Stereo matching

Reading: Chapter 11 In Szeliski's book

Schedule (tentative)

#	date	topic
1	Sep.19	Introduction and geometry
2	Sep.26	Camera models and calibration
3	Oct.3	Invariant features
4	Oct.10	Optical flow & Particle Filters
5	Oct.17	Multiple-view geometry
6	Oct.24	Model fitting (RANSAC, EM, …)
7	Oct.31	Image segmentation
8	Nov.7	**Stereo Matching & MVS**
9	Nov.14	Structure-from-Motion & SLAM
10	Nov.21	Specific object recognition
11	Nov.28	Shape from X
12	Dec.5	Object category recognition
13	Dec.12	Tracking
14	Dec.19	Research Overview & Lab tours

An Application: Mobile Robot Navigation

The Stanford Cart,
H. Moravec, 1979.

The INRIA Mobile Robot, 1990.

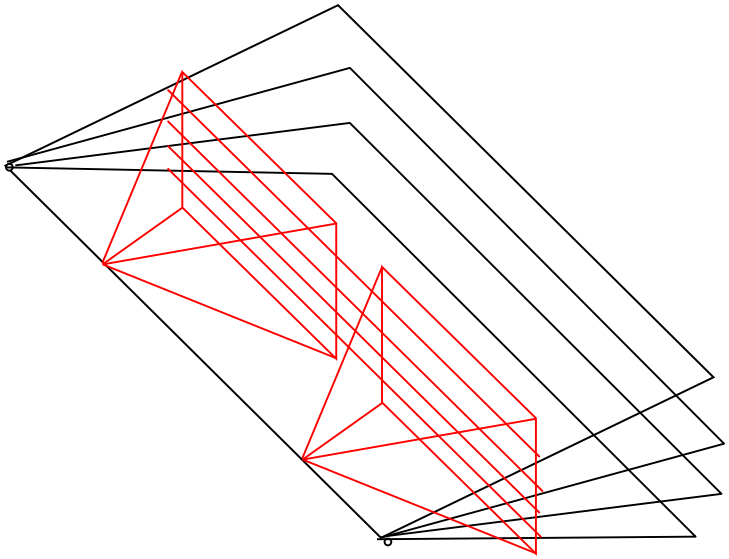
Courtesy O. Faugeras and H. Moravec.

Stereo

NASA Mars Rover

6D Vision

Standard stereo geometry



PointGrey Bumblebee

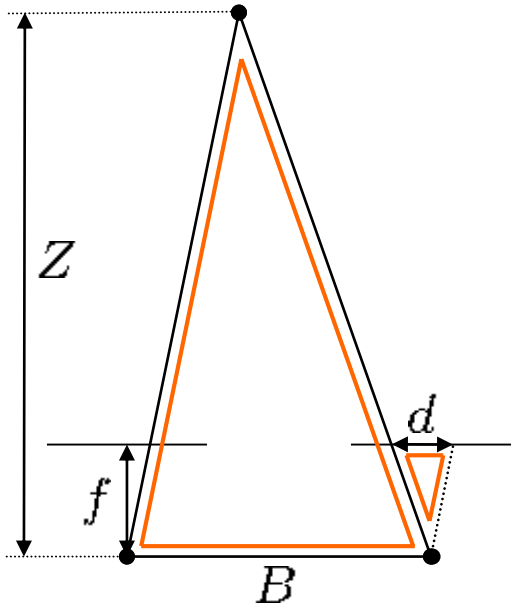
pure translation along X-axis

$$\mathbf{F} = [\mathrm{t}]_\times = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & -1 & 0 \end{bmatrix}$$

$$\mathbf{F}\mathbf{x} = \begin{bmatrix} 0 \\ 1 \\ -y \end{bmatrix}$$

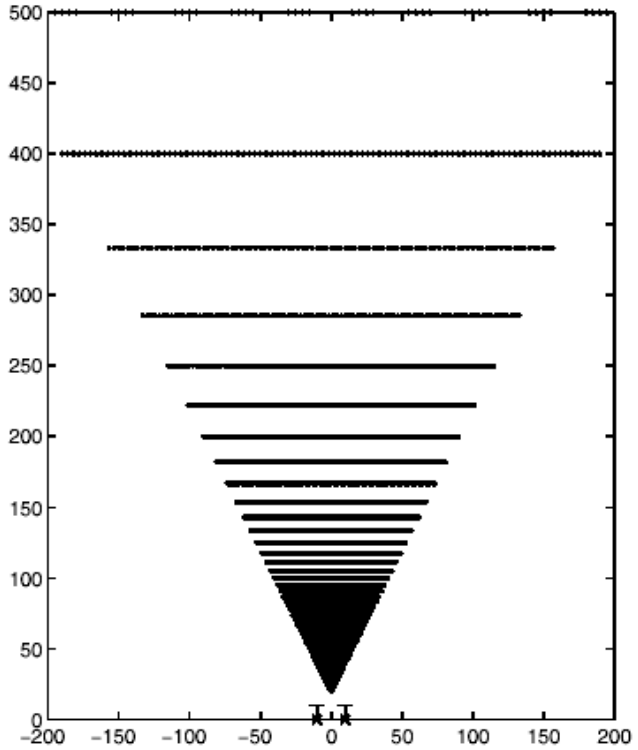
$$\mathbf{F}^\top \mathbf{x}' = \begin{bmatrix} 0 \\ 1 \\ -y' \end{bmatrix}$$

Standard stereo geometry



$$\frac{B}{Z} = \frac{d}{f}$$

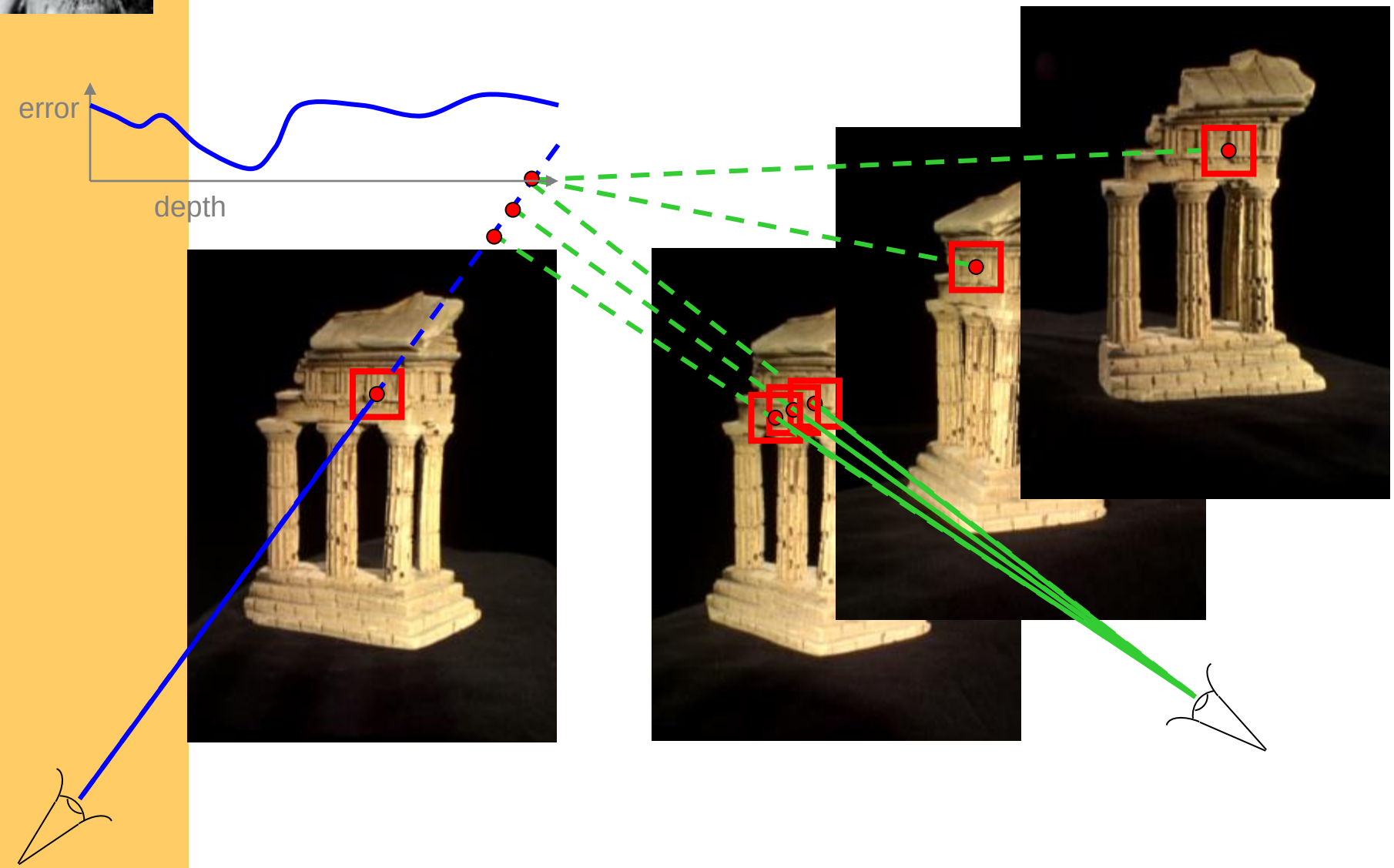
$$d = -\frac{Bf}{Z}$$



$$\frac{dd}{dZ} = \frac{Bf}{Z^2}$$

$$\Delta Z = \frac{Z^2}{Bf}\Delta d$$

Stereo: basic idea



Stereo matching

- Search is limited to epipolar line (1D)
- Look for most similar pixel

```
for x=1:w,
  for y=1:h,
    bestdist=inf;
    for i=-dr:0,
      if (dist(pix(x,y),pix(x+i,y))<bestdist)
         d(x,y)=i; best=sim(pix(x,y),pix(x+i,y)); end
    end
  end
end
```

