scene”, EGSR 2007

Enhanced video

System Overview



Estimate Geometry

↓

Texture Map with Photos

↓

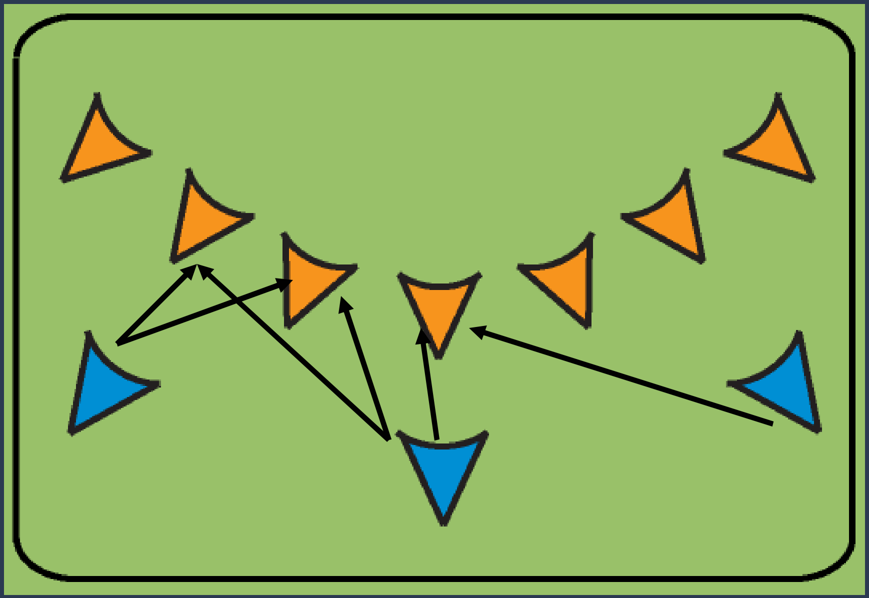
Gradient Domain fusion of images and video views

Geometry Estimation

- Structure from Motion
  - Using Video
- Multi-View Stereo
  - Using photographs

Novel View Interpolation

- Objective
  - Reconstruct every video frame (orange cones) using nearby photos (blue cones)



Video Reconstruction: Graph Cuts

Labeling

Label-1

Label-2

Video Reconstruction

Reconstructed
Video Frame

Label-1

Label-2

Video reconstruction

Original video

Video reconstruction

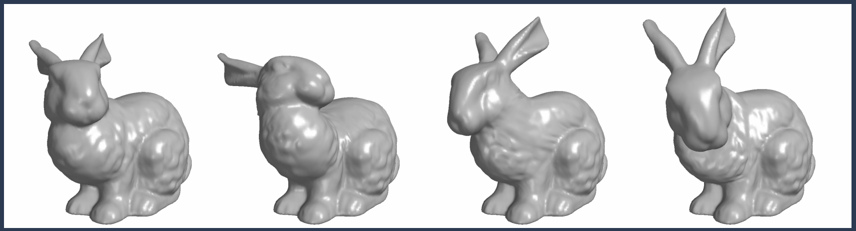
Reconstructed video

Spacetime Fusion

- Frame by frame fusion is not temporally smooth
- 3D Gradient field of enhanced video
- Spatial gradients – G_x and G_y
  - as defined earlier
- Temporal gradients – G_t
  - $G_t(x, y, t) = V(x, y, t) - V(x, y, t - 1)$

Advanced Topics

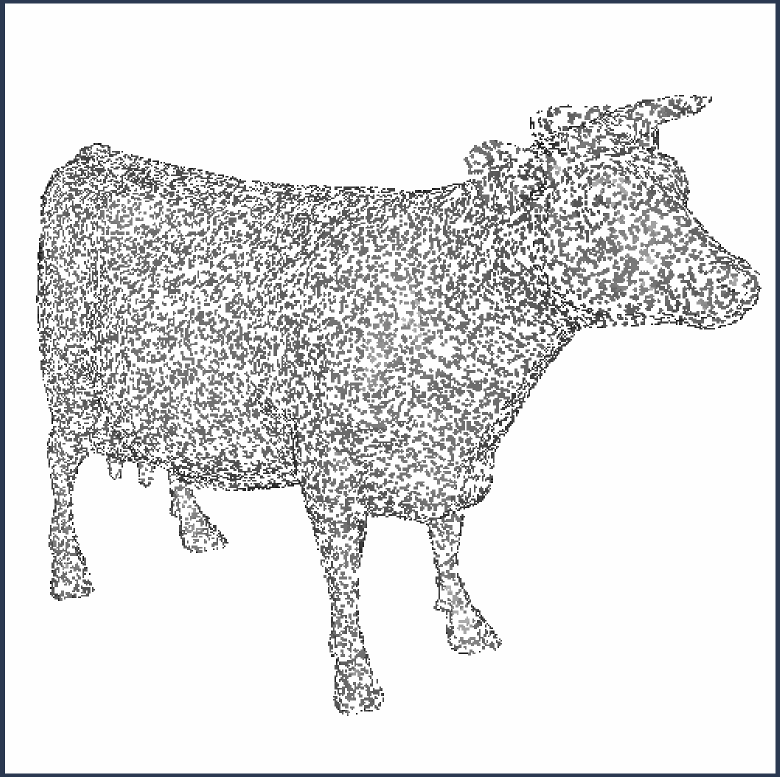
- Video Manipulations
  - Space-time gradients
- Mesh Deformations
  - 3D gradients

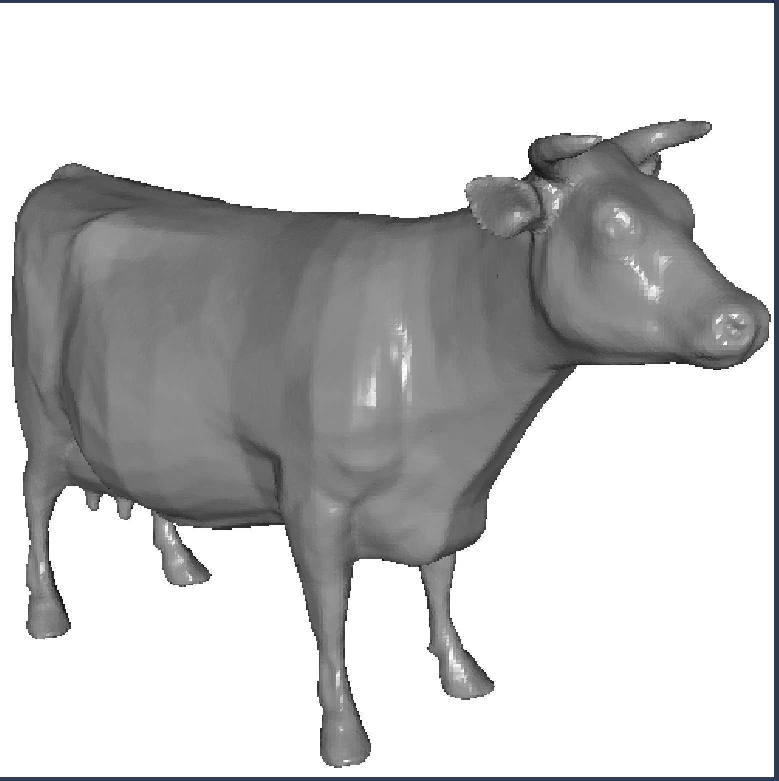


- Color2gray
  - Higher order differences
- Gradient Camera
  - High dynamic range imaging
  - Gradient operations at sensor level

Poisson Surface Reconstruction

Generate a mesh from a set of surface samples



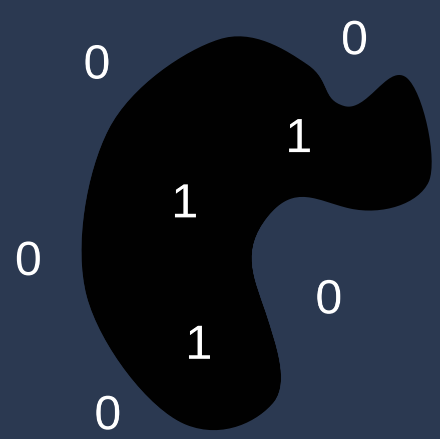


Michael Kazhdan, Matthew Bolitho and Hugues Hoppe, ”Poisson Surface Reconstruction”, Eurographics Symposium on Geometry Processing 2006, 61-70.

