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Juergen Gall

Stereo

MA-INF 2201 - Computer Vision

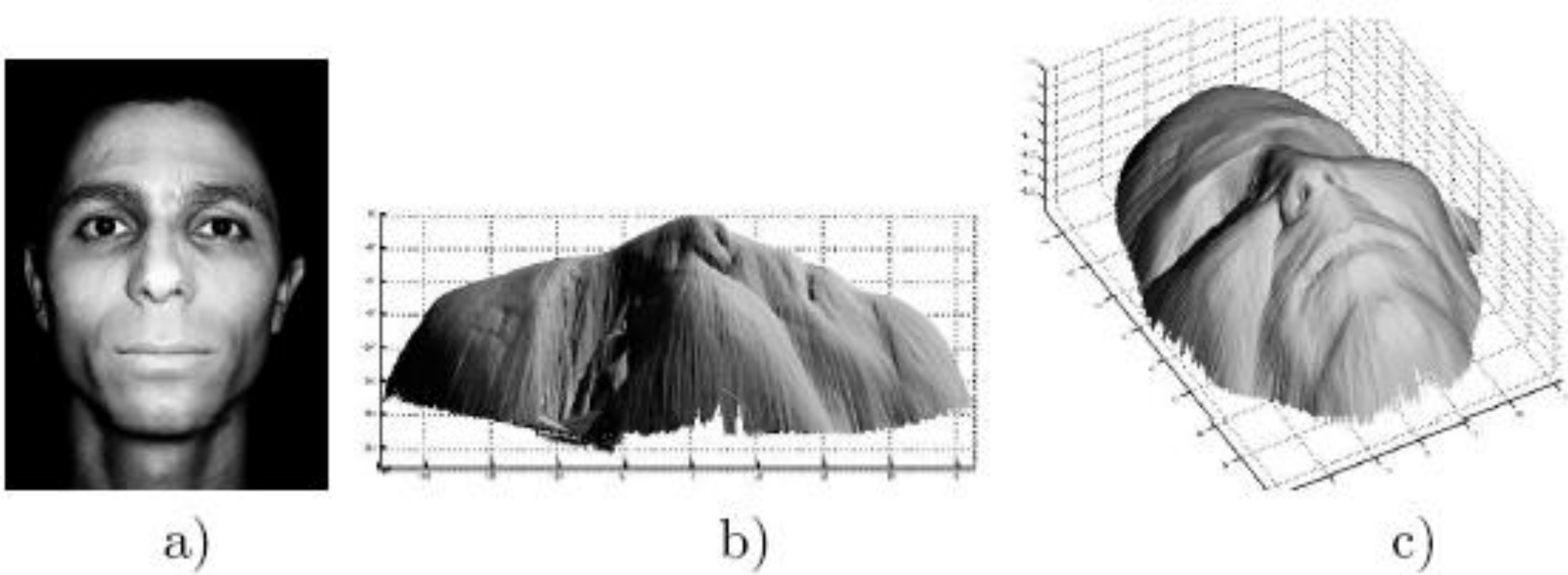
WS24/25

3D Reconstruction

What cues help us to perceive 3d shape and depth?

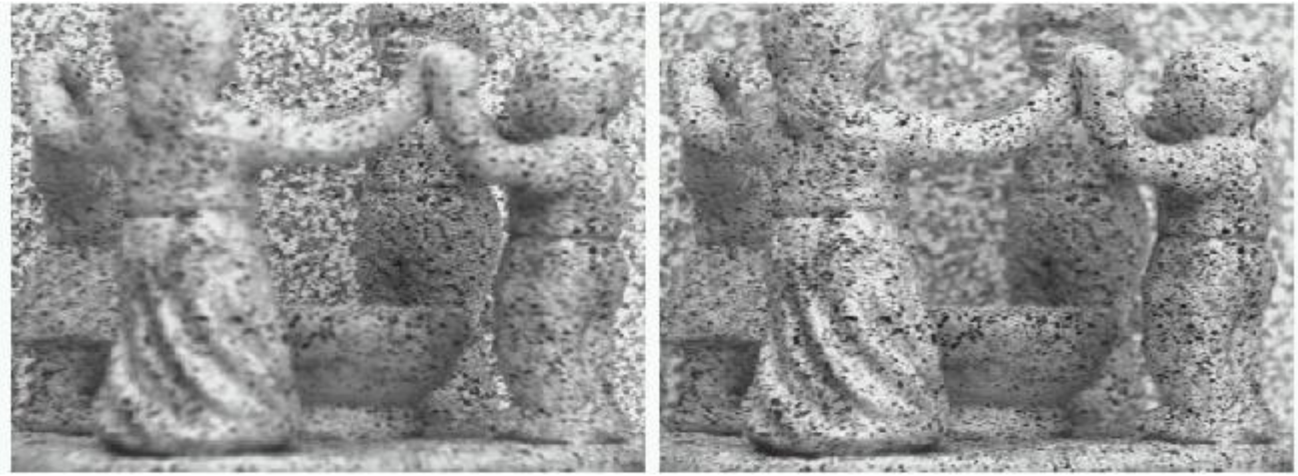
Kristen Grauman

Shading

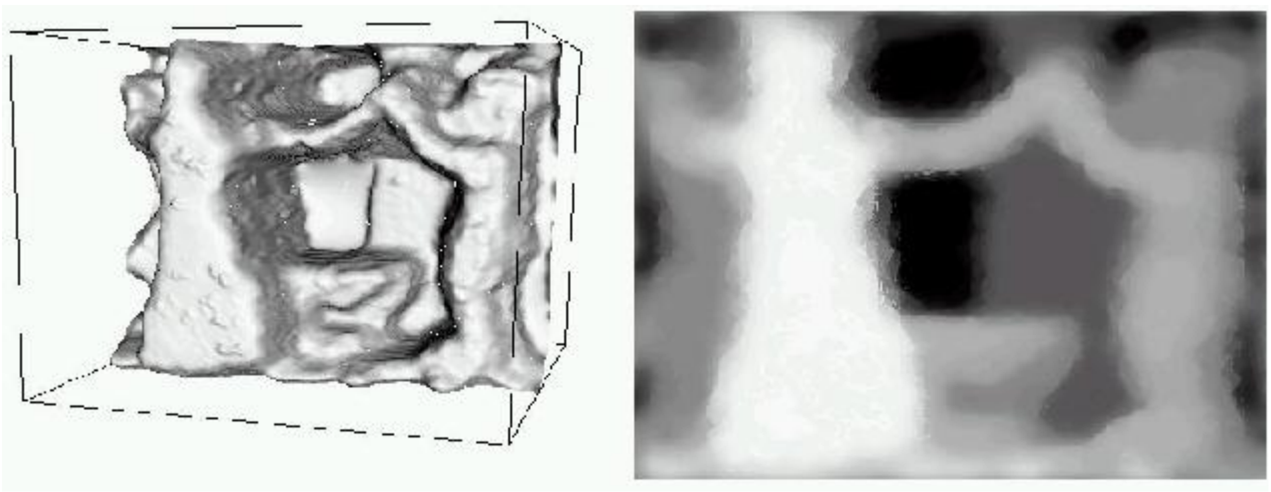


[Figure from Prados & Faugeras 2006]

Focus/defocus



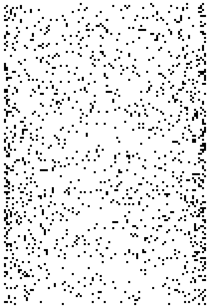
Images from same point of view, different camera parameters



3d shape / depth estimates

[figs from H. Jin and P. Favaro, 2002]

Motion



Figures from L. Zhang

http://www.brainconnection.com/teasers/?main=illusion/motion-shape

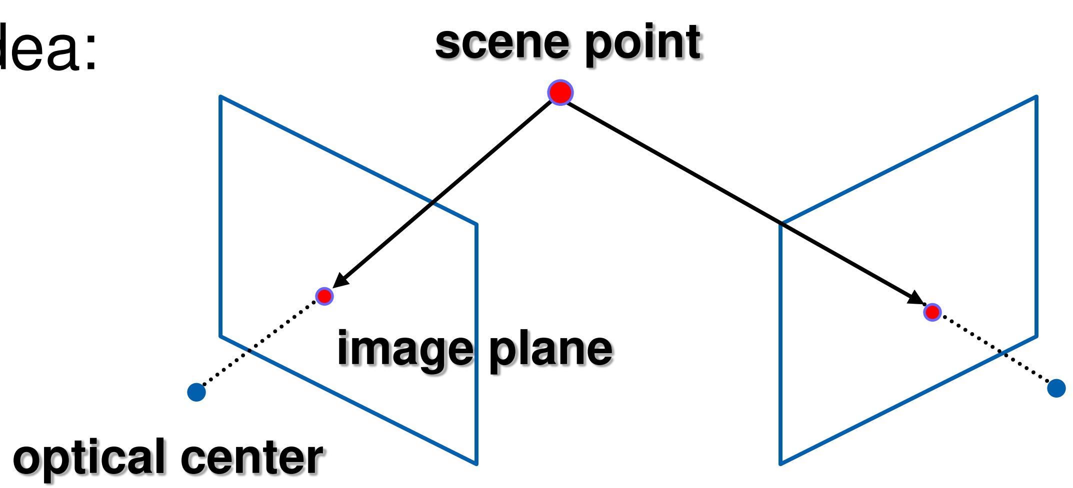
Estimating scene shape

"Shape from X": Shading, Texture, Focus, Motion…

Stereo:

- shape from "motion" between two views
- infer 3d shape of scene from two (multiple) images from different viewpoints

Main idea:



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Human eye

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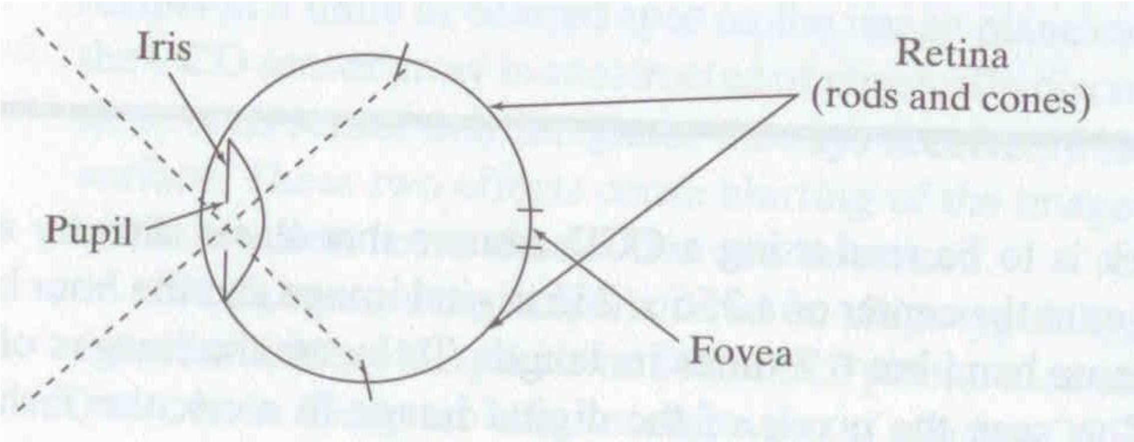
Rough analogy with human visual system:



Pupil/Iris – control amount of light passing through lens

Retina - contains sensor cells, where image is formed

Fovea – highest concentration of cones

Fig from Shapiro and Stockman

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Human stereopsis: disparity

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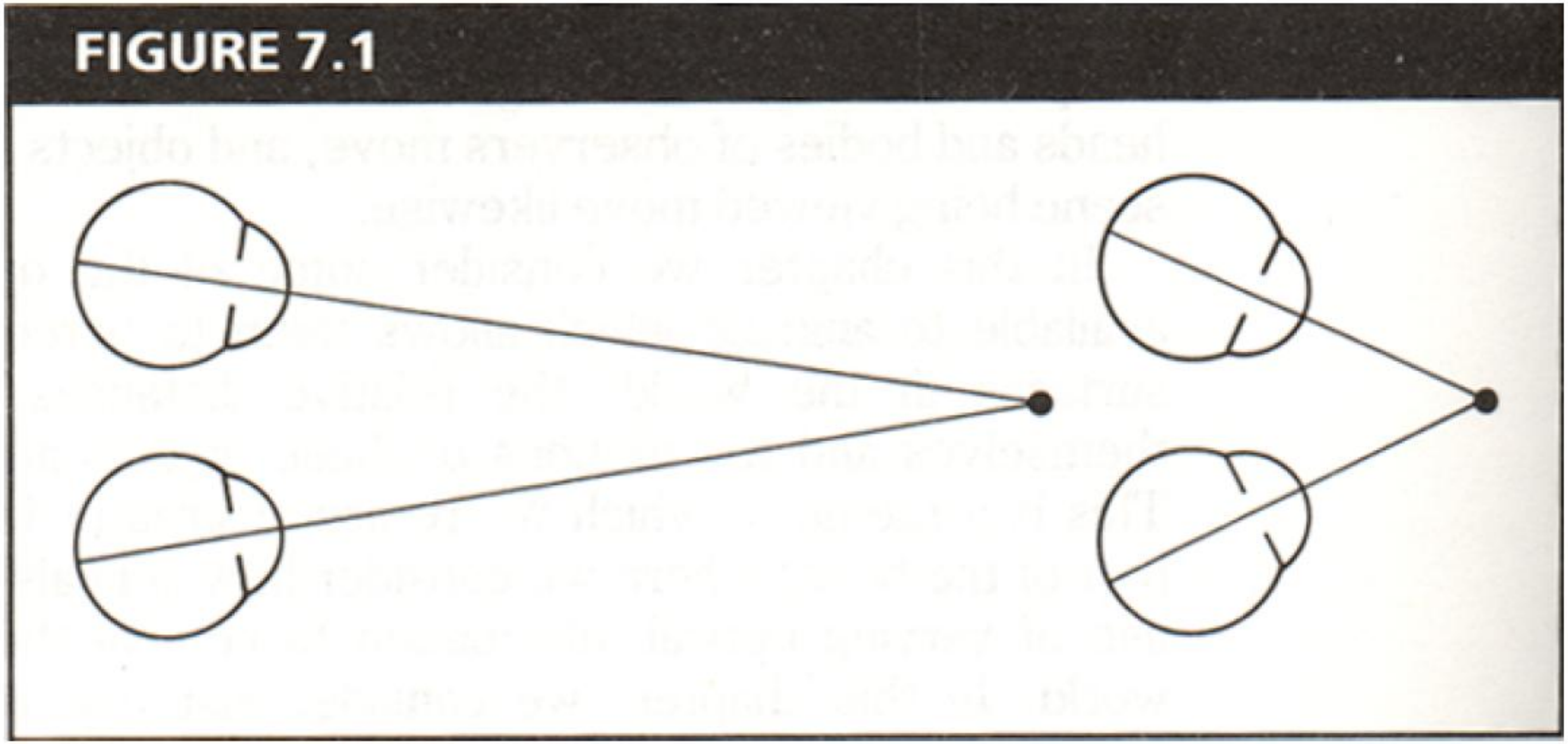

From Bruce and Green, Visual Perception, Physiology, Psychology and Ecology

- Human eyes fixate on point in space – rotate so that corresponding images form in centers of fovea

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Human stereopsis: disparity

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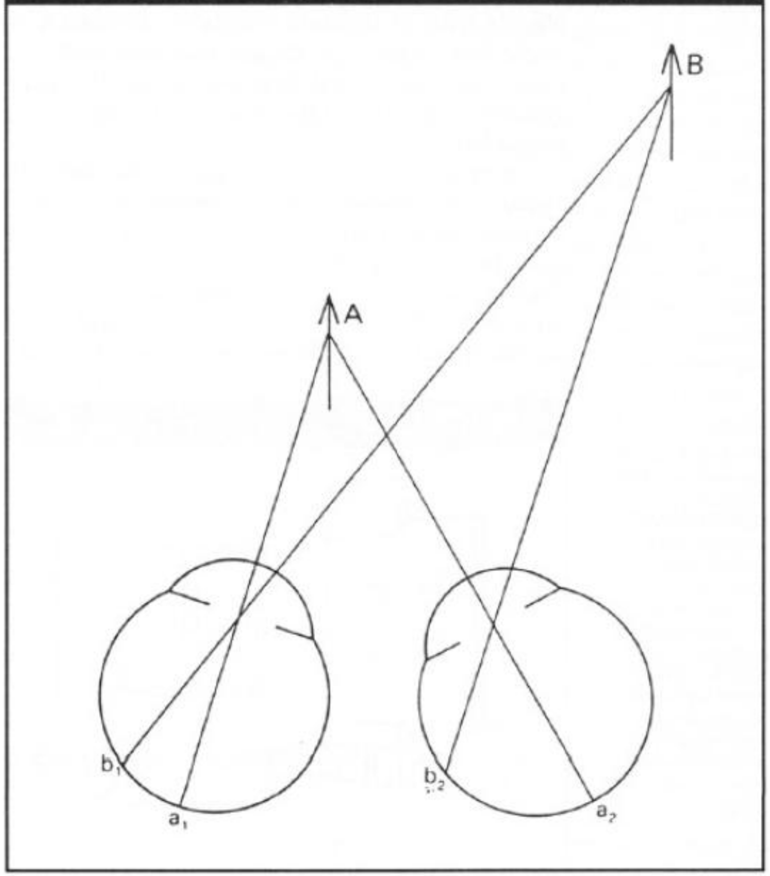
FIGURE 7.3



From Bruce and Green, Visual Perception, Physiology, Psychology and Ecology

Disparity occurs when eyes fixate on one object; others appear at different visual angles

Adapted from David Forsyth, UC Berkeley

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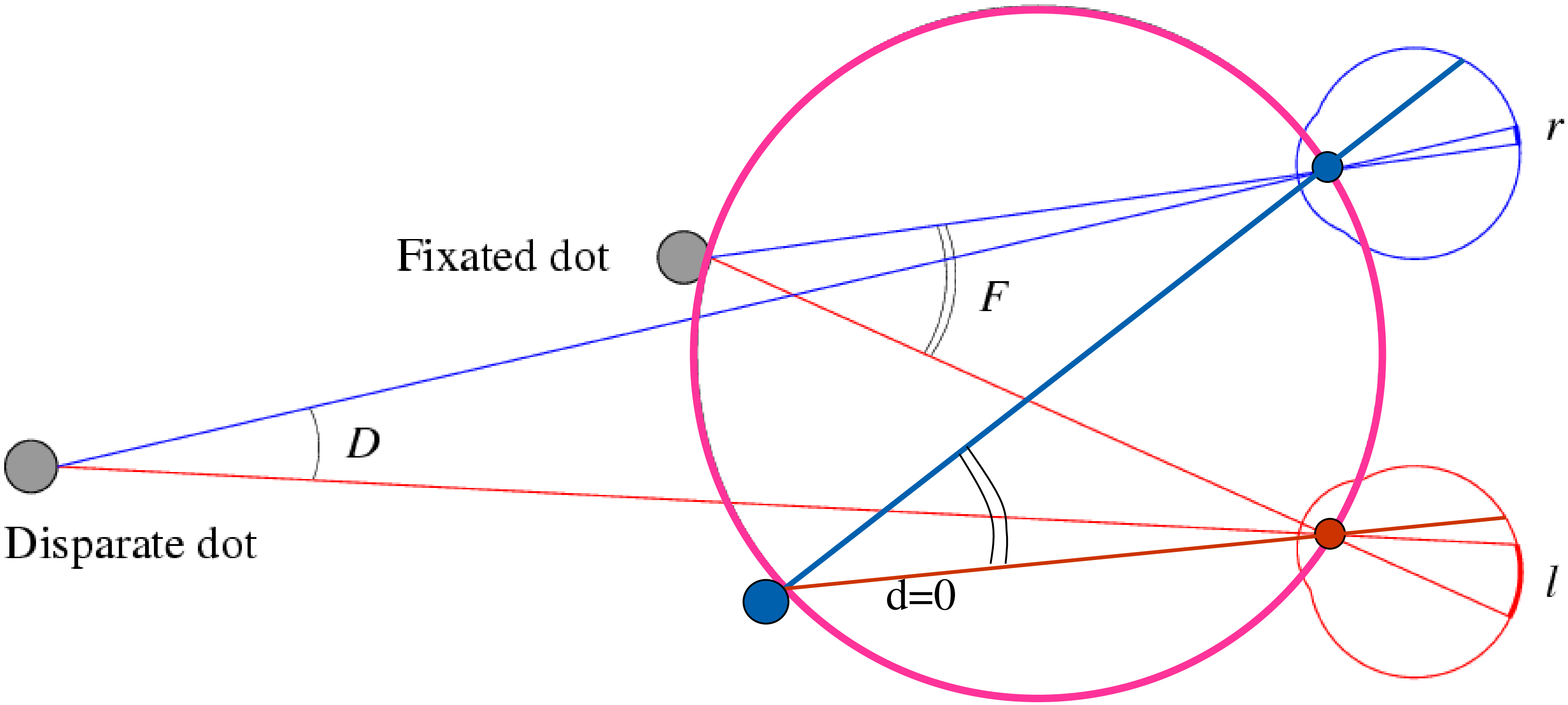
Human stereopsis: disparity



