# Active Vision:
# Range Data
# Chapter 12.2/12.3 Szelisky CV

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CS 6320, Spring 2012

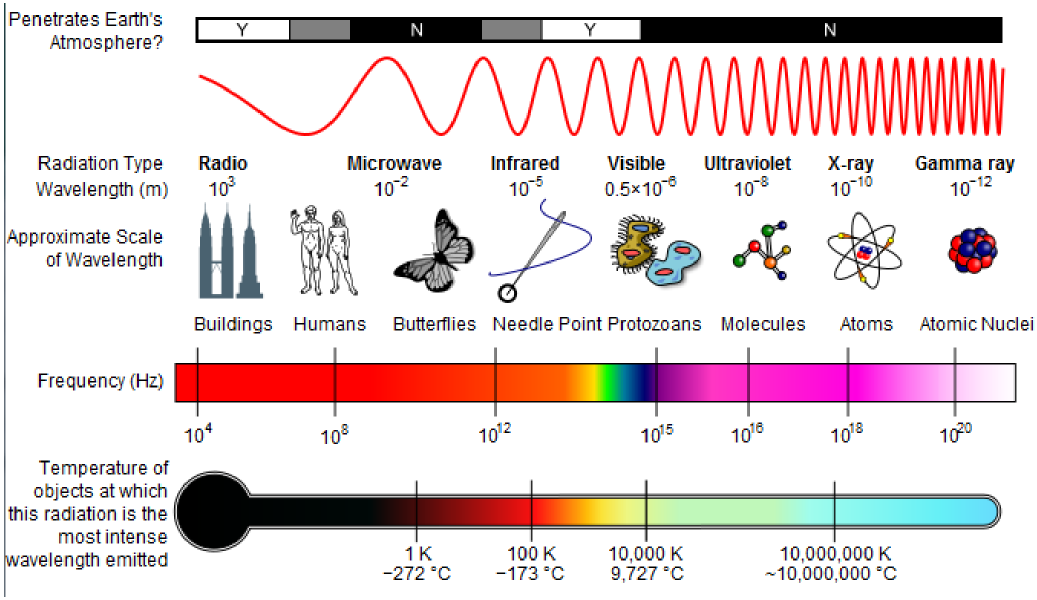
(credit: some slides from F&P book Computer Vision)

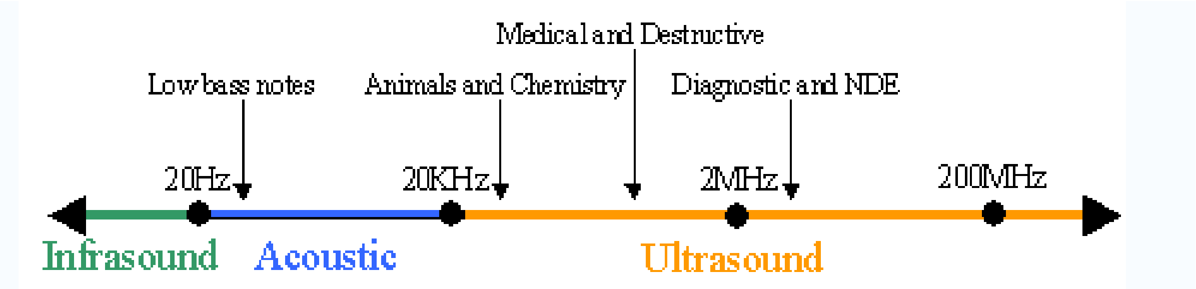
# Contents

- Range cameras and physical principle
- Processing of range image data
  - Patches of homogeneous properties
  - Extended Gaussian Image (EGI)
  - Discontinuities: Local curvatures
  - Registration of Range Data: ICP
- Applications

Material: Szelisky coursebook Computer Vision 12.2/12/3

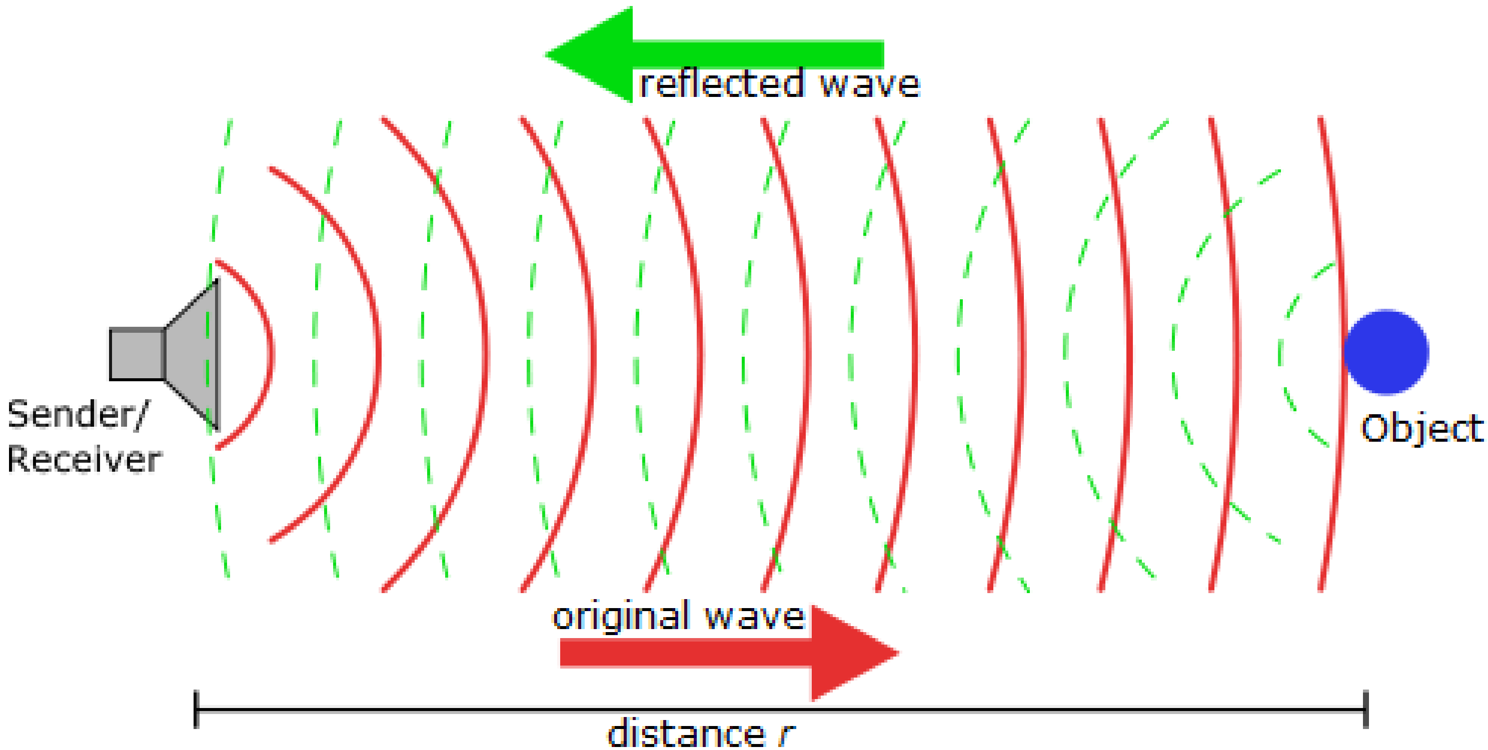
# Physical Principles




Source: Wikipedia

# SONAR (Sound navigation and ranging)



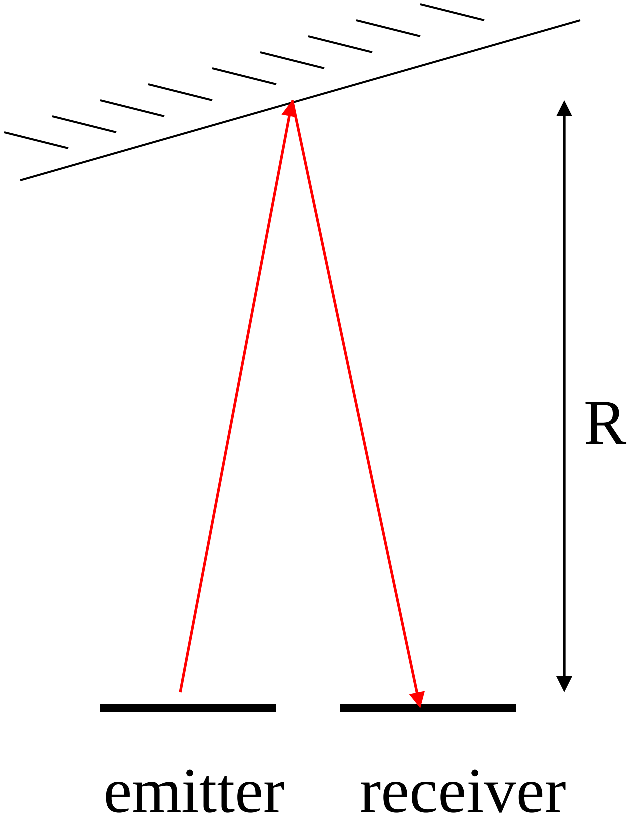

**Principle**: Wave with known velocity v traveling distance 2*r → takes time $t_f$

# Bats

Bats use a variety of ultrasonic ranging (echolocation) techniques to detect their prey. They can detect frequencies as high as 100 kHz, although there is some disagreement on the upper limit.[22]
(see also dolphins, shrews, whales).

# Time of Flight (TOF)

**Basic principle: Time of Flight (TOF): Emit signal, wait for echo, measure time difference**



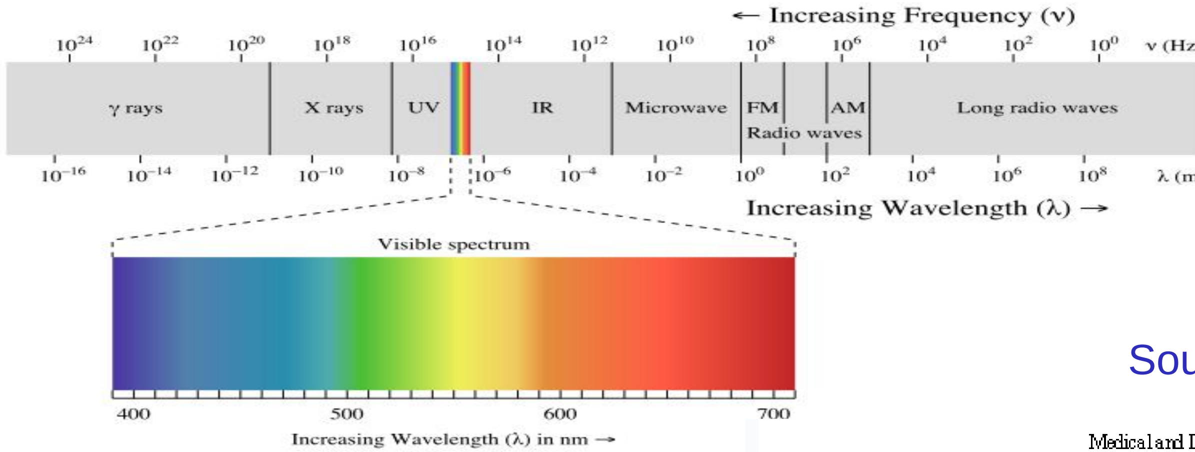

Range measurement:

- Velocity *v* is known
- $t_f$ to be measured

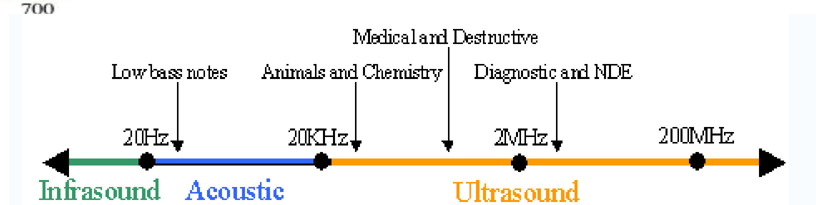
$$2R = v * t_f$$

$$R = \frac{v * t_f}{2}$$

# Wavelengths for TOF




Source: Wikipedia




- Radar (microwaves: $c = c_{light}$, $\lambda = 0.02$m, f = 15GHz)
- Light/Laser (light: $c_{light} = 3*10^{-8}$ m/sec, $\lambda$ = 400nm to 700nm, f= 7 to $4*10^{6}$ GHz )
- Sound (sound: c = 331 m/sec, $\lambda = 0.02$m, f = 20Hz to 20kHz)
- Ultrasound (sound: c = 331 m/sec, $\lambda = 0.017$mm, f = 2MHz )

# TOF ctd.

Resolution:

Challenge for electronics:

$$t_f = \frac{2*R}{v}$$

$$\Delta t_f = \frac{2*\Delta R}{v}$$

Example:

- Sound: v=330m/sec
  △R=1cm → △t=60μs
- Light: $c=3*10^8$m/sec
  △R=1cm → △t=67ps (picoseconds)

# Ultrasound


- Example: **Polaroid**
- Material or topology may absorb arbitrary frequencies: Transmits several frequences (Polaroid: 60,57,53,50kHz)
- Engineering principle: Use pulsed frequency (f) and digital counter (n)
- Range of counter: $2^k$-1 (e.g. 16bit)
- Range of unique depth measurement: R*
- Example: f=50kHz, v=330m/sec, k=16: R*=216m, 1count: 6.6mm)
- Problem: wide bundle (30°)

$$t_f = \frac{n}{f}$$

$$R = \frac{t_f * v}{2} = \frac{n * v}{2f}$$

$$R* = \frac{(2^k - 1) * v}{2f}$$

# Pulsed Time of Flight

- Advantages:
  - Large working volume (up to 100 m.)
- Disadvantages:
  - Not-so-great accuracy (at best ~5 mm.)
    - Requires getting timing to ~30 picoseconds
    - Does not scale with working volume
- Often used for scanning buildings, rooms, archeological sites, etc.