Approach

- Reconstruct the surface by solving for the indicator function of the shape.

$$\chi_M(p) = \begin{cases} 1 & \text{if } p \in M \\ 0 & \text{if } p \notin M \end{cases}$$



Indicator function

χ_M

Challenge

- How to construct the indicator function?

Oriented points

Indicator function

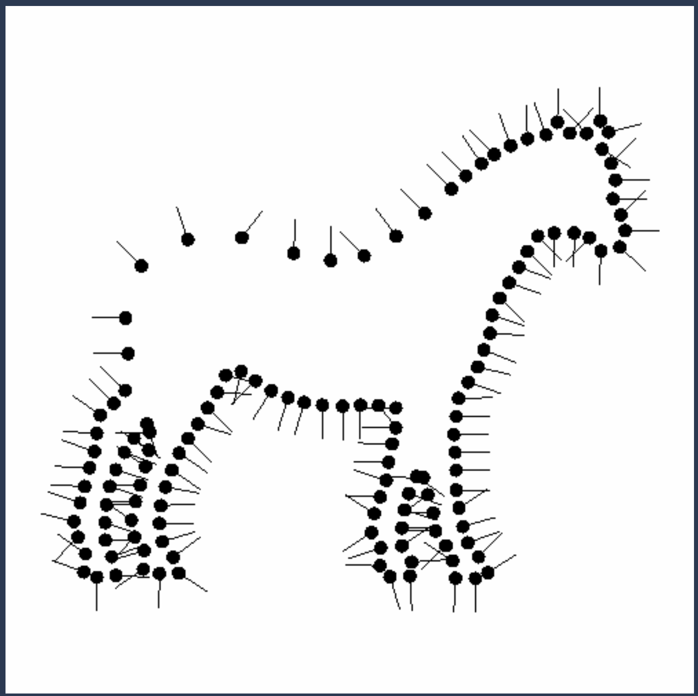
χ_M

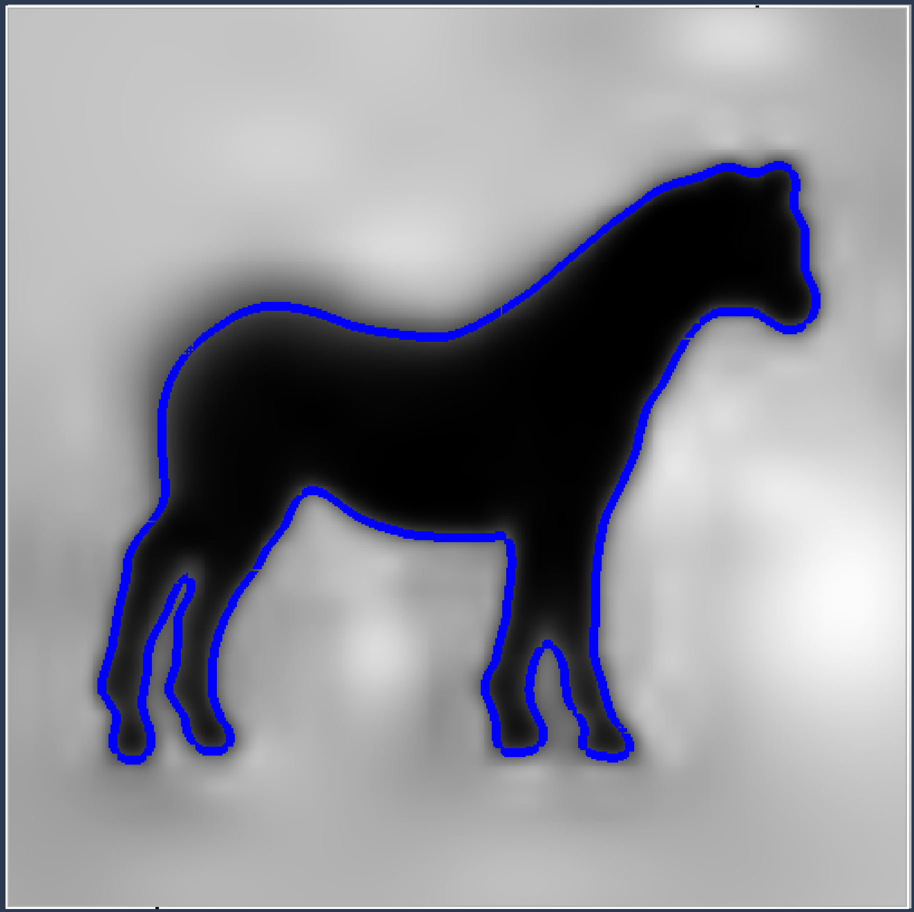
Integration

- Represent the points by a vector field $\vec{V}$
- Find the function χ whose gradient best approximates $\vec{V}$:

$$\min_{\chi} \left\| \nabla \chi - \vec{V} \right\|$$

Solve Poisson Equation

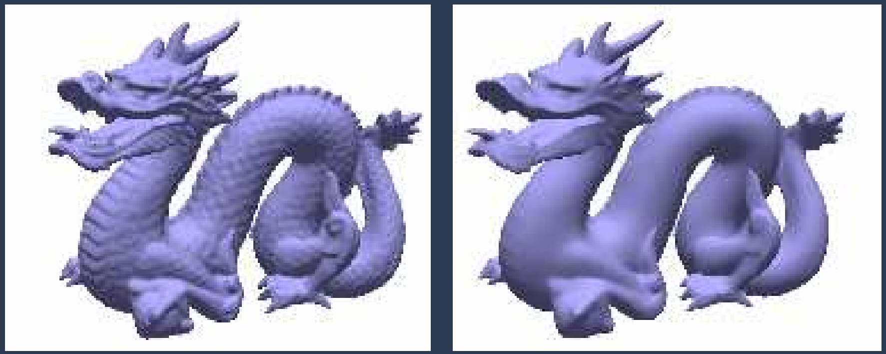
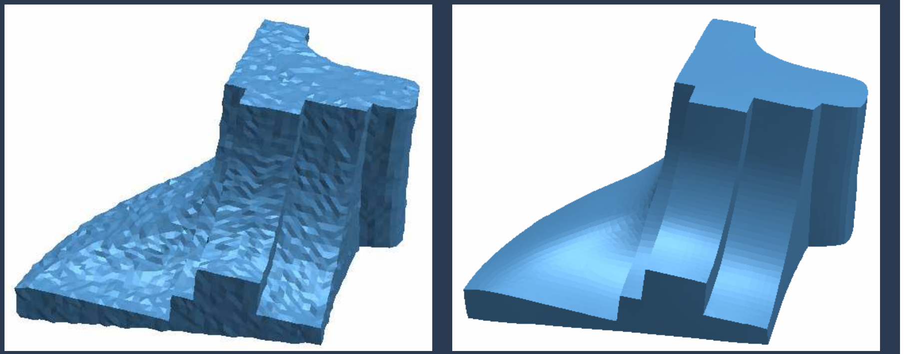




Extract Iso-Surface

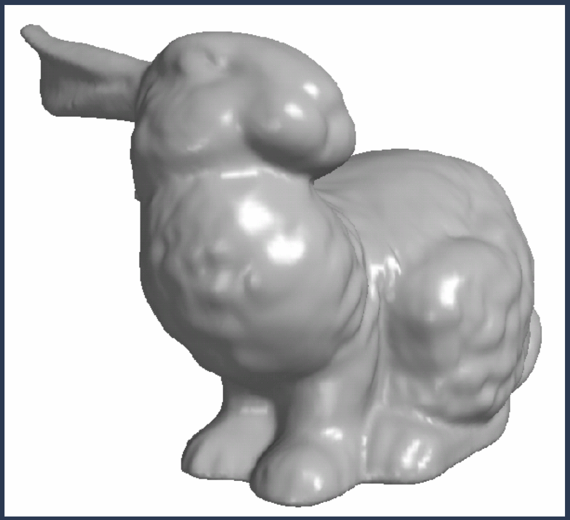
Mesh Denoising by Bilateral Filtering of Normals