Disparity: $d = r\text{-}l = D\text{-}F.$

Forsyth & Ponce

http://www.well.com/~jimg/stereo/stereo_list.html

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Stereo vision

Two cameras, simultaneous views

Single moving camera and static scene

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Binocular stereo

Given a calibrated binocular stereo pair, fuse it to produce a depth image

image 1

image 2

Dense depth map

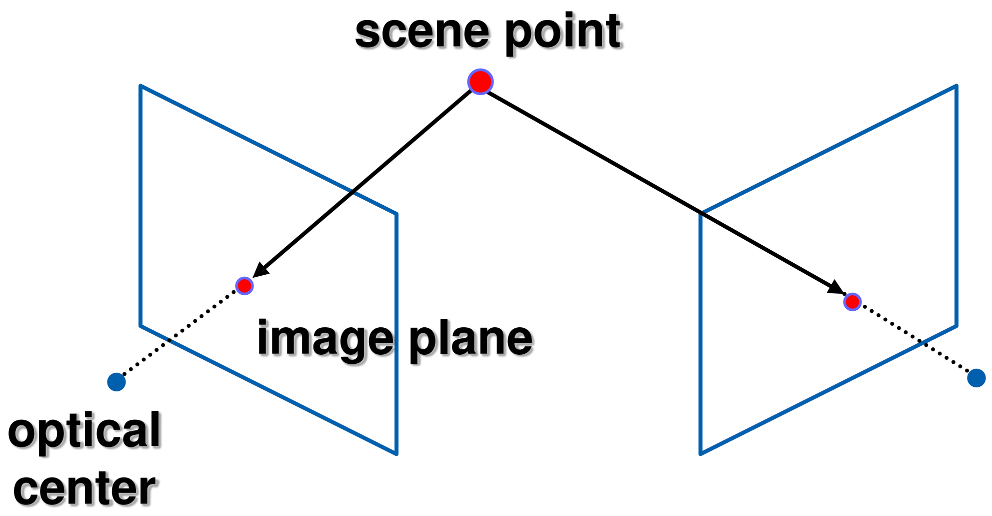
Lazebnik

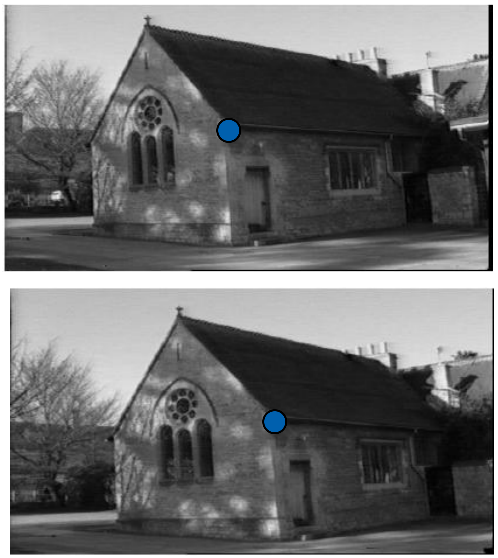
Estimating depth with stereo

Stereo: shape from "motion" between two views

We'll need to consider:

- Info on camera pose ("calibration")
- Image point correspondences





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Basic stereo matching algorithm

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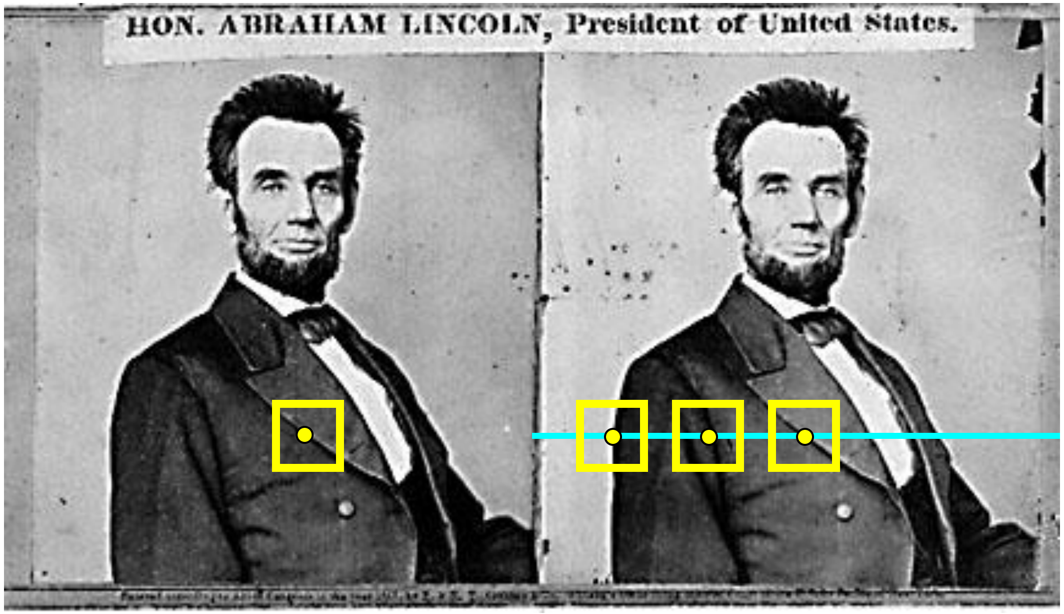

- For each pixel in the first image
  - Find corresponding epipolar line in the right image
  - Examine all pixels on the epipolar line and pick the best match
  - Triangulate the matches to get depth information
- Simplest case: epipolar lines are scanlines

Lazebnik

Simplest Case: Parallel images

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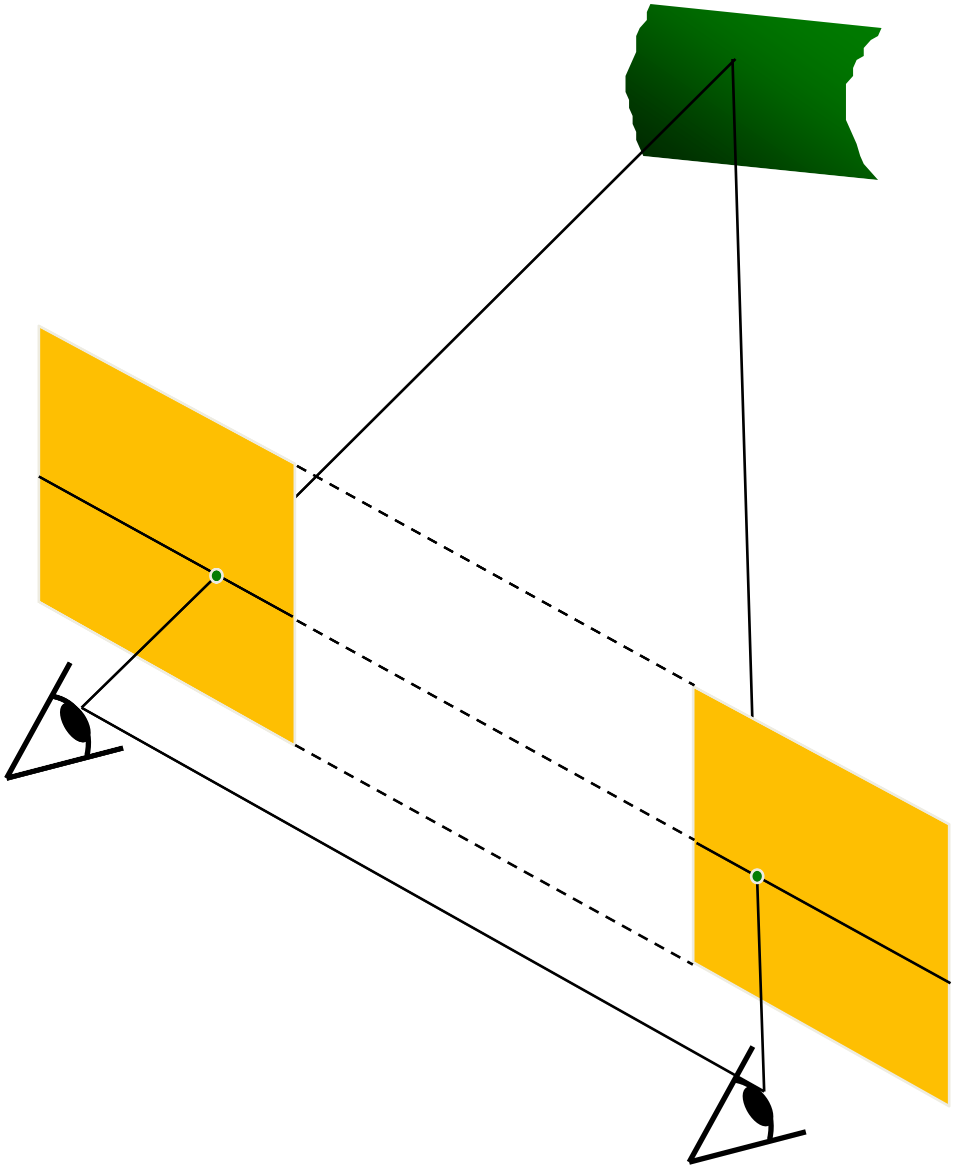

- Image planes of cameras are parallel to each other and to the baseline
- Camera centers are at same height
- Focal lengths are the same
- Then, epipolar lines fall along the horizontal scan lines of the images

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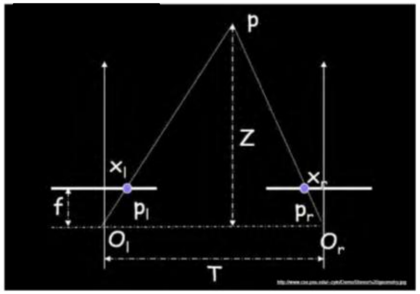
Recall: Essential matrix



$$\mathbf{R} = \mathbf{I}$$

$$\mathbf{T} = [-d, 0, 0]^{\mathrm{T}}$$

$$\mathbf{E} = [\mathbf{T}_{\mathbf{x}}]\mathbf{R} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & d \\ 0 & -d & 0 \end{pmatrix}$$

$$\mathbf{p} = [x, y, f]$$

$$\mathbf{p'} = [x', y', f]$$

$$\mathbf{p}'^{\mathrm{T}}\mathbf{E}\mathbf{p} = 0$$

$$\begin{bmatrix} x' & y' & f \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & d \\ 0 & -d & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ f \end{bmatrix} = 0$$

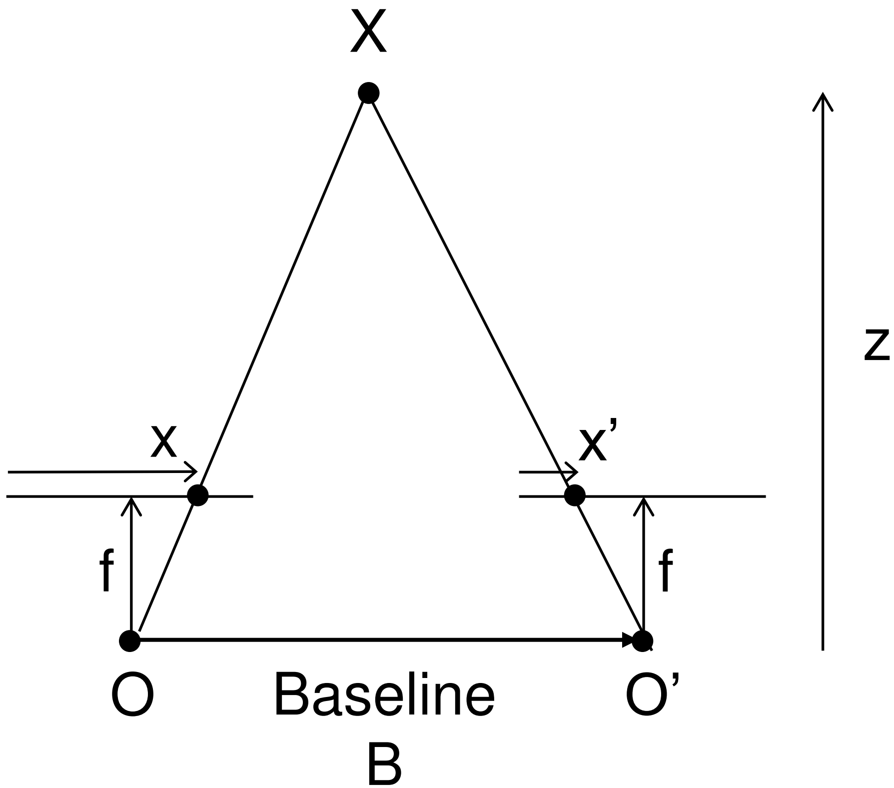
$$\Leftrightarrow \begin{bmatrix} x' & y' & f \end{bmatrix} \begin{bmatrix} 0 \\ df \\ -dy \end{bmatrix} = 0$$

$$\boxed{\Leftrightarrow y = y'}$$

For the parallel cameras, image of any point must lie on same horizontal line in each image plane.

Kristen Grauman

Depth from disparity



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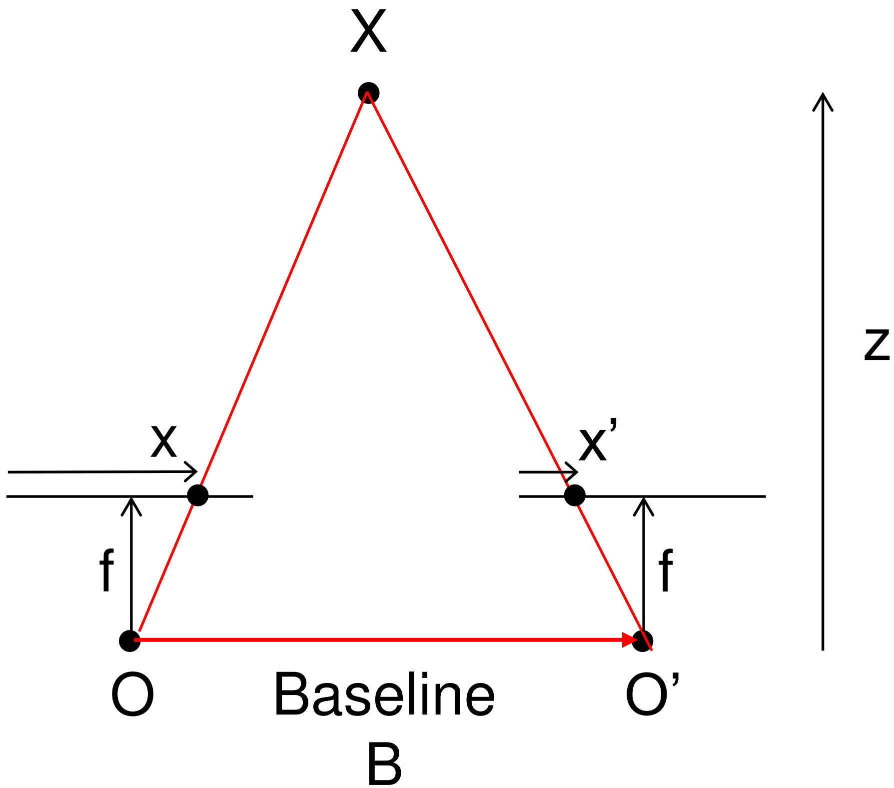
Depth from disparity



$$\frac{Z}{B}$$

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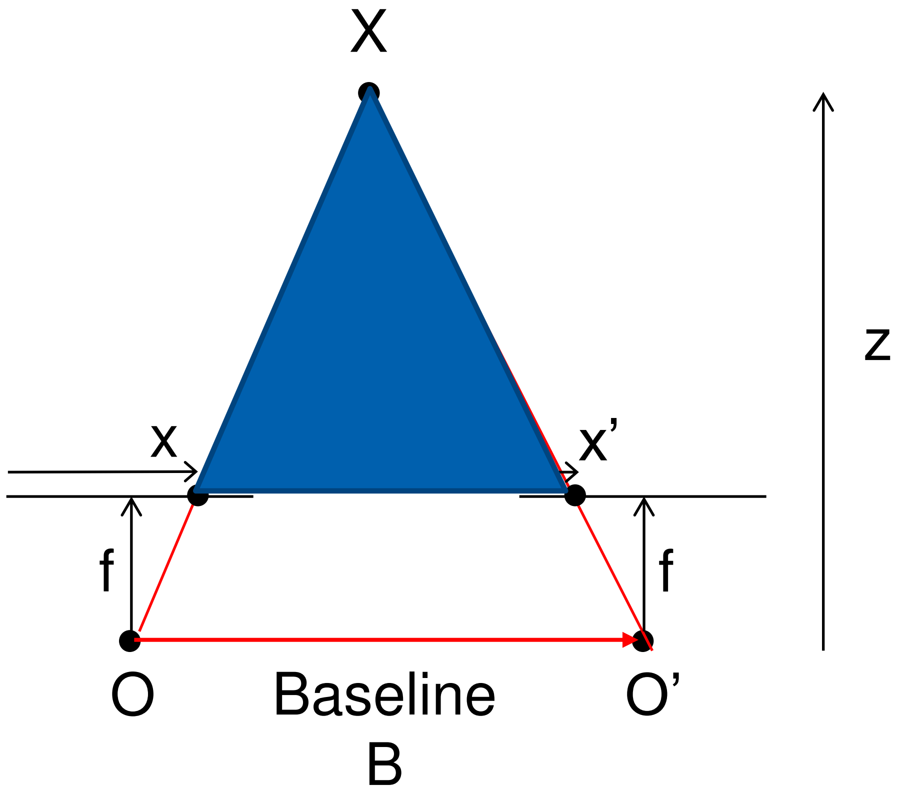
Depth from disparity



$$\frac{Z}{B} = \frac{Z - f}{B + x' - x}$$

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Depth from disparity

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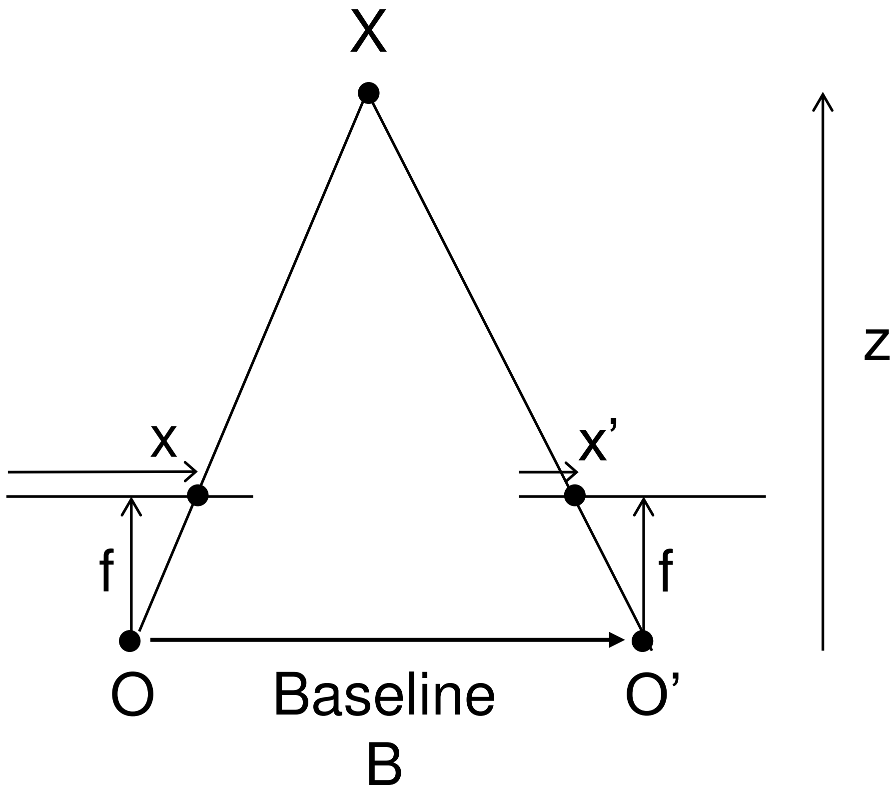

$$disparity = x - x' = \frac{B \cdot f}{z}$$

Disparity is inversely proportional to depth!