Stereopsis

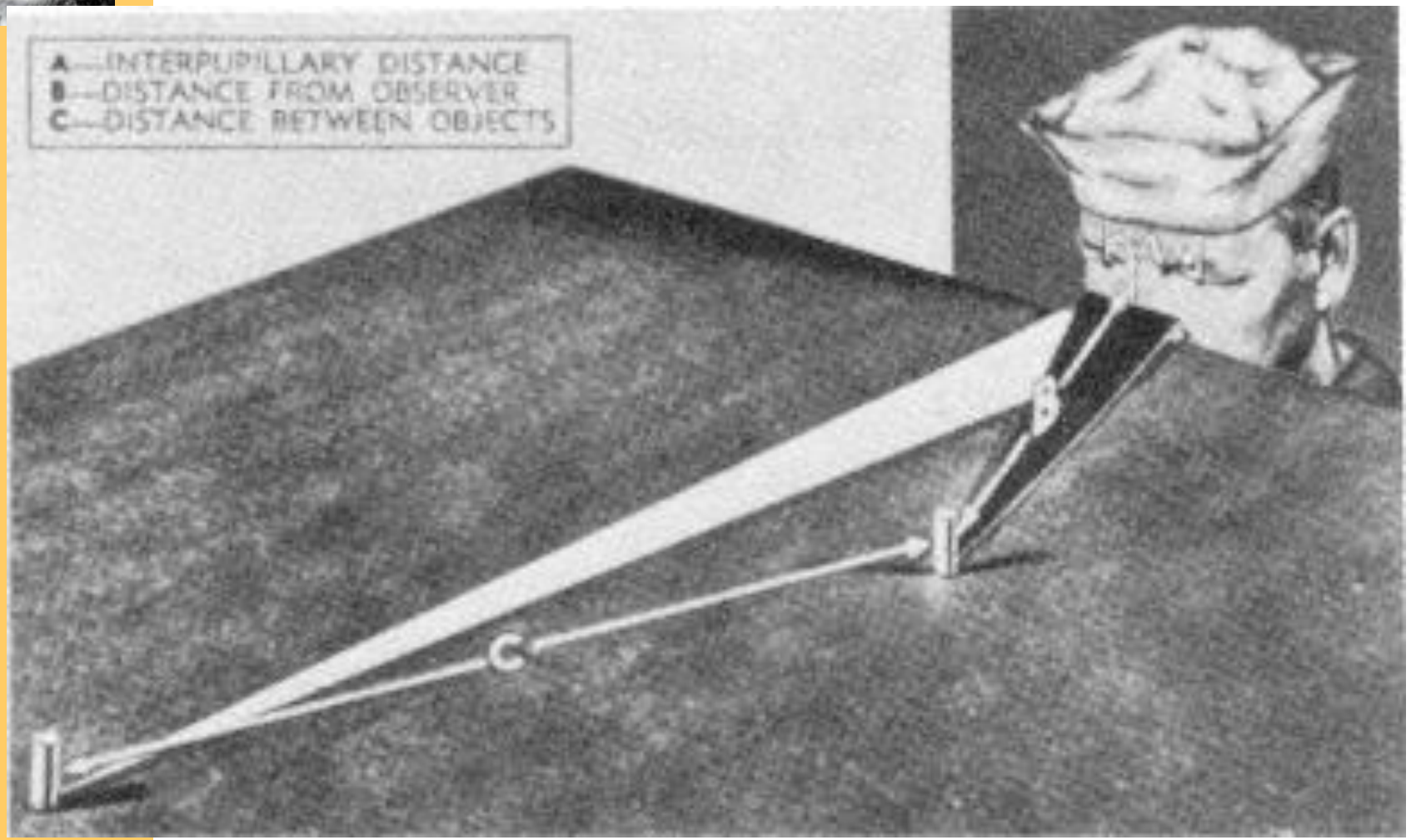
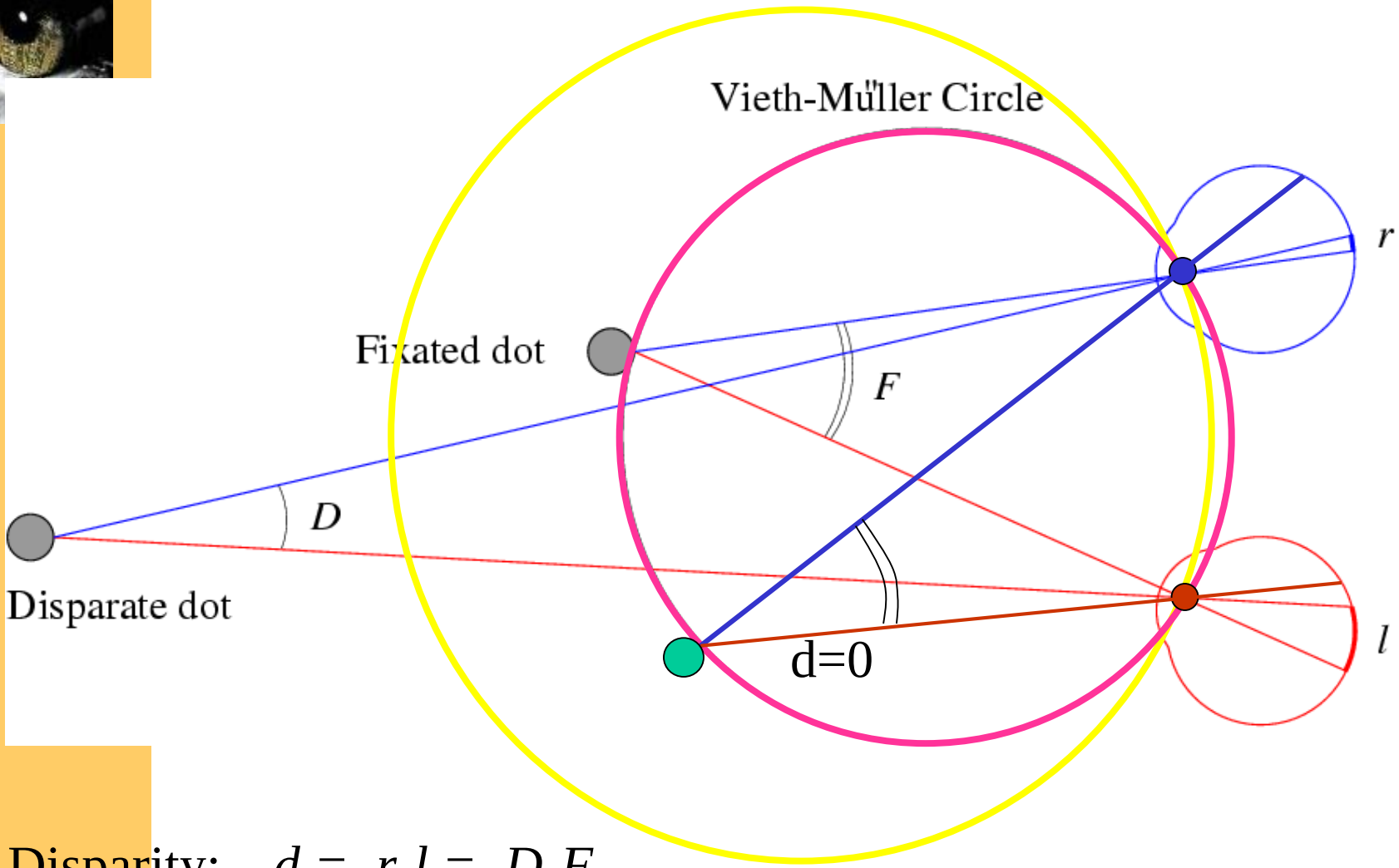


Figure from US Navy Manual of Basic Optics and Optical Instruments, prepared by Bureau of Naval Personnel. Reprinted by Dover Publications, Inc., 1969.

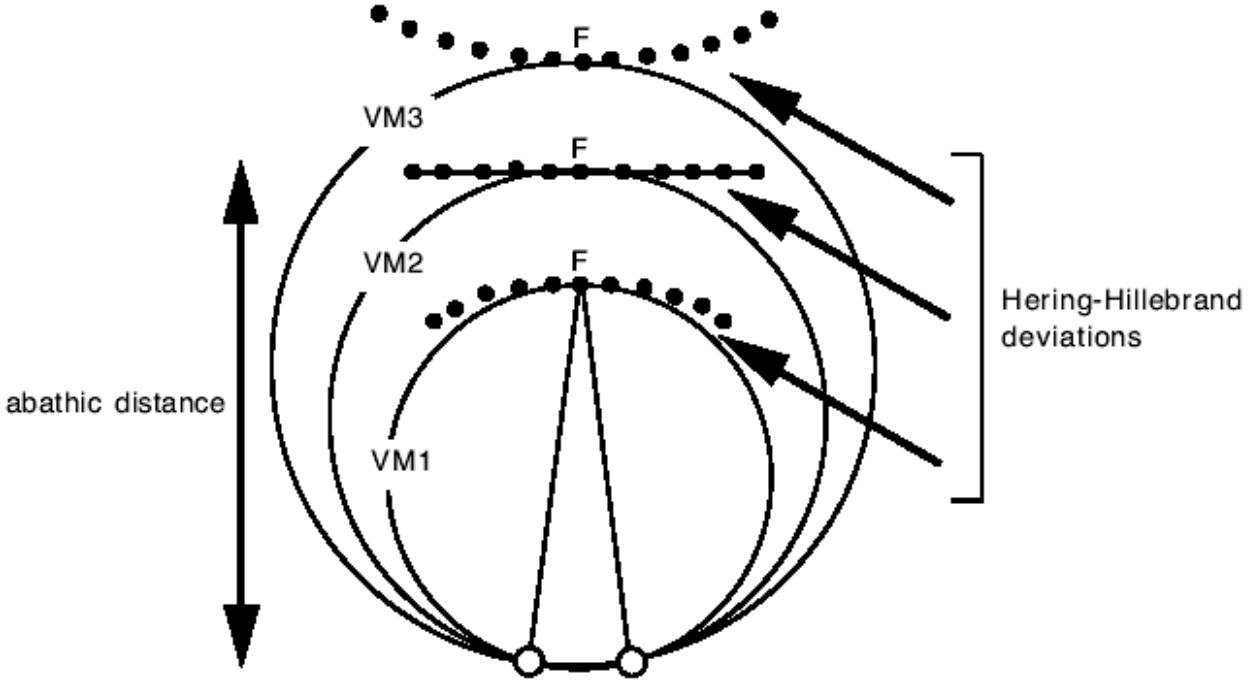
Human Stereopsis: Reconstruction



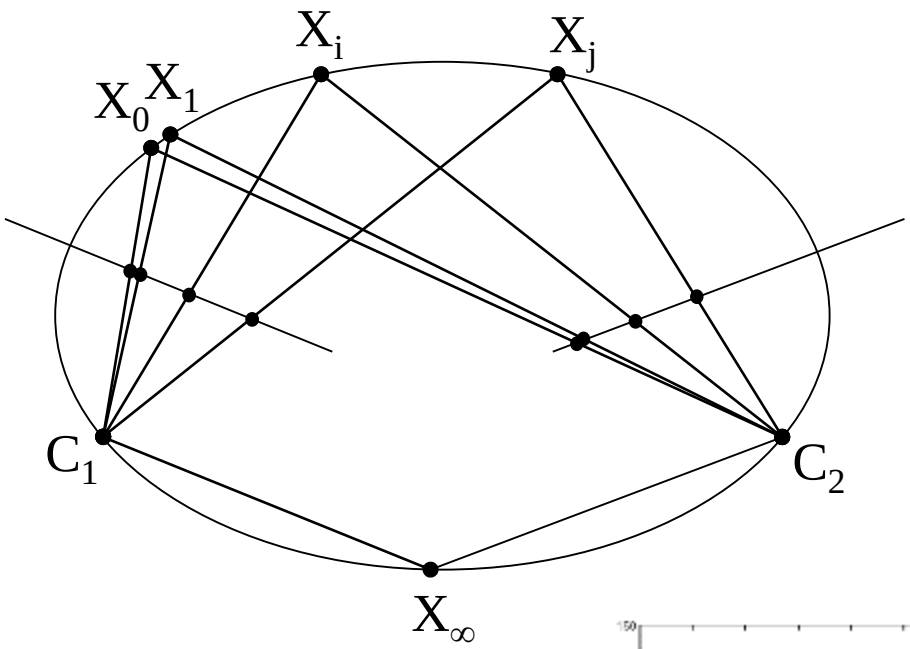
Disparity: $d = r\text{-}l = D\text{-}F$.

In 3D, the horopter.

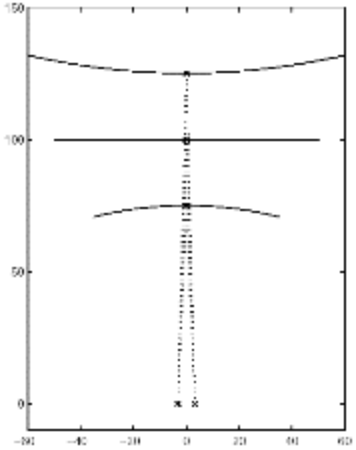
Human Stereopsis: experimental horopter…

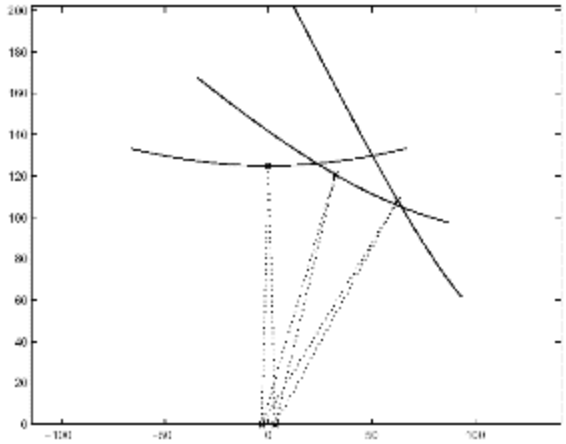


Iso-disparity curves: planar retinas



$$\frac{\begin{vmatrix} 0 & i \\ 1 & 1 \end{vmatrix}}{\begin{vmatrix} 0 & 1 \\ 1 & 1 \end{vmatrix}} : \frac{\begin{vmatrix} 1 & 1 \\ 1 & 0 \end{vmatrix}}{\begin{vmatrix} i & 1 \\ 1 & 0 \end{vmatrix}} = \frac{-i}{-1} : \frac{-1}{-1} = i$$





the retina act as if it were flat!

Human Stereopsis: Reconstruction

What if F is not known?

Helmoltz (1909):

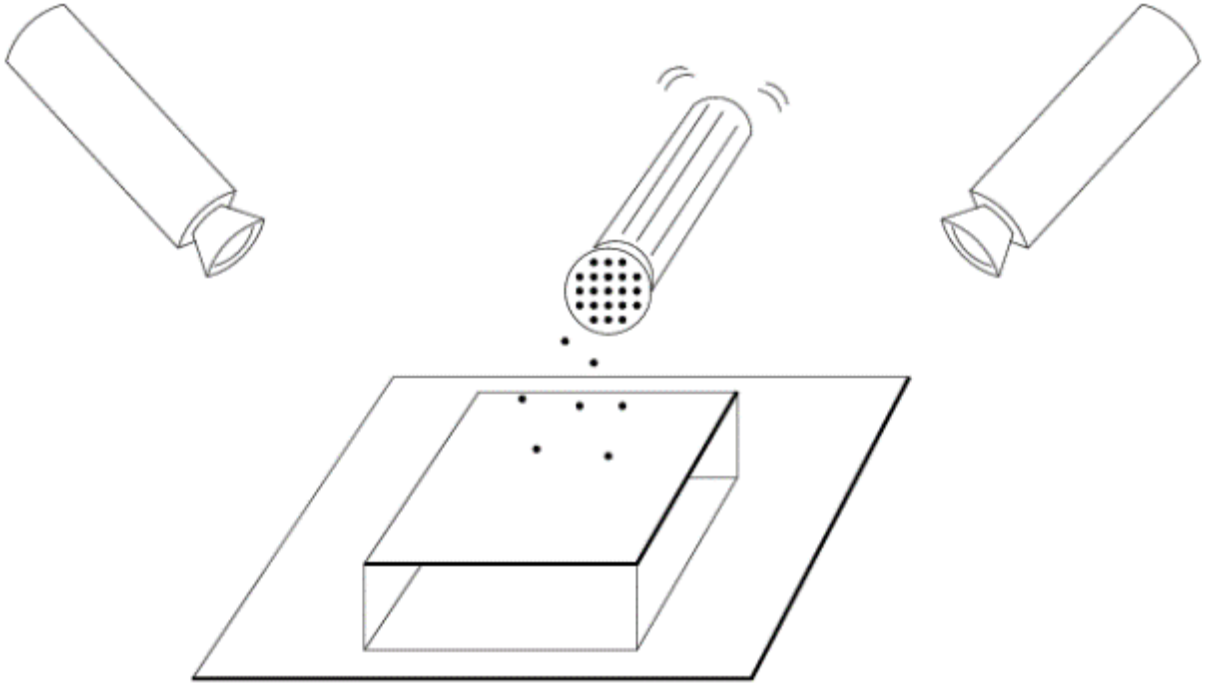
- There is evidence showing the vergence angles cannot be measured precisely.
- Humans get fooled by bas-relief sculptures.
- There is an analytical explanation for this.
- Relative depth can be judged accurately.