- Bilateral Filtering of Normals
- Find transformation between original and filtered normals
- Apply to gradients
- Integrate

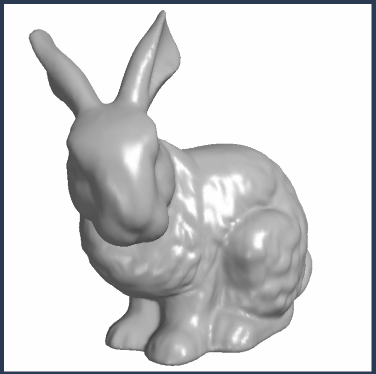
Mesh Editing: Object Merging

Mesh Deformation



Poisson Mesh Editing

- Achieve global effects while maintaining local shape
- Modify Local differential properties independent of neighbors
- Artifacts can be distributed during least-squares minimization



Y. Yu, K. Zhou, D. Xu, X. Shi, H. Bao, B. Guo and H.-Y. Shum, Mesh Editing with Poisson-Based Gradient Field Manipulation, SIGGRAPH 2004

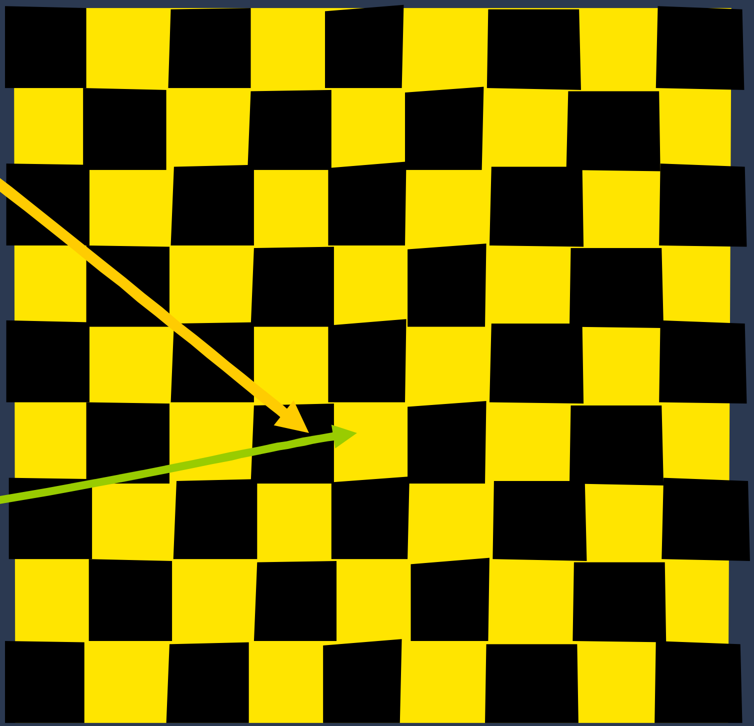
Advanced Topics

- Video Manipulations
  - Space-time gradients
- Mesh Deformations
  - 3D gradients
- Color2Gray
  - Larger neighborhoods

- Gradient Camera
  - High dynamic range imaging
  - Gradient operations at sensor level

- Gradients are local differences

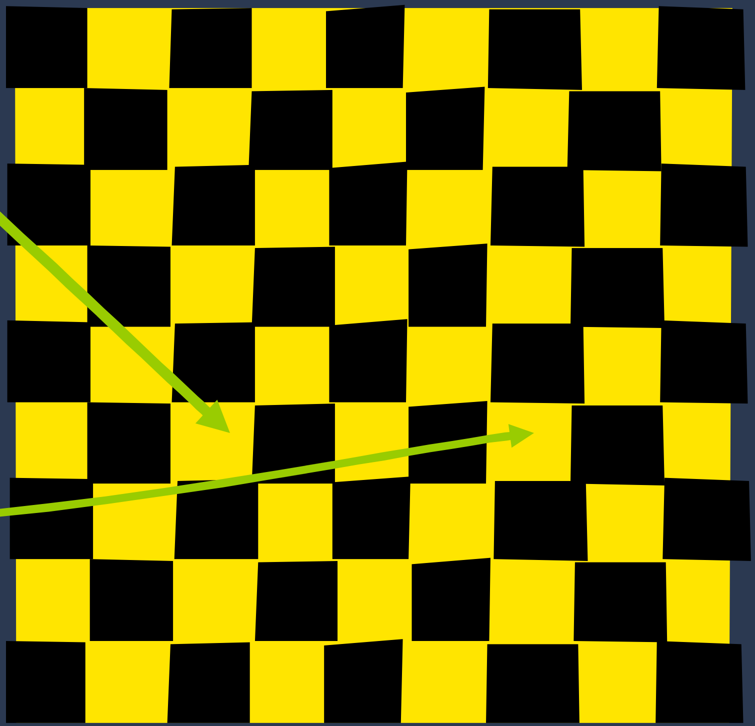
$$g_x(x,y) = I(x,y) - I(x-1,y)$$



- Allow differences over larger image regions

$$g_x(x,y) = I(x,y) - I(x-k,y)$$

k_{th}
neighborhood
difference

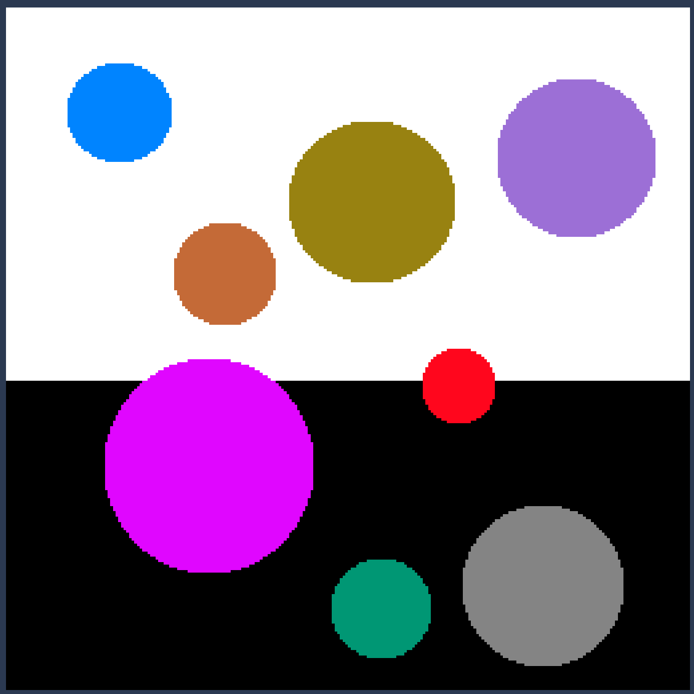


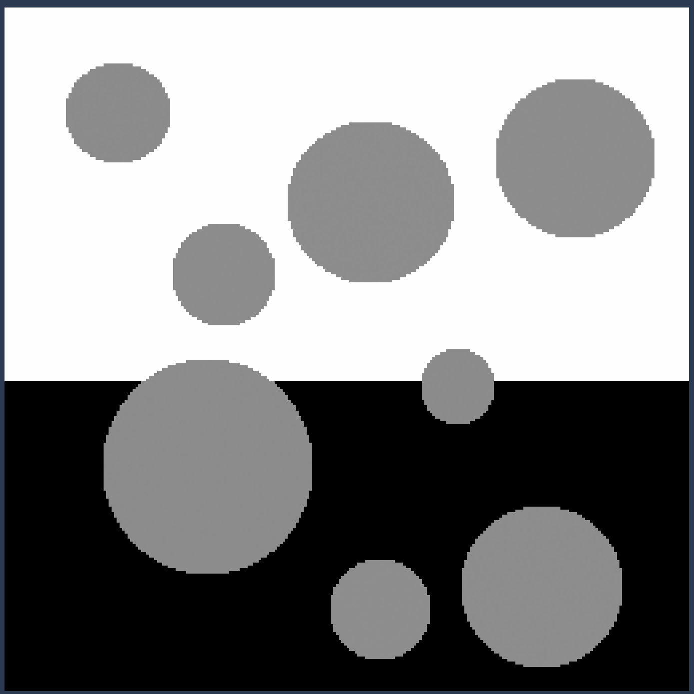
Color

Grayscale

Color2Gray

Isoluminant Colors


Color


Grayscale

Color2Gray

- Find perceptual grayscale difference between RGB pixel i and j

  (gradient) δ_{ij}

- Desired output image f(x,y)