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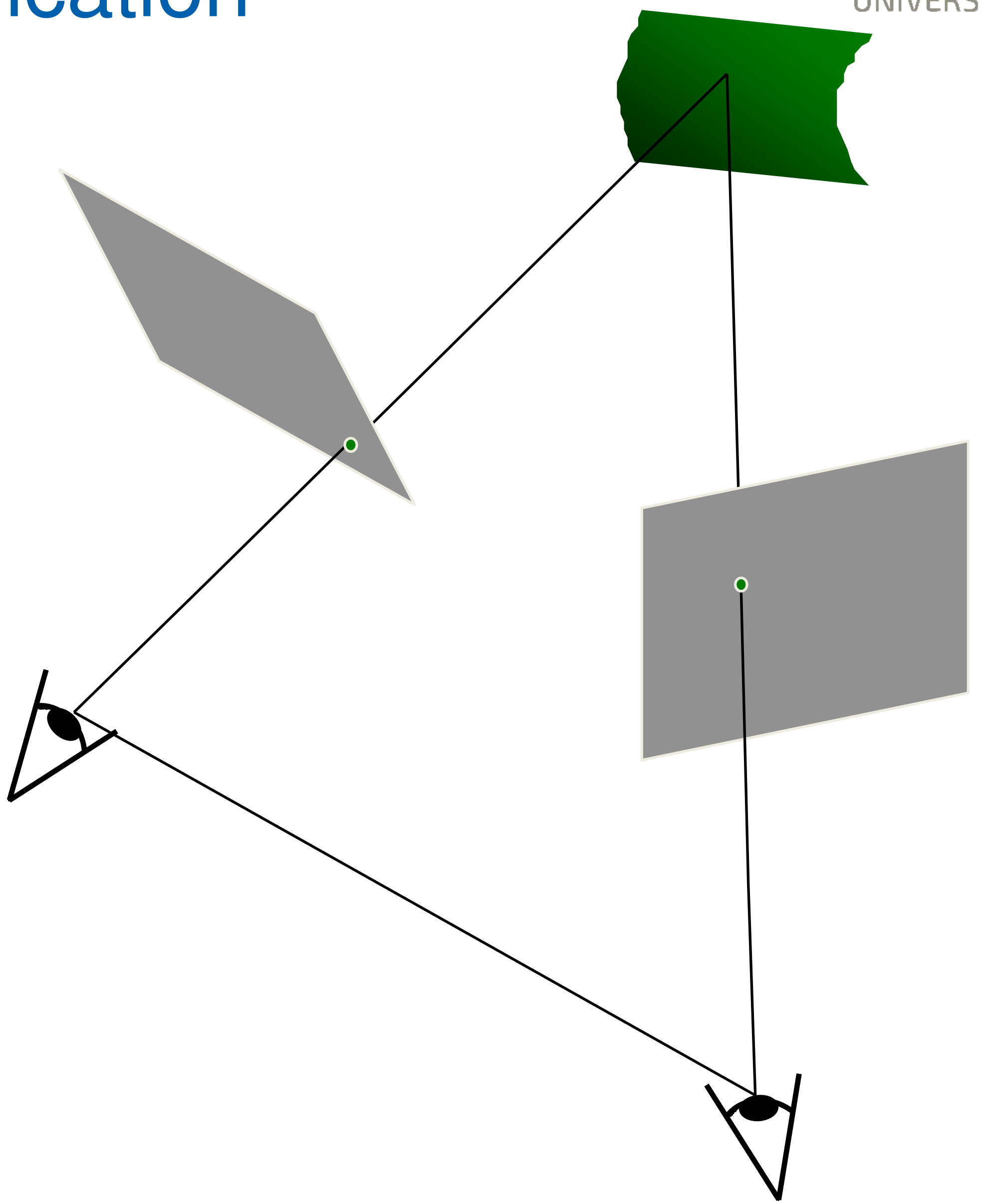
Stereo image rectification



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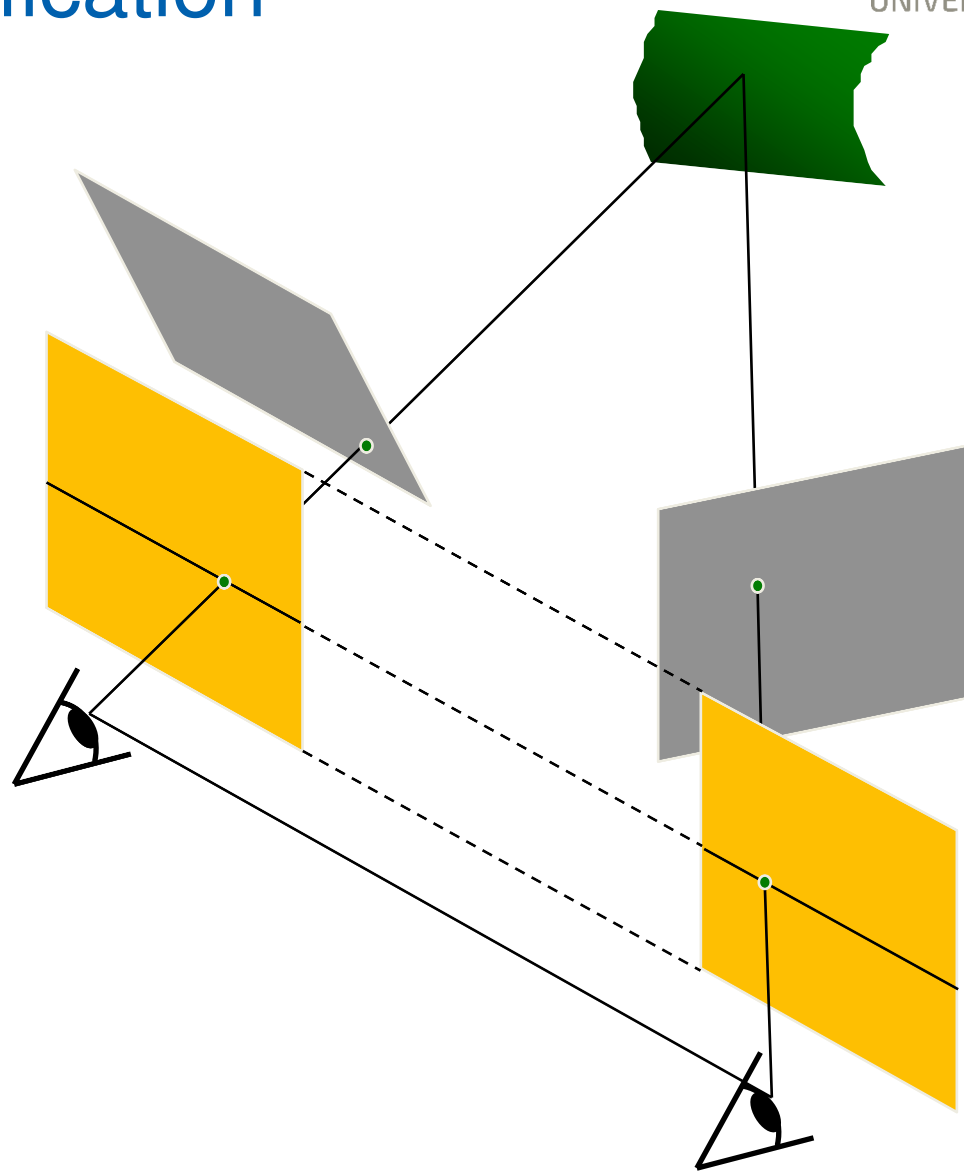
Stereo image rectification

- Reproject image planes onto a common plane parallel to the line between optical centers
- Pixel motion is horizontal after this transformation
- Two homographies (3x3 transform), one for each input image reprojection
- C. Loop and Z. Zhang. Computing Rectifying Homographies for Stereo Vision. IEEE Conf. Computer Vision and Pattern Recognition, 1999.



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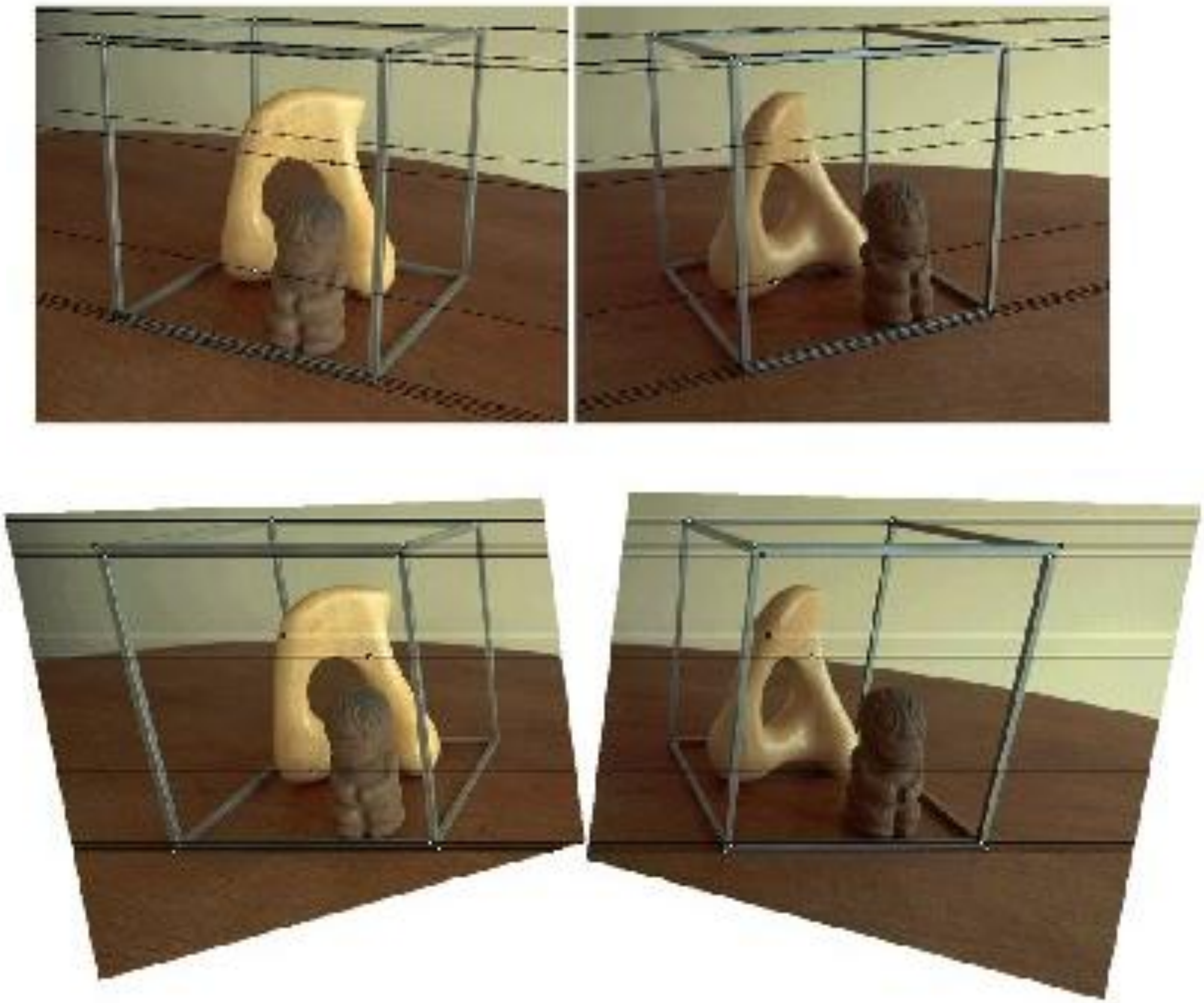
Rectification example



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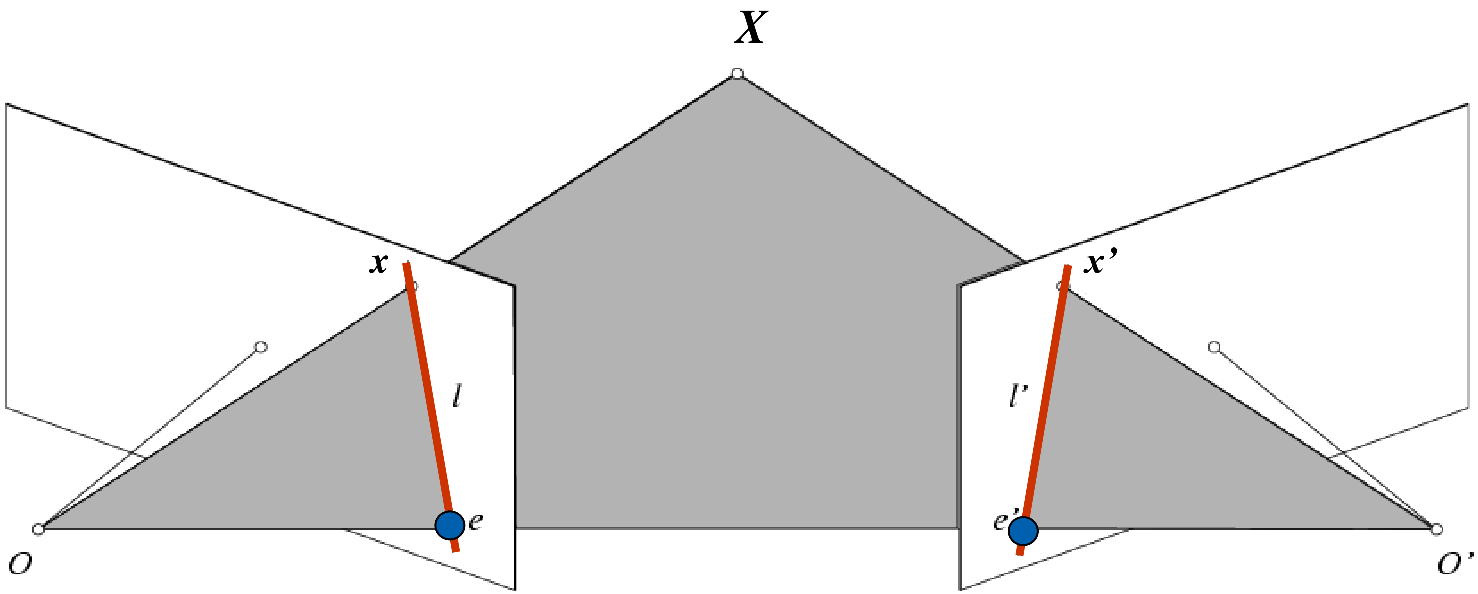
Recall: Epipolar constraint



$$x^T F x' = 0 \quad \text{with} \quad F = K^{-T} E K'^{-1}$$

- $F x'$ is the epipolar line associated with x' ($l = F x'$)
- $F^T x$ is the epipolar line associated with x ($l' = F^T x$)
- $F e' = 0$ and $F^T e = 0$
- F is singular (rank two)
- F has seven degrees of freedom

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Rectification

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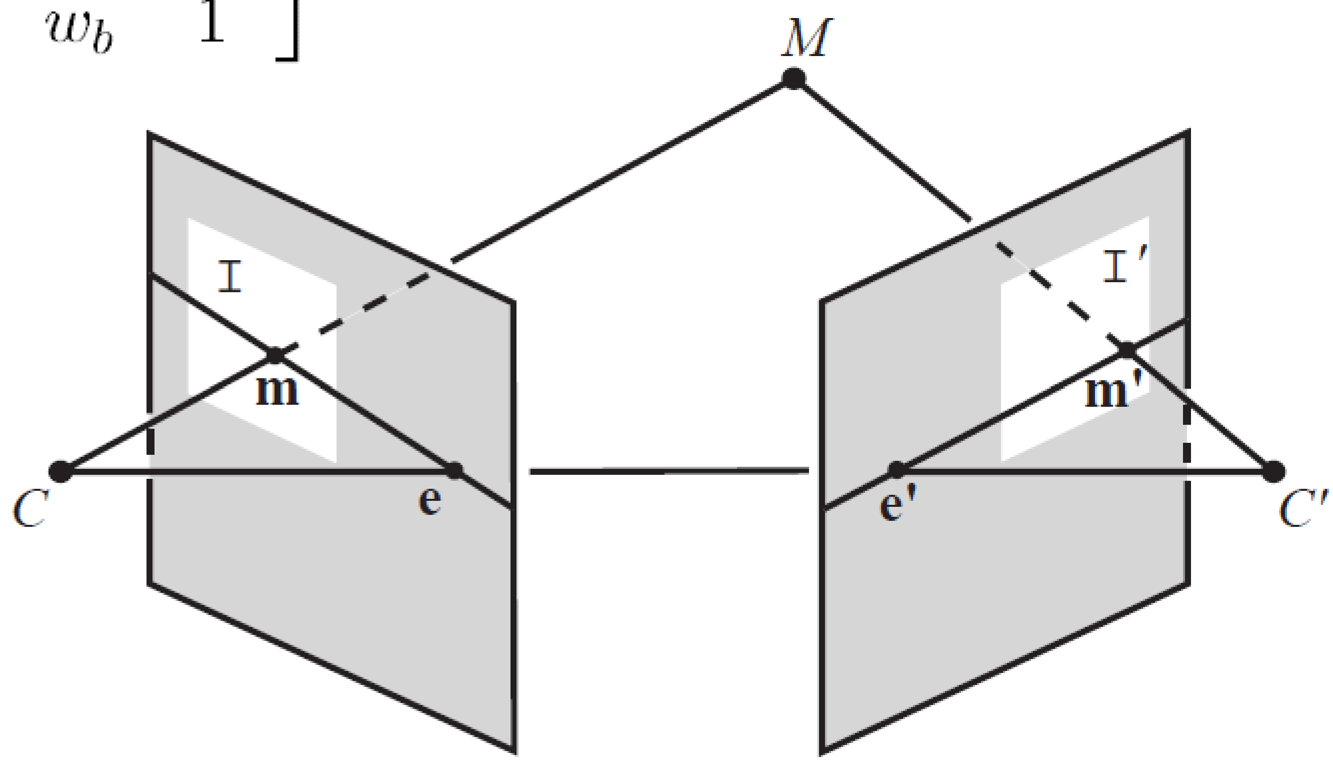
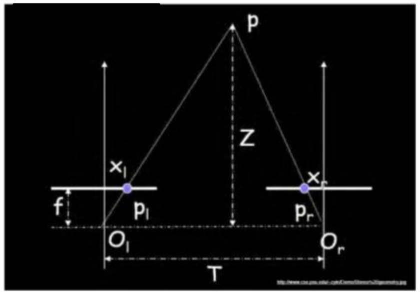
Estimate two homographies **H** and **H’**

$$\mathbf{H} = \begin{bmatrix} u_a & u_b & u_c \\ v_a & v_b & v_c \\ w_a & w_b & 1 \end{bmatrix}$$



Recall: Essential matrix



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$$\mathbf{p}'^{\mathrm{T}}\mathbf{E}\mathbf{p} = 0$$

$$\begin{bmatrix} x' & y' & f \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & d \\ 0 & -d & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ f \end{bmatrix} = 0$$

$$\Leftrightarrow \begin{bmatrix} x' & y' & f \end{bmatrix} \begin{bmatrix} 0 \\ df \\ -dy \end{bmatrix} = 0$$

$$\boxed{\Leftrightarrow y = y'}$$

For the parallel cameras, image of any point must lie on same horizontal line in each image plane.