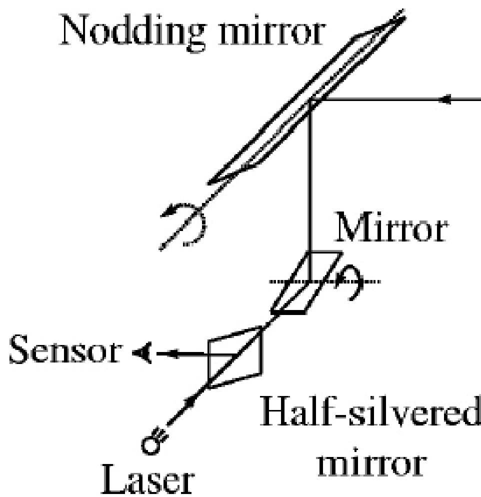
# Laser

- Very narrow bundle: high spatial resolution
- But: High temporal resolution of measurement electronics (pico-seconds)
- Example: 1cm depth resolution: 70 pico sec
- Reliable measurements: Large #pulses
- Alternative to TOF:
  - Phase Shift encoding
  - Modulation of laser with sin-wave of frequency $f_{AM}$
  - Phase shift due to time of flight

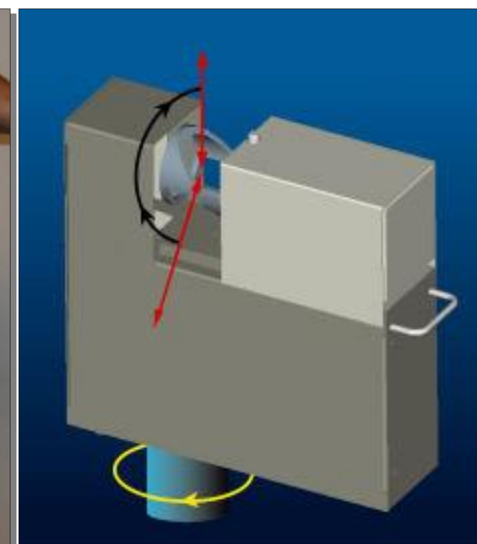
# Pulsed Time of Flight

- Basic idea: send out pulse of light (usually laser), time how long it takes to return

$$d = \frac{1}{2} c \Delta t$$







[DeltaSphere by http://www.3rdtech.com/](http://www.3rdtech.com/)

# Depth cameras

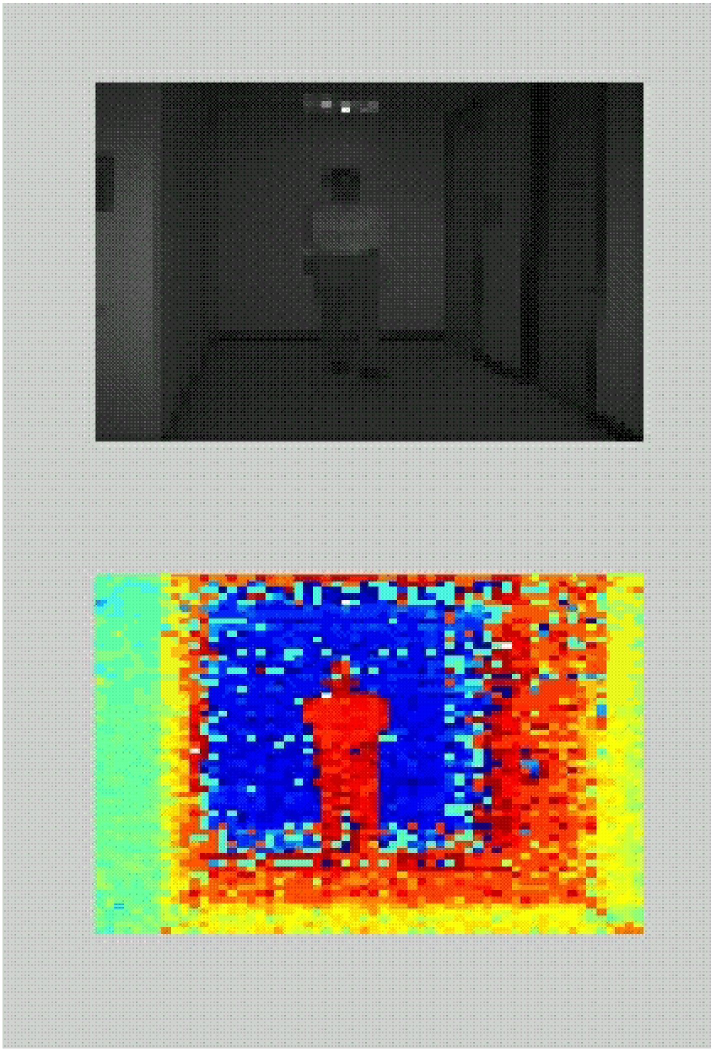
2D array of time-of-flight sensors

e.g. Canesta's CMOS 3D sensor

jitter too big on single measurement,

but averages out on many

(10,000 measurements$\Rightarrow$100x improvement)



Canesta: Principle: http://en.wikipedia.org/wiki/Canesta
Demo:
http://www.youtube.com/watch?v=5_PVx1NbUZQ&noredirect=1

# Range Image Data

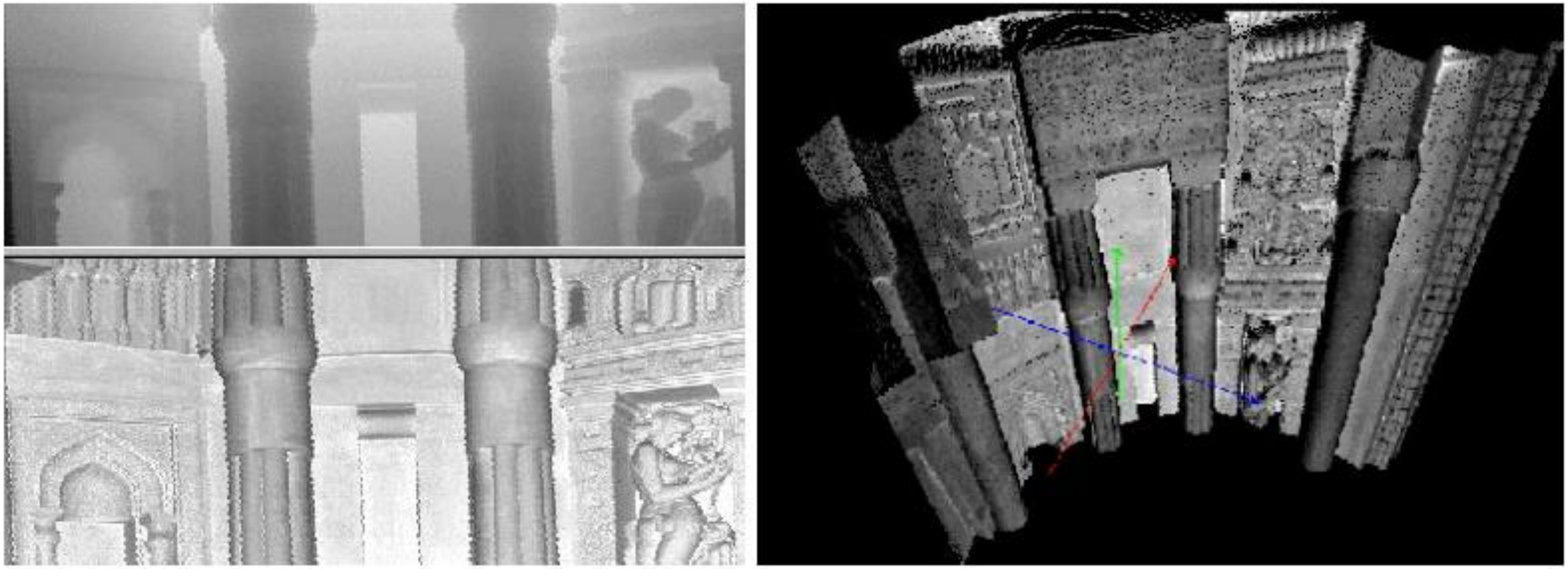
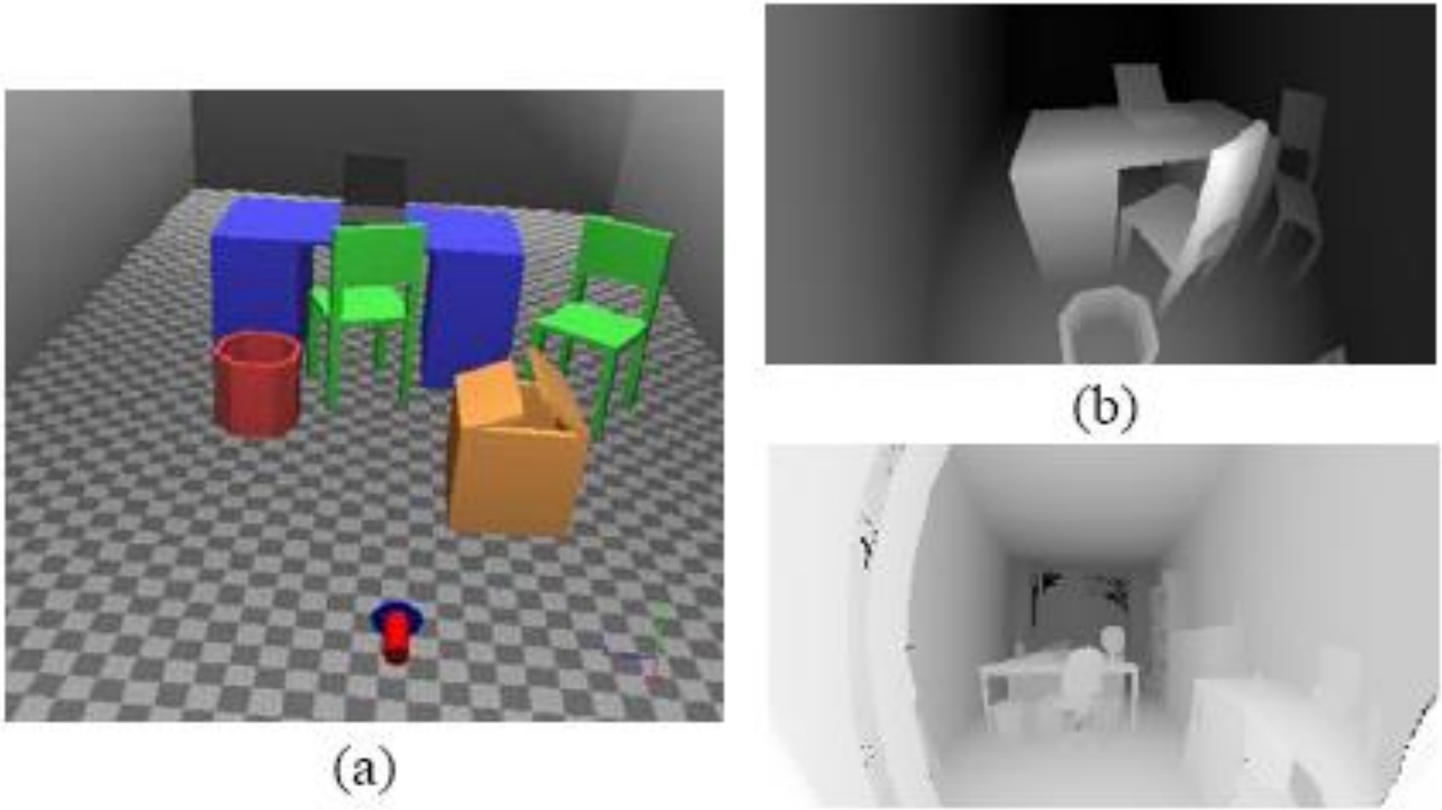


**Figure 24.3.** Range data captured by the AM phase shift range finder described in [Hancock *et al.*, 1998]: (left) range and intensity images; (right) perspective plot of the range data. Reprinted from [Hebert, 2000], Figure 5.