Human Stereopsis: Binocular Fusion

How are the correspondences established?

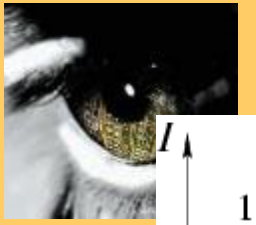
Julesz (1971): Is the mechanism for binocular fusion a monocular process or a binocular one??

- There is anecdotal evidence for the latter (camouflage).

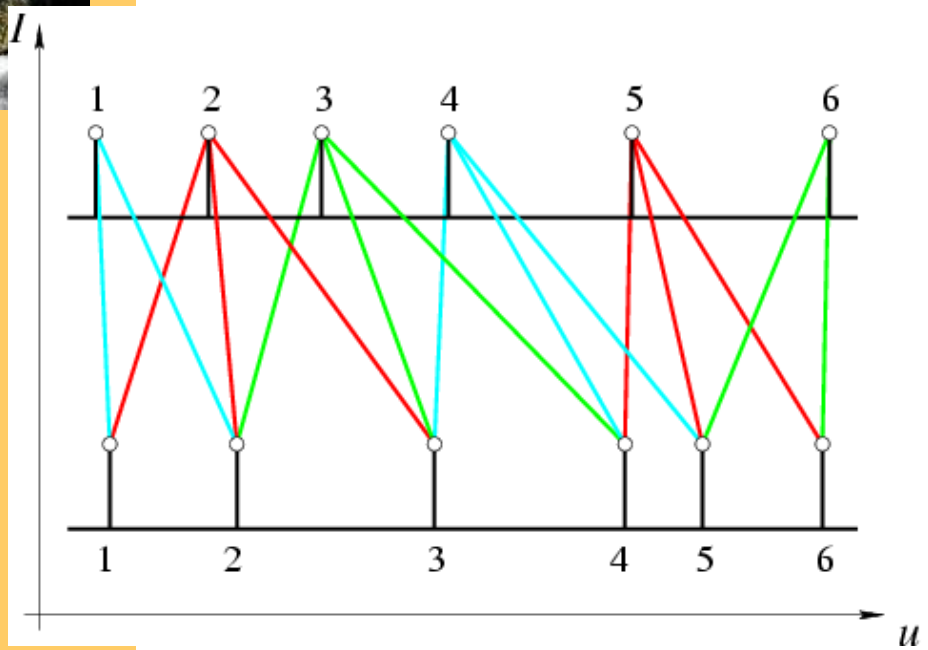


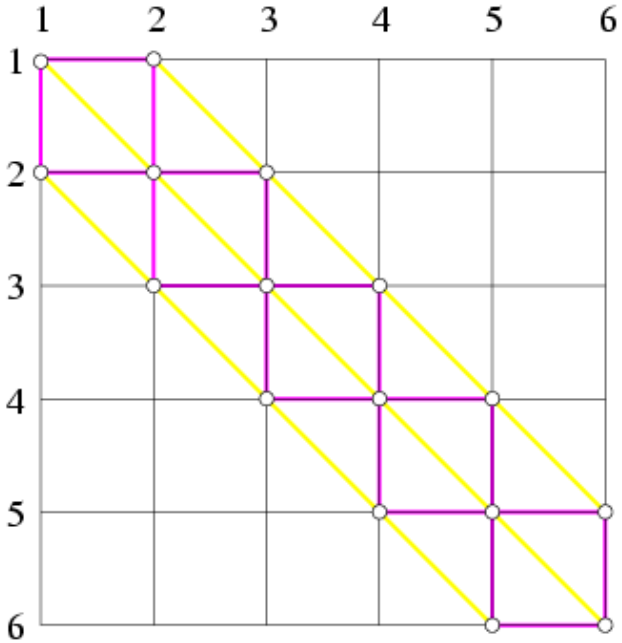
- Random dot stereograms provide an objective answer

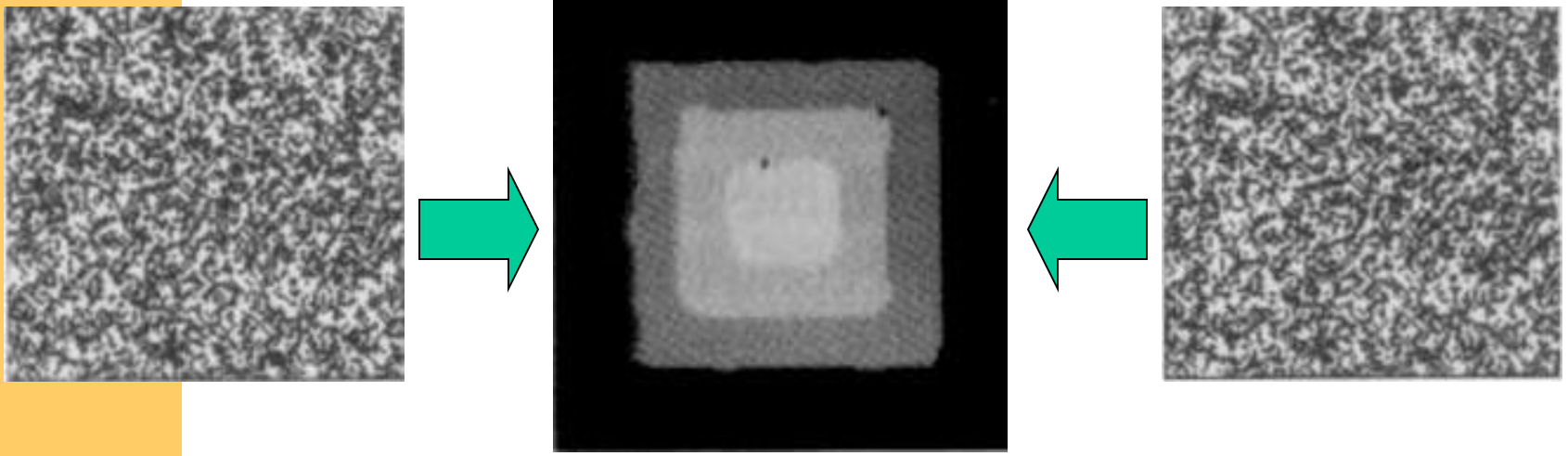
BP!



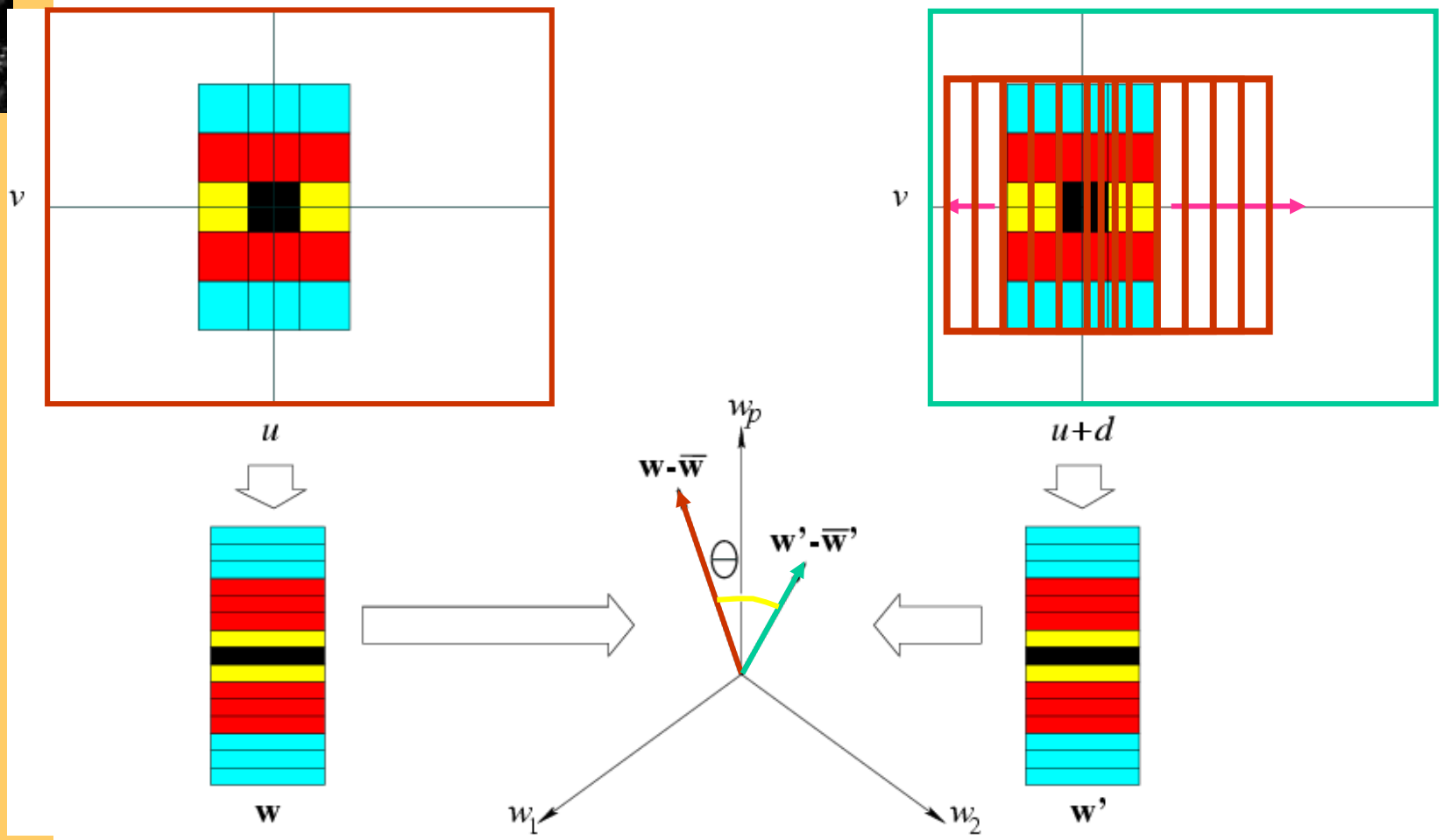
A Cooperative Model (Marr and Poggio, 1976)







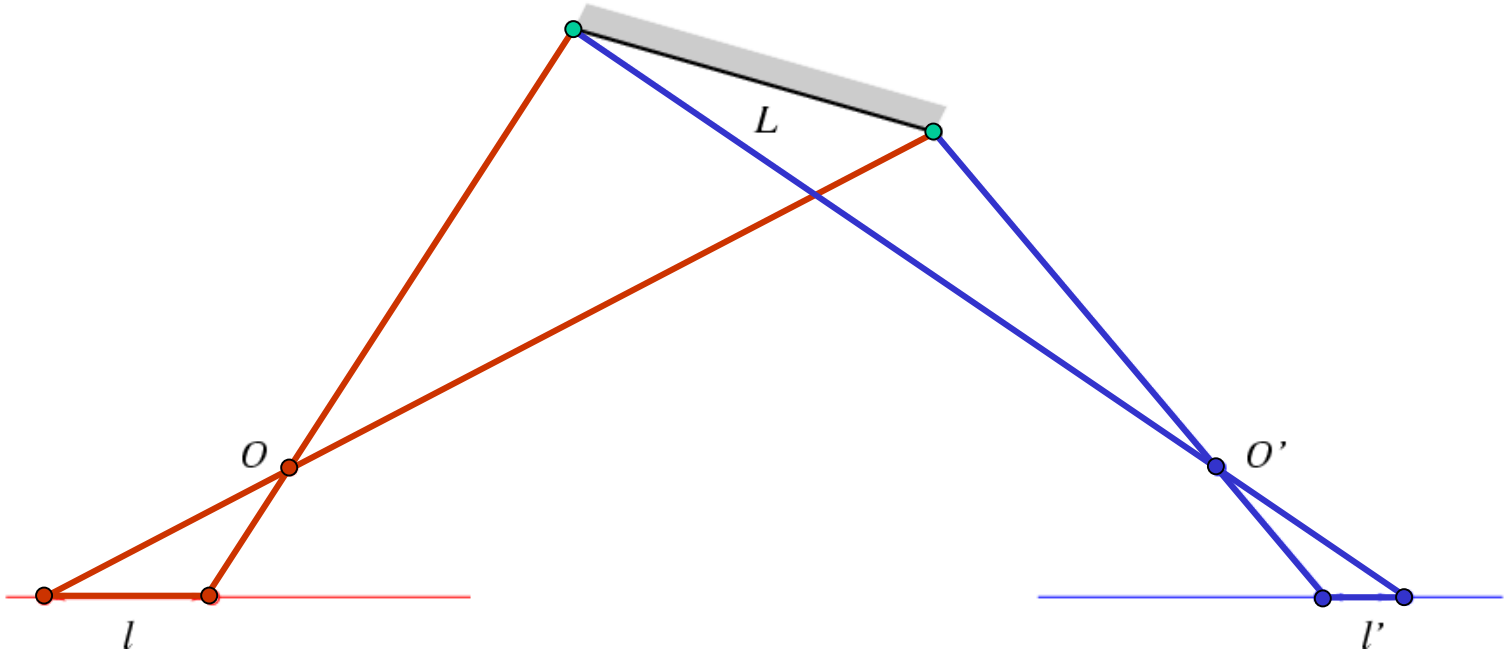
Correlation Methods (1970--)



Slide the window along the epipolar line until $w.w'$ is maximized.