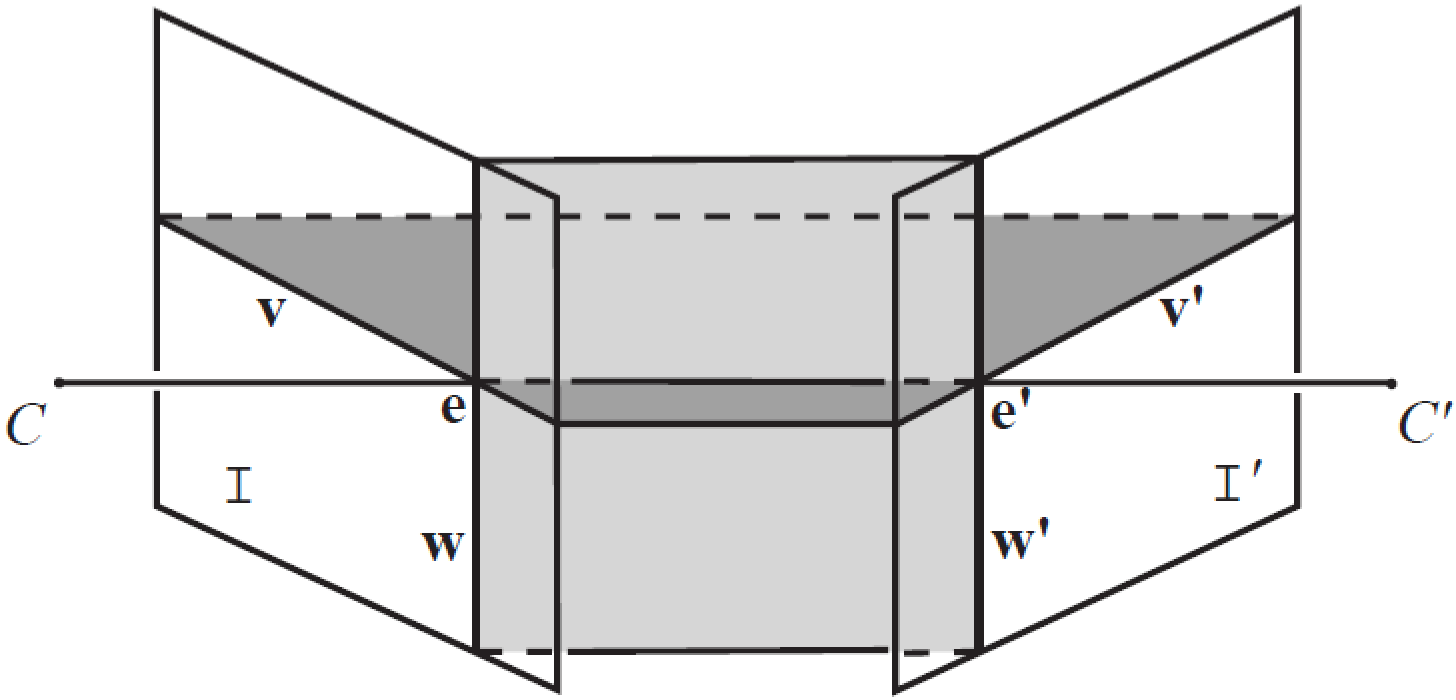
Kristen Grauman

Rectification

- Map epipoles to infinity (1,0,0) (canonical form)
- Fundamental matrix after rectification:

$$\bar{\mathbf{F}} = [\,\mathbf{i}\,]_\times = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix}$$

Rectification



$$\mathbf{H} = \begin{bmatrix} \mathbf{u}^T \\ \mathbf{v}^T \\ \mathbf{w}^T \end{bmatrix} = \begin{bmatrix} u_a & u_b & u_c \\ v_a & v_b & v_c \\ w_a & w_b & w_c \end{bmatrix}$$

$$\mathbf{He} = \begin{bmatrix} \mathbf{u}^T\mathbf{e} & \mathbf{v}^T\mathbf{e} & \mathbf{w}^T\mathbf{e} \end{bmatrix}^T = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}^T$$

Decompose homography

- Decompose **H** into affine transformation $\mathbf{H}_a$ and projective transformation $\mathbf{H}_p$
- Decompose affine trans. $\mathbf{H}_a$ into similarity trans. $\mathbf{H}_r$ and shearing trans. $\mathbf{H}_s$
- $\mathbf{H} = \mathbf{H}_a\mathbf{H}_p = \mathbf{H}_s\mathbf{H}_r\mathbf{H}_p$

$$\mathbf{H} = \begin{bmatrix} u_a & u_b & u_c \\ v_a & v_b & v_c \\ w_a & w_b & 1 \end{bmatrix}$$

$$\mathbf{H}_s = \begin{bmatrix} s_a & s_b & s_c \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{H}_r = \begin{bmatrix} v_b - v_c w_b & v_c w_a - v_a & 0 \\ v_a - v_c w_a & v_b - v_c w_b & v_c \\ 0 & 0 & 1 \end{bmatrix} \qquad \mathbf{H}_p = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ w_a & w_b & 1 \end{bmatrix}$$

Rectification example

$\mathbf{H}_p$

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Rectification example

$\mathbf{H}_p$

$\mathbf{H}_r\mathbf{H}_p$

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Rectification example

$H_r H_p$

$H_s H_r H_p$

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Estimate projective transformation

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- Estimate $\mathbf{H}_p$: $\mathbf{H}_p = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ w_a & w_b & 1 \end{bmatrix}$
- All pixels from images $\mathbf{p}_i = [p_{i,u}\ p_{i,v}\ 1]^T$ are mapped by $\mathbf{H}_p$ with homogenous component: $w_i = \mathbf{w}^T \mathbf{p}_i$
- After rectification, the homogenous component should be the same for all points including the mean:

$$\mathbf{p}_c = \frac{1}{n} \sum_{i=1}^{n} \mathbf{p}_i$$

- Minimize non-affine distortion: (is zero for affine transformation) $\sum_{i=1}^{n} \left[\frac{\mathbf{w}^T(\mathbf{p}_i - \mathbf{p}_c)}{\mathbf{w}^T \mathbf{p}_c} \right]^2$

Estimate projective transformation

- Estimate $\mathbf{H}_p$:
- All pixels from images

$$\mathbf{H}_p = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ w_a & w_b & 1 \end{bmatrix}$$

$$\mathbf{P} = \begin{bmatrix} p_{1,u} - p_{c,u} & p_{2,u} - p_{c,u} & \cdots & p_{n,u} - p_{c,u} \\ p_{1,v} - p_{c,v} & p_{2,v} - p_{c,v} & \cdots & p_{n,v} - p_{c,v} \\ 0 & 0 & \cdots & 0 \end{bmatrix} \quad \mathbf{p}_c = \frac{1}{n} \sum_{i=1}^{n} \mathbf{p}_i$$

- Minimize: $$\frac{\mathbf{w}^T \mathbf{P} \mathbf{P}^T \mathbf{w}}{\mathbf{w}^T \mathbf{p}_c \mathbf{p}_c^T \mathbf{w}}$$

- Relation: $$\mathbf{w} = [\,\mathbf{e}\,]_\times \mathbf{z}$$ $$\mathbf{w}' = \mathbf{F} \mathbf{z}$$

Estimate projective transformation

- Estimate $\mathbf{H}_p$:
- All pixels from images

$$\mathbf{H}_p = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ w_a & w_b & 1 \end{bmatrix}$$

$$\mathbf{P} = \begin{bmatrix} p_{1,u} - p_{c,u} & p_{2,u} - p_{c,u} & \cdots & p_{n,u} - p_{c,u} \\ p_{1,v} - p_{c,v} & p_{2,v} - p_{c,v} & \cdots & p_{n,v} - p_{c,v} \\ 0 & 0 & \cdots & 0 \end{bmatrix} \quad \mathbf{p}_c = \frac{1}{n}\sum_{i=1}^{n} \mathbf{p}_i$$

- Minimize:

$$\frac{\mathbf{z}^T \overbrace{[\mathbf{e}]_\times^T \mathbf{P}\mathbf{P}^T [\mathbf{e}]_\times}^{\mathbf{A}} \mathbf{z}}{\mathbf{z}^T \underbrace{[\mathbf{e}]_\times^T \mathbf{p}_c\mathbf{p}_c^T [\mathbf{e}]_\times}_{\mathbf{B}} \mathbf{z}} + \frac{\mathbf{z}^T \overbrace{\mathbf{F}^T \mathbf{P}'\mathbf{P}'^T \mathbf{F}}^{\mathbf{A}'} \mathbf{z}}{\mathbf{z}^T \underbrace{\mathbf{F}^T \mathbf{p}'_c\mathbf{p}'^T_c \mathbf{F}}_{\mathbf{B}'} \mathbf{z}}$$

$$\mathbf{w} = [\mathbf{e}]_\times \mathbf{z}$$

$$\mathbf{w}' = \mathbf{F}\mathbf{z}$$

- Cholesky decomposition: $\mathbf{A} = \mathbf{D}^T\mathbf{D}$
- **y** is eigenvector with highest eigenvalue of $\mathbf{D}^{-T}\mathbf{B}\mathbf{D}^{-1}$
- **w and w'** is given by $\mathbf{w} = [\mathbf{e}]_\times \mathbf{z}$ $\quad \mathbf{w}' = \mathbf{F}\mathbf{z}$ $\quad \mathbf{z} = \mathbf{D}^{-1}\mathbf{y}$

Rectification example

$\mathbf{H}_p$

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Estimate similarity transformation

- We know fundamental matrix **F** and

$$\mathbf{H}_p = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ w_a & w_b & 1 \end{bmatrix}$$

- Similarity matrix is then given by

$$\mathbf{H}_r = \begin{bmatrix} F_{32} - w_b F_{33} & w_a F_{33} - F_{31} & 0 \\ F_{31} - w_a F_{33} & F_{32} - w_b F_{33} & F_{33} + v'_c \\ 0 & 0 & 1 \end{bmatrix}$$

- v'_c is set such that pixels (v) start with zero

Rectification example

$\mathbf{H}_p$

$\mathbf{H}_r\mathbf{H}_p$

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Map image back to image size

- Homographies $\mathbf{H}_r\mathbf{H}_p$ rectify images, but might introduce unnecessary distortion, e.g., images are very small or very large.
- Map images back to original size (shearing):

$$\mathbf{S} = \begin{bmatrix} a & b & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

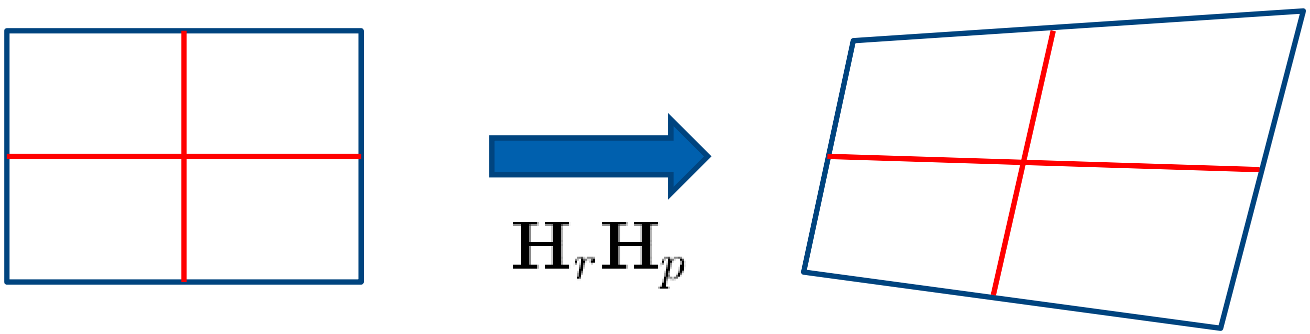
Map image back to image size

- Define reference lines:

$\mathbf{a} = [\,\frac{w-1}{2}\;\; 0\;\; 1\,]^T$, $\mathbf{b} = [\,w-1\;\; \frac{h-1}{2}\;\; 1\,]^T$, $\mathbf{c} = [\,\frac{w-1}{2}\;\; h-1\;\; 1\,]^T$, and $\mathbf{d} = [\,0\;\; \frac{h-1}{2}\;\; 1\,]^T$

$$\hat{\mathbf{a}} = \mathbf{H}_r\mathbf{H}_p\mathbf{a}$$

$$\begin{aligned} \mathbf{x} &= \hat{\mathbf{b}} - \hat{\mathbf{d}}, \\ \mathbf{y} &= \hat{\mathbf{c}} - \hat{\mathbf{a}}. \end{aligned}$$



- Make lines perpendicular and keep width and height ratio:

$$(\mathbf{S}\mathbf{x})^T(\mathbf{S}\mathbf{y}) = 0, \quad \frac{(\mathbf{S}\mathbf{x})^T(\mathbf{S}\mathbf{x})}{(\mathbf{S}\mathbf{y})^T(\mathbf{S}\mathbf{y})} = \frac{w^2}{h^2}.$$

Map image back to image size

- Map images back to original size (shearing):

$$\mathbf{S} = \begin{bmatrix} a & b & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$a = \frac{h^2 x_v^2 + w^2 y_v^2}{hw(x_v y_u - x_u y_v)} \qquad b = \frac{h^2 x_u x_v + w^2 y_u y_v}{hw(x_u y_v - x_v y_u)}$$

- Add translation and scale to preserve image area and pixels start at zero

Rectification example

$\mathbf{H}_p$

Lazebnik

Rectification example

$\mathbf{H}_p$

$\mathbf{H}_r\mathbf{H}_p$

Lazebnik

Rectification example

$H_r H_p$

$H_s H_r H_p$

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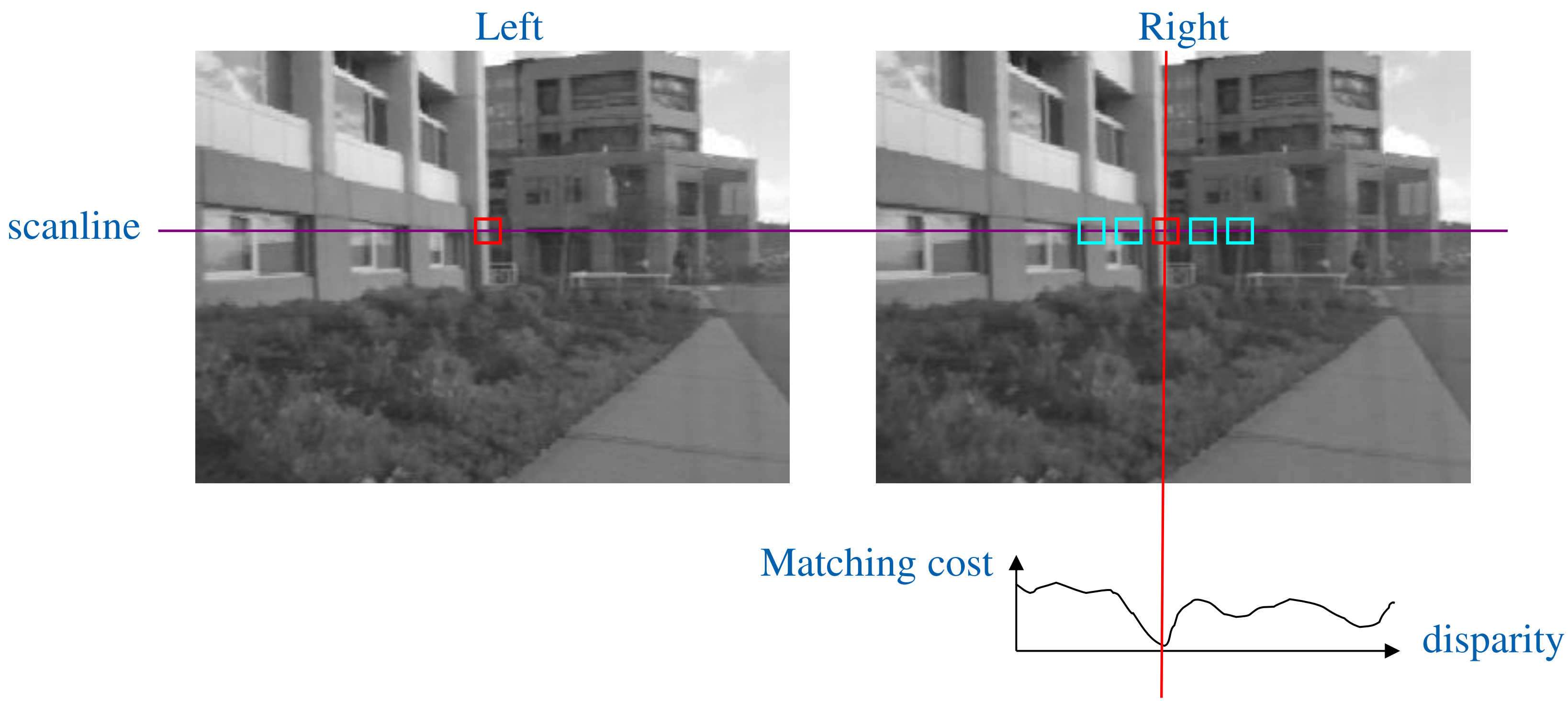
Correspondence search



- Slide a window along the right scanline and compare contents of that window with the reference window in the left image
- Matching cost: SSD or normalized correlation

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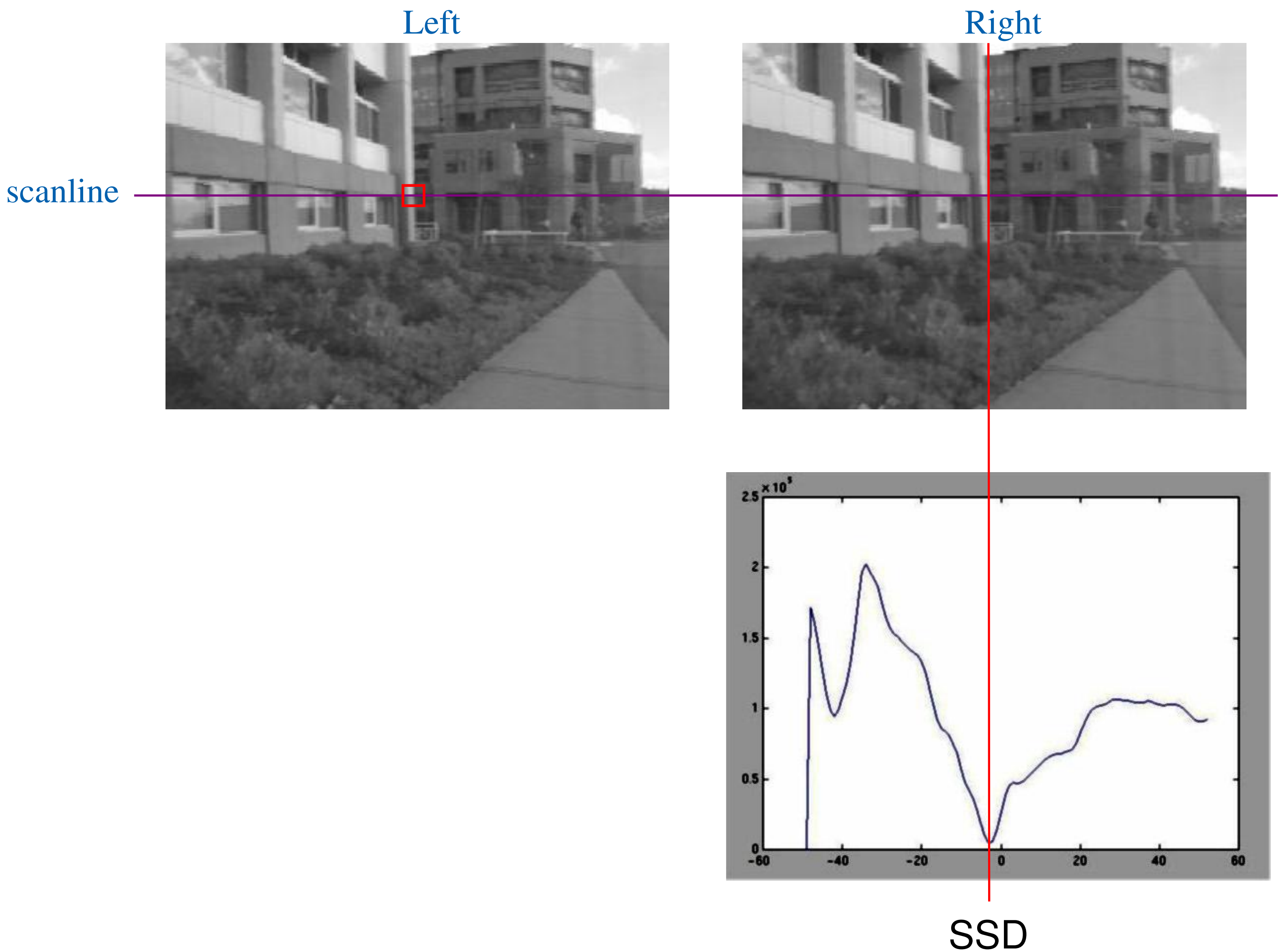
Correspondence search