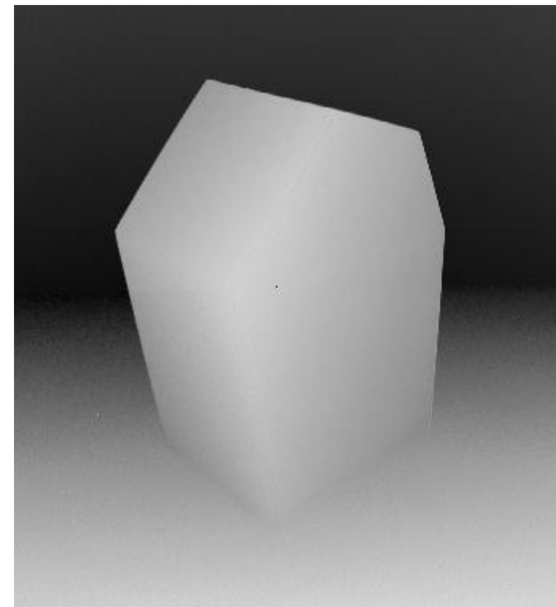
# Input Data



(a) (b) (c)

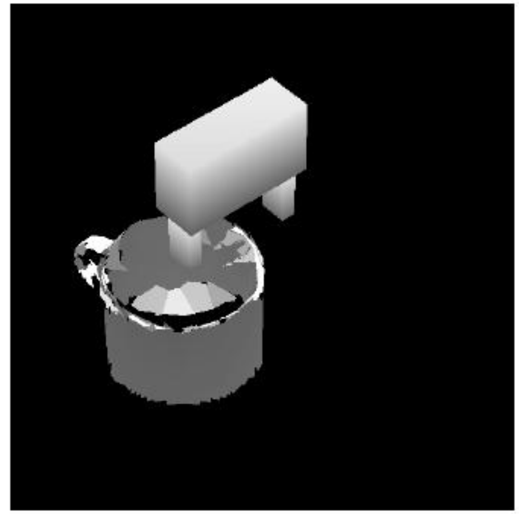
Simulated and real range images

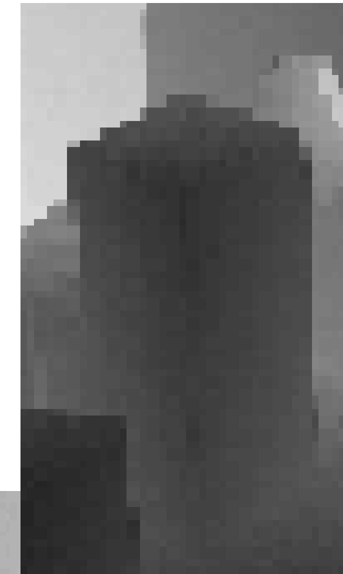
# What is special about range images?



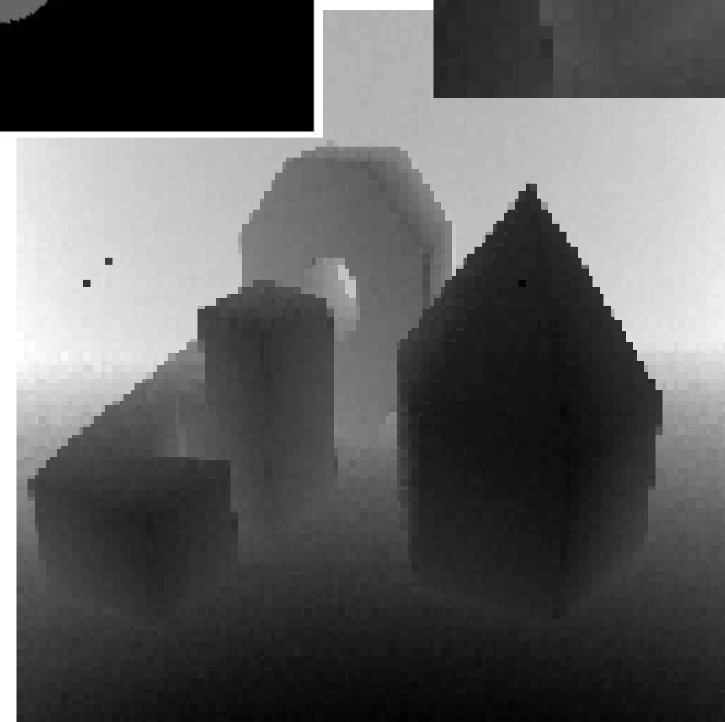
Object faces?
Object boundaries?

# What is different in range images?

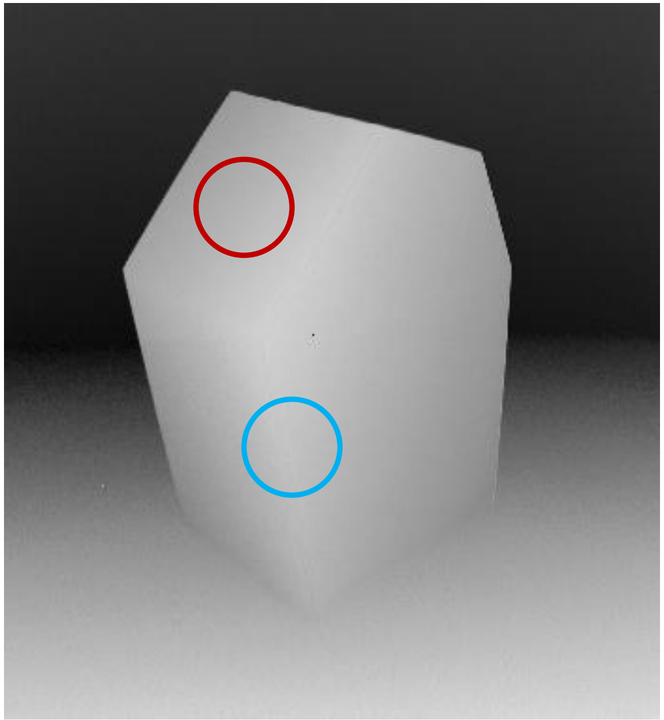


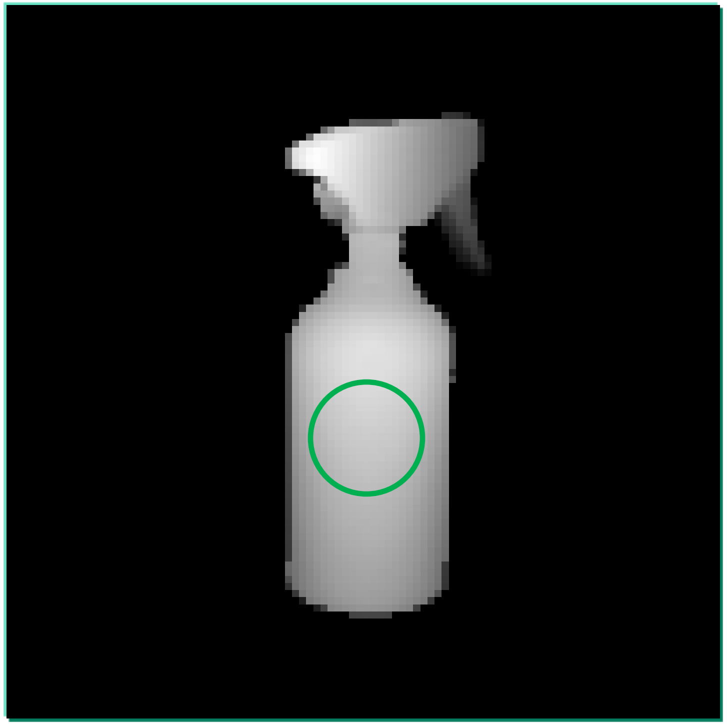


Object faces?
Object boundaries?



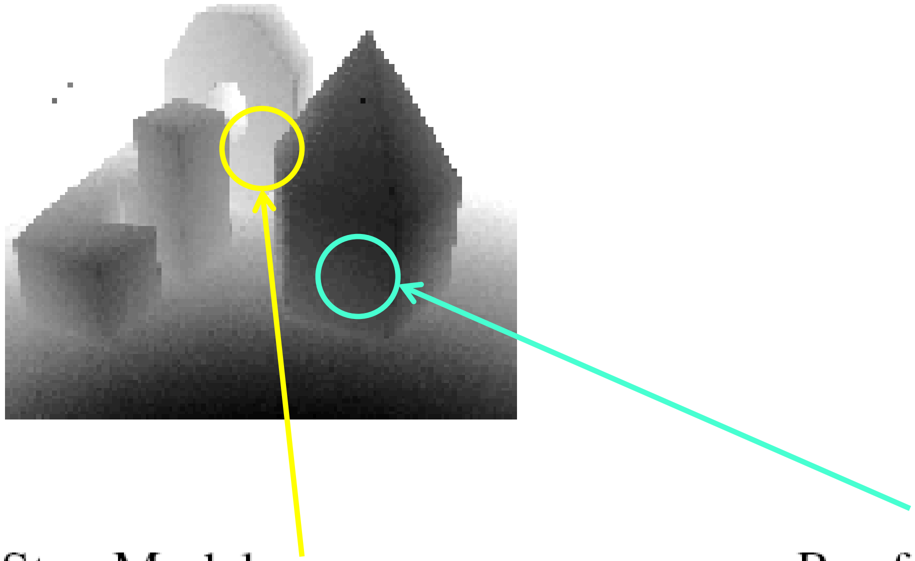
# What is special about range images?

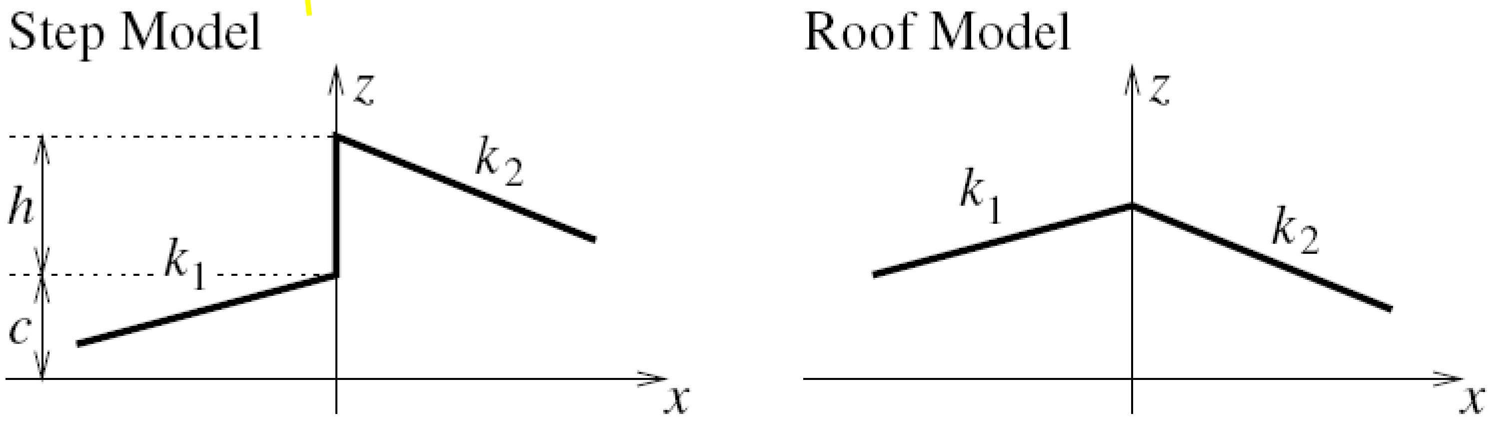




- Homogeneous in surface normals
- Crest line: Abrupt change of surface normals
- Continuous change of normals, homogeneous in curvature