- Minimize Error functional J

$$J = \iint_N (f_i - f_j - \delta_{ij})^2$$

- N: region of influence
  As N increases, the sparseness of linear system decreases

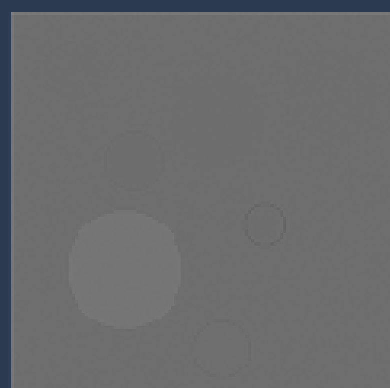
Amy Gooch, Sven Olsen, Jack Tumblin, Bruce Gooch, “Color2Gray: Salience-Preserving Color Removal”, SIGGRAPH 2005

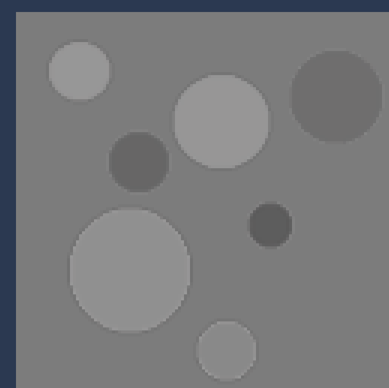
Original

PhotoshopGrey

Color2Gray

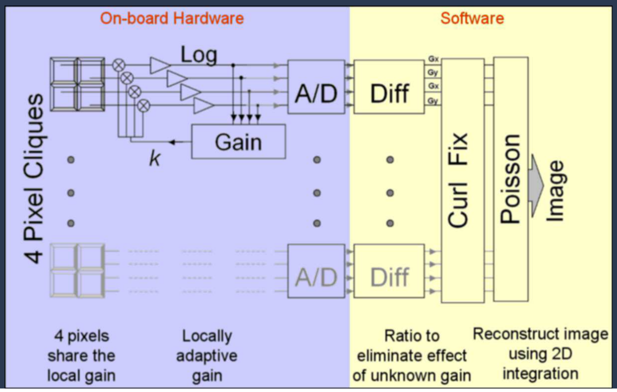

Original


PhotoshopGrey


Color2Grey

Advance Topics

- Video Manipulations
  - Space-time gradients
- Mesh Deformations
  - 3D gradients
- Color2gray
  - Higher order differences
- Gradient Camera
  - High dynamic range imaging
  - Gradient operations at sensor level



Gradient Camera

- Sense gradients directly instead of image intensities
- Enables
  - High Dynamic Range Imaging
  - Gradient domain operations at sensor level

Jack Tumblin, Amit Agrawal & Ramesh Raskar, “Why I Want A Gradient Camera”, CVPR 2005

High Dynamic Range Imaging

Small exposure: Dark inside

Large exposure: Outside Saturated

Tone Mapped HDR Image

Desired Image

Short Exposure

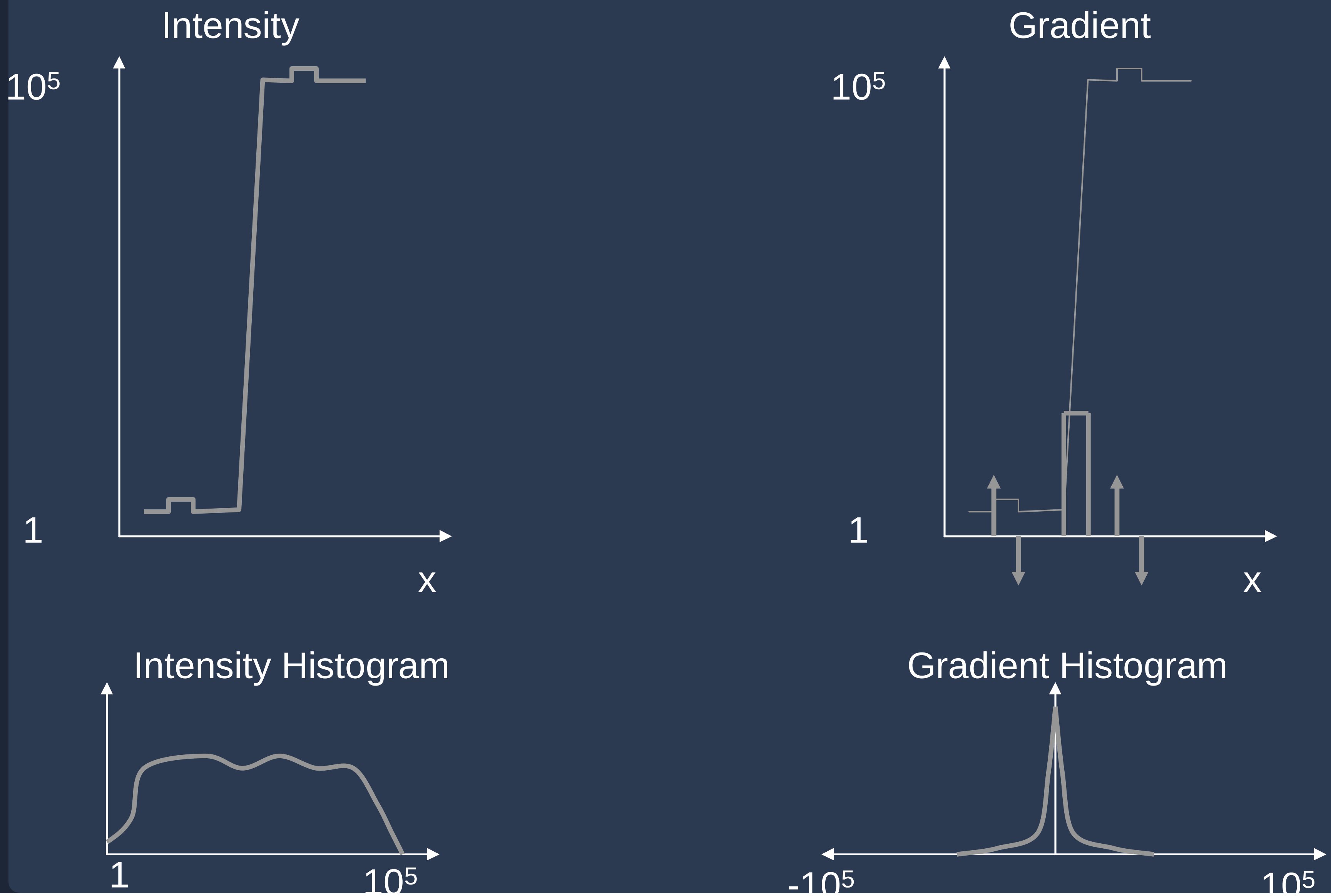
Long Exposure

Software Tone Mapping

High Dynamic Range Imaging

- How can we make a high dynamic range sensor?
  - Avoid exposure bracketing (multiple images)
- Optical Contrast Mask
  - Spatial light modulators
  - Complex, require additional elements, may lose resolution
- Adaptive sensors
  - E.g. log cameras
  - Lose contrast in high radiance regions
- Locally adaptive gain (Silicon Retinas)
  - Lose low frequency information