Normalized Correlation: minimize θ instead. ⟺ Minimize $|w-w'|^2$.

Correlation Methods: Foreshortening Problems

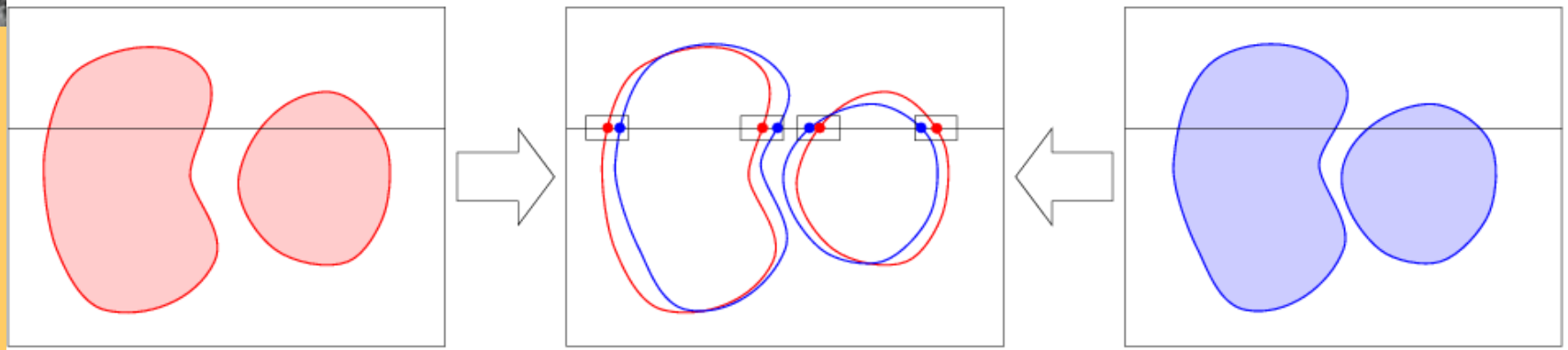


Solution: add a second pass using disparity estimates to warp the correlation windows, e.g. Devernay and Faugeras (1994).

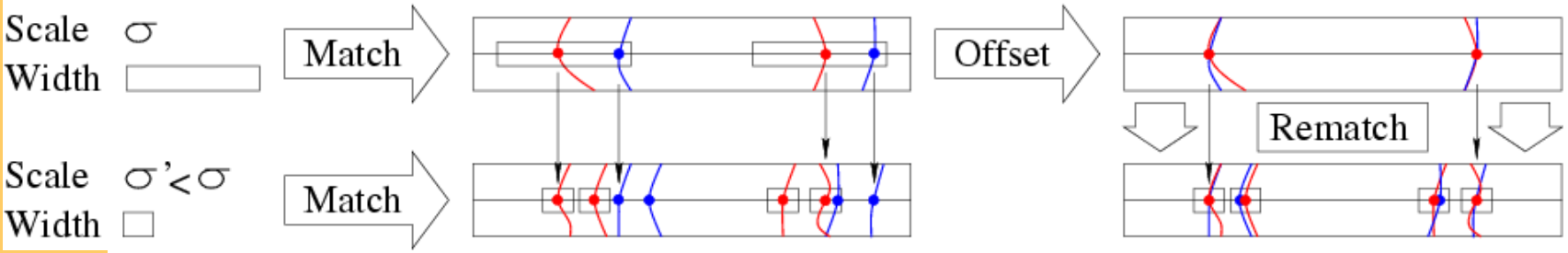
Reprinted from "Computing Differential Properties of 3D Shapes from Stereopsis without 3D Models," by F. Devernay and O. Faugeras, Proc. IEEE Conf. on Computer Vision and Pattern Recognition (1994). © 1994 IEEE.

Multi-Scale Edge Matching (Marr, Poggio and Grimson, 1979-81)

Matching zero-crossings at a single scale



Matching zero-crossings at multiple scales



- Edges are found by repeatedly smoothing the image and detecting the zero crossings of the second derivative (Laplacian).
- Matches at coarse scales are used to offset the search for matches at fine scales (equivalent to eye movements).

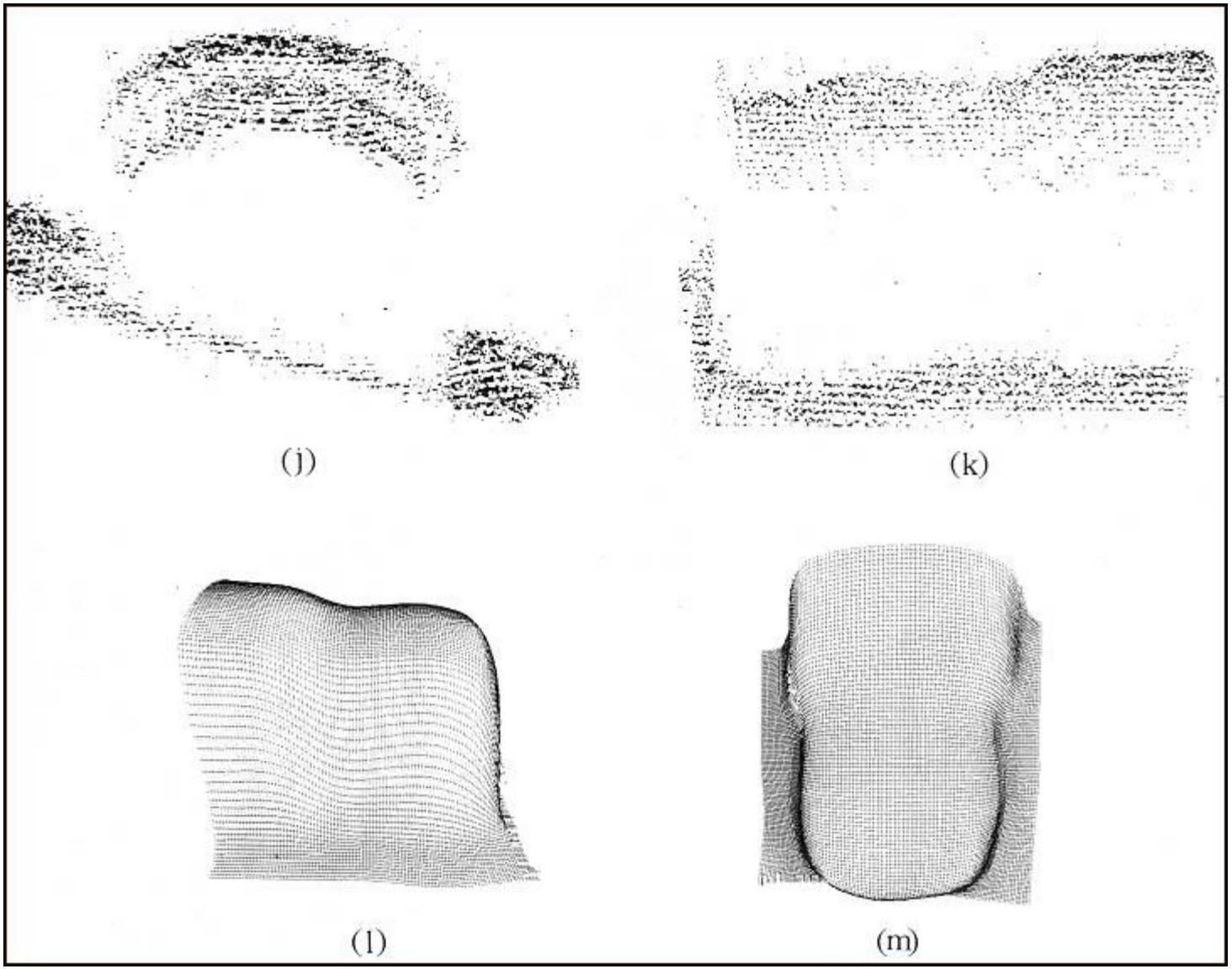
Multi-Scale Edge Matching (Marr, Poggio and Grimson, 1979-81)

One of the two input images

Image Laplacian

Zeros of the Laplacian

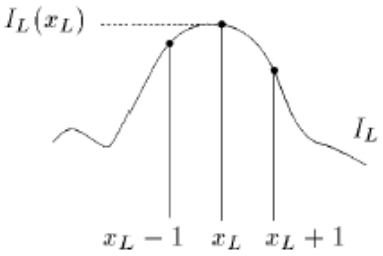
Multi-Scale Edge Matching (Marr, Poggio and Grimson, 1979-81)

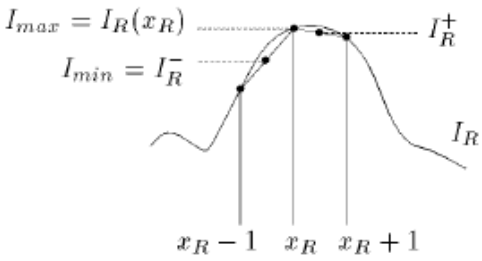


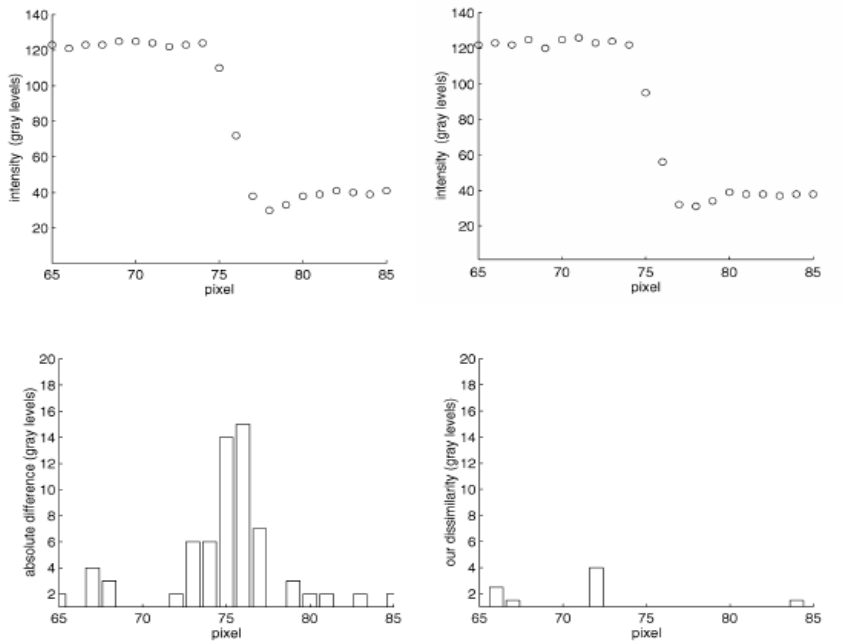
Reprinted from Vision: A Computational Investigation into the Human Representation and Processing of Visual Information by David Marr.