# Types of Discontinuities in Range Images

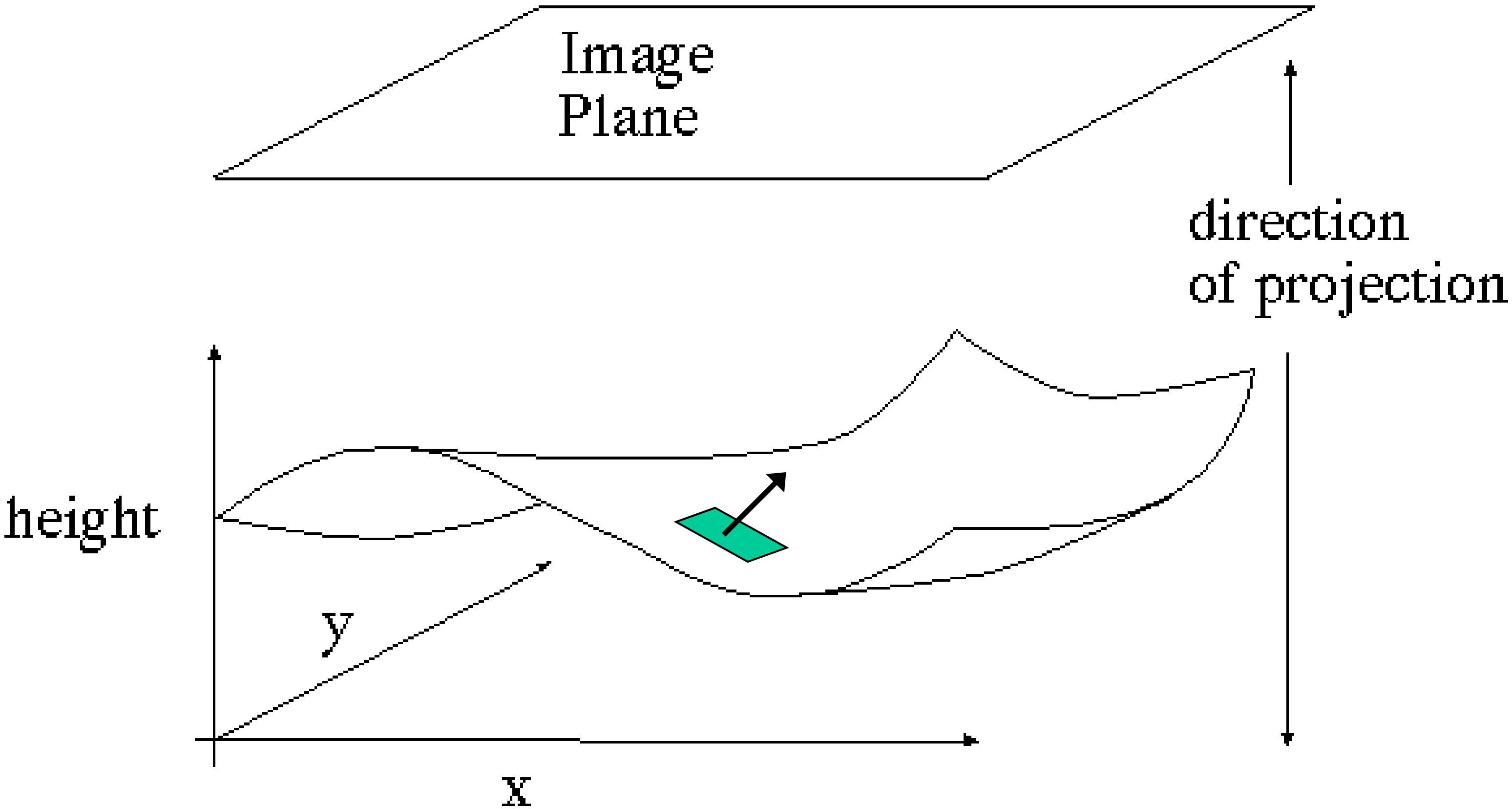




# Properties of object surfaces in range images

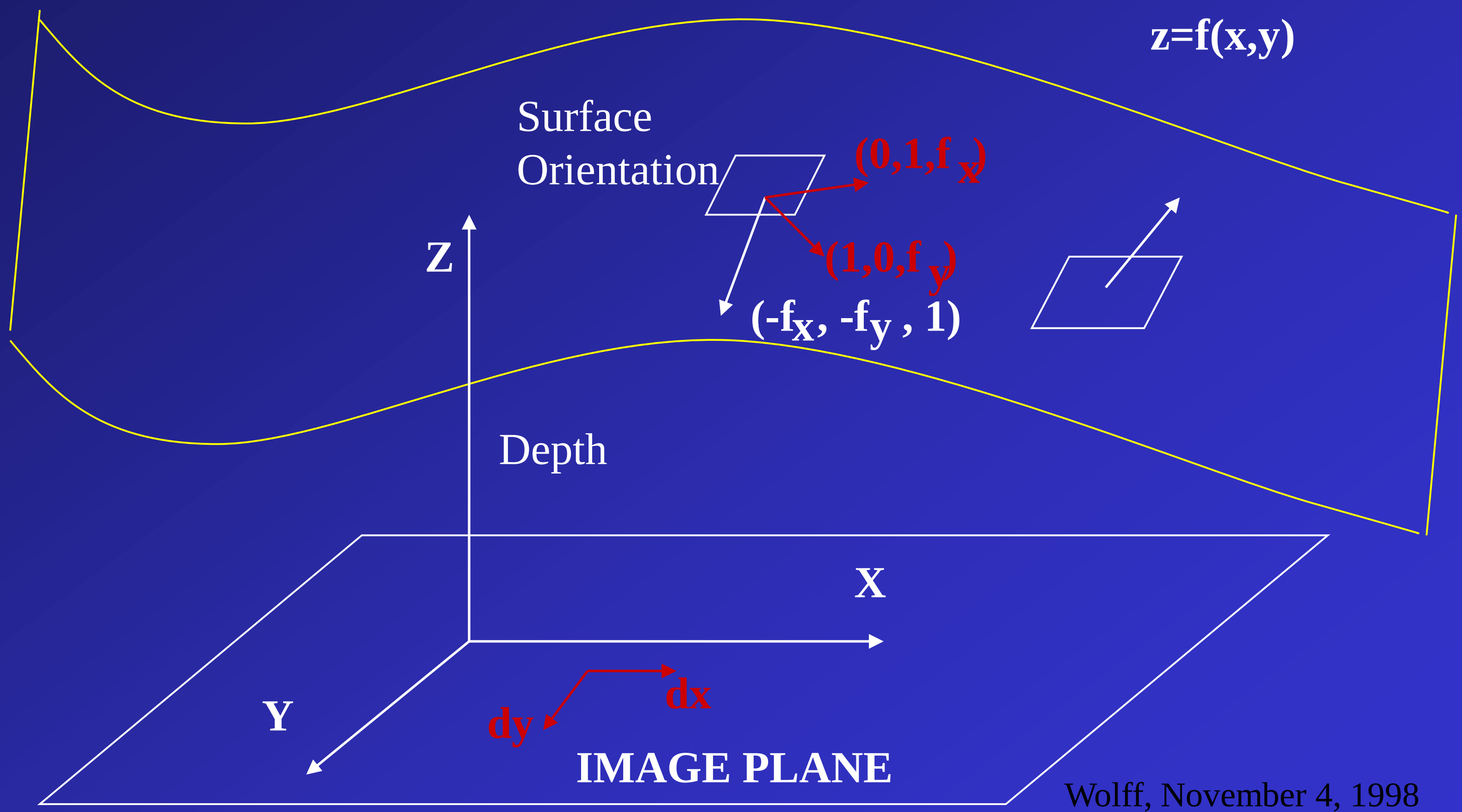
- Homogeneity of surface properties in:
  - Surface normals
  - Curvature
- Discontinuities between surfaces:
  - “roof edges”: locations with change of normals
  - “step edges”: discontinuous depth (e.g. hidden objects)

Remember:
# Shape from Shading: “Monge” Patch



# Surface Orientation and Surface Normal

$$(f_x, f_y, -1) = (0,1,f_x) \times (1,0,f_y)$$



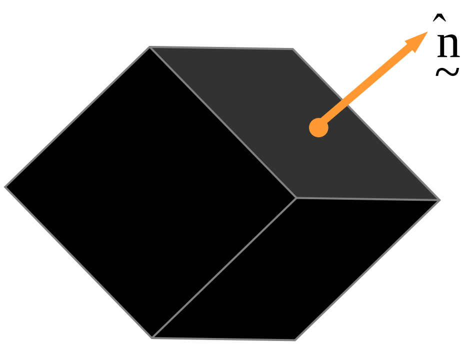
# Surface Orientation and Surface Normal

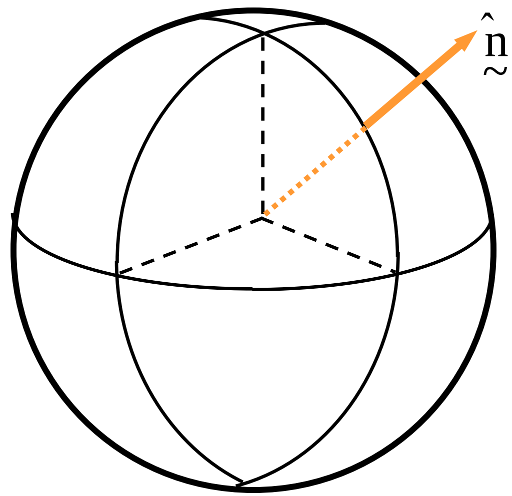
$$(-f_x, -f_y, 1) = (-p, -q, 1)$$

**p, q comprise a gradient or gradient space representation for local surface orientation.**

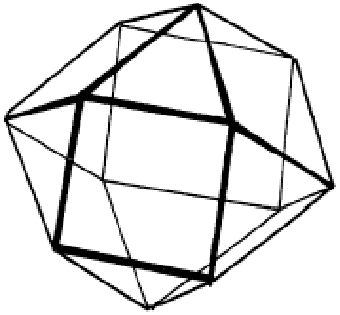
# Object Representation: The Gaussian Image (EGI)

- Surface normal information for any object is mapped onto a unit (Gaussian) sphere by finding the point on the sphere with the same surface normal:



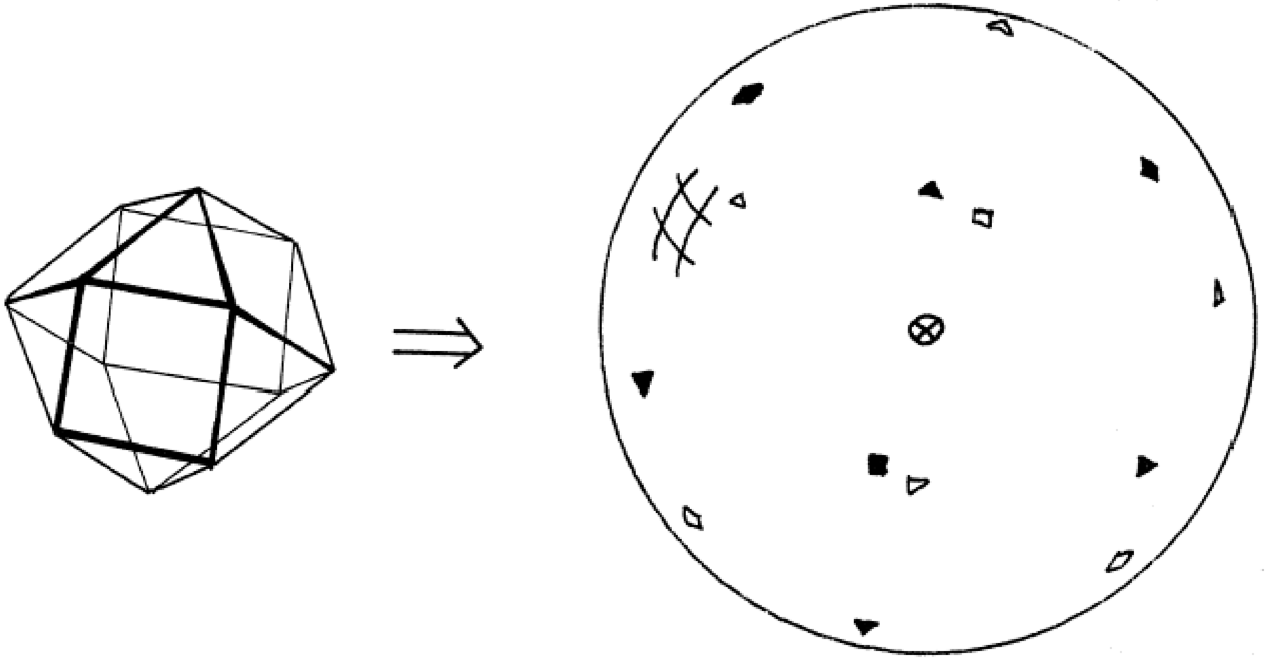



# Example (K. Horn)



*www.cs.jhu.edu/~misha/Fall04/**EGI**1.ppt*

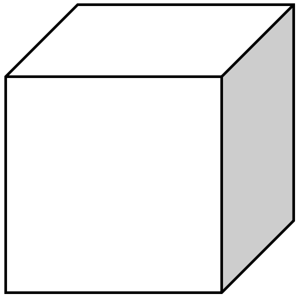
# Example (K. Horn)