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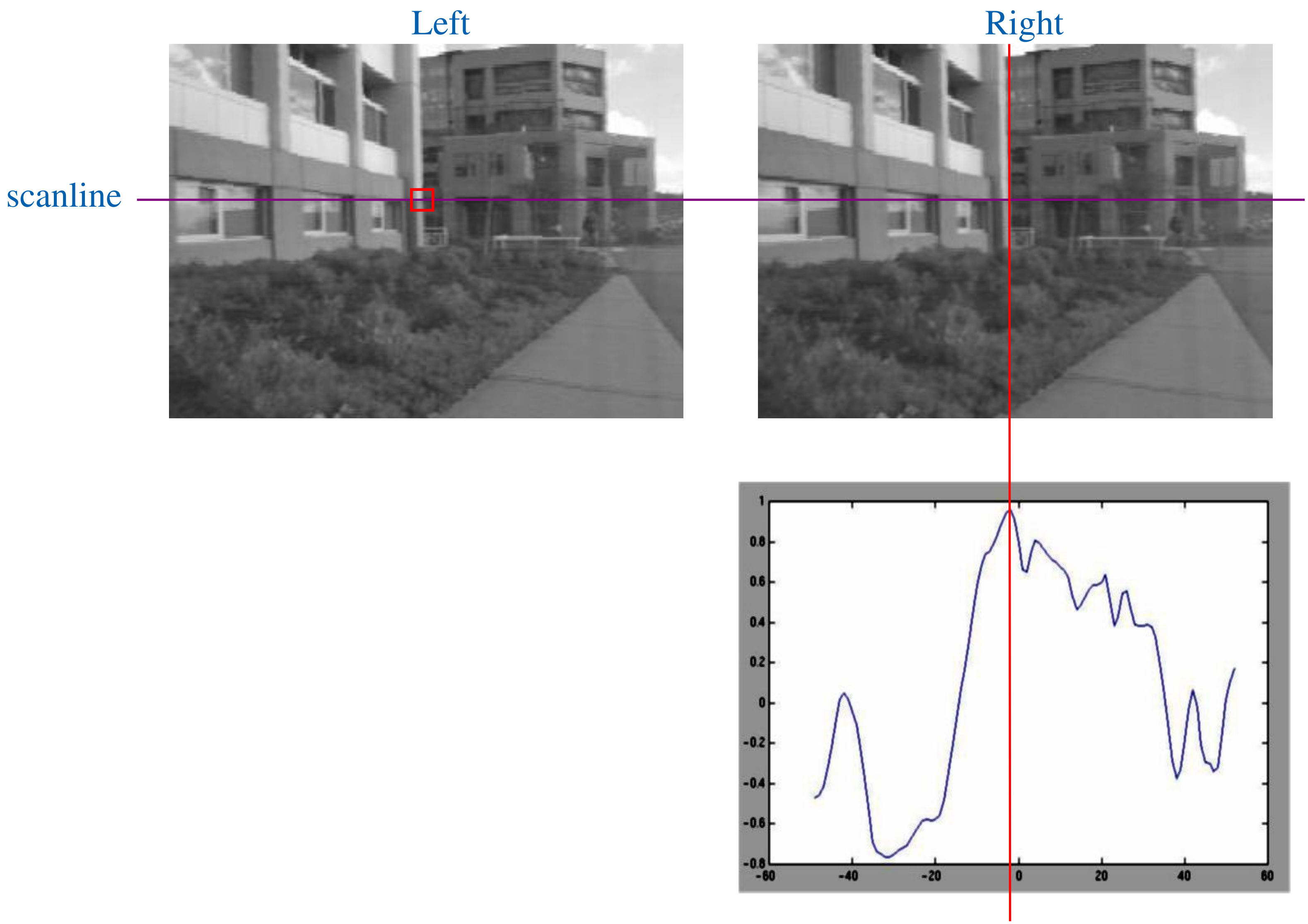
Correspondence search



Norm. corr

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Basic stereo matching algorithm

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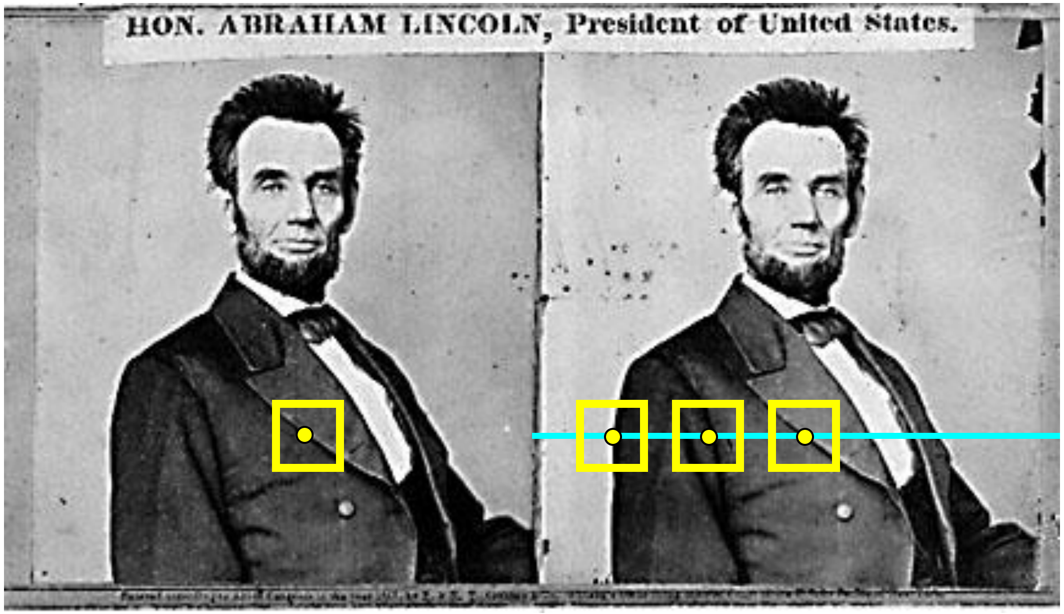

- If necessary, rectify the two stereo images to transform epipolar lines into scanlines
- For each pixel x in the first image
  - Find corresponding epipolar scanline in the right image
  - Examine all pixels on the scanline and pick the best match x'
  - Compute disparity x-x' and set depth(x) = B*f/(x-x')

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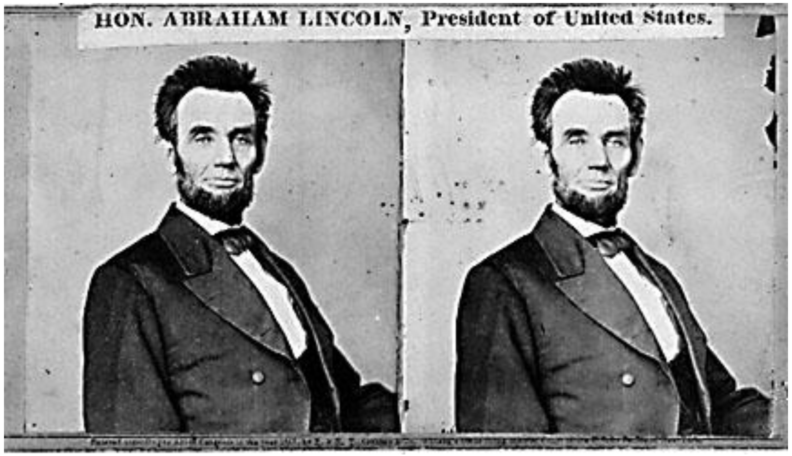
Failures of correspondence search



Textureless surfaces

Occlusions, repetition

Non-Lambertian surfaces, specularities

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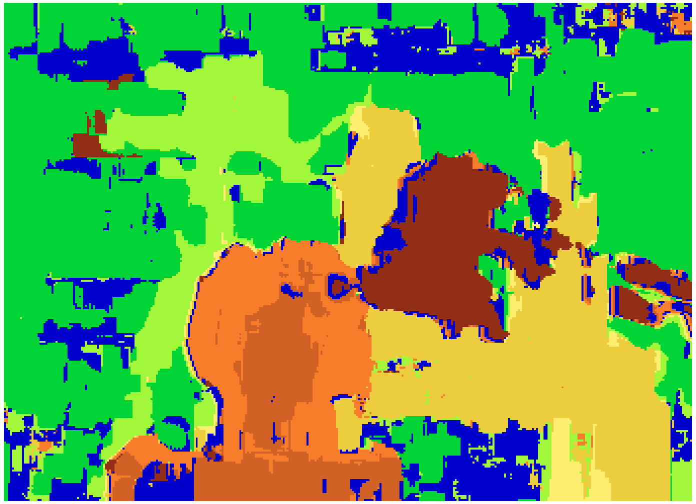
Results with window search

Data

Window-based matching



Ground truth

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How can we improve window-based matching?

- The similarity constraint is local (each reference window is matched independently)
- Need to enforce some correspondence constraints

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Non-local constraints

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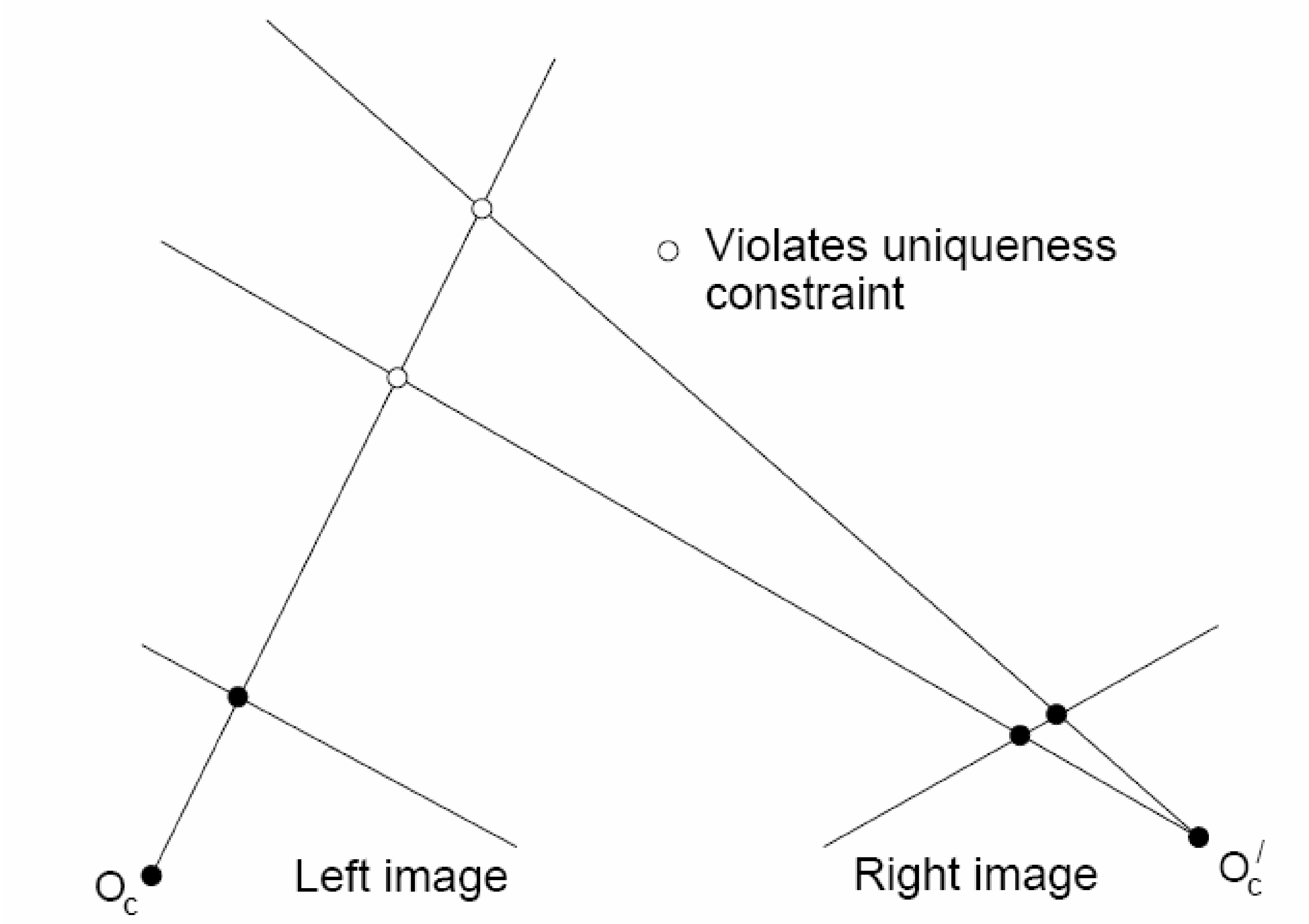
Uniqueness: For any point in one image, there should be at most one matching point in the other image

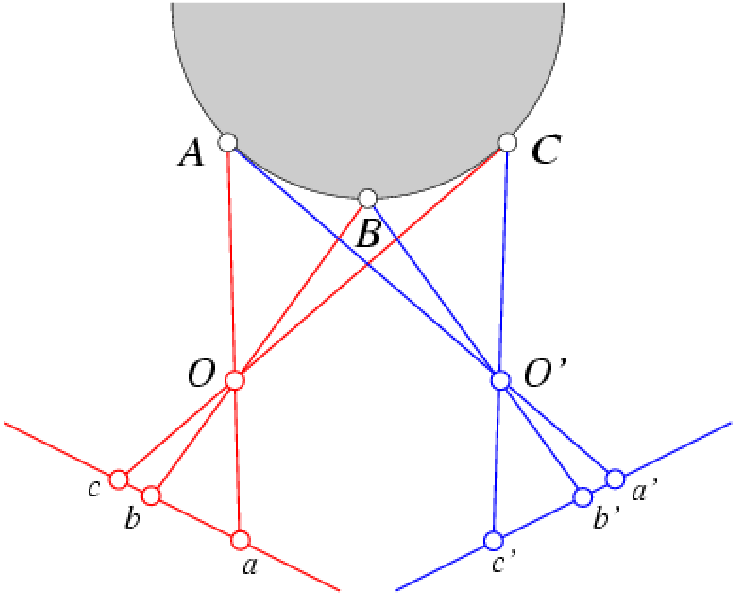


Lazebnik

Non-local constraints

Uniqueness
- For any point in one image, there should be at most one matching point in the other image

Ordering
- Corresponding points should be in the same order in both views



Lazebnik

Non-local constraints

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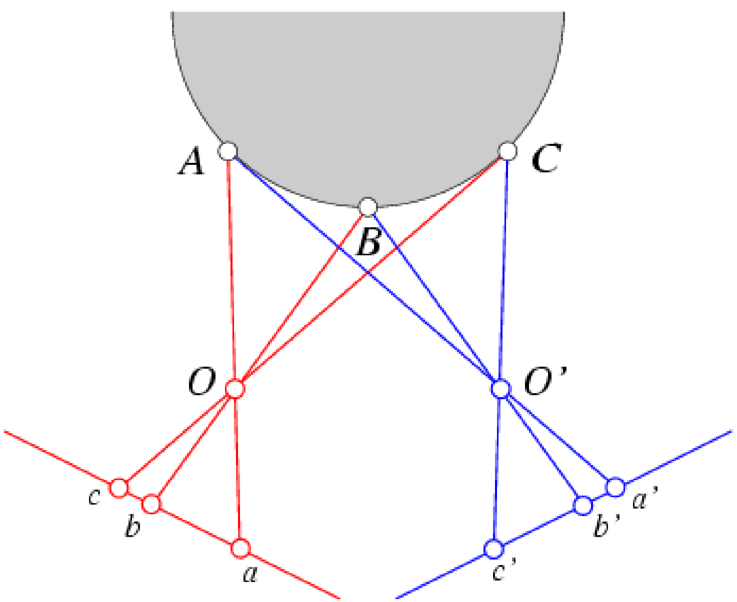

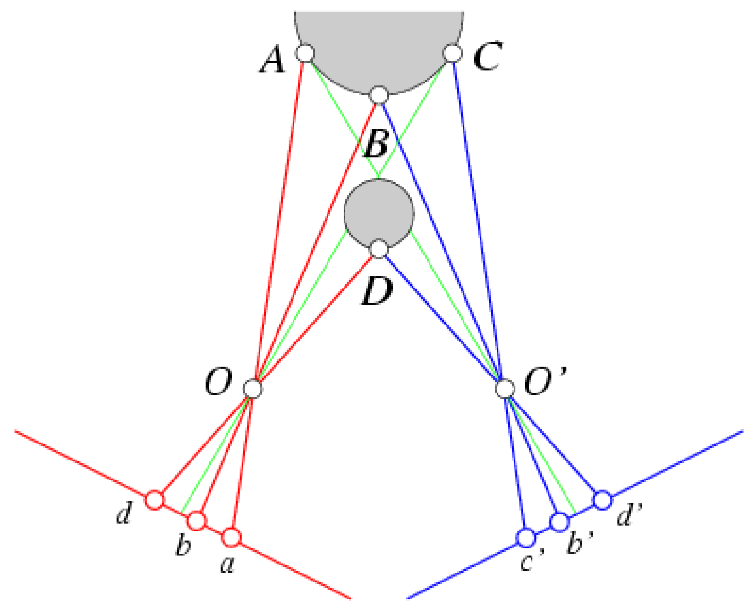

Ordering constraint doesn’t hold

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Non-local constraints

Uniqueness

– For any point in one image, there should be at most one matching point in the other image

Ordering

– Corresponding points should be in the same order in both views

Smoothness

– We expect disparity values to change slowly (for the most part)

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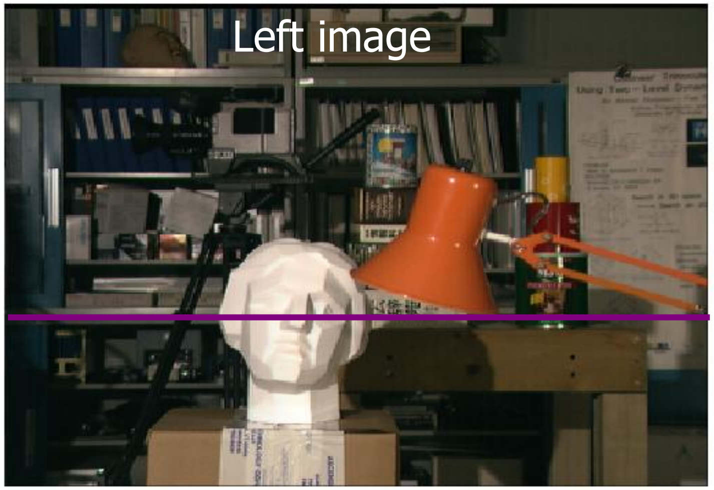
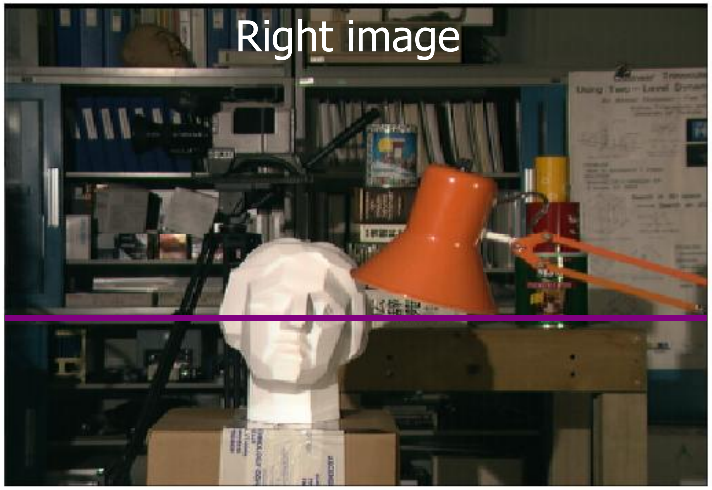
Scanline stereo