Pixel Dissimilarity

- Absolute difference of intensities
  c=|I1(x,y)- I2(x-d,y)|
- Interval matching [Birchfield & Tomasi 98]
  - Considers sensor integration
  - Represents pixels as intervals







Alternative Dissimilarity Measures

- Rank and Census transforms [Zabih ECCV94]
- Rank transform:
  - Define window containing R pixels around each pixel
  - Count the number of pixels with lower intensities than center pixel in the window
  - Replace intensity with rank (0..R-1)
  - Compute SAD on rank-transformed images
- Census transform:
  - Use bit string, defined by neighbors, instead of scalar rank
- Robust against illumination changes

Rank and Census Transform Results

- Noise free, random dot stereograms
- Different gain and bias

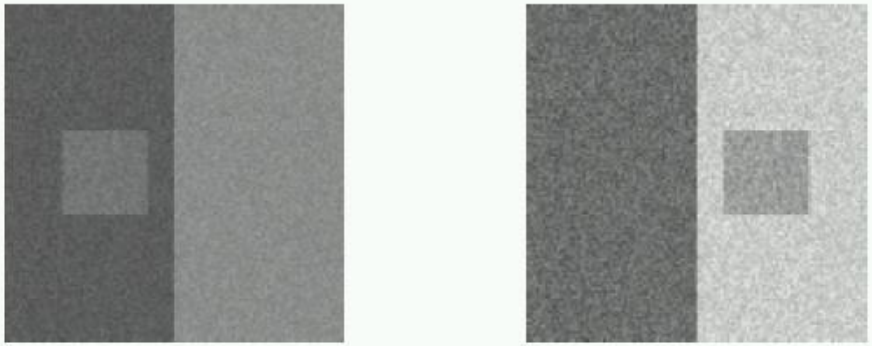


Fig. 2. Right and left random-dot stereograms

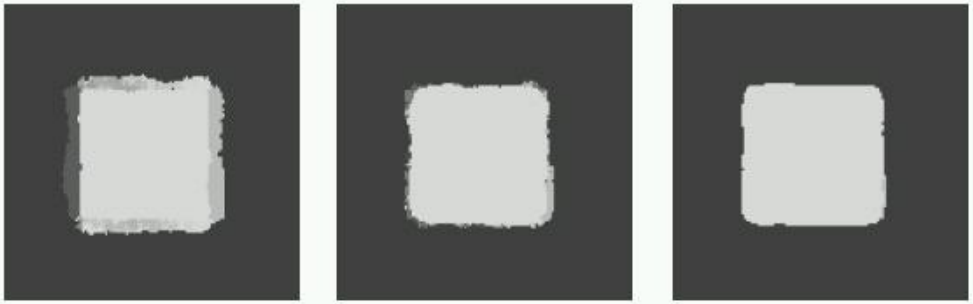
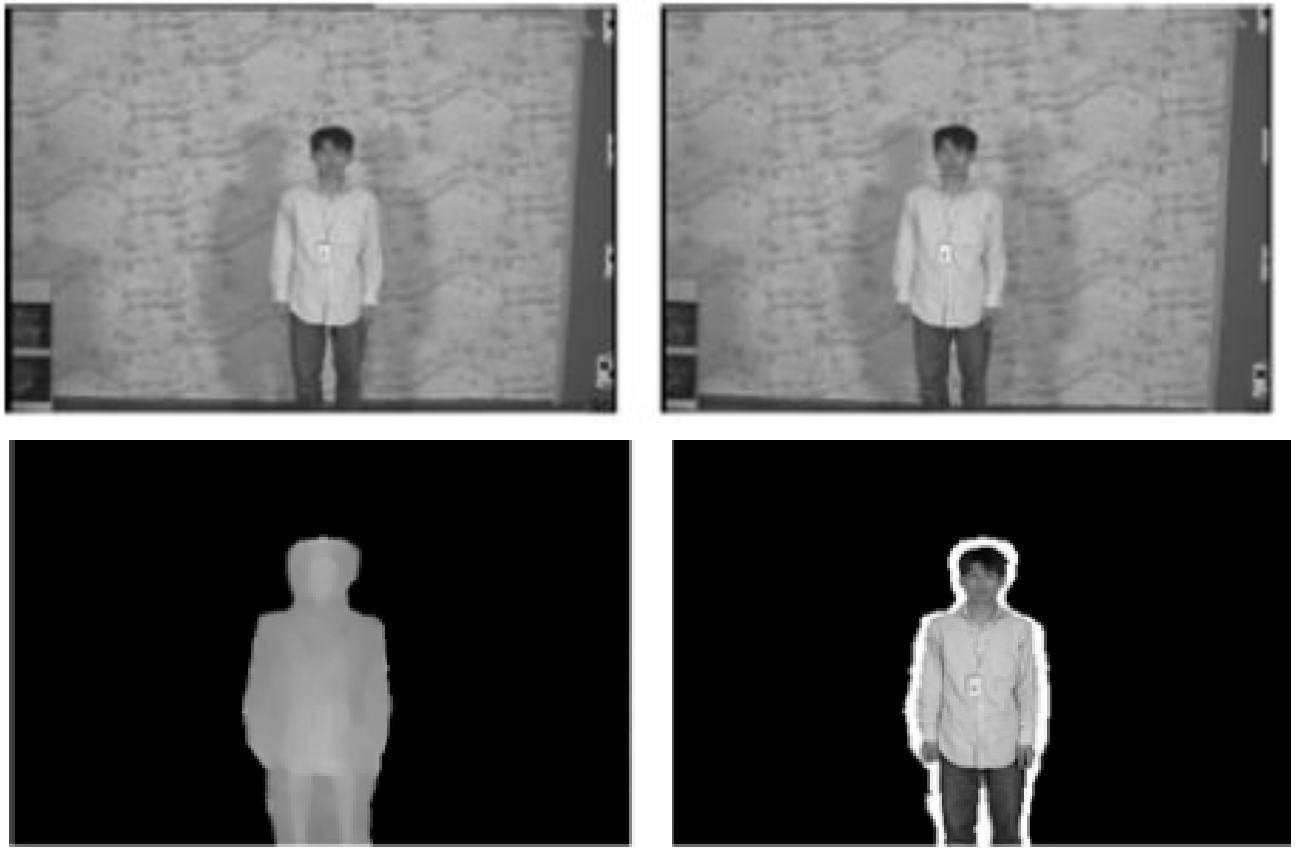


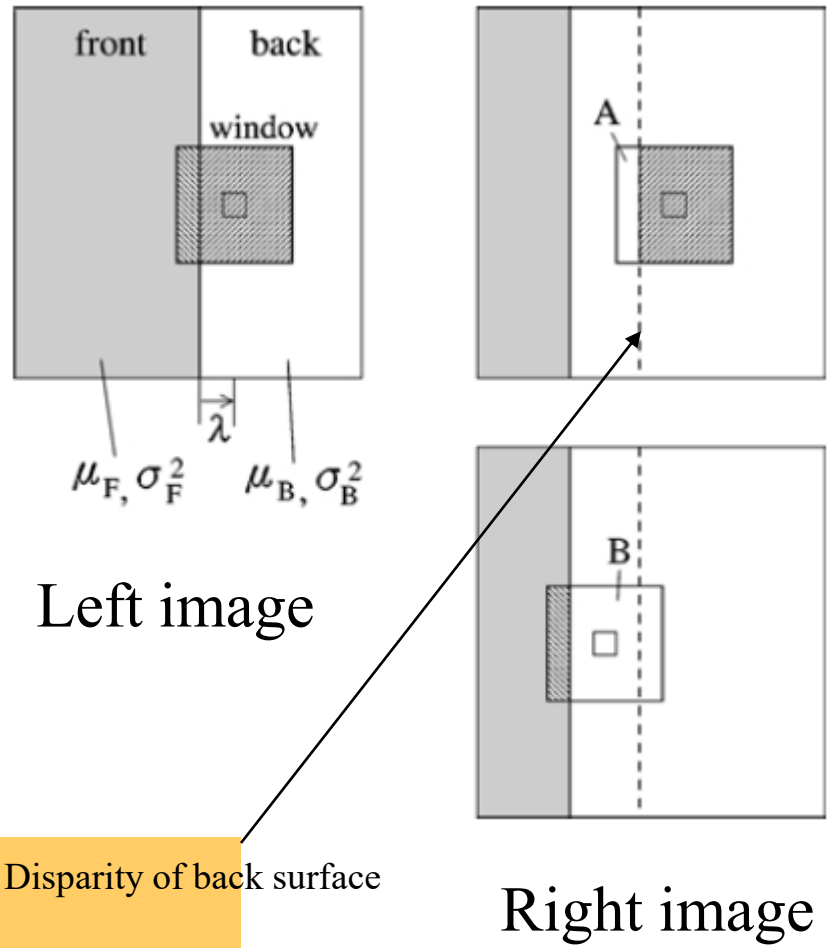
Fig. 3. Disparities from normalized correlation, rank and census transforms

Systematic Errors of Area-based Stereo

- Ambiguous matches in textureless regions
- Surface over-extension [Okutomi IJCV02]



Surface Over-extension

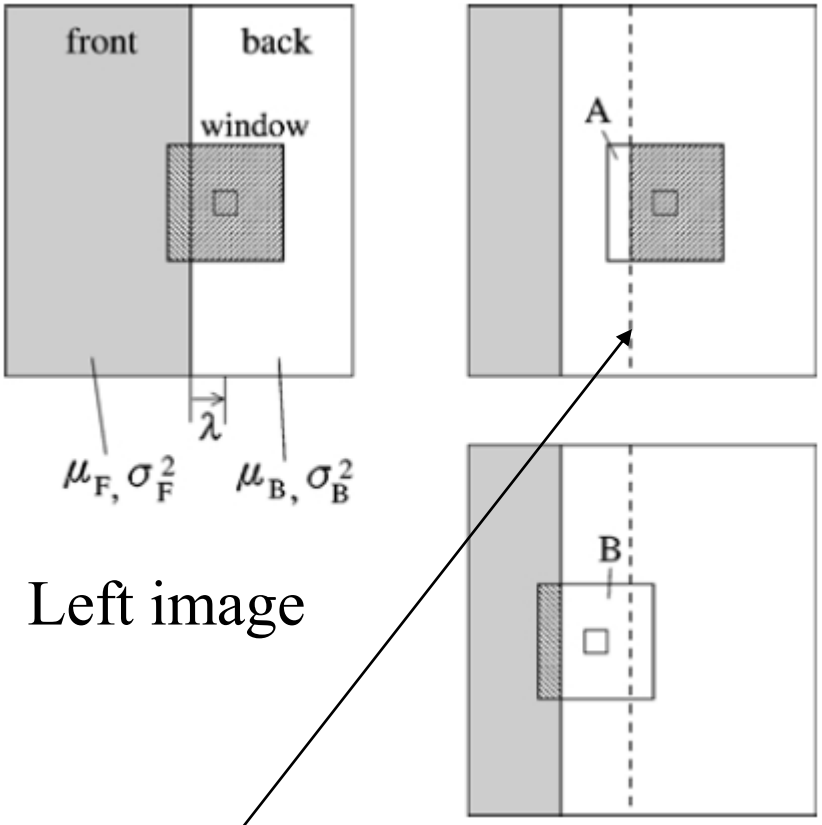


- Expected value of $E[(x-y)^2]$ for x in left and y in right image is:

  Case A: $\sigma_F^2 + \sigma_B^2 + (\mu_F - \mu_B)^2$ for $w/2-\lambda$ pixels in each row

  Case B: $2\,\sigma_B^2$ for $w/2+\lambda$ pixels in each row

Surface Over-extension



Left image

Right image

Disparity of back surface

- Discontinuity perpendicular to epipolar lines

$$\left(\sigma_F^2 + \sigma_B^2 + (\mu_F - \mu_B)^2\right)\left(\frac{w}{2} - \lambda\right) w = 2\sigma_B^2\left(\frac{w}{2} + \lambda\right) w.$$

$$\lambda = \frac{\sigma_F^2 - \sigma_B^2 + (\mu_F - \mu_B)^2}{\sigma_F^2 + 3\sigma_B^2 + (\mu_F - \mu_B)^2}\,\frac{w}{2}.$$

- Discontinuity parallel to epipolar lines

$$\lambda = \frac{\sigma_F^2 - \sigma_B^2}{\sigma_F^2 + \sigma_B^2}\,\frac{w}{2}.$$

Over-extension and shrinkage

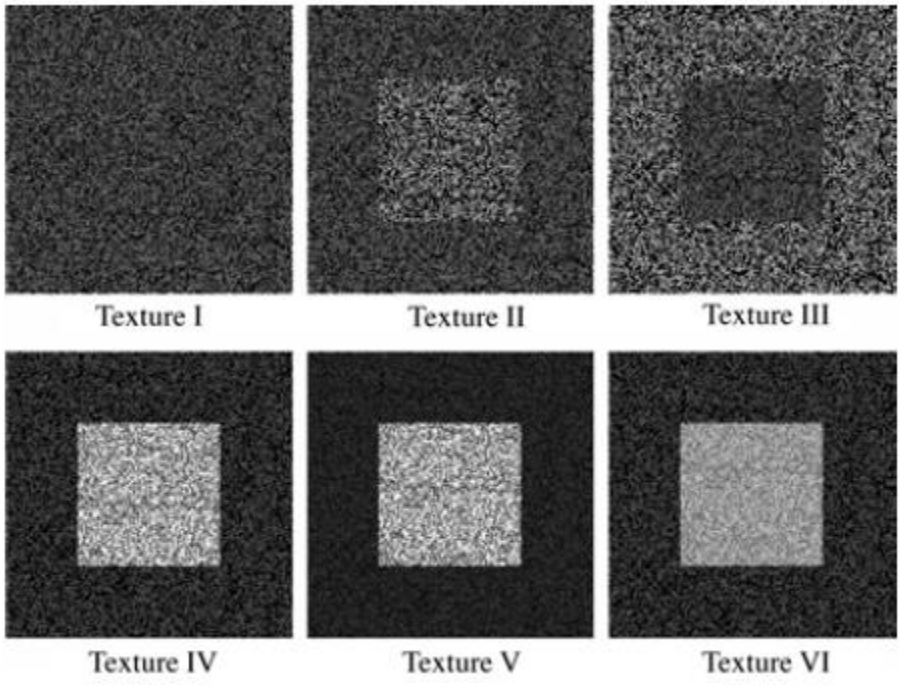
Turns out that: $-\frac{w}{6} \leq \lambda \leq \frac{w}{2}$