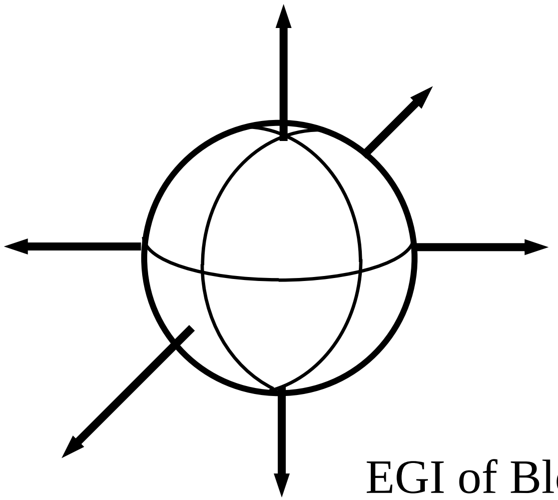
*www.cs.jhu.edu/~misha/Fall04/**EGI**1.ppt*

# The Extended Gaussian Image

- We can extend the Gaussian image by
  - placing a mass at each point on the sphere equal to the area of the surface having the given normal
  - masses are represented by vectors parallel to the normals, with length equal to the mass (VOTING)
- An example:

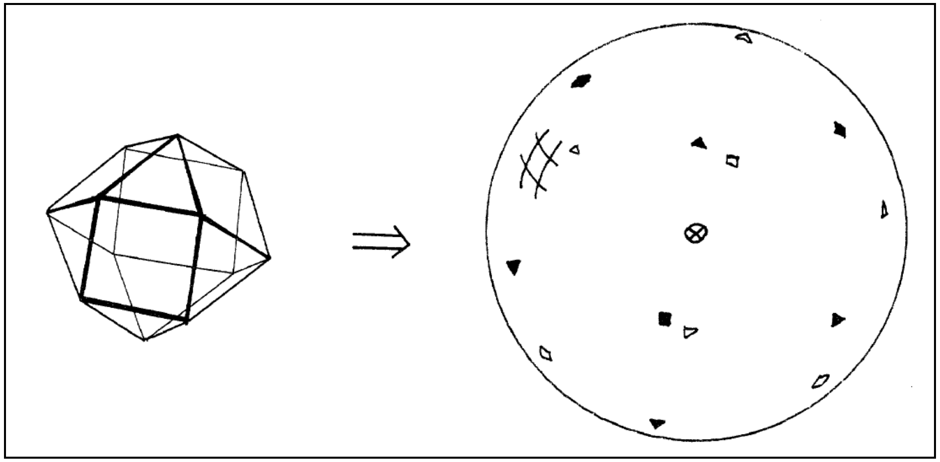


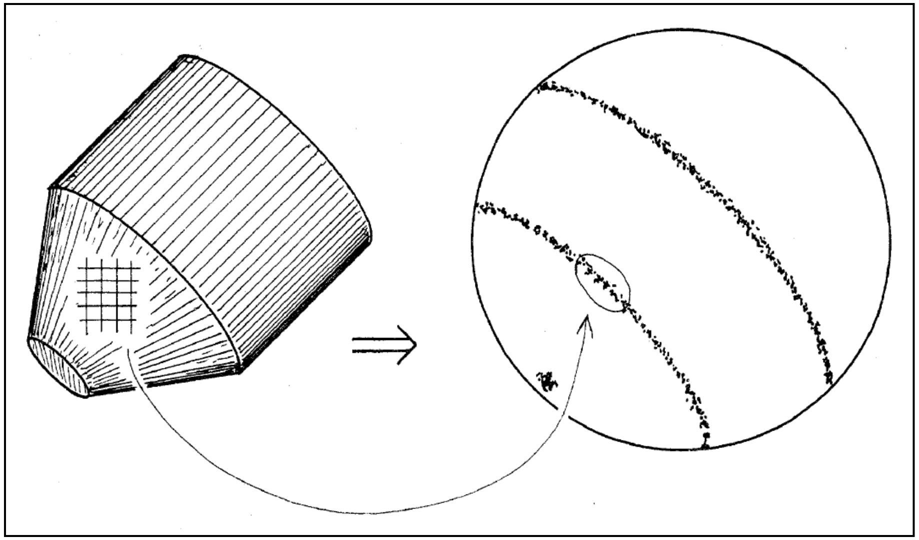
Block



EGI of Block

# K. Horn, MIT, 1983

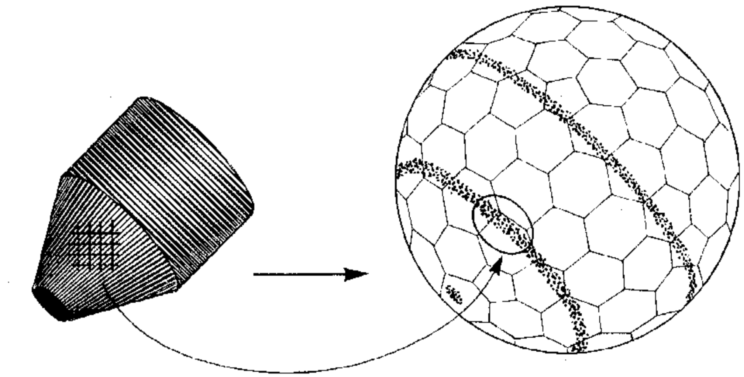




http://people.csail.mit.edu/bkph/AIM/AIM-740-OPT.pdf

# The Discrete Case EGI

- To represent the information of the Gaussian sphere in a computer, the sphere is divided into cells:



- For each image cell on the left, a surface orientation is found and accumulated in the corresponding cell of the sphere.

# Properties of the Gaussian Image

- This mapping is called the *Gaussian image* of the object when the surface normals for each point on the object are placed such that:
  - tails lie at the center of the Gaussian sphere
  - heads lie on the sphere at the matching normal point
- In areas of convex objects with positive curvature, no two points will have the same normal.
- Patches on the surface with zero curvature (lines or areas) correspond to a single point on the sphere.
- Rotations of the object correspond to rotations of the sphere.

# Using the EGI

- EGIs for different objects or object types may be computed and stored in a model database as a surface normal vector histogram.
- Given a depth image, surface normals may be extracted by plane fitting.
- By comparing EGI histogram of the extracted normals and those in the database, the identity and orientation of the object may be found.

# Properties of object surfaces in range images

- Homogeneity of surface properties in:
  - Surface normals
  - Curvature
- Discontinuities between surfaces:
  - “roof edges”: continuous depth but change of normals
  - “step edges”: discontinuous depth (e.g. hidden objects)

# Segmentation into planar patches

- F&P page 476/477
- Idea: Break object surface into sets of flat pieces
  - Clustering of surface normals via EGI
  - Region growing: Iterative merging of planar patches via graph/arc-costs

# Segmentation into planar patches

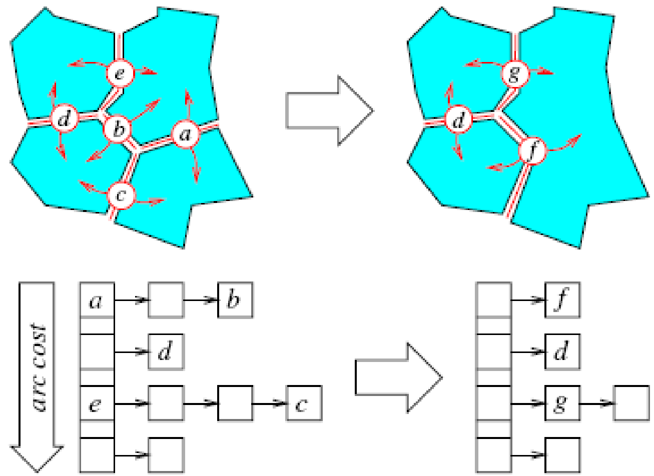



**Figure 24.11.** This diagram illustrates one iteration of the region growing process during which the two patches incident to the minimum-cost arc labelled $a$ are merged. The heap shown in the bottom part of the figure is updated as well: the arcs $a$, $b$, $c$ and $e$ are deleted, and two new arcs $f$ and $g$ are created and inserted in the heap.

Iterative merging of planar patches:

- Graph nodes: Patches with best fitting plane
- Graph arcs: costs corresponding to average error between combined set of points and plane that best fits these points
- Iteration: Find best arc, merge, next …

# Segmentation into planar patches

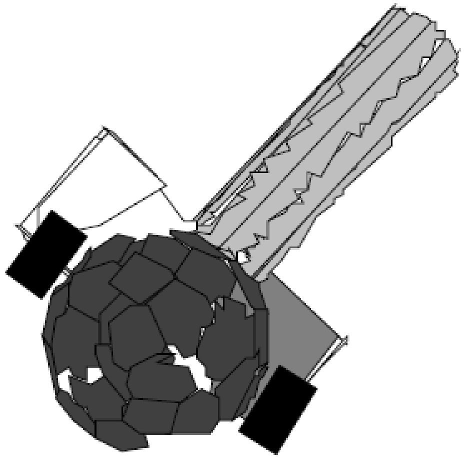


Figure 7: One of several grasping possibilities.