Natural Scene Properties



Gradient Camera

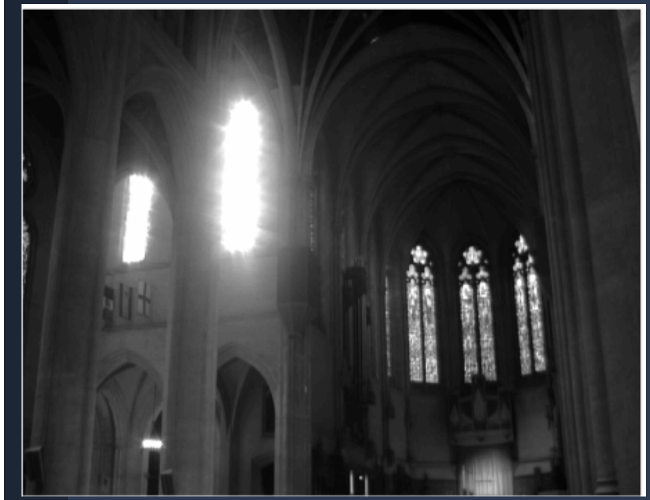
- Two main features
  1. Sense ratio (or log-difference) between neighboring pixel intensity
     At each pixel, measure (∇_x , ∇_y) , $\nabla_x = I_{x+1,y} / I_{x,y}$, $\nabla_y = I_{x,y+1} / I_{x,y}$
  2. With locally adaptive gain, but no need to store gain to recover image

- Gradient camera is very similar to locally adaptive gain camera

- Locally Adaptive Gain Camera
  – Gain is **different** for each pixel
  – Problem: Loses low frequency detail and preserves only high frequency features (edges)

- Gradient Camera
  – The gain is **same** for four adjacent pixels but different for each quad-pixels
  – Ratio between two pixels is measured with same gain on both pixels making the gain irrelevant ! Original image can be recovered
  – Reconstruct original image in software using Poisson Equation

Gradient Camera

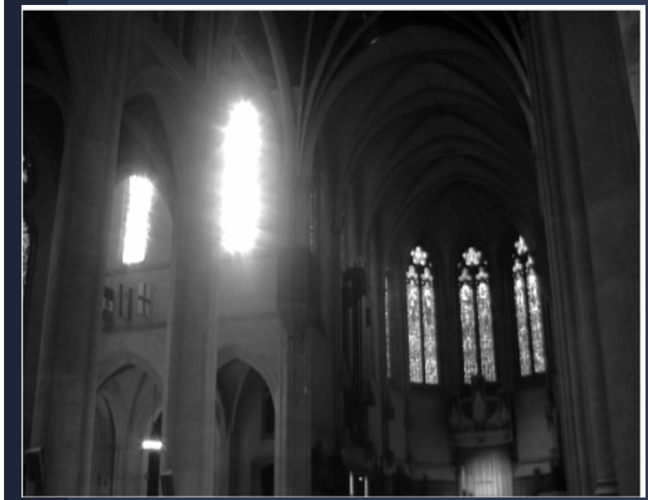


Scene

Intensity camera
saturation map

Intensity cameras fail to capture range

Gradient Camera



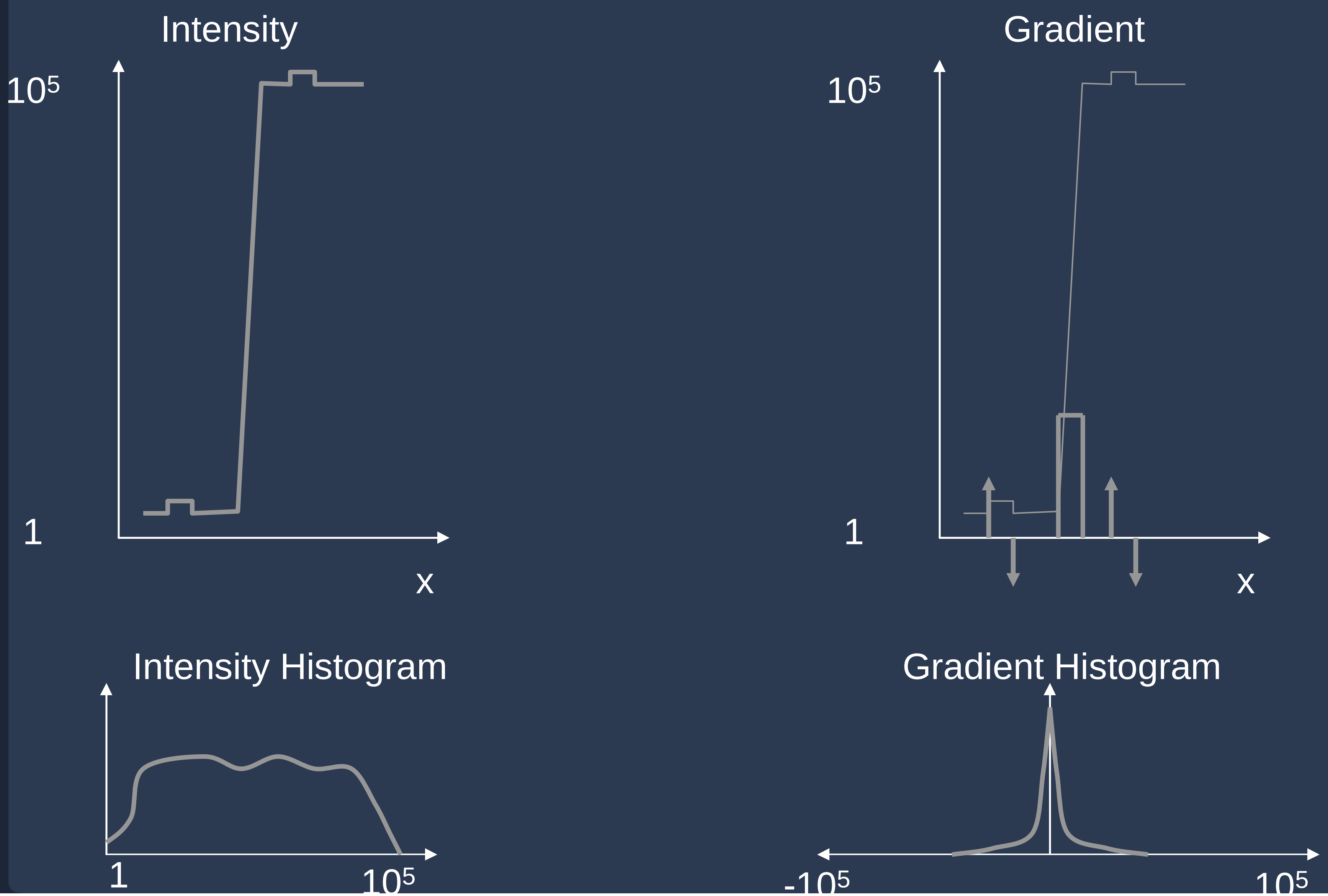
Scene

Intensity camera saturation map

Gradient camera saturation map

Intensity cameras fail to capture range
But, gradients saturate at very few isolated pixels

Natural Scene Properties



X gradient

Y gradient

At each pixel, 2 values:

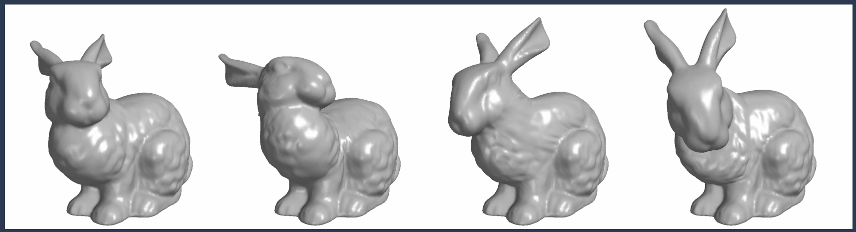
Gradient = (Gx, Gy)

How to find original image
from 2D forward differences ?