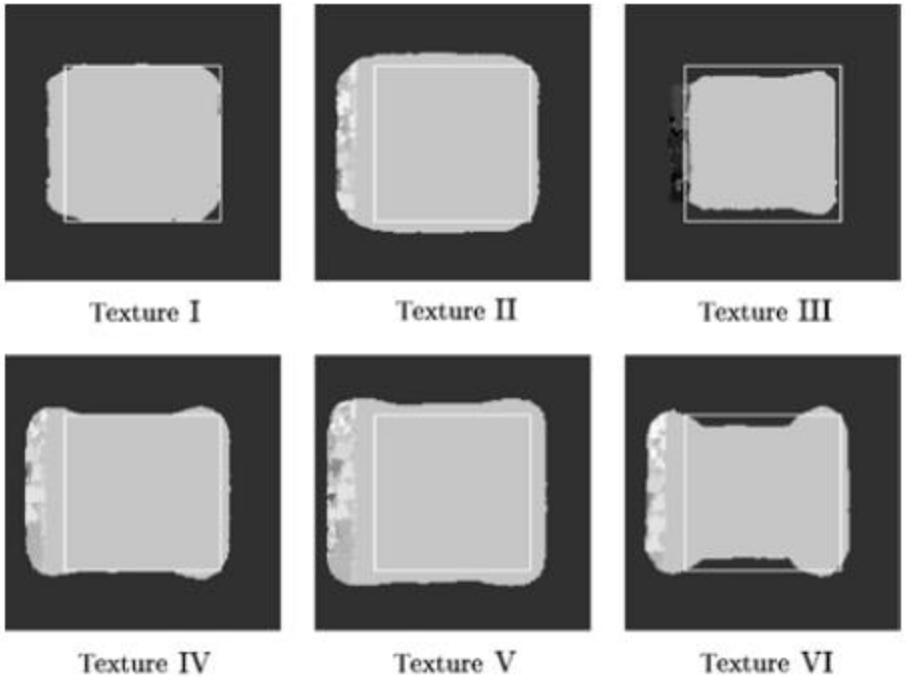
for discontinuities perpendicular to epipolar lines

And: $-\frac{w}{2} \leq \lambda \leq \frac{w}{2}$

for discontinuities parallel to epipolar lines

Random Dot Stereogram Experiments



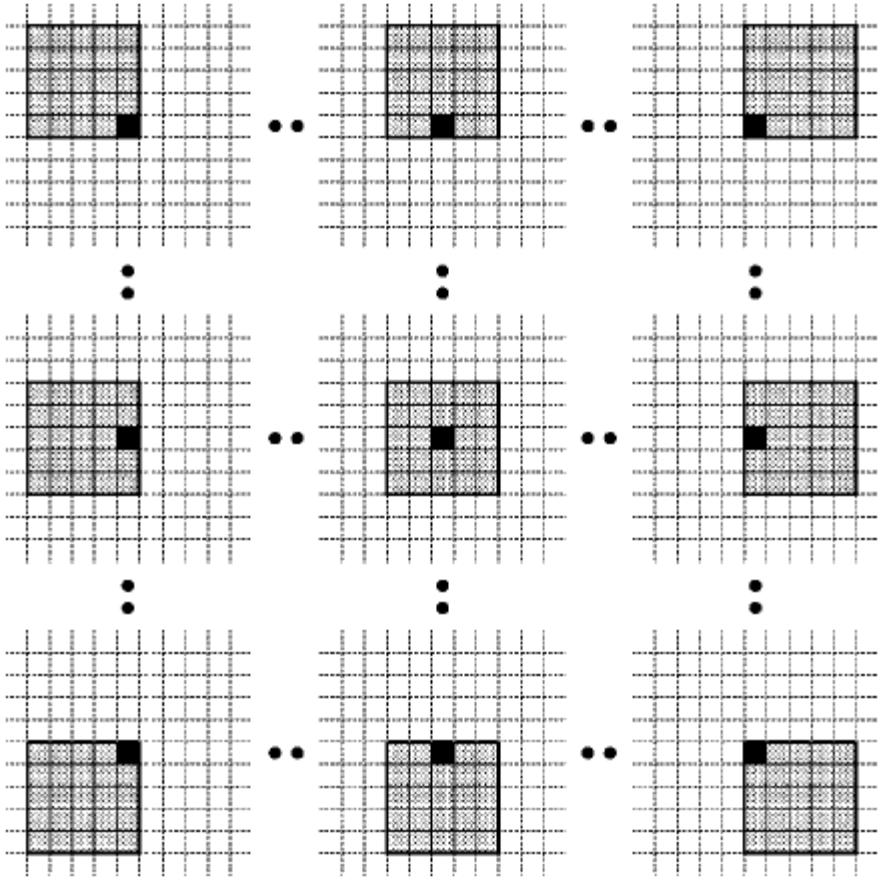


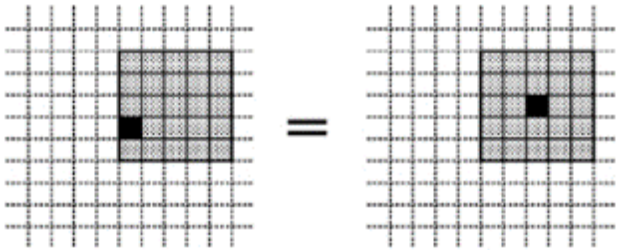
	Front surface		Back surface	
	μ_F	σ_F	μ_B	σ_B
I	100	50	100	50
II	100	100	100	50
III	100	50	100	100
IV	200	50	100	50
V	200	50	100	25
VI	200	25	100	50

Random Dot Stereogram Experiments

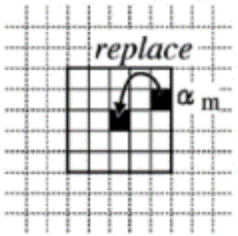
	Perpendicular		Parallel		Perpendicular		Parallel		Perpendicular		Parallel	
w	Theoretical	Actual	Theoretical	Actual	Theoretical	Actual	Theoretical	Actual	Theoretical	Actual	Theoretical	Actual
	Texture I				Texture II				Texture III			
7	0.00	0.03	0.00	0.05	1.50	1.53	2.10	2.08	−0.81	−0.69	−2.10	−1.87
11	0.00	0.08	0.00	0.13	2.36	2.35	3.30	3.32	−1.27	−1.04	−3.30	−3.09
17	0.00	0.09	0.00	0.13	3.64	3.75	5.10	5.29	−1.96	−2.00	−5.10	−5.00
25	0.00	0.12	0.00	0.42	5.36	5.20	7.50	7.73	−2.88	−3.00	−7.50	−7.53
35	0.00	0.40	0.00	−0.33	7.50	7.50	10.50	10.25	−4.04	−4.50	−10.50	−10.75
	Texture IV				Texture V				Texture VI			
7	1.75	1.81	0.00	0.23	2.89	2.87	2.10	2.27	1.57	1.49	−2.10	−1.87
11	2.75	2.74	0.00	0.56	4.54	4.60	3.30	3.61	2.47	2.52	−3.30	−3.02
17	4.25	4.32	0.00	0.68	7.02	7.11	5.10	5.47	3.81	3.88	−5.10	−4.87
25	6.25	6.15	0.00	0.65	10.33	10.20	7.50	7.75	5.50	5.80	−7.50	−7.43
35	8.75	9.00	0.00	0.90	14.46	14.45	10.50	10.80	7.84	8.00	−10.50	−10.35

Offset Windows





(a)



- Equivalent to using min nearby cost
- Result: loss of depth accuracy

Discontinuity Detection

- Use offset windows only where appropriate
  - Bi-modal distribution of SSD
  - Pixel of interest different than mode within window

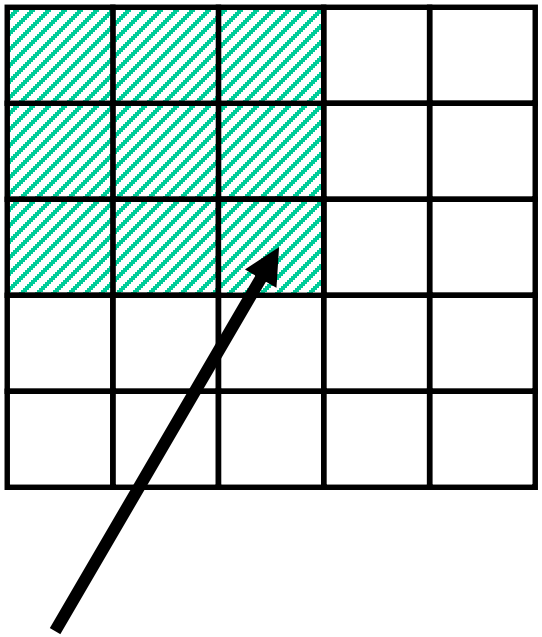
Compact Windows

- [Veksler CVPR03]: Adapt windows size based on:
  - Average matching error per pixel
  - Variance of matching error
  - Window size (to bias towards larger windows)

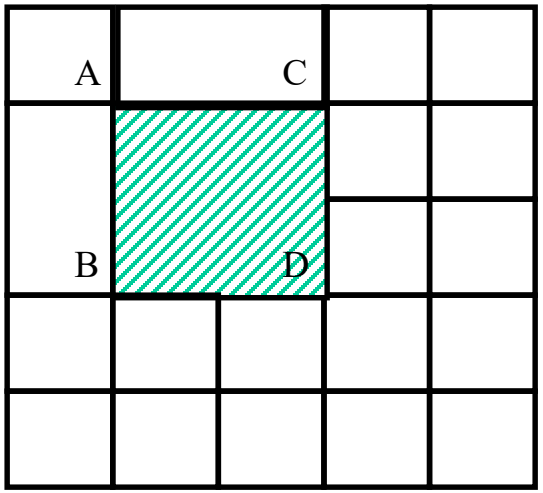
$$C_d(W) = \overline{e} + \alpha \cdot var(e) + \frac{\beta}{\sqrt{W} + \gamma}.$$

- Pick window that minimizes cost

Integral Image



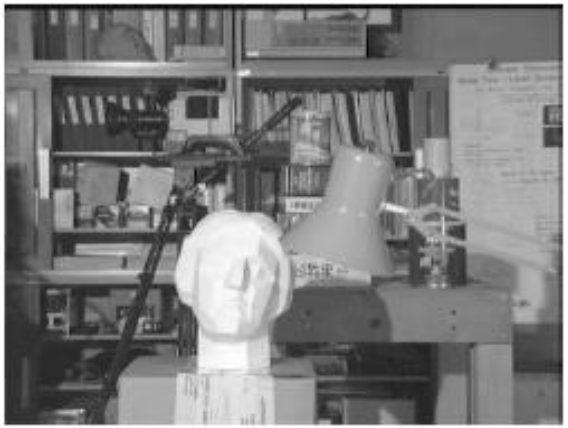
Sum of shaded part



Shaded area = A+D-B-C
Independent of size

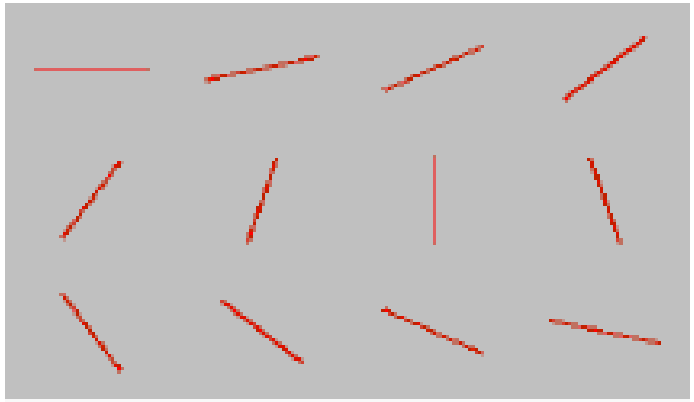
Compute an integral image for pixel dissimilarity at each possible disparity