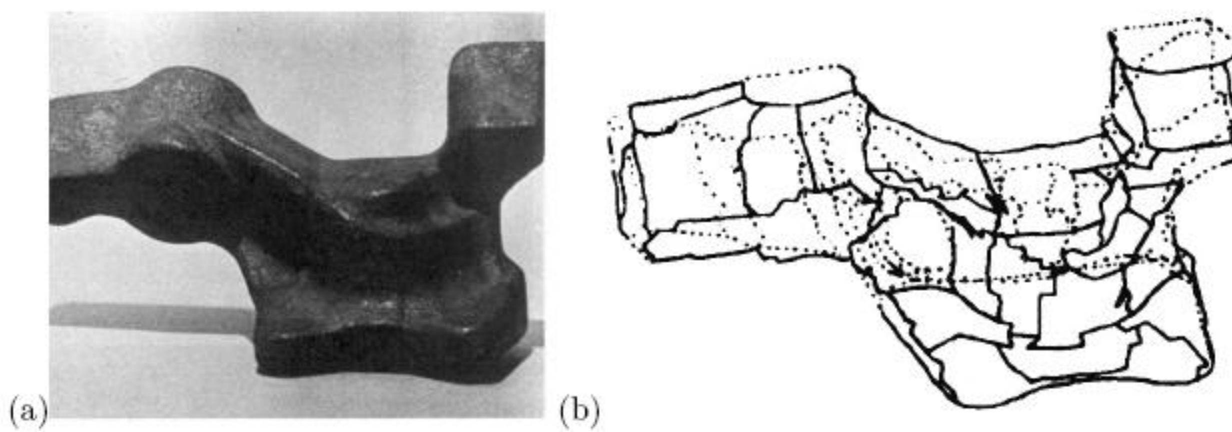
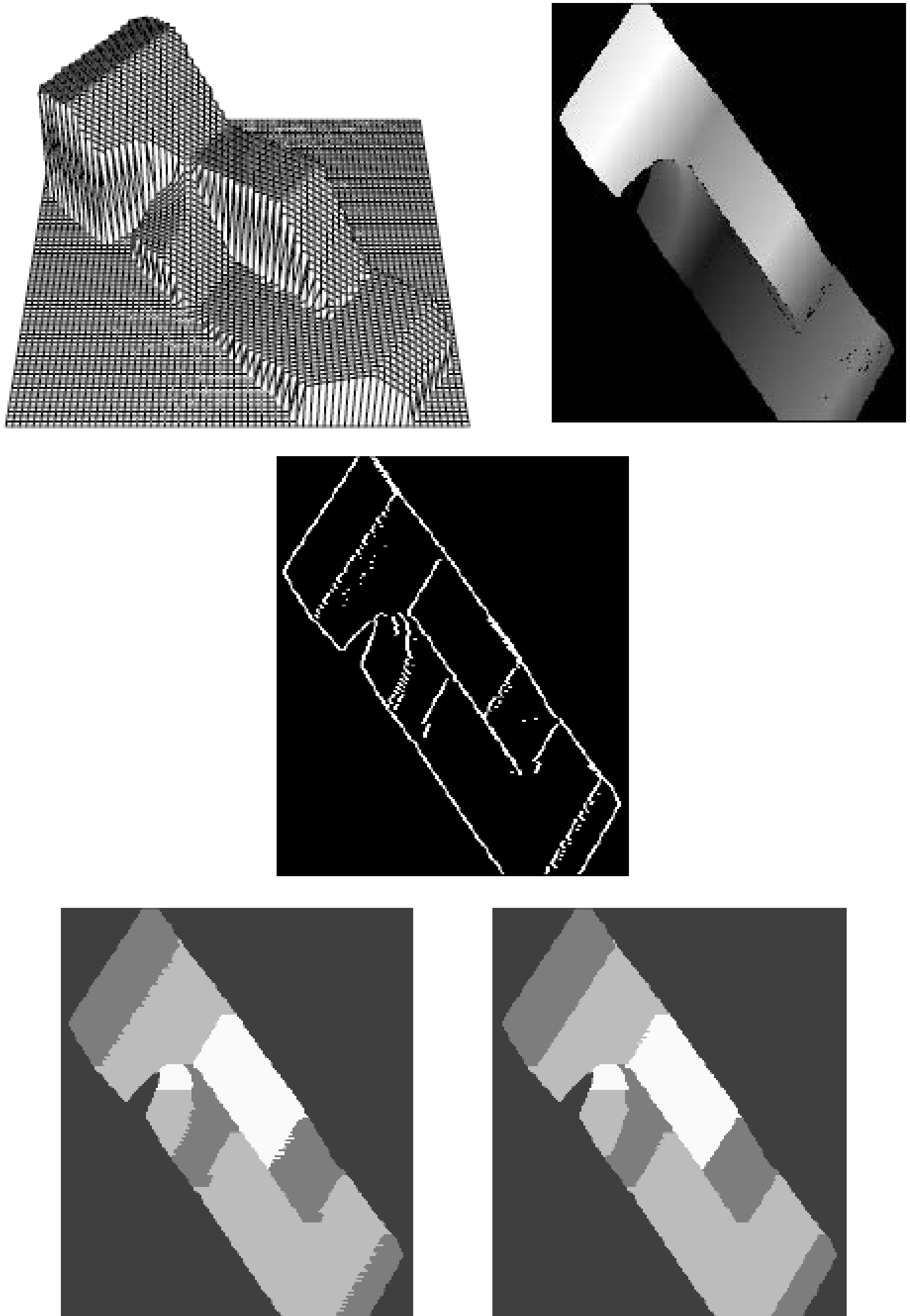
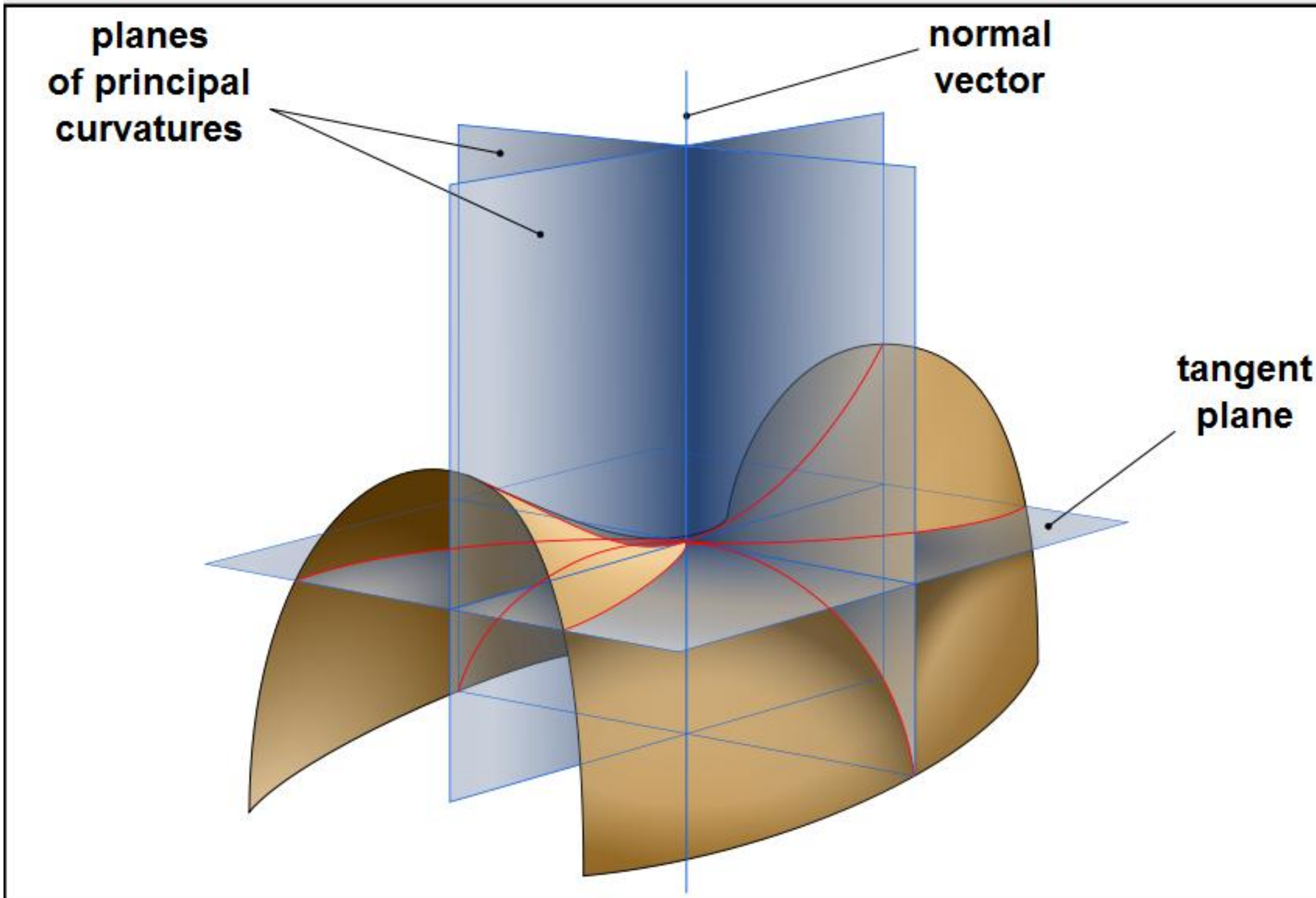


**Figure 24.12.** The Renault part: (a) photo of the part and (b) its model. Reprinted from [Faugeras and Hebert, 1986], Figures 1 and 6.



Segmentation into planar patches

# From flat pieces to curvature: Differential Geometry



## Elements of Analytical Differential Geometry (see F&P)

- Parametric surface: $\boldsymbol{x} : U \times \mathbb{R}^2 \rightarrow \mathbb{R}^3$

- Unit surface normal: $\boldsymbol{N} = \dfrac{1}{|\boldsymbol{x}_u \times \boldsymbol{x}_v|} (\boldsymbol{x}_u \times \boldsymbol{x}_v)$

- First fundamental form:

$$\mathrm{I}(\boldsymbol{t}, \boldsymbol{t}) = Eu'^2 + 2Fu'v' + Gv'^2 \qquad \begin{cases} E = \boldsymbol{x}_u . \boldsymbol{x}_u \\ F = \boldsymbol{x}_u . \boldsymbol{x}_v \\ G = \boldsymbol{x}_v . \boldsymbol{x}_v \end{cases}$$

- Second fundamental form:

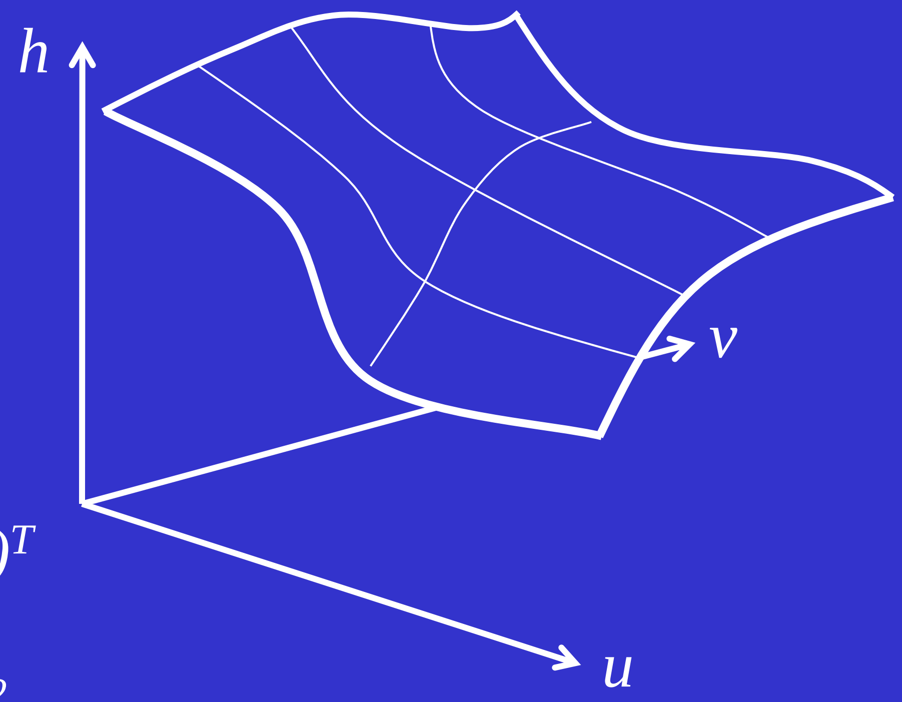
$$\mathrm{II}(\boldsymbol{t}, \boldsymbol{t}) = eu'^2 + 2fu'v' + gv'^2 \qquad \begin{cases} e = -\boldsymbol{N} . \boldsymbol{x}_{uu} \\ f = -\boldsymbol{N} . \boldsymbol{x}_{uv} \\ g = -\boldsymbol{N} . \boldsymbol{x}_{vv} \end{cases}$$

- Normal (direction $\boldsymbol{t}$) and Gaussian curvatures:

$$\kappa_t = \frac{\mathrm{II}(\boldsymbol{t}, \boldsymbol{t})}{\mathrm{I}(\boldsymbol{t}, \boldsymbol{t})} \qquad K = \frac{eg - f^2}{EG - F^2}$$

# Example: Monge Patches

$$\boxed{\mathbf{x}(u, v) = (u, v, h(u, v))}$$



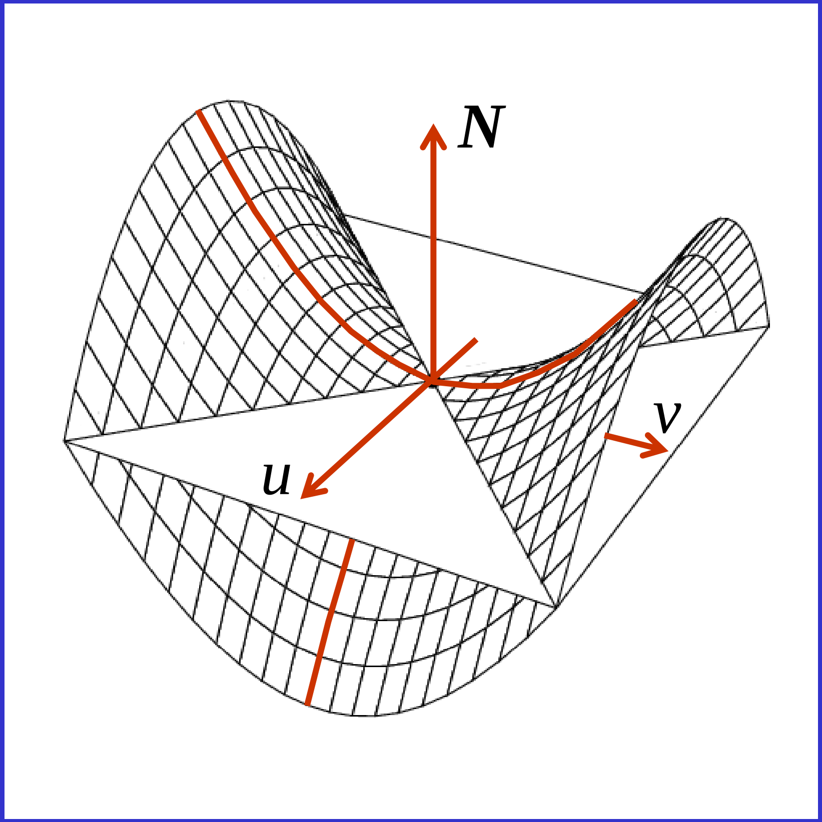

In this case

- $\mathbf{N} = \dfrac{1}{(1+h_u^2+h_v^2)^{1/2}} (-h_u, -h_v, 1)^T$
- $E = 1+h_u^2;\ F = h_u h_v;\ G = 1+h_v^2$
- $e = \dfrac{-h_{uu}}{(1+h_u^2+h_v^2)^{1/2}};\ f = \dfrac{-h_{uv}}{(1+h_u^2+h_v^2)^{1/2}};\ g = \dfrac{-h_{vv}}{(1+h_u^2+h_v^2)^{1/2}}$

And the Gaussian curvature is: $K = \dfrac{h_{uu}h_{vv}-h_{uv}^2}{(1+h_u^2+h_v^2)^2}$ .