Solve Poisson
Equation in 2D

Advanced Topics

- Video Manipulations
  - Space-time gradients
- Mesh Deformations
  - 3D gradients



- Color2Gray
  - Large Neighborhood differences
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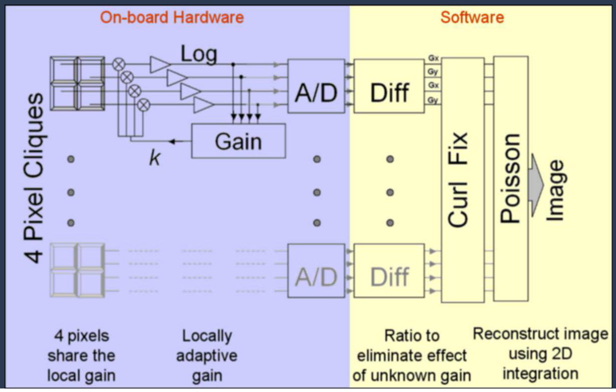
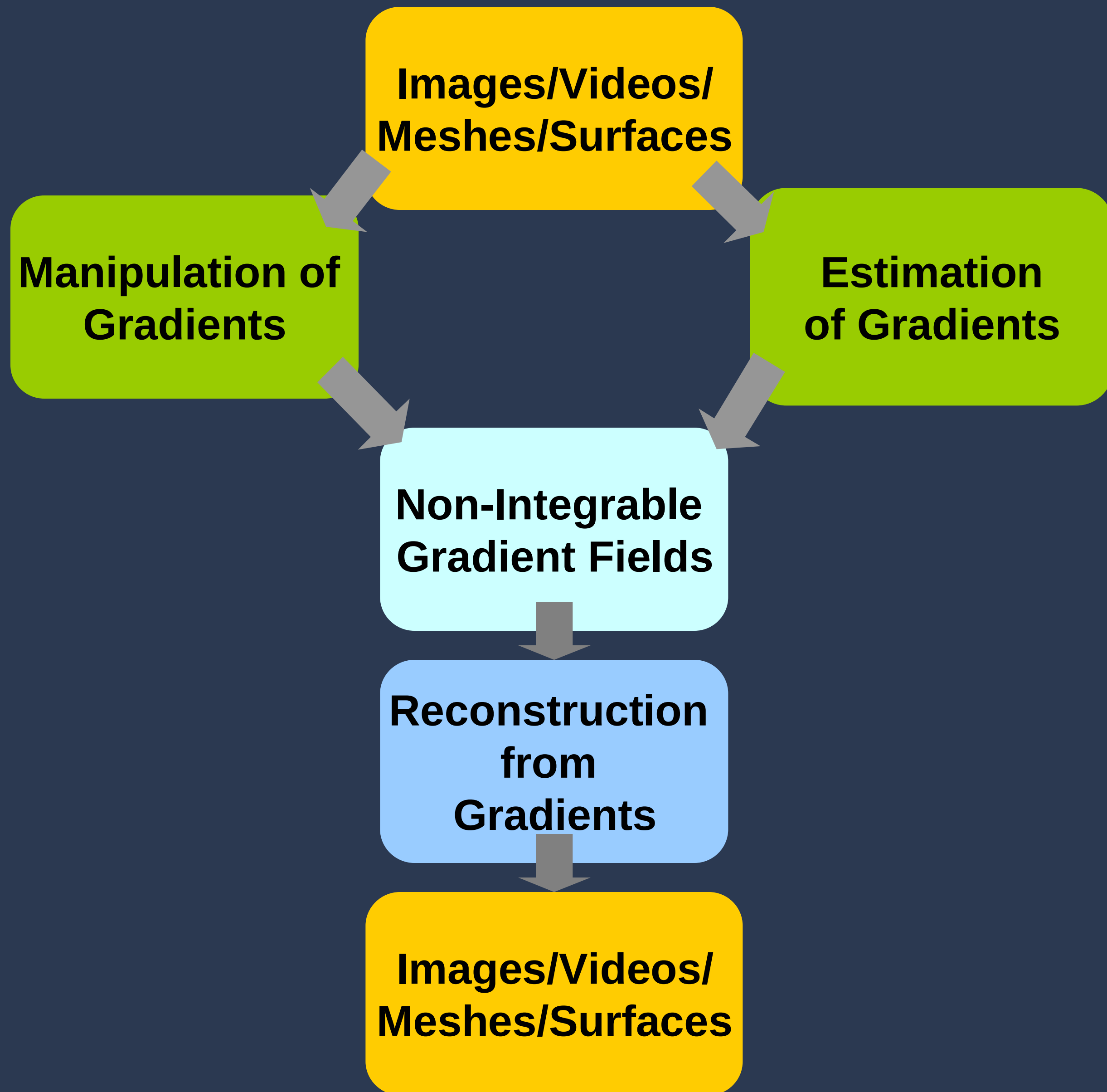


Gradient Domain Manipulations



Acknowledgements

- Slides Credits
  - Rick Szeliski, Microsoft
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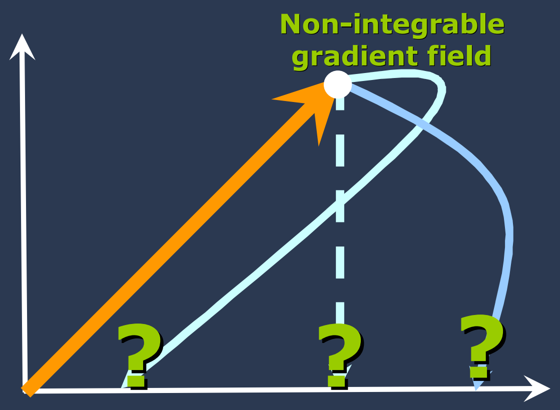
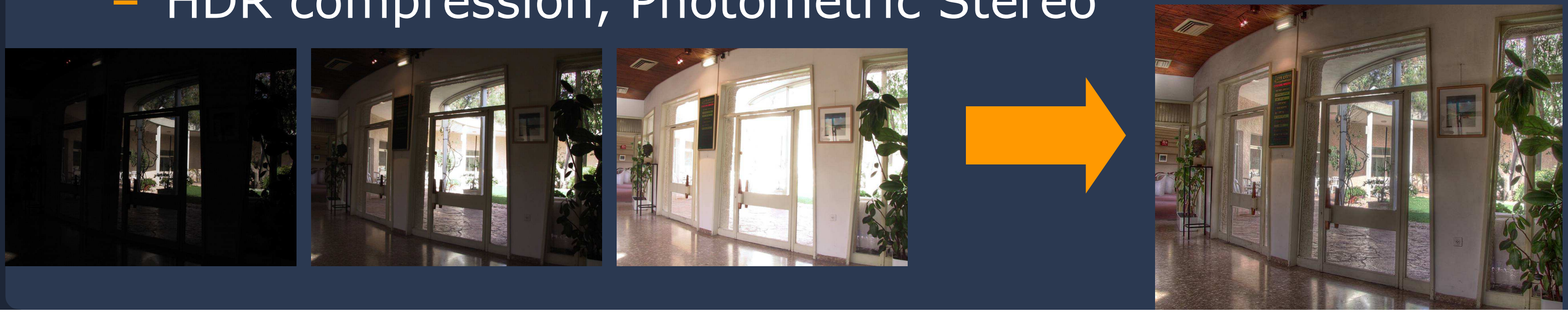
  - Patrick Perez, IRISA / INRIA Rennes
  - Pravin Bhat, University of Washington
  - Yun Zheng, Zhejiang University
- Image Credits
  - Rannan Fattal, Jian Sun, G.D.Finlayson, and many more

Summary

- Basics
  - Curl, Divergence, Intgerability
- Non-integrable gradient fields in vision/graphics
  - Estimation & Manipulation of gradients



- Reconstruction from gradients
- Motivating applications
  - HDR compression, Photometric Stereo