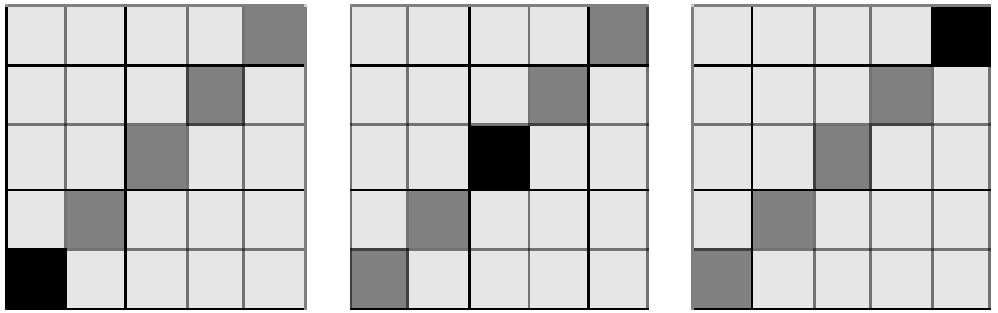
Results using Compact Windows



Rod-shaped filters

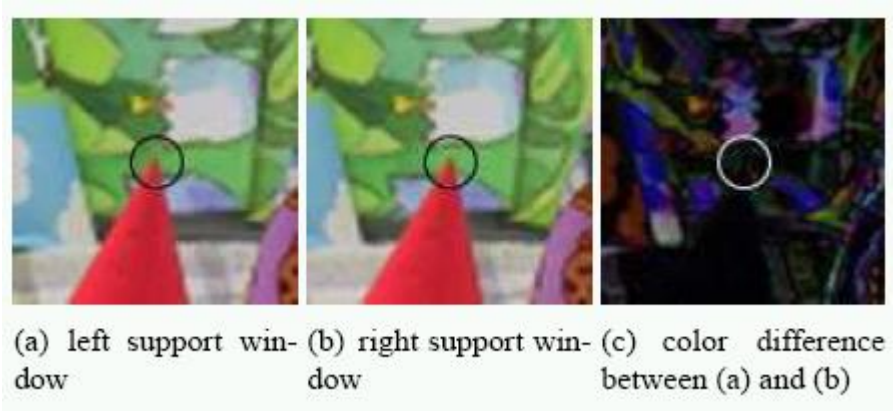
- Instead of square windows aggregate cost in rod-shaped shiftable windows [Kim CVPR05]
- Search for one that minimizes the cost (assume that it is an iso-disparity curve)
- Typically use 36 orientations





Locally Adaptive Support

Apply weights to contributions of neighboring
pixels according to similarity and proximity [Yoon CVPR05]



(a) left support window (b) right support window (c) color difference between (a) and (b)

Locally Adaptive Support

- Similarity in CIE Lab color space:

$$\Delta c_{pq} = \sqrt{(L_p - L_q)^2 + (a_p - a_q)^2 + (b_p - b_q)^2}$$

- Proximity: Euclidean distance

- Weights:

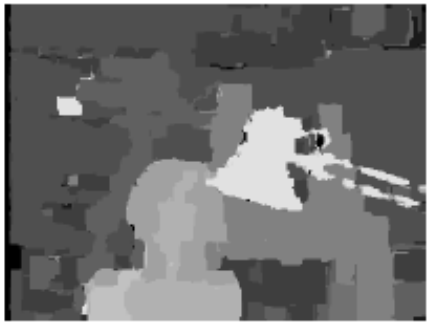
$$w(p,q) = k \cdot \exp\left(-\left(\frac{\Delta c_{pq}}{\gamma_c} + \frac{\Delta g_{pq}}{\gamma_p}\right)\right)$$

Locally Adaptive Support: Results

(a) left image

(b) ground truth

(c) shiftable win. [7]



(d) compact win. [3]

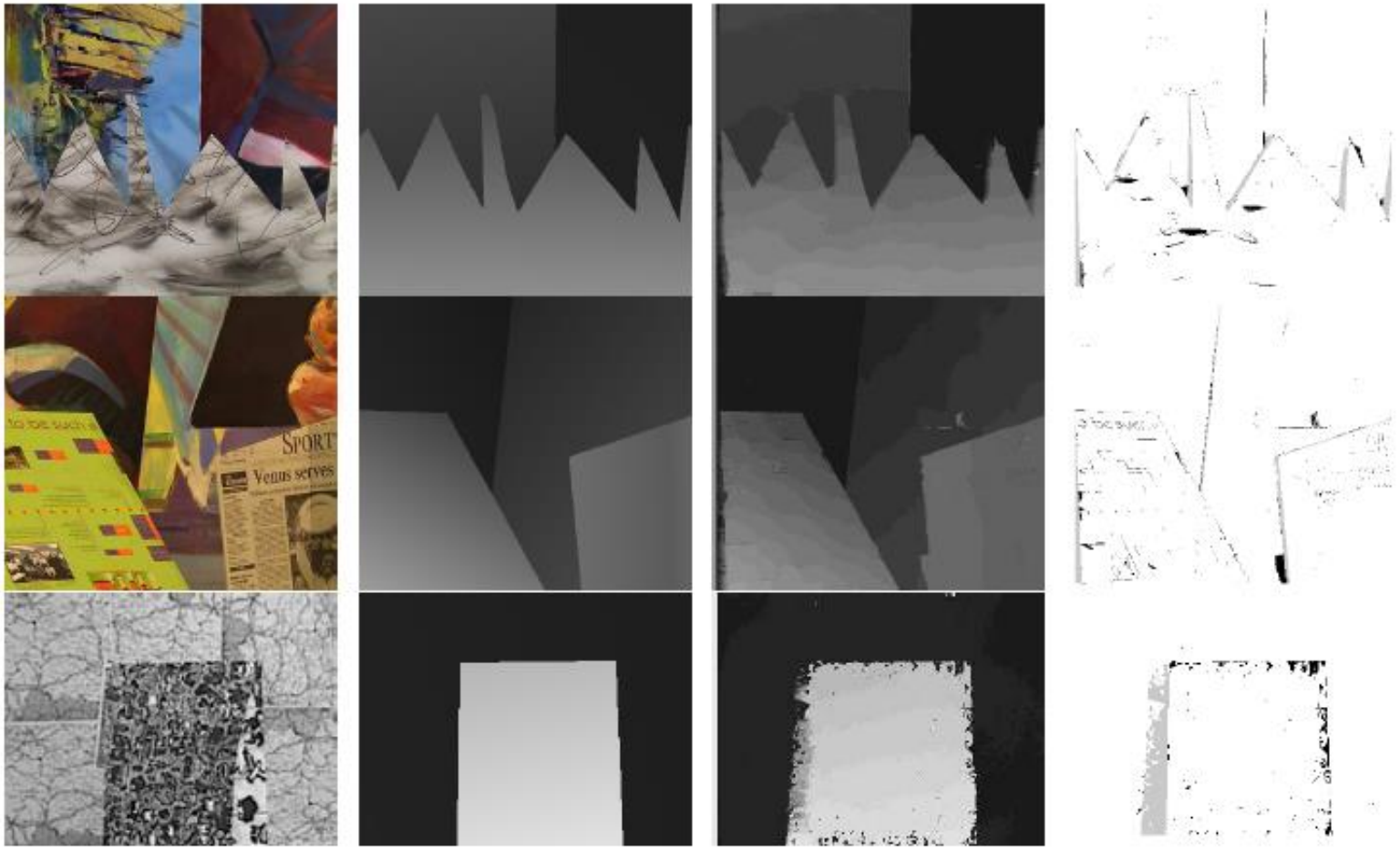
(e) variable win. [4]

(f) Bay. diff. [19]

Locally Adaptive Support

(h) bad pixels (error > 1)

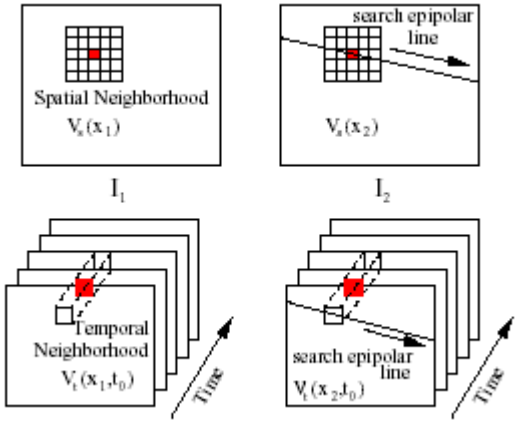
Locally Adaptive Support: Results



(a) left image (b) ground truth (c) our result (d) bad pixels (error > 1)

Cool ideas

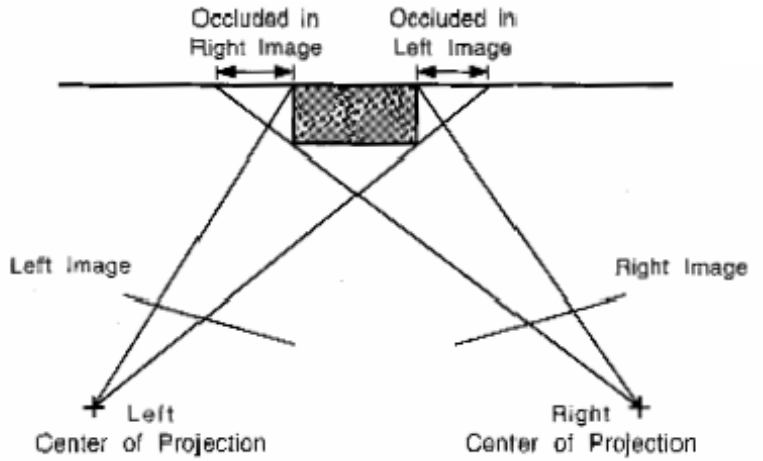
- Space-time stereo
  (varying illumination, not shape)



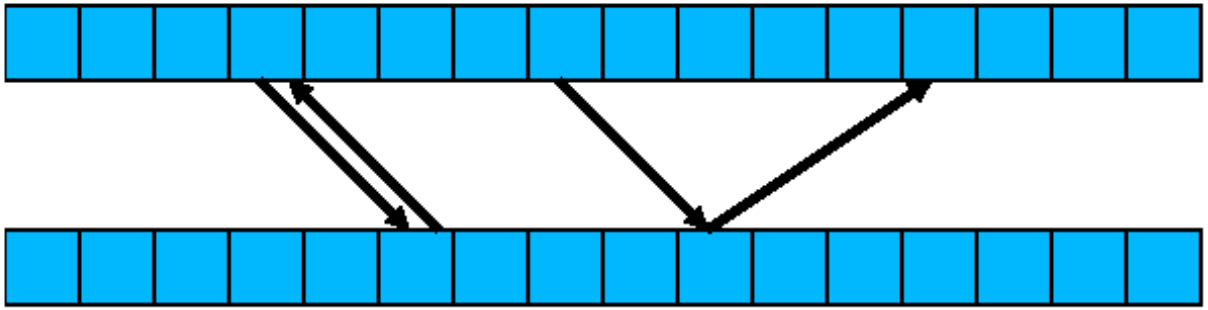
Challenges

- Ill-posed inverse problem
  - Recover 3-D structure from 2-D information
- Difficulties
  - Uniform regions
  - Half-occluded pixels

Occlusions

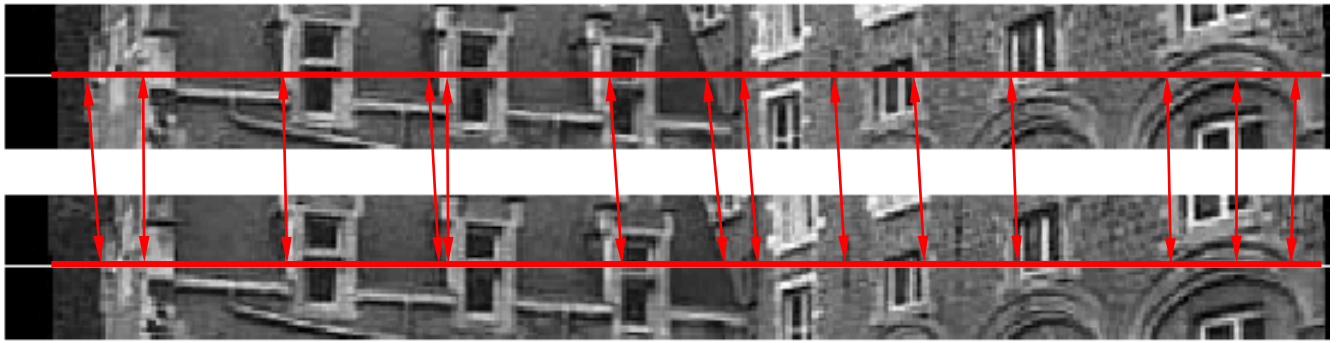


→ Consistency test

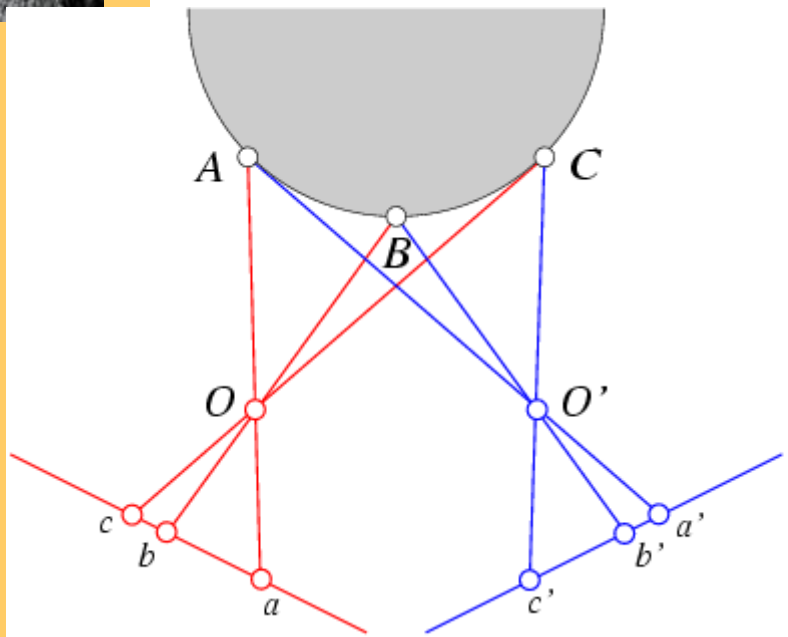


(Slide from Pascal Fua)