# Example: Local Surface Parameterization

- $u,v$ axes = principal directions
- $h$ axis = surface normal

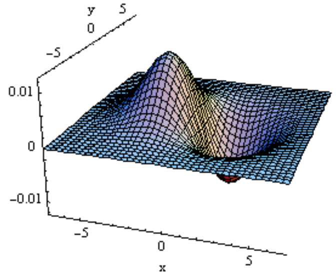



In this case:

- $h(0,0)=h_u(0,0)=h_v(0,0)=0$
- $\boldsymbol{N}=(0,0,1)^T$
- $h_{uv}(0,0)=0,\ \kappa_1= -\,h_{uu}(0,0),\ \kappa_2= -\,h_{vv}(0,0)$

Taylor expansion of order 2 ⇒ $h(u,v) \;=\; -\tfrac{1}{2}\ (\kappa_1\, u^2 + \kappa_2\, v^2)$

# Calculation of Partial Derivatives

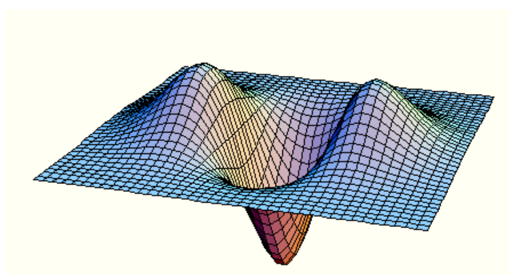



by convolving the smoothed image with the masks:

$$\frac{\partial}{\partial x} = \frac{1}{6}\begin{array}{|c|c|c|}\hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline \end{array} \quad \text{and} \quad \frac{\partial}{\partial y} = \frac{1}{6}\begin{array}{|r|r|r|}\hline 1 & 1 & 1 \\ \hline 0 & 0 & 0 \\ \hline -1 & -1 & -1 \\ \hline \end{array},$$

and the Hessian is computed by convolving the smoothed image with the masks

$$\frac{\partial^2}{\partial x^2} = \frac{1}{3}\begin{array}{|c|c|c|}\hline 1 & -2 & 1 \\ \hline 1 & -2 & 1 \\ \hline 1 & -2 & 1 \\ \hline \end{array}, \quad \frac{\partial^2}{\partial x \partial y} = \frac{1}{4}\begin{array}{|r|c|r|}\hline -1 & 0 & 1 \\ \hline 0 & 0 & 0 \\ \hline 1 & 0 & -1 \\ \hline \end{array} \quad \text{and} \quad \frac{\partial^2}{\partial y^2} = \frac{1}{3}\begin{array}{|r|r|r|}\hline 1 & 1 & 1 \\ \hline -2 & -2 & -2 \\ \hline 1 & 1 & 1 \\ \hline \end{array}.$$



# Principal Directions

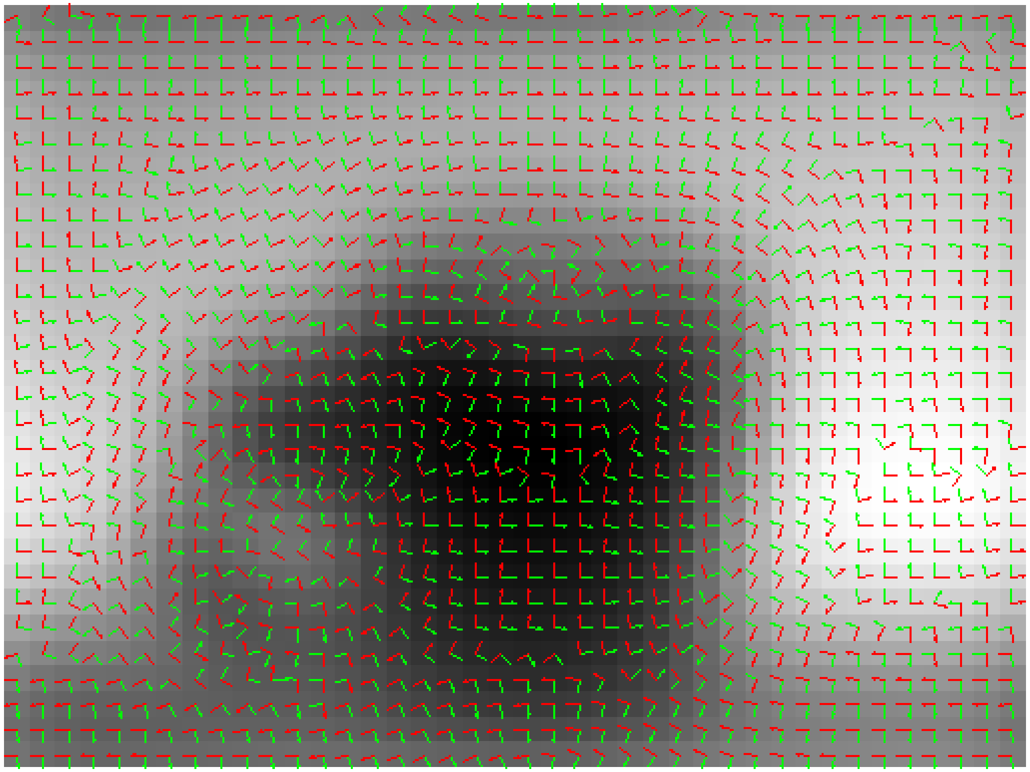


Figure 6.1 Frames of the normalized principal curvature directions at a scale of 1 pixel. Image resolution $32^2$ pixels. Green: maximal principal curvature direction; red: minimal principal curvature direction.

# Calculation of principal curvatures

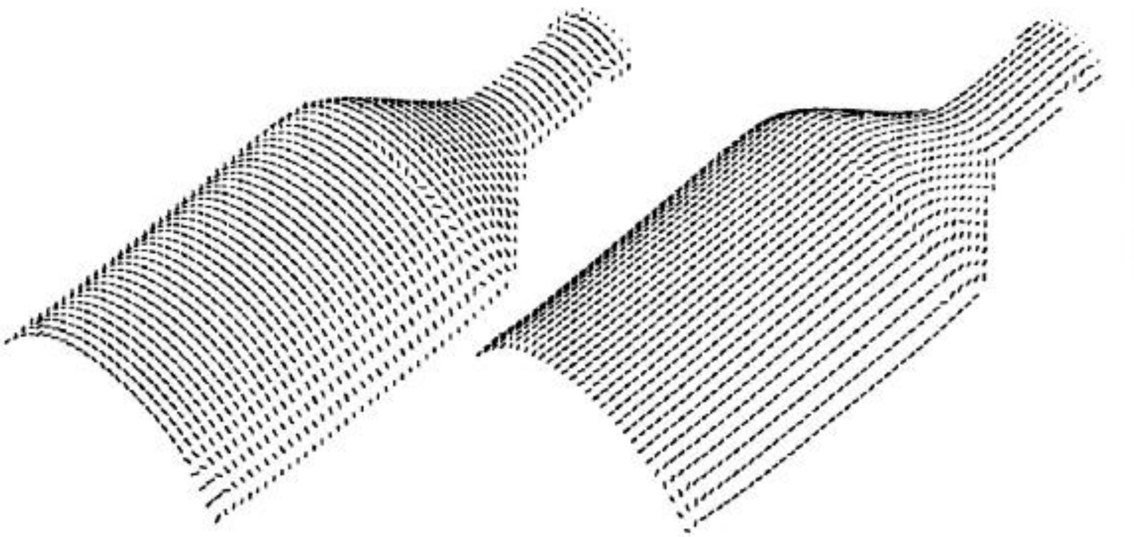
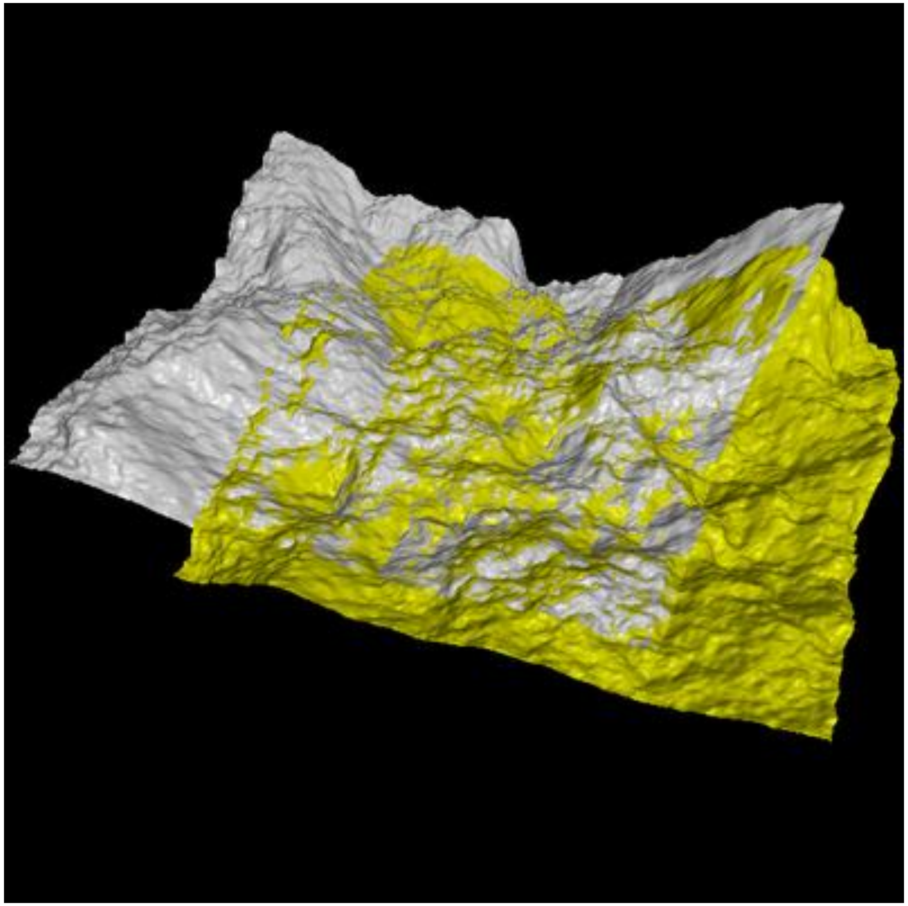


**Figure 24.8.** The two principal direction fields for the oil bottle. Reprinted from [Brady *et al.*, 1985], Figure 18.

Note that the principal curvatures are homogeneous across the large lower part of the bottle → can serve as homogeneous features for clustering

# The Problem

Align two partially-overlapping meshes given initial guess for relative transform



# Range Image Registration ctd.

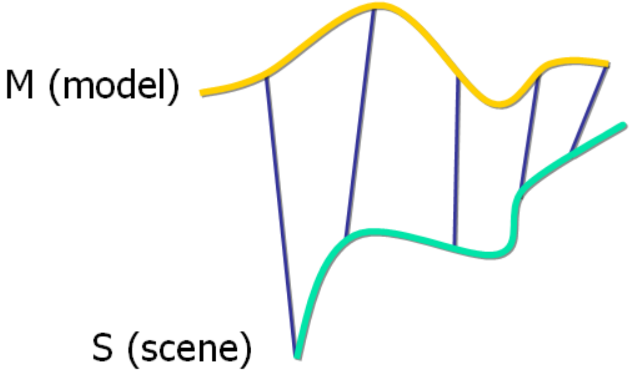
- Concept:
  - Determine rigid transformation between pairs of range surfaces
  - Minimize average distance between point sets
  - **ICP**: **I**terative **C**losest **P**oint algorithm (Besl & McKay 1992)

# Corresponding Point Set Alignment

- Let M be a model point set.
- Let S be a scene point set.

We assume :

1. $N_M = N_S$.
2. Each point $S_i$ correspond to $M_i$ .