- Gradient Domain Manipulation of images

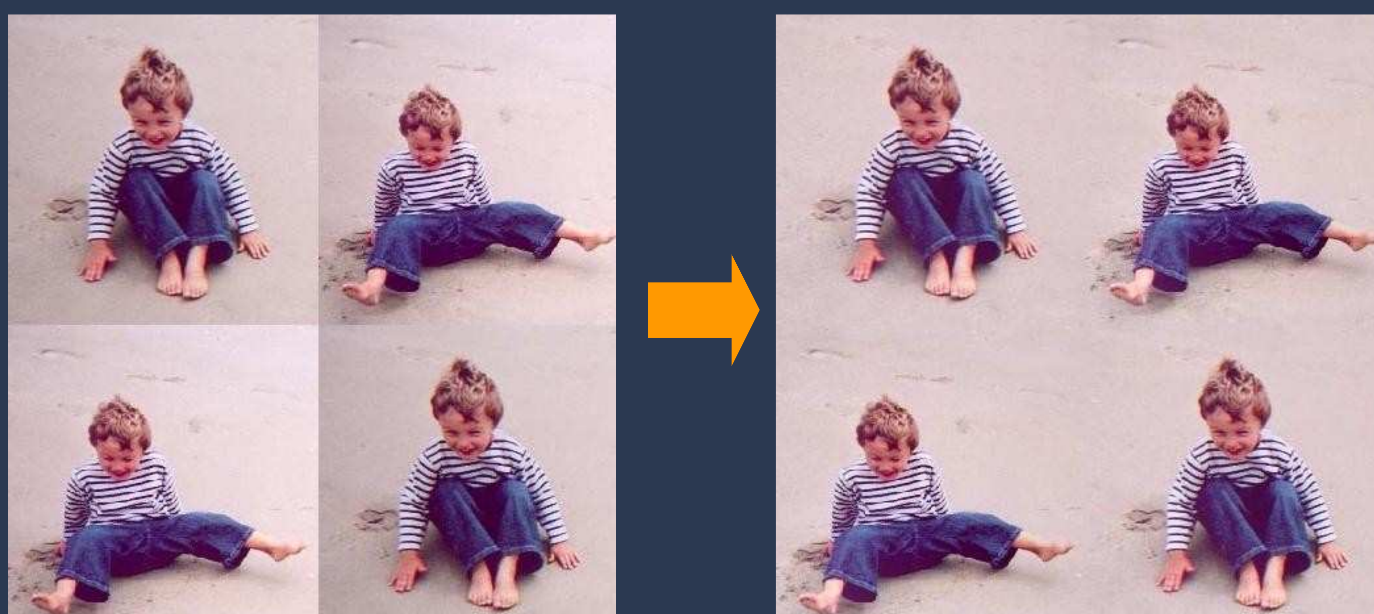
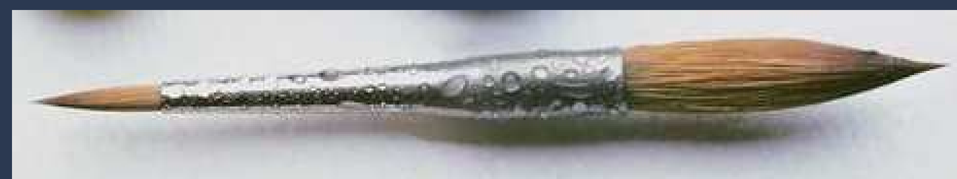
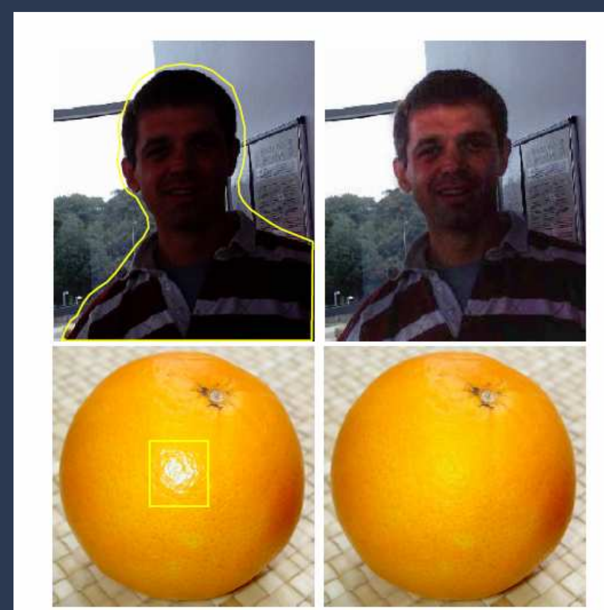