Try to coherently match pixels on the entire scanline

Different scanlines are still optimized independently





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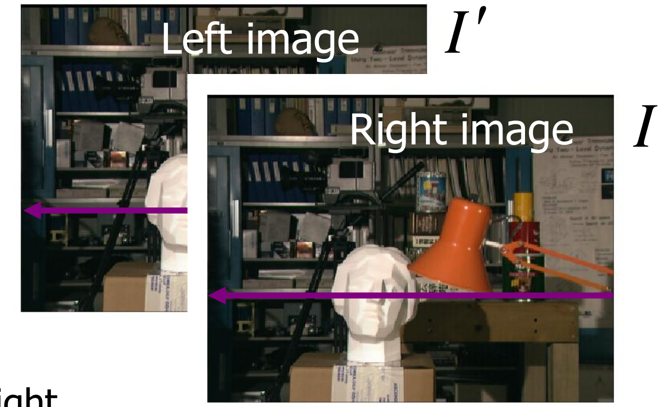
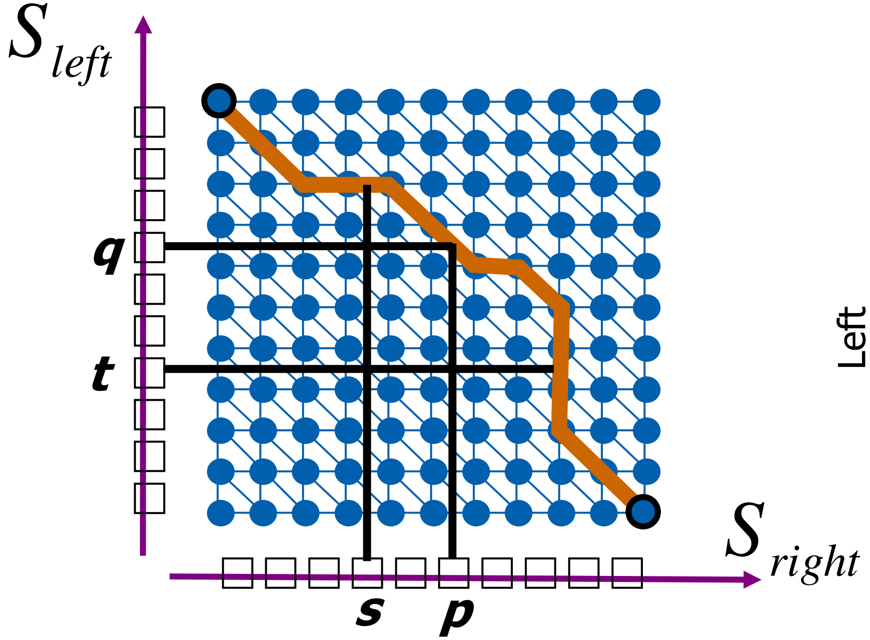
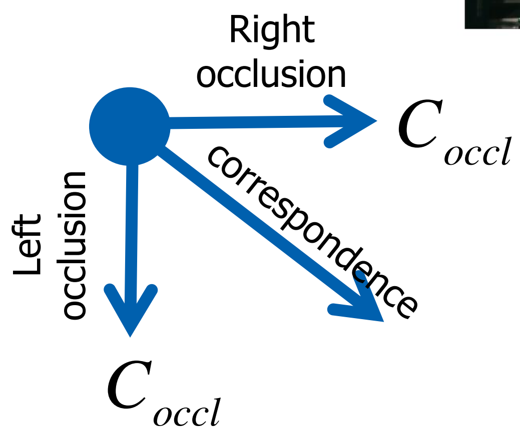
“Shortest paths” for scan-line stereo







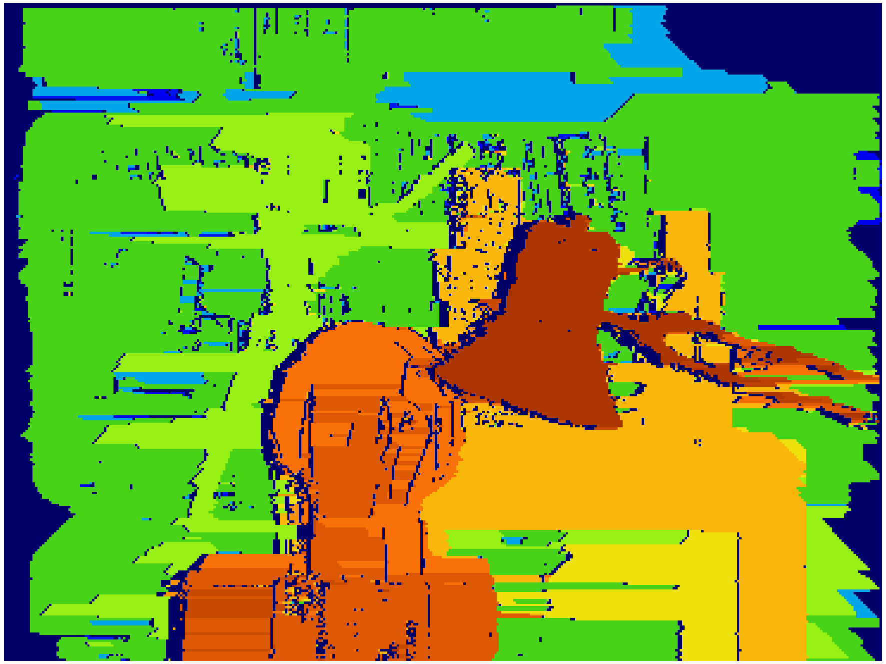
Can be implemented with dynamic programming

Ohta & Kanade ’85, Cox et al. ‘96

Y. Boykov

Coherent stereo on 2D grid

Scanline stereo generates streaking artifacts



Can’t use dynamic programming to find spatially coherent disparities/ correspondences on a 2D grid

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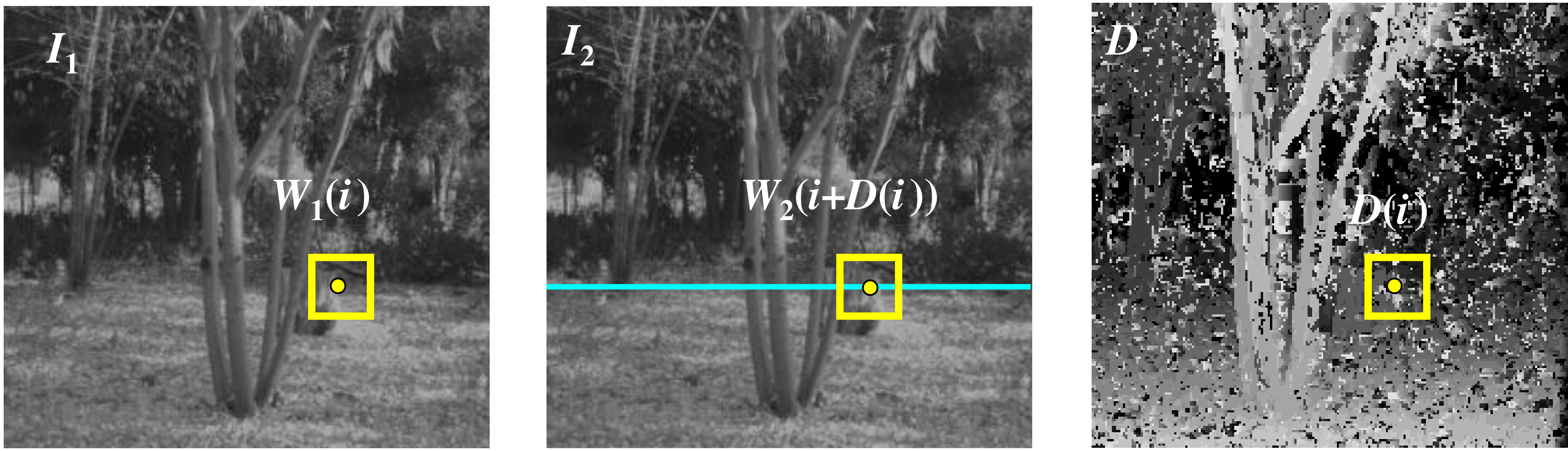
Stereo matching as energy minimization



$$E(D) = \underbrace{\sum_i \left(W_1(i) - W_2(i + D(i))\right)^2}_{\textit{data term}} + \lambda \underbrace{\sum_{\text{neighbors } i,j} \rho\left(D(i) - D(j)\right)}_{\textit{smoothness term}}$$

Energy functions of this form can be minimized using graph cuts

Y. Boykov, O. Veksler, and R. Zabih, Fast Approximate Energy Minimization via Graph Cuts, PAMI 2001

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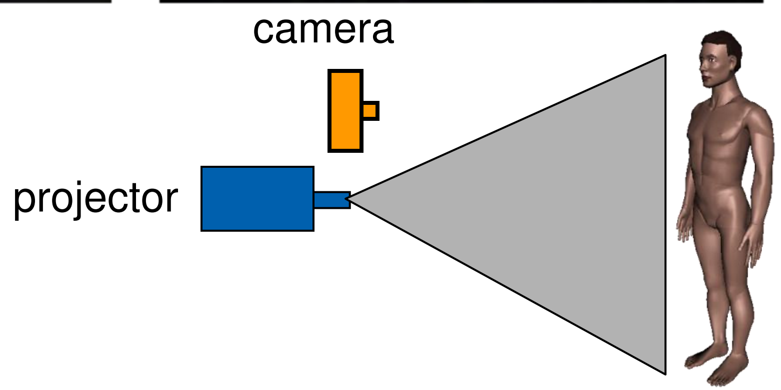
Active stereo with structured light

Project “structured” light patterns onto the object

– Simplifies the correspondence problem

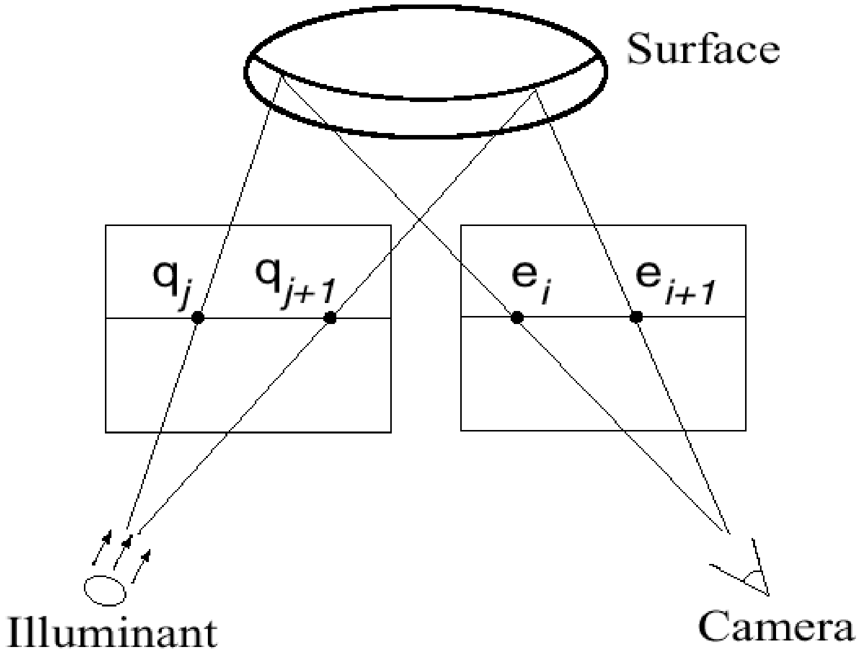
– Allows us to use only one camera

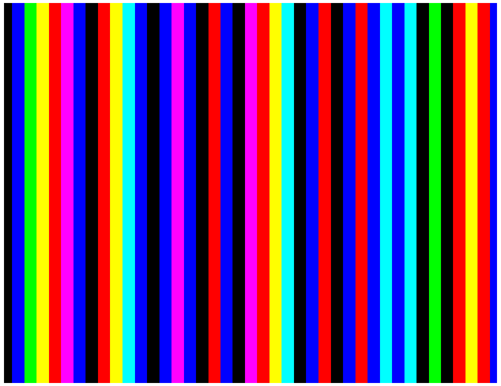


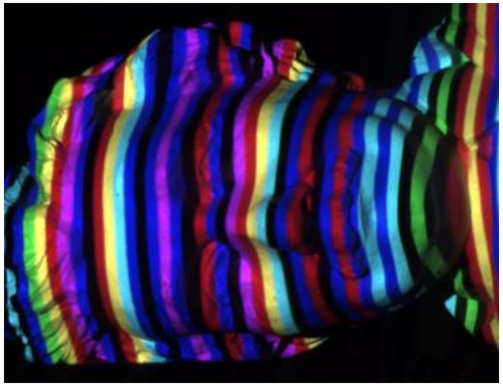
L. Zhang, B. Curless, and S. M. Seitz. Rapid Shape Acquisition Using Color Structured Light and Multi-pass Dynamic Programming. *3DPVT* 2002

Lazebnik

Active stereo with structured light







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Aligning range images

A single range scan is not sufficient to describe a complex surface

Need techniques to register multiple range images

B. Curless and M. Levoy, A Volumetric Method for Building Complex Models from Range Images, SIGGRAPH 1996

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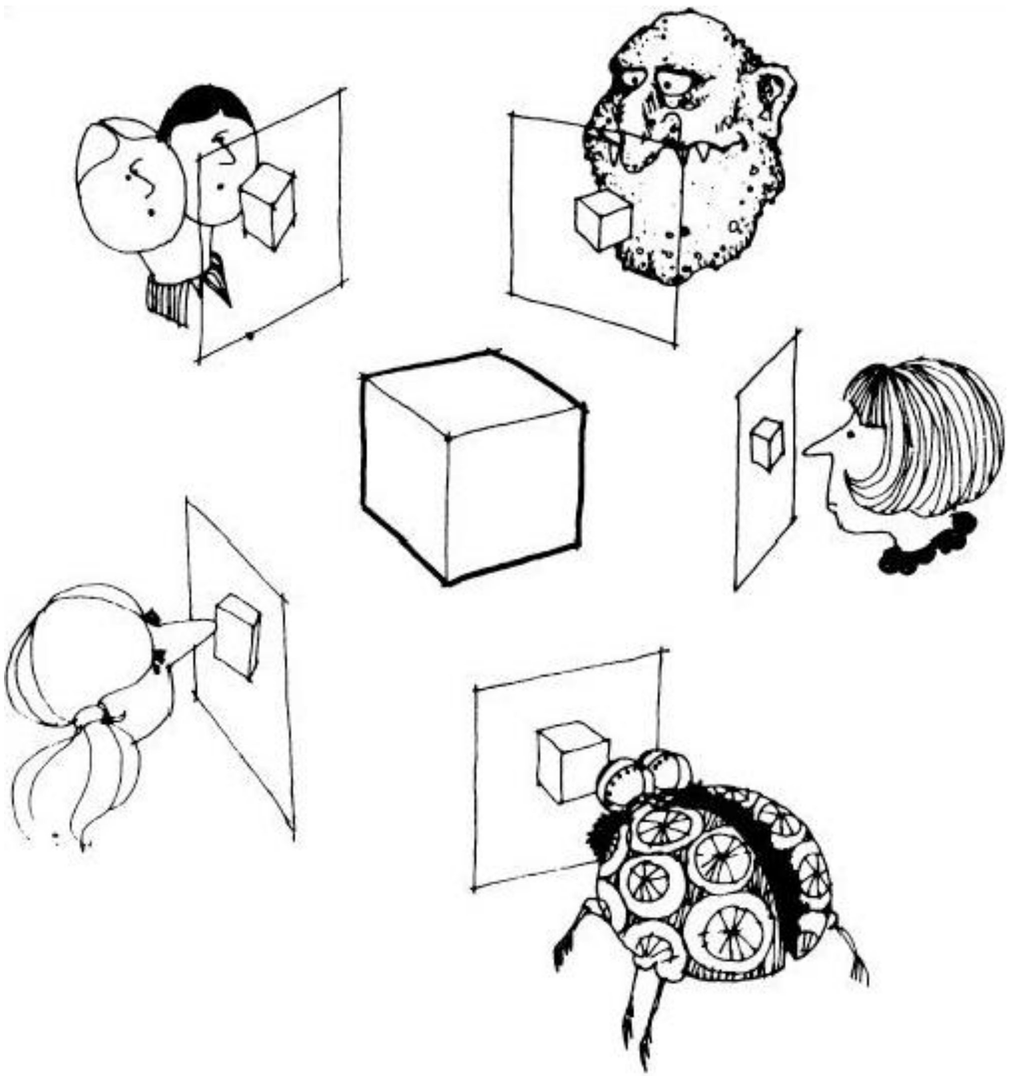
Multi-view stereo



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What is stereo vision?