# Corresponding Point Set Alignment

The MSE objective function :

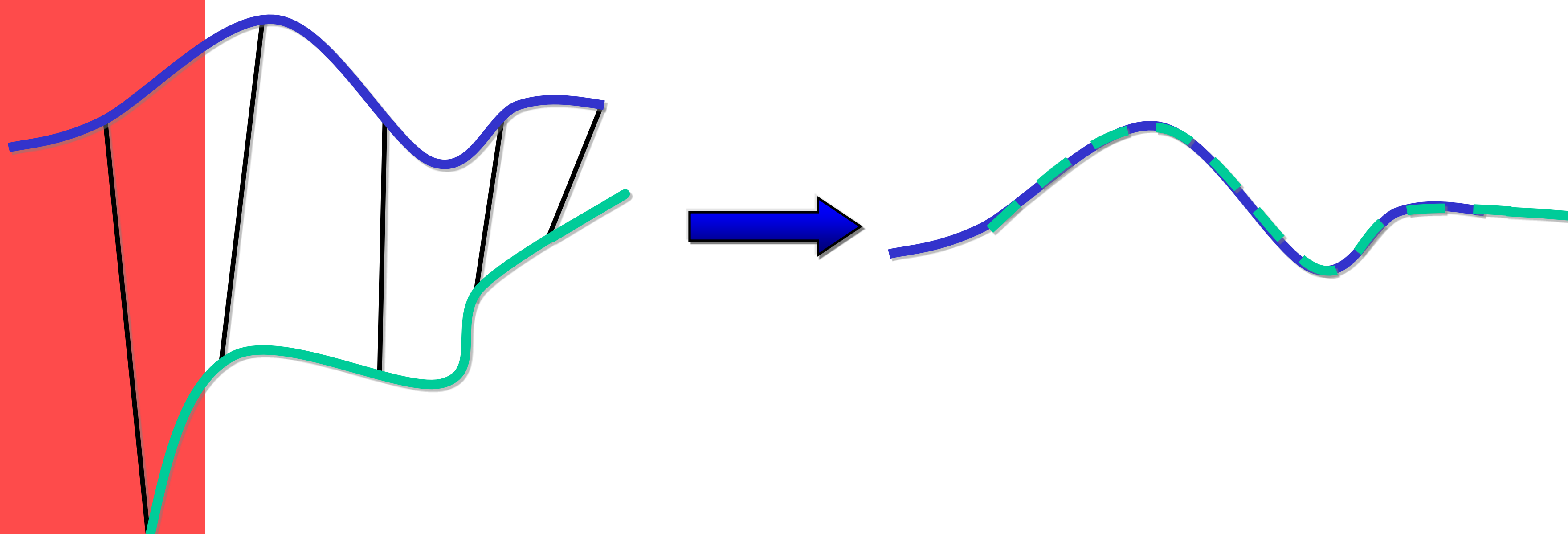
$$f(R,T) = \frac{1}{N_S} \sum_{i=1}^{N_S} \left\| m_i - Rot(s_i) - Trans(si) \right\|^2$$

The alignment is :

$$(rot, trans, d_{mse}) = \Phi(M, S)$$

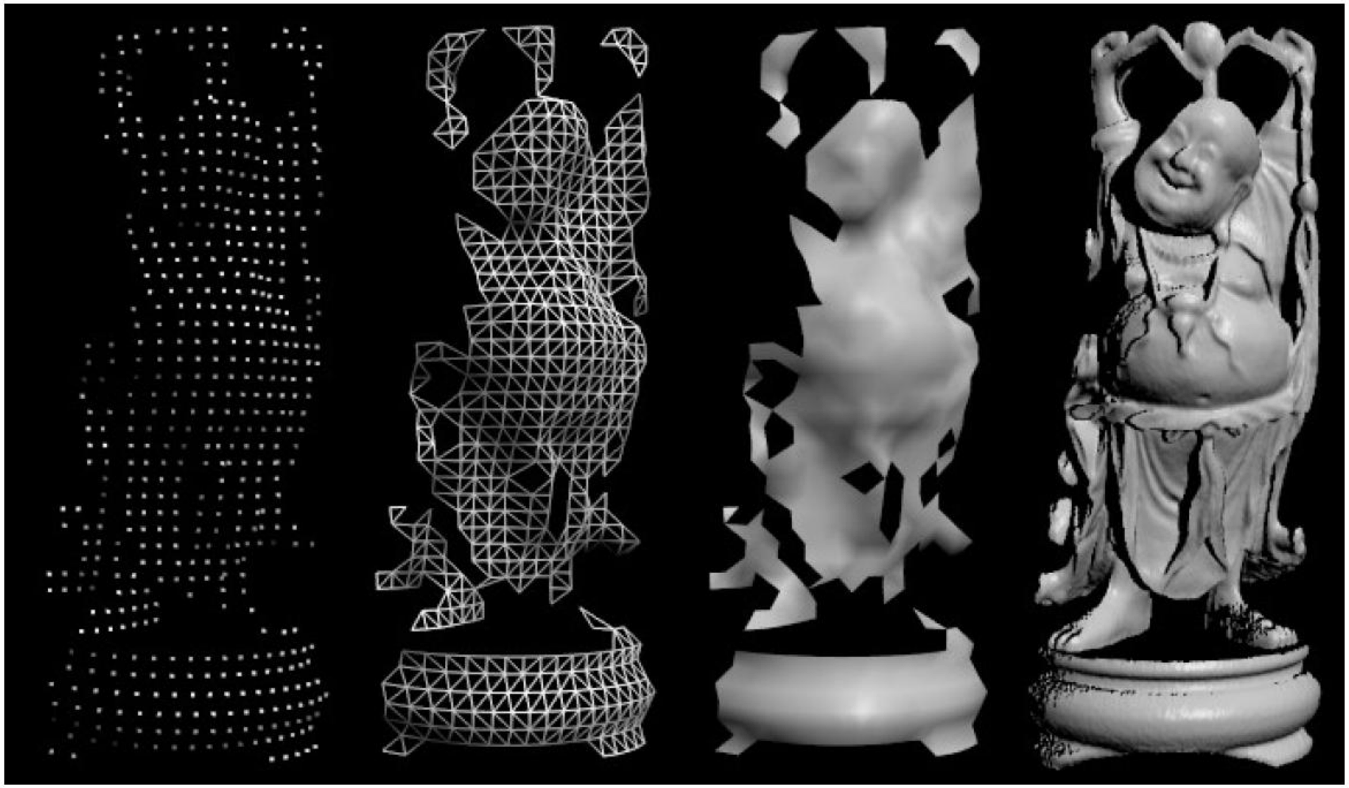
# Aligning 3D Data

- If correct correspondences are known, can find correct relative rotation/translation



# Example: 3D Data Integration

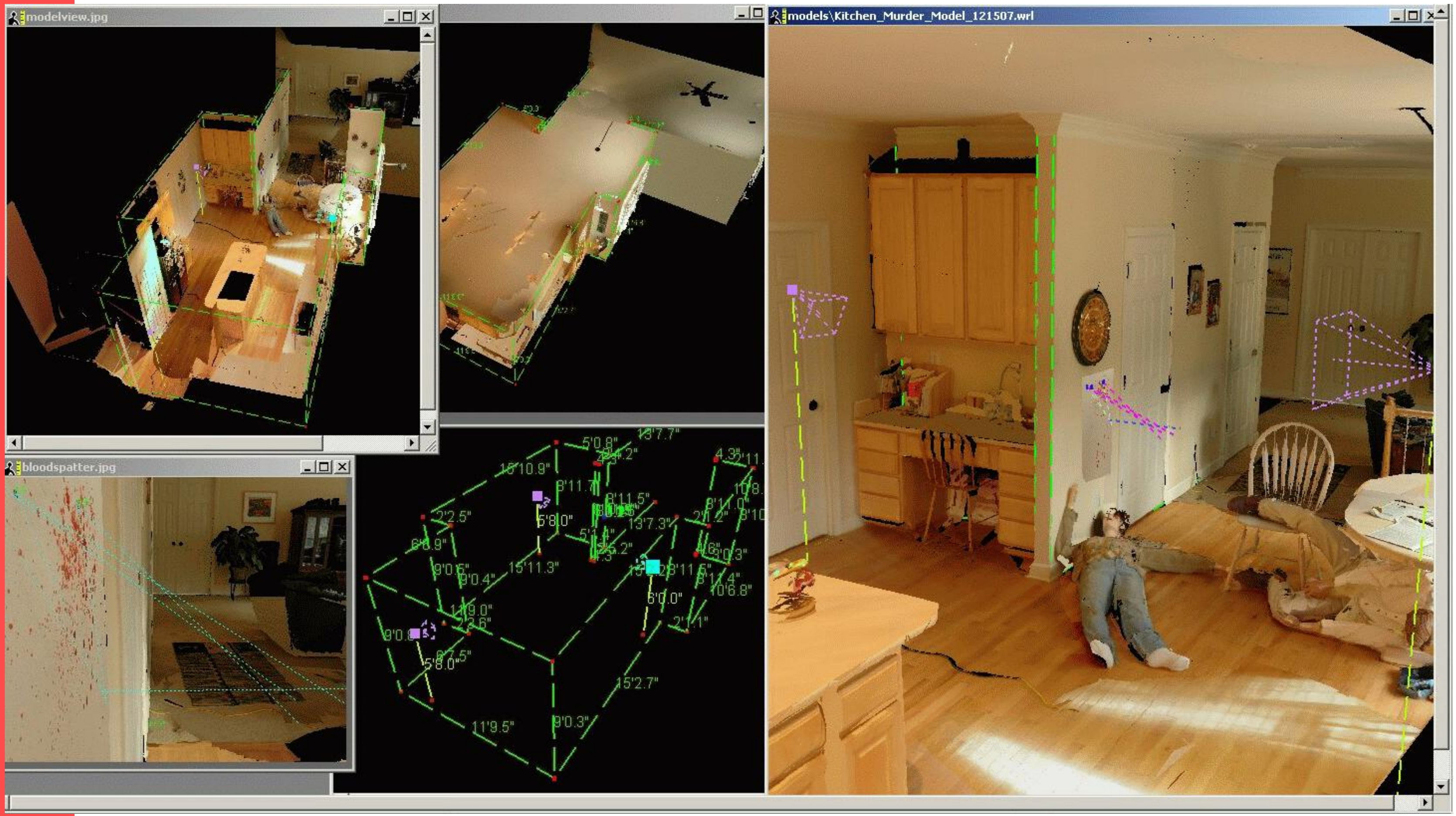
- Range image registration



# Example: 3D Data Integration

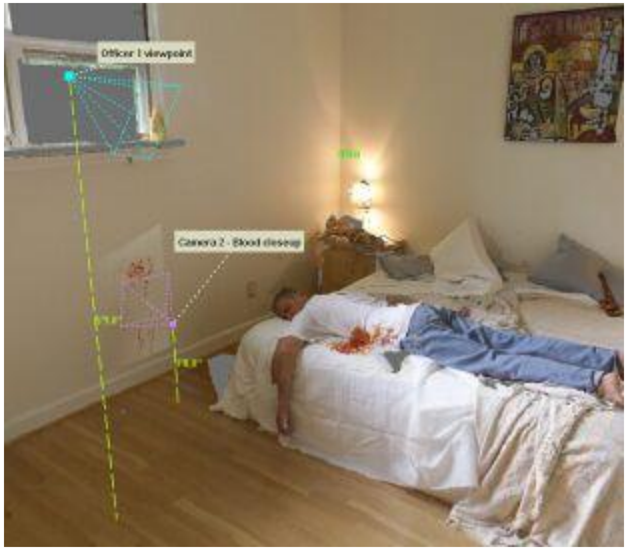

**Figure 24.17.** 3D Fax of a statuette of a Buddha. From left to right: photograph of the statuette; range image; integrated 3D model; model after hole filling; physical model obtained via stereolithography. Reprinted from [Curless and Levoy, 1996], Figure 10.

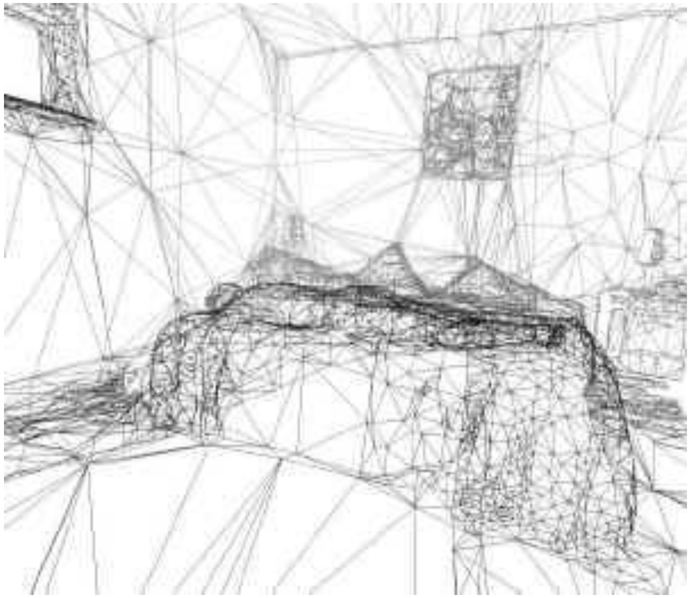
# Applications: Crime Scene, Forensic Analysis




http://www.deltasphere.com/

# Applications: Crime Scene, Forensic Analysis



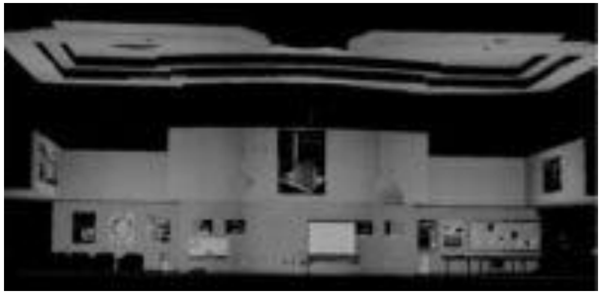
http://www.deltasphere.com/

# Applications

Museums, Cultural Exhibits

Archeology

Military Simulation and Training



Architecture and Construction

# Range Finders: Some References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# Conclusions

**Wide range of application areas including:**

- Action recognition and tracking
- Object pose recognition for robotic control
- Obstacle detection for automotive control
- Human-computer interaction
- Video surveillance
- Scene segmentation and obstacle detection
- Computer assisted surgical intervention
- Industrial applications of TOF cameras
- Automotive applications of TOF cameras
- Virtual reality applications
- Integration of range and intensity imaging sensor outputs

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