Image Editing



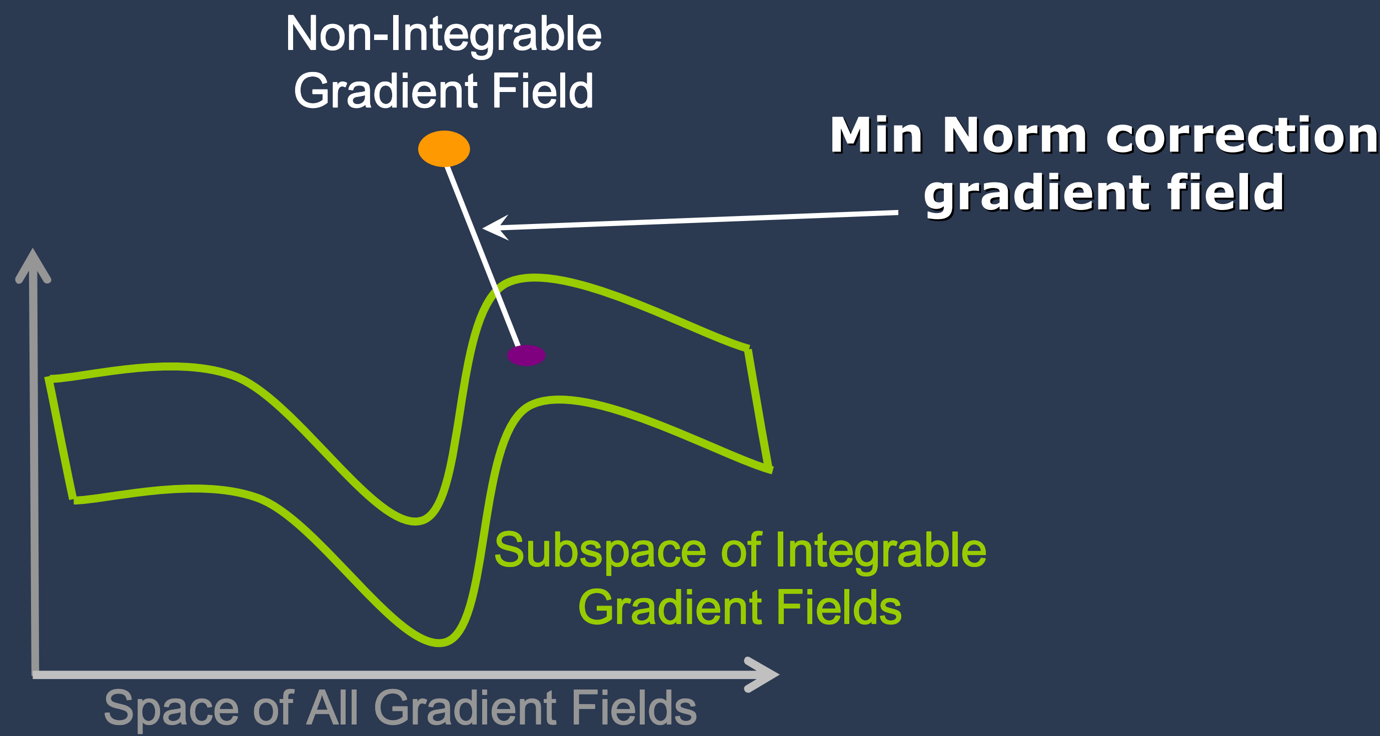


Changing Local Illumination

Edge Suppression under Significant Illumination Variations

Fusion of day and night images

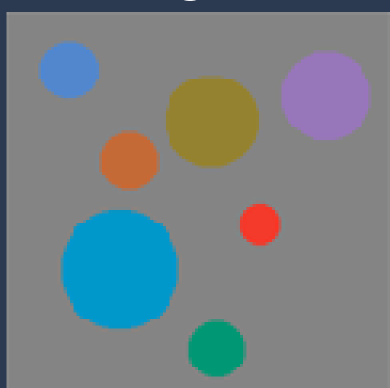
Poisson Solver

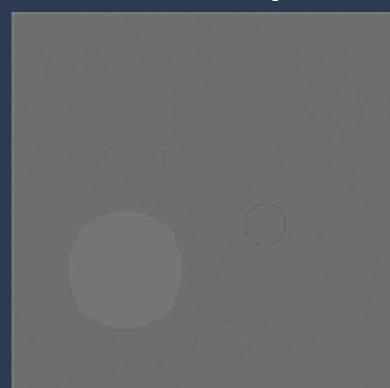


Original

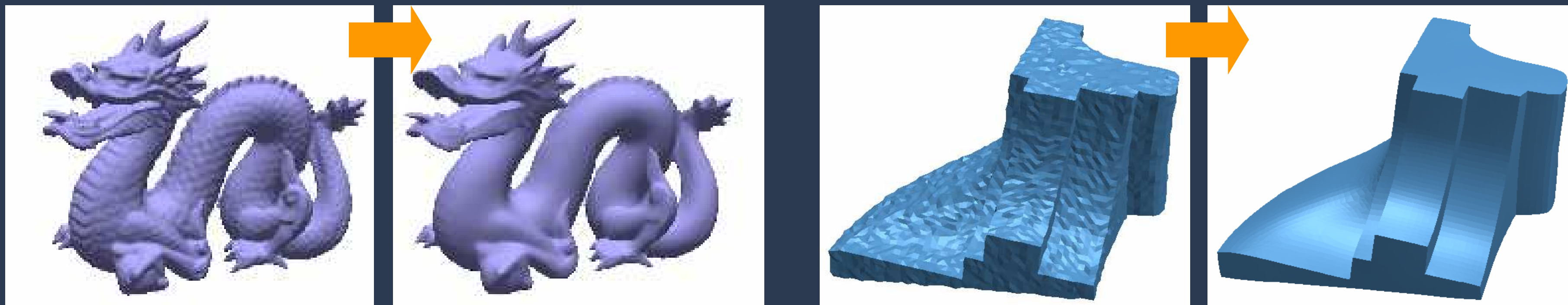
PhotoshopGrey

Color2Gray

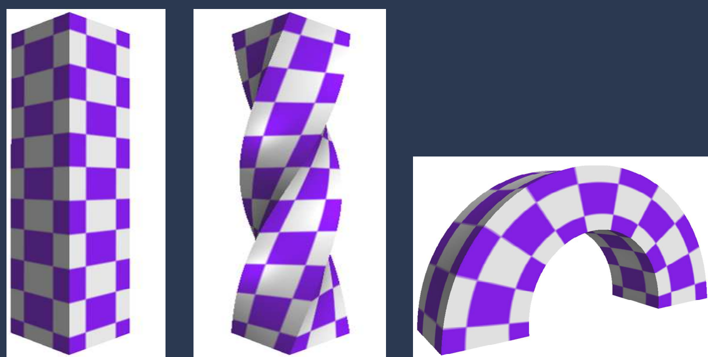




Color to Gray Conversion



Mesh Smoothing



(a) (b) (c)

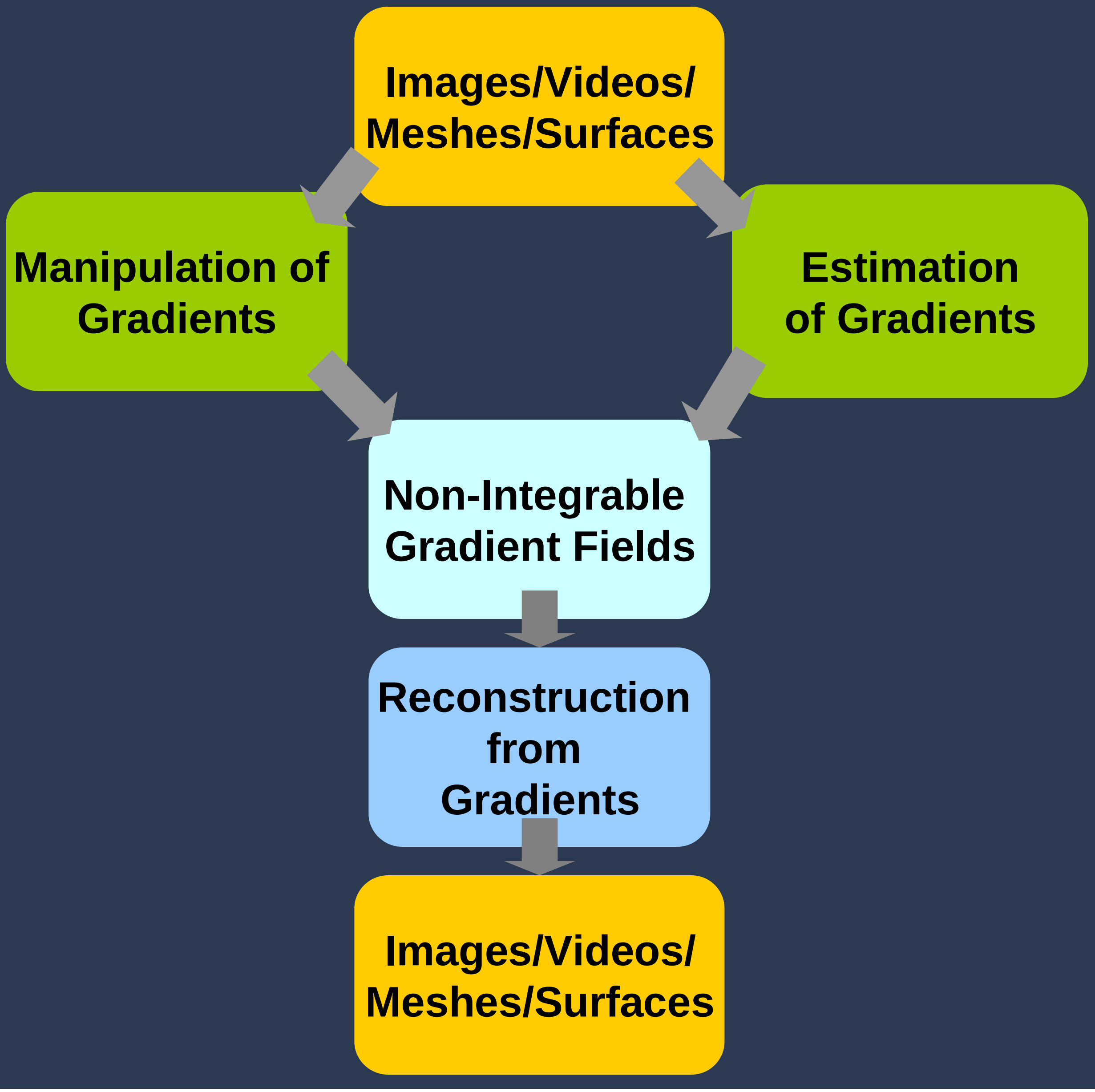
Mesh defomations

High Dynamic Range Compression

Future Directions

- Gradient Manipulations
  - Intuitive, easy to use manipulations, user interactions
  - Vector operations, edge suppression
  - Multi-modal sensor data, e.g. visible/IR
- Reconstruction from Gradients
  - Faster solutions, consumer cameras ~ 15 MP, on-chip
  - Better approaches, robust, feature preserving
  - Other domains: phase unwrapping

Gradient Domain Manipulations



Course: Gradient Domain Techniques

Course Web Page

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