Generic problem formulation: given several images of the same object or scene, compute a representation of its 3D shape

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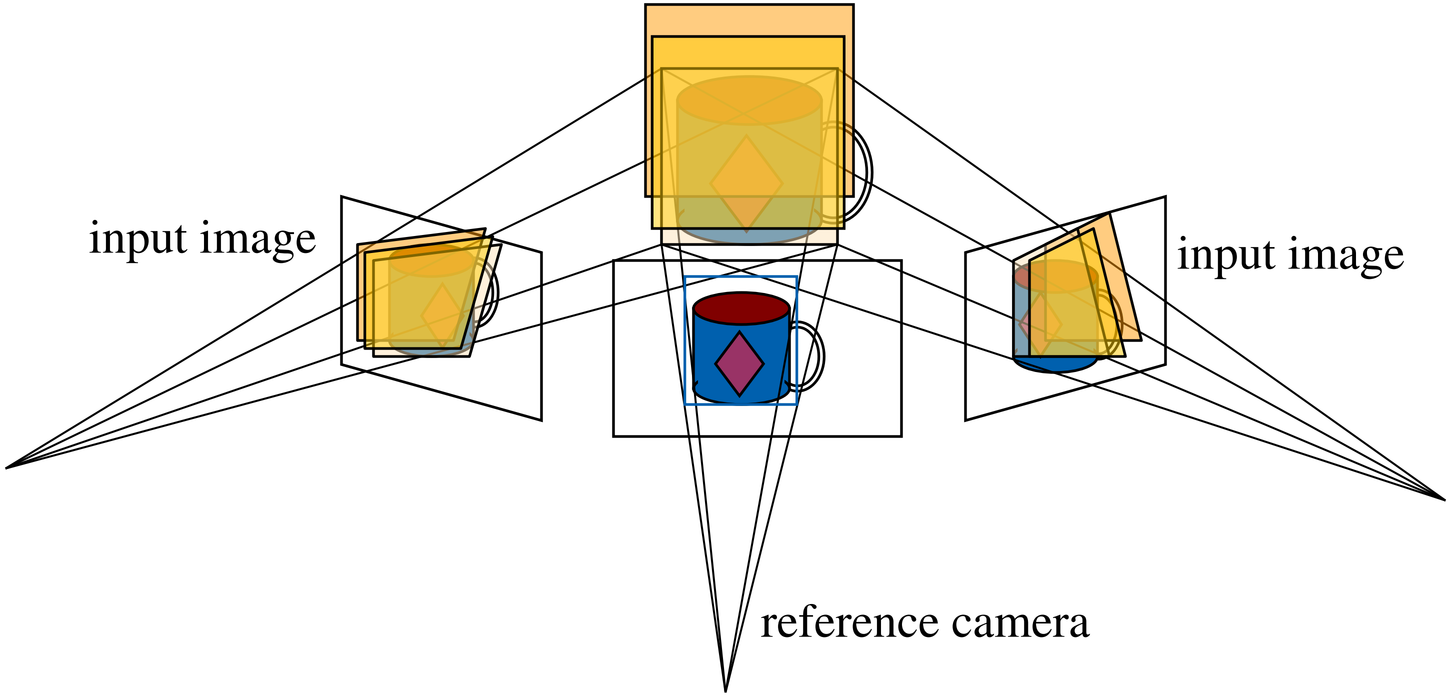
Plane Sweep Stereo

- Choose a reference view
- Sweep family of planes at different depths with respect to the reference camera



Each plane defines a homography warping each input image into the reference view

R. Collins. A space-sweep approach to true multi-image matching. CVPR 1996.

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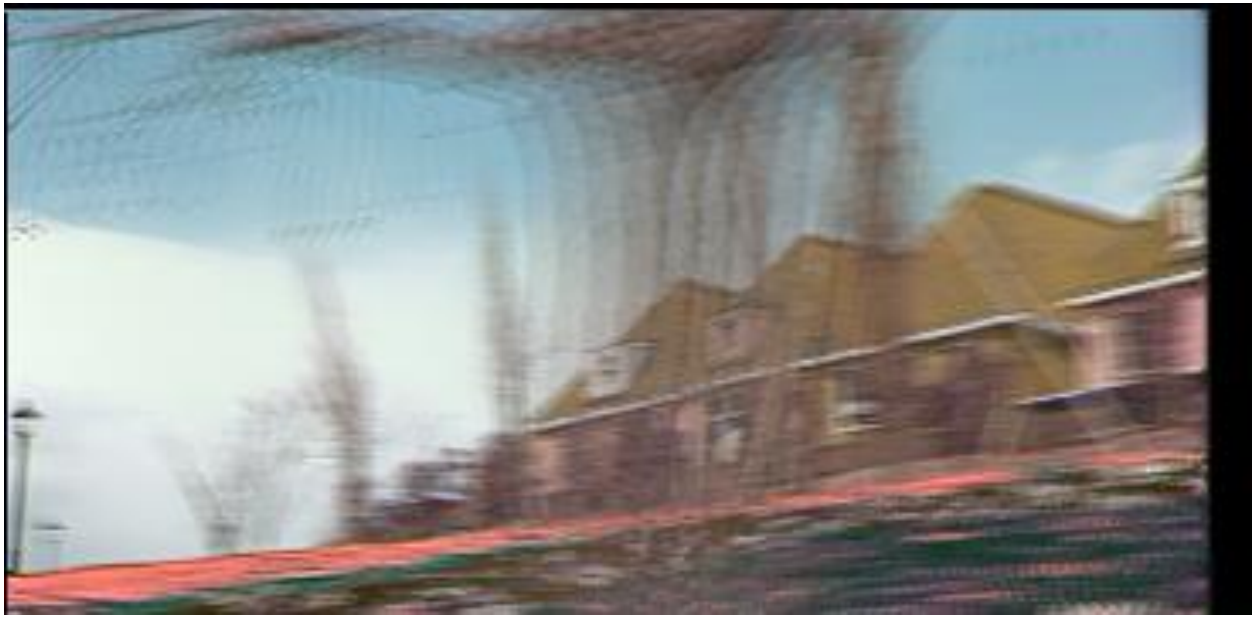
Plane Sweep Stereo

- For each depth plane
  - For each pixel in the composite image stack, compute the variance



- For each pixel, select the depth that gives the lowest variance

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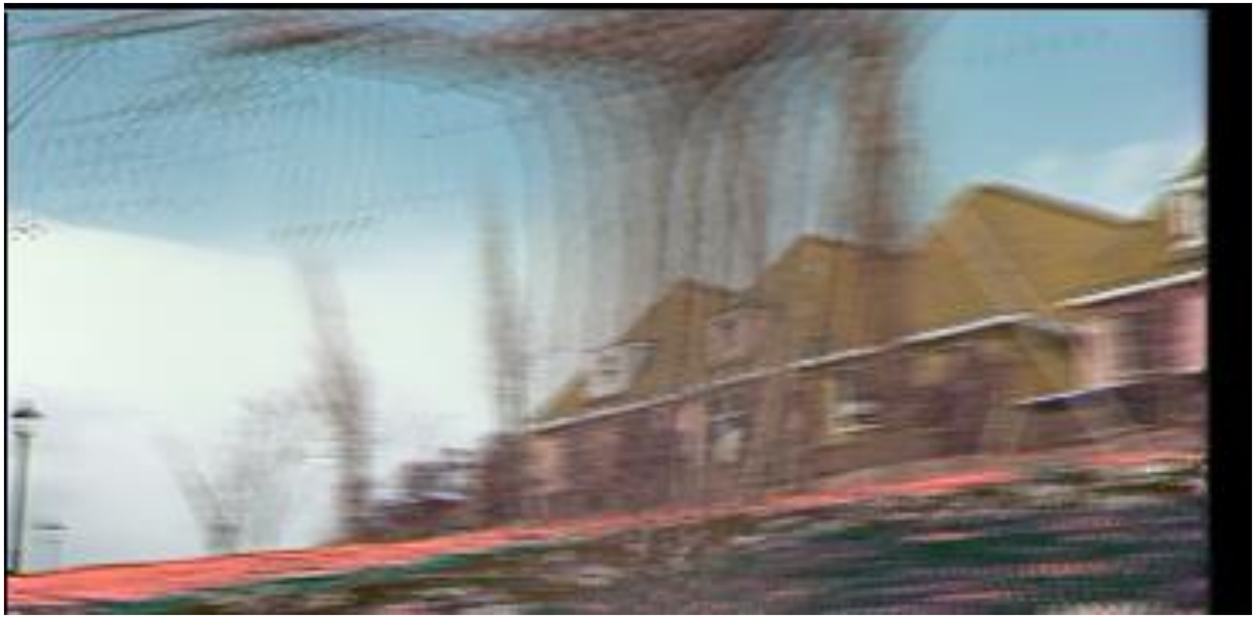
Plane Sweep Stereo

- For each depth plane
  - For each pixel in the composite image stack, compute the variance



- For each pixel, select the depth that gives the lowest variance

- Can be accelerated using graphics hardware

R. Yang and M. Pollefeys. *Multi-Resolution Real-Time Stereo on Commodity Graphics Hardware*, CVPR 2003

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Volumetric Stereo

- In plane sweep stereo, the sampling of the scene depends on the reference view
- We can use a voxel volume to get a view-independent representation

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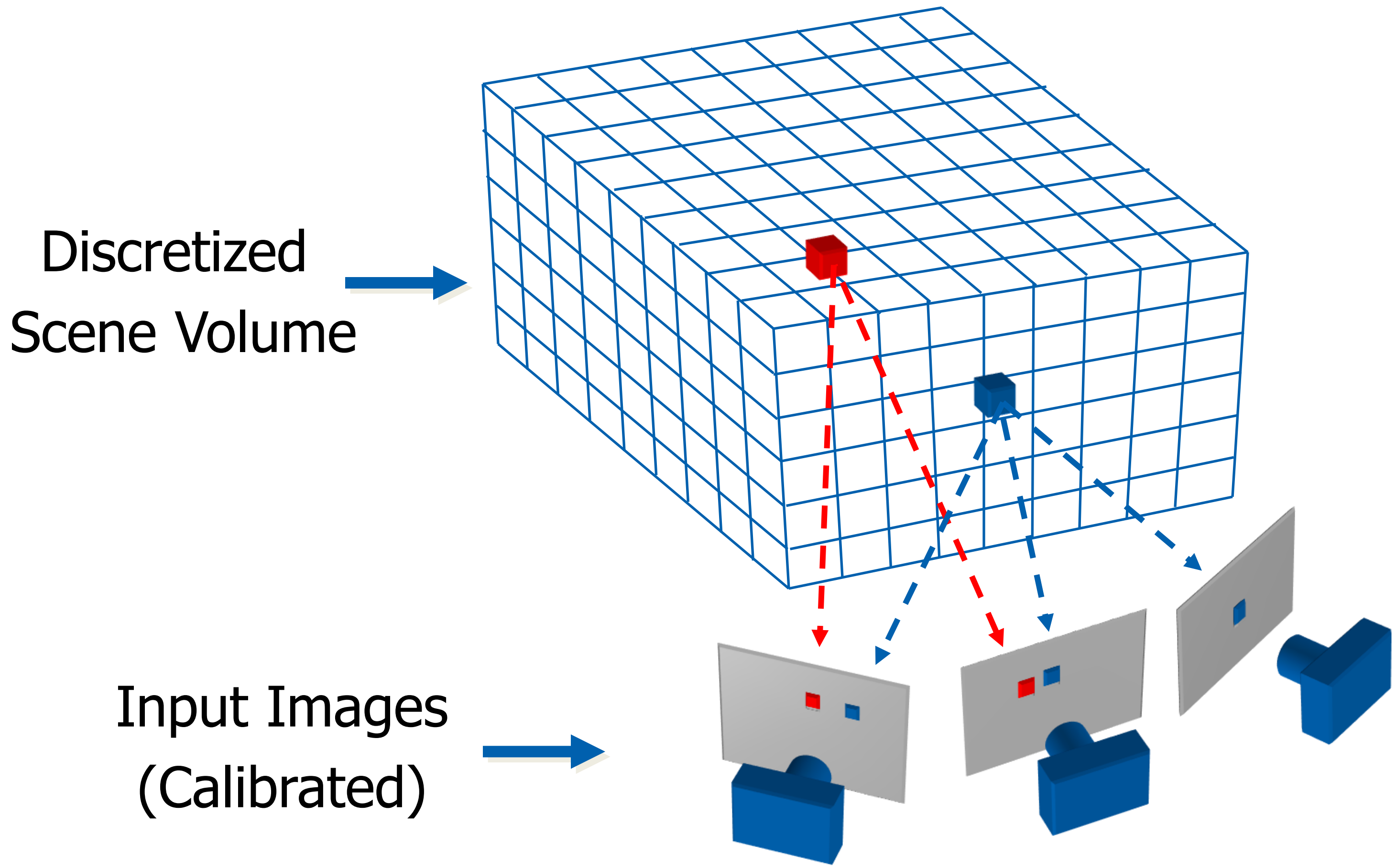
Volumetric Stereo / Voxel Coloring



Goal: Assign RGB values to voxels in V *photo-consistent* with images

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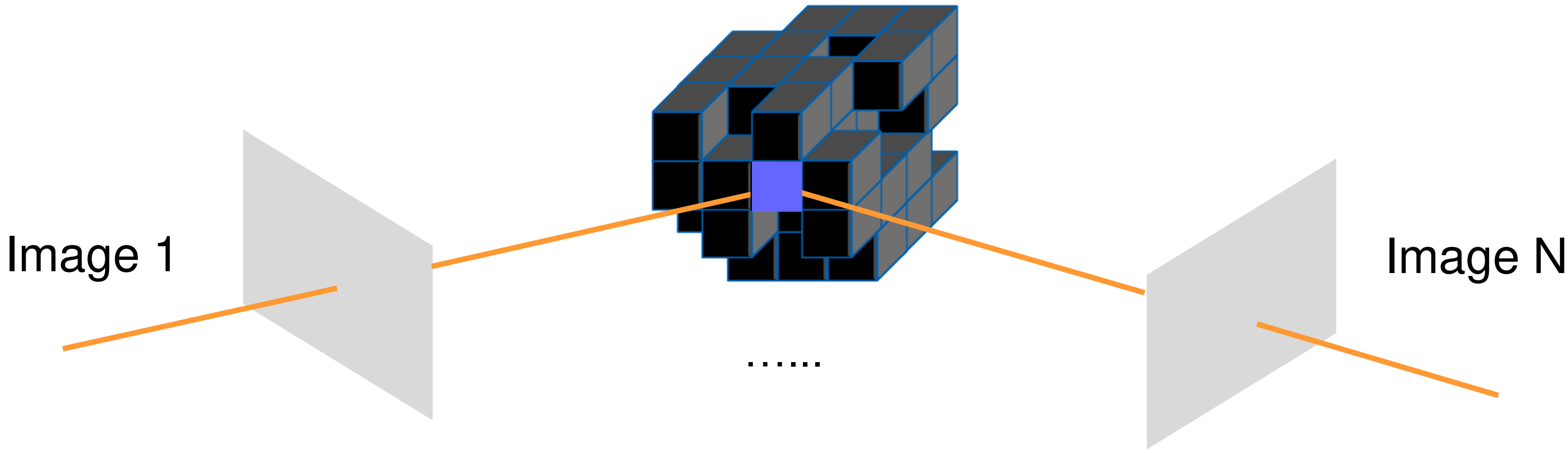
Space Carving



Space Carving Algorithm

- Initialize to a volume V containing the true scene
- Choose a voxel on the outside of the volume
- Project to visible input images
- Carve if not photo-consistent
- Repeat until convergence

K. N. Kutulakos and S. M. Seitz, **A Theory of Shape by Space Carving**, *ICCV* 1999

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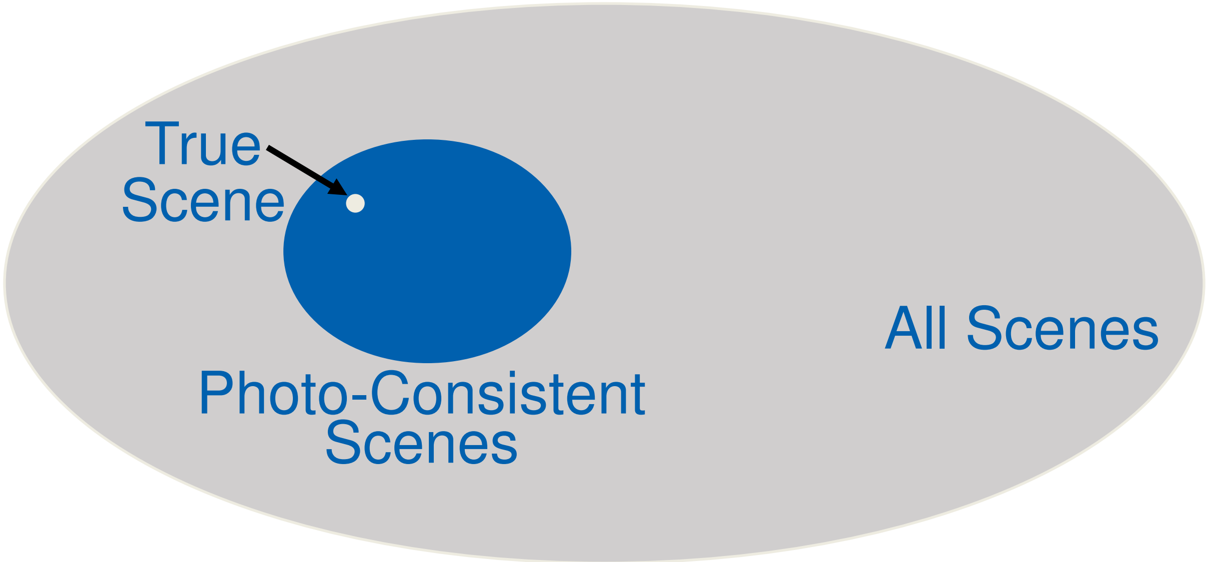
Photo-consistency

- A photo-consistent scene is a scene that exactly reproduces your input images from the same camera viewpoints
- You can't use your input cameras and images to tell the difference between a photo-consistent scene and the true scene



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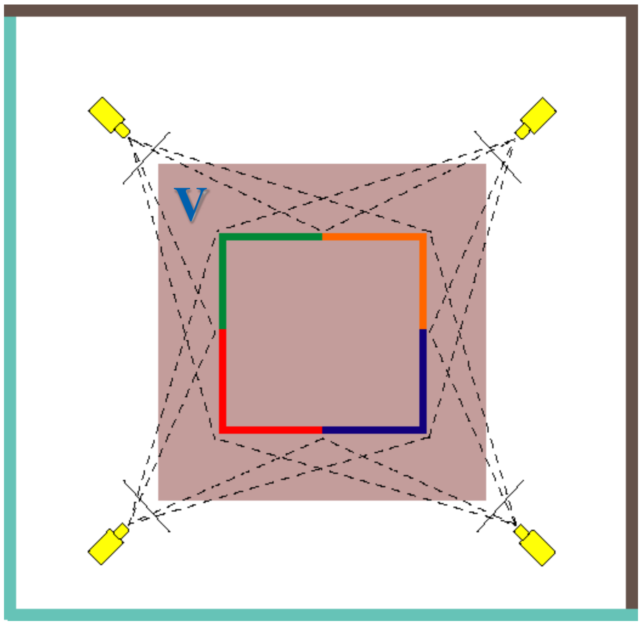
Which shape do you get?



True Scene

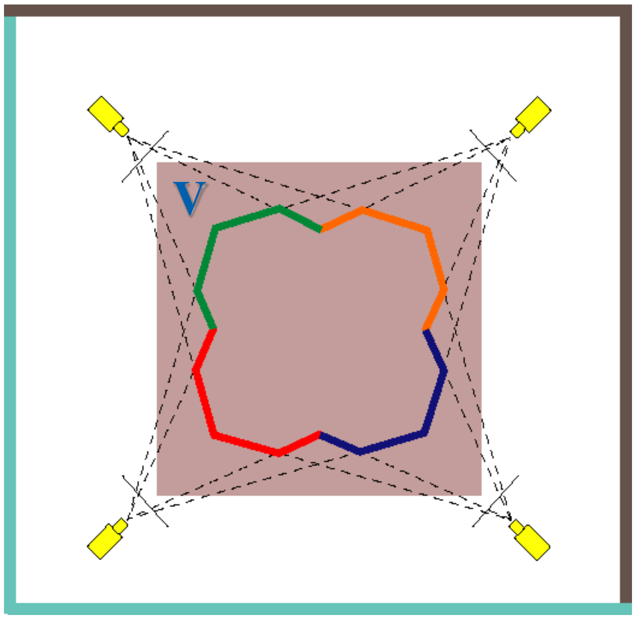


Photo Hull

- The Photo Hull *is the UNION of all photo-consistent scenes in V*
  - It is a photo-consistent scene reconstruction
  - Tightest possible bound on the true scene

Source: S. Seitz

Space Carving Results: African Violet

Input Image (1 of 45)

Reconstruction

Reconstruction

Reconstruction

Source: S. Seitz

Space Carving Results: Hand

Input Image
(1 of 100)

Views of Reconstruction

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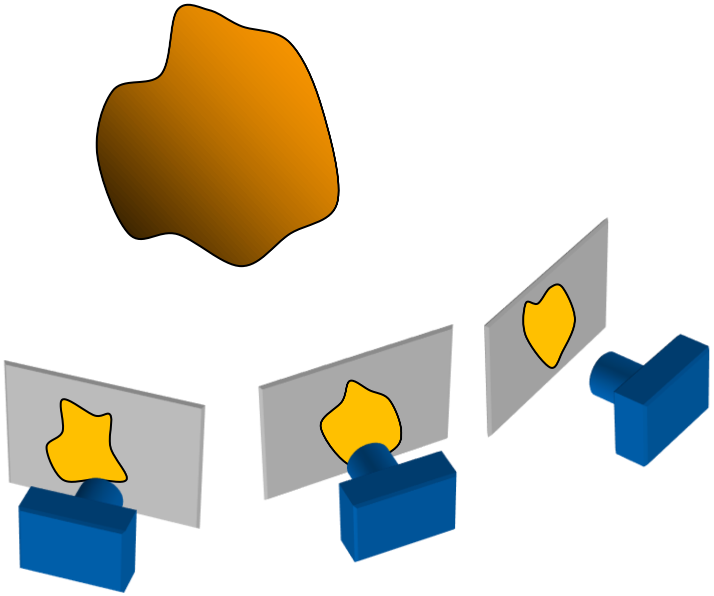
Reconstruction from Silhouettes

- The case of binary images: a voxel is photo-consistent if it lies inside the object’s silhouette in all views

Binary Images



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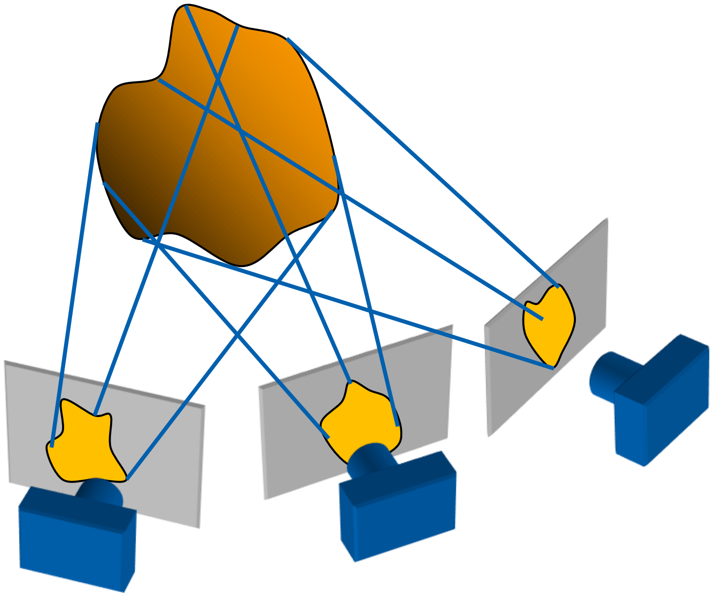
Reconstruction from Silhouettes

- The case of binary images: a voxel is photo-consistent if it lies inside the object's silhouette in all views

Binary Images



Finding the silhouette-consistent shape (*visual hull*):
- *Backproject* each silhouette
- Intersect backprojected volumes

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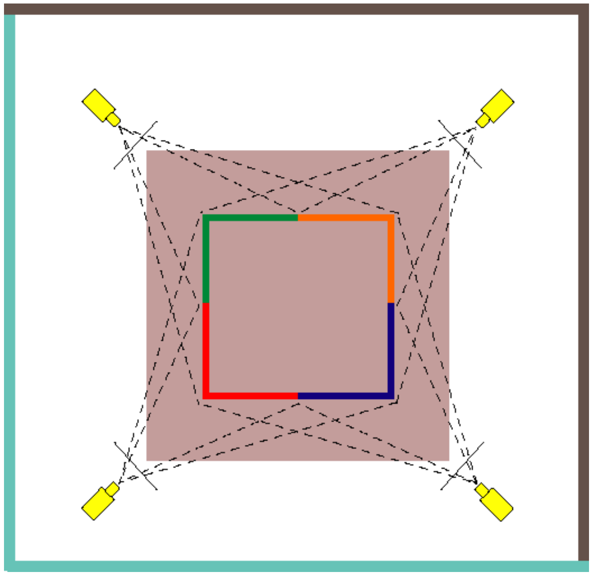
Photo-consistency vs. silhouette-consistency



True Scene

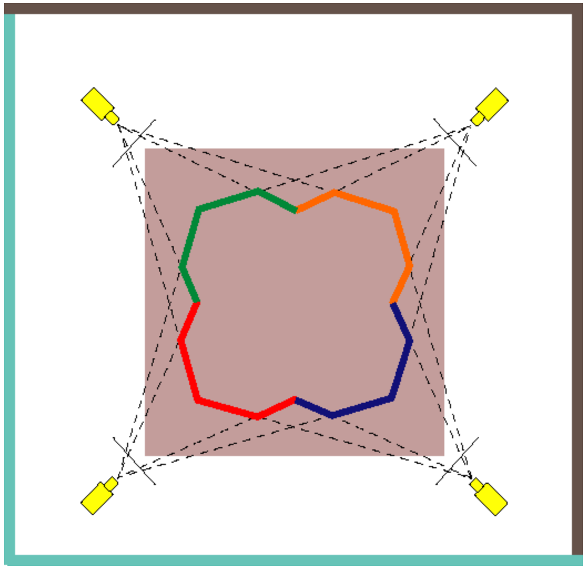
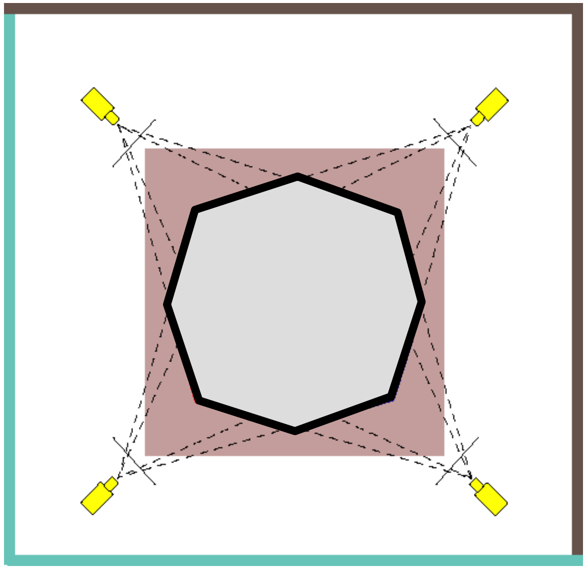


Photo Hull



Visual Hull

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Carved visual hulls

1. Compute visual hull
2. Use dynamic programming to find rims and constrain them to be fixed
3. Carve the visual hull to optimize photo-consistency

Yasutaka Furukawa and Jean Ponce, **Carved Visual Hulls for Image-Based Modeling**, ECCV 2006.

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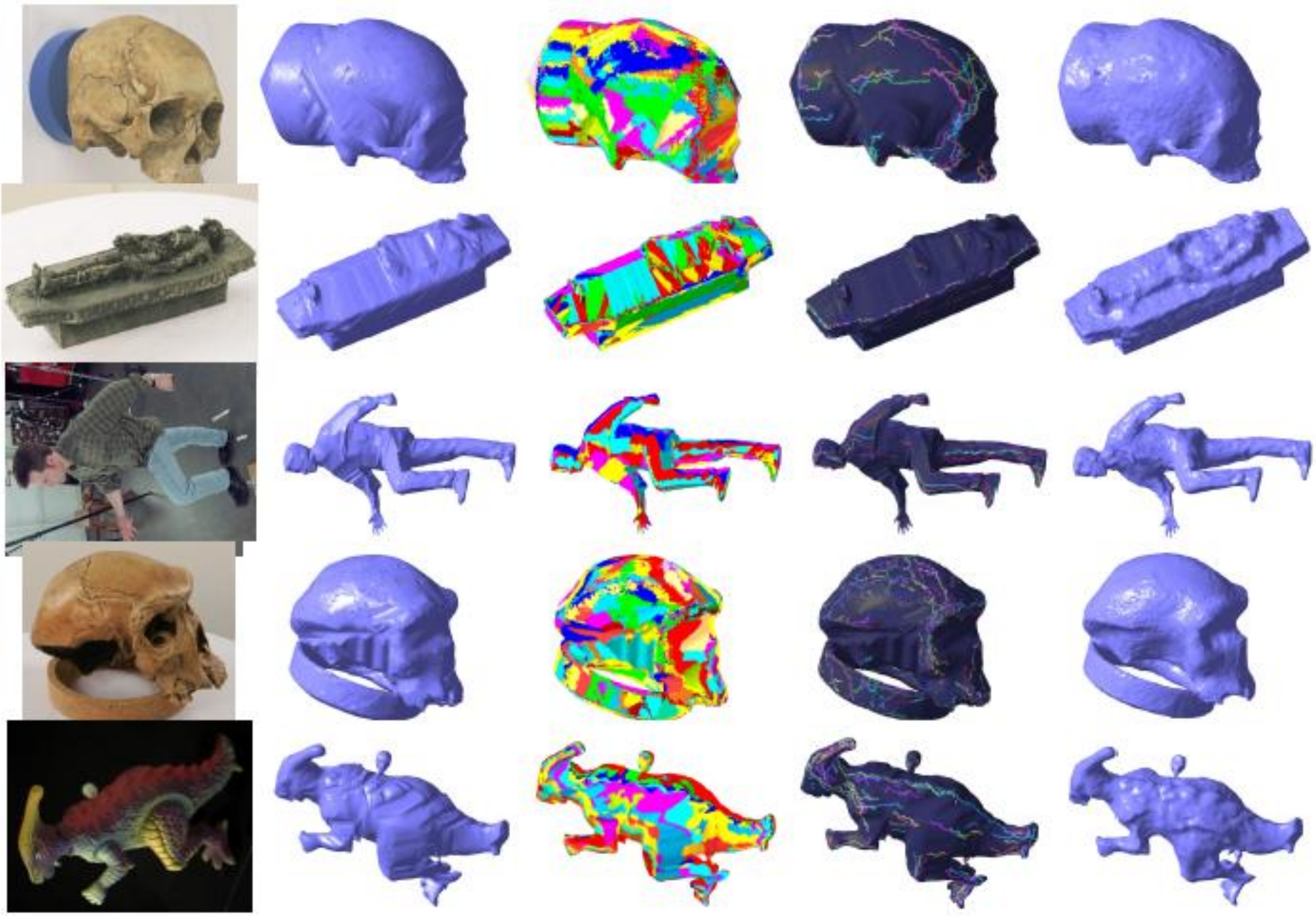
Carved visual hulls



Yasutaka Furukawa and Jean Ponce, **Carved Visual Hulls for Image-Based Modeling**, ECCV 2006.

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Carved visual hulls: Pros and cons

- Pros
  - Visual hull gives a reasonable initial mesh that can be iteratively deformed
- Cons
  - Need silhouette extraction
  - Have to compute a lot of points that don't lie on the object
  - Finding rims is difficult
  - The carving step can get caught in local minima
- Possible solution: use sparse feature correspondences as initialization

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From feature matching to dense stereo

1. Extract features
2. Get a sparse set of initial matches
3. Iteratively expand matches to nearby locations
4. Use visibility constraints to filter out false matches
5. Perform surface reconstruction

Yasutaka Furukawa and Jean Ponce, **Accurate, Dense, and Robust Multi-View Stereopsis**, CVPR 2007.

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From feature matching to dense stereo

Yasutaka Furukawa and Jean Ponce, **Accurate, Dense, and Robust Multi-View Stereopsis**, CVPR 2007.

Lazebnik

Towards Internet-Scale Multi-View Stereo

Yasutaka Furukawa, Brian Curless, Steven M. Seitz and Richard Szeliski, Towards Internet-scale Multi-view Stereo, CVPR 2010.

Lazebnik

Fast stereo for Internet photo collections

- Start with a cluster of registered views
- Obtain a depth map for every view using plane sweeping stereo with normalized cross-correlation

Frahm et al. Building Rome on a Cloudless Day, ECCV 2010.

Lazebnik

Plane sweeping stereo

- Need to register individual depth maps into a single 3D model
- Problem: depth maps are very noisy

Frahm et al. Building Rome on a Cloudless Day, ECCV 2010.

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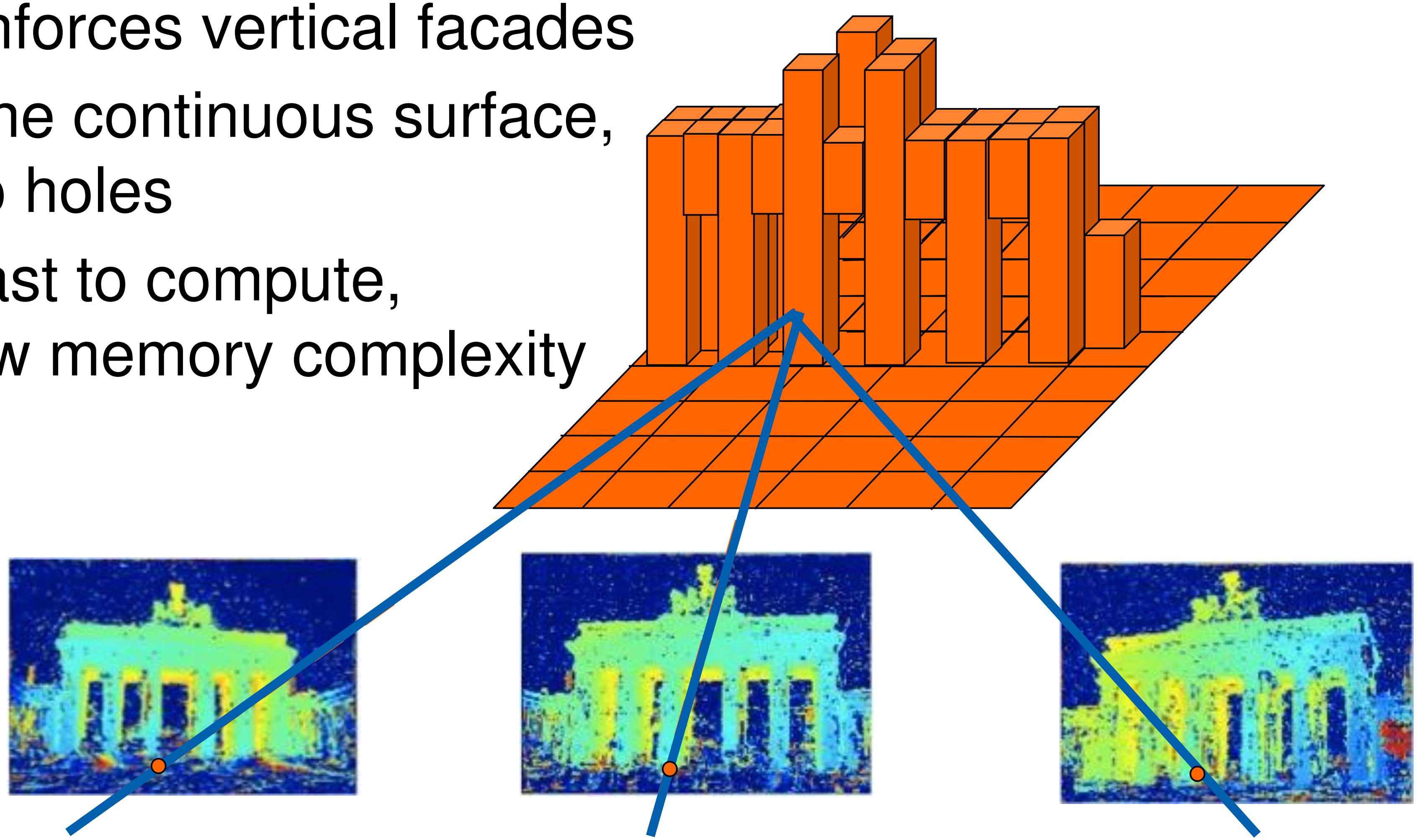
Robust stereo fusion using a heightmap

- Enforces vertical facades
- One continuous surface, no holes
- Fast to compute, low memory complexity



David Gallup, Marc Pollefeys, Jan-Michael Frahm, “3D Reconstruction using an n-Layer Heightmap”, DAGM 2010

Lazebnik

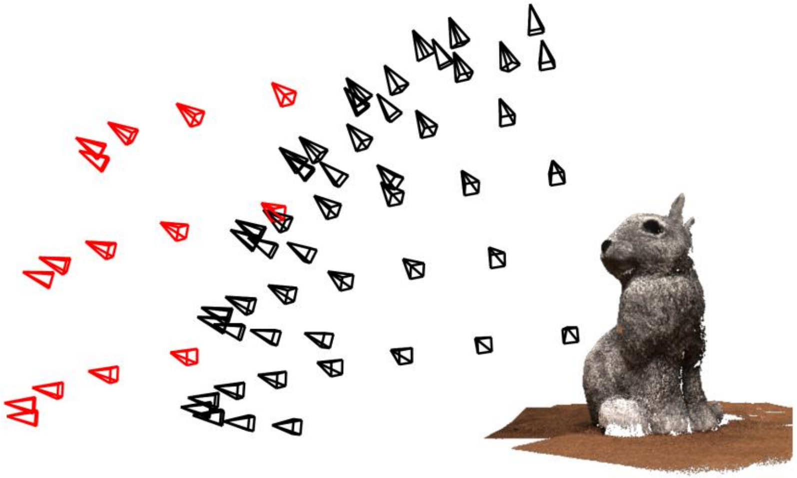
Results

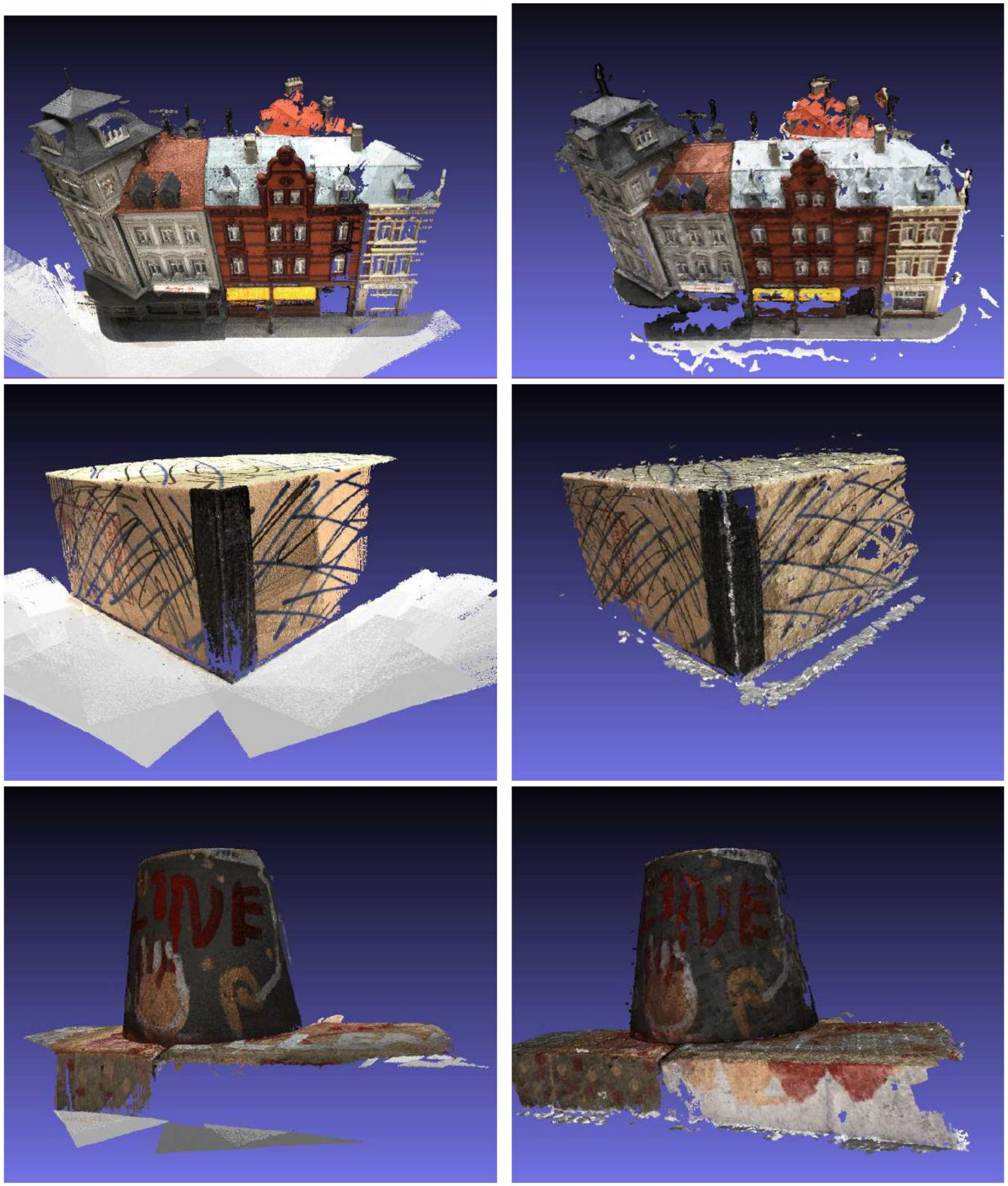
Frahm et al., “Building Rome on a Cloudless Day,” ECCV 2010.

Lazebnik

Results

Reconstruction with CNNs (CV-II)





Mengqi et al., “SurfaceNet: An End-to-end 3D Neural Network for Multiview Stereopsis” ICCV 2017.

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