Exploiting scene constraints



The Ordering Constraint

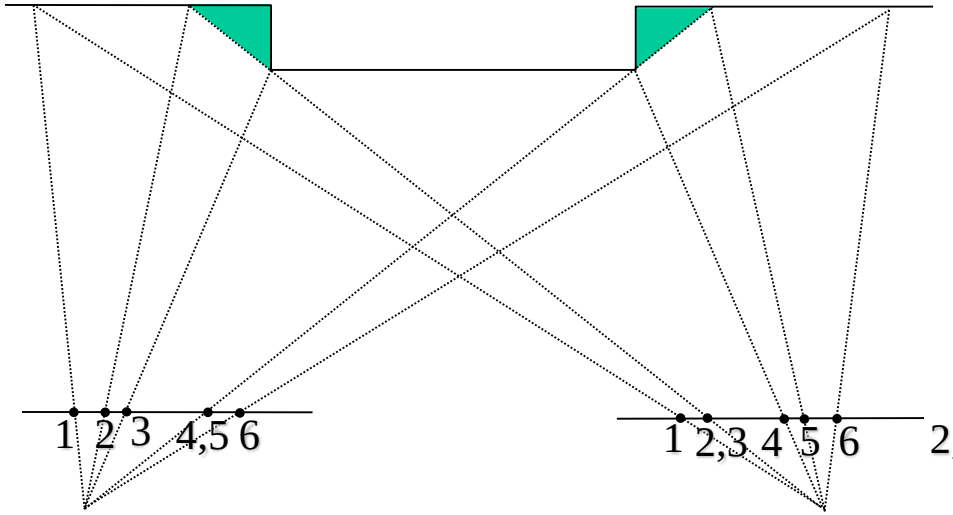


In general the points are in the same order on both epipolar lines.

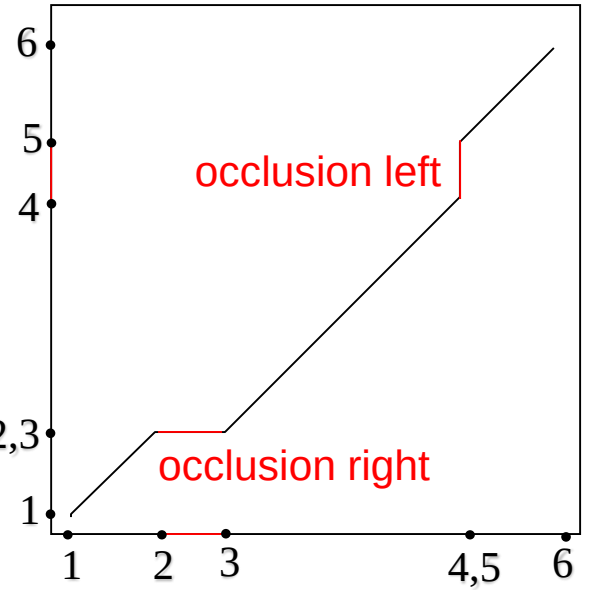
But it is not always the case..

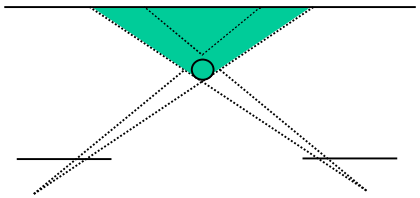
Ordering constraint

surface slice



surface as a path



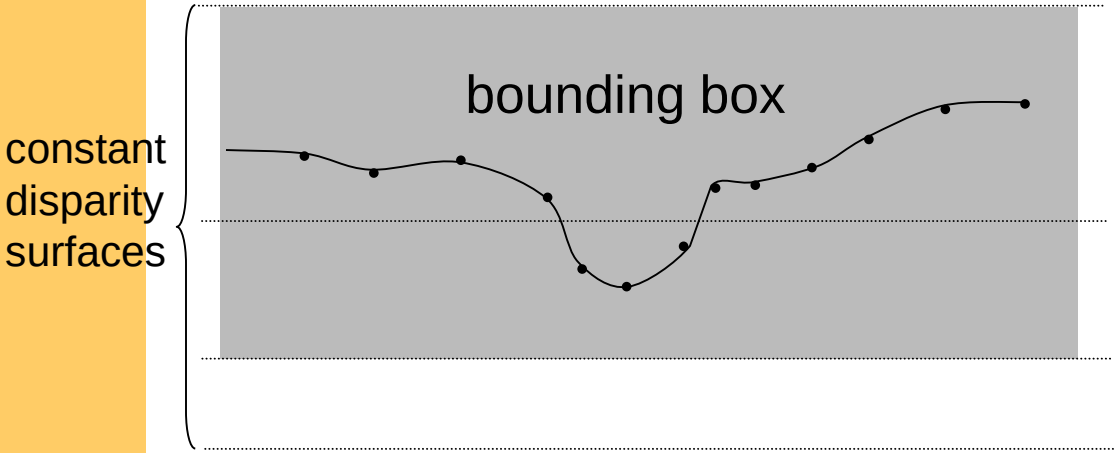


Uniqueness constraint

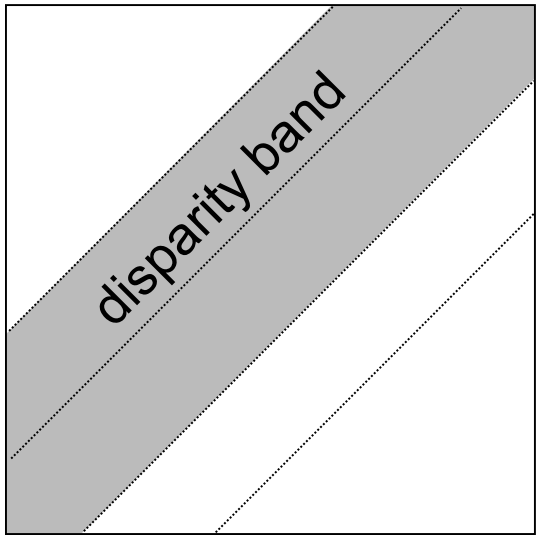
- In an image pair each pixel has at most one corresponding pixel
  - In general one corresponding pixel
  - In case of occlusion there is none

Disparity constraint

surface slice

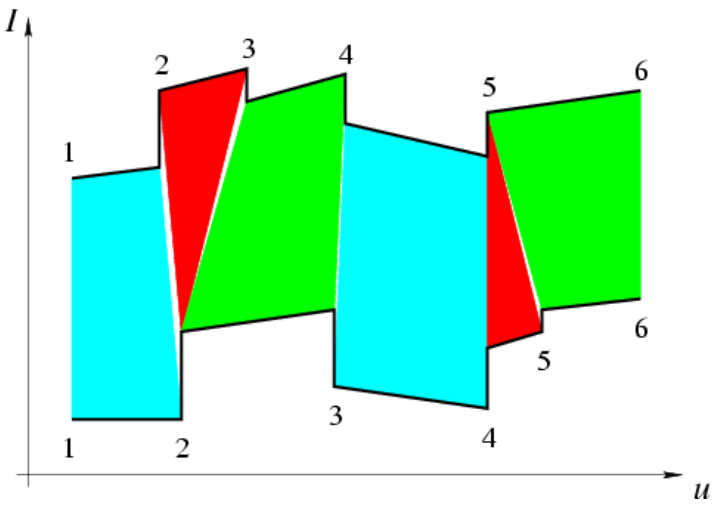


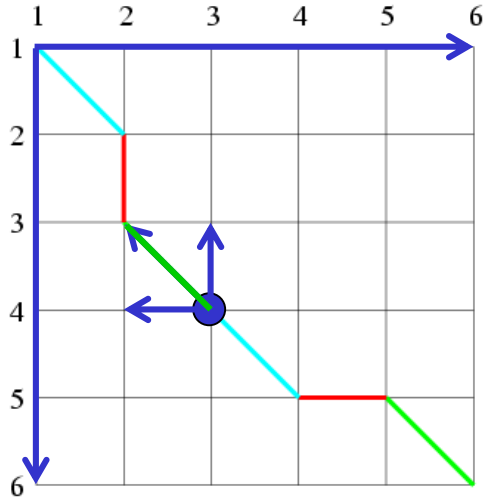
surface as a path



use reconstructed features
to determine bounding box

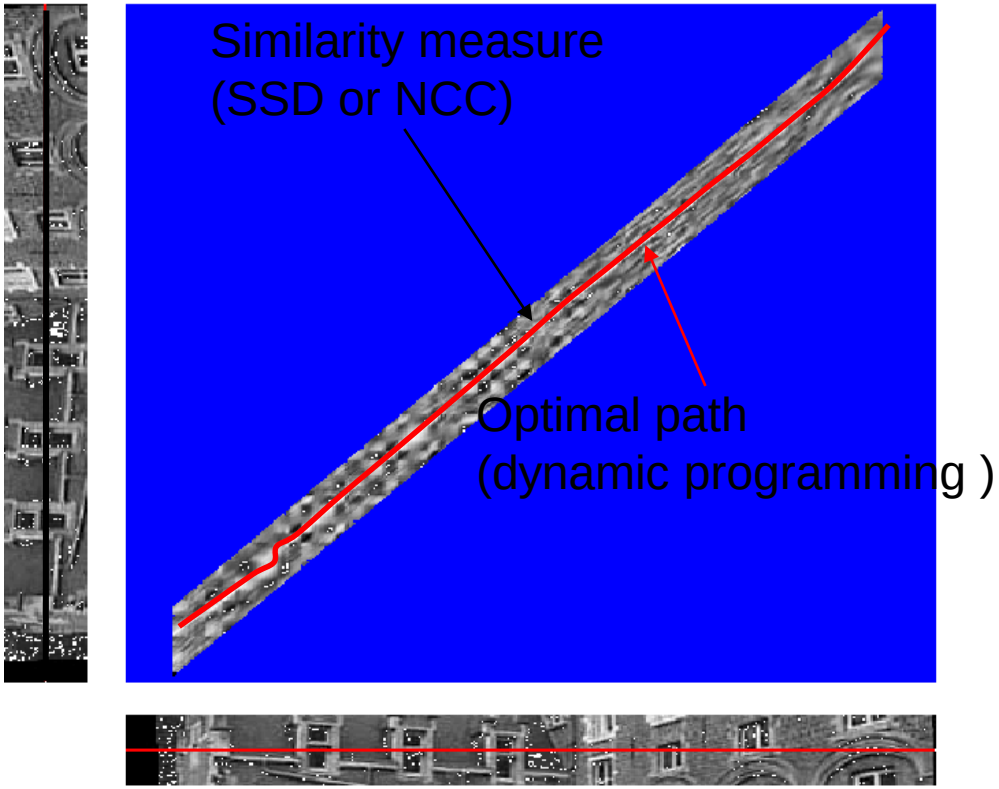
Dynamic Programming (Baker and Binford, 1981)






```
% Loop over all nodes (k, l) in ascending order.
for k = 1 to m do
  for l = 1 to n do
    % Initialize optimal cost C(k, l) and backward pointer B(k, l).
    C(k, l) ← +∞; B(k, l) ← nil;
    % Loop over all inferior neighbors (i, j) of (k, l).
    for (i, j) ∈ Inferior − Neighbors(k, l) do
      % Compute new path cost and update backward pointer if necessary.
      d ← C(i, j) + Arc − Cost(i, j, k, l);
      if d < C(k, l) then C(k, l) ← d; B(k, l) ← (i, j) endif;
      endfor;
    endfor;
  endfor;
% Construct optimal path by following backward pointers from (m, n).
P ← {(m, n)}; (i, j) ← (m, n);
while B(i, j) ≠ nil do (i, j) ← B(i, j); P ← {(i, j)} ∪ P endwhile.
```

Stereo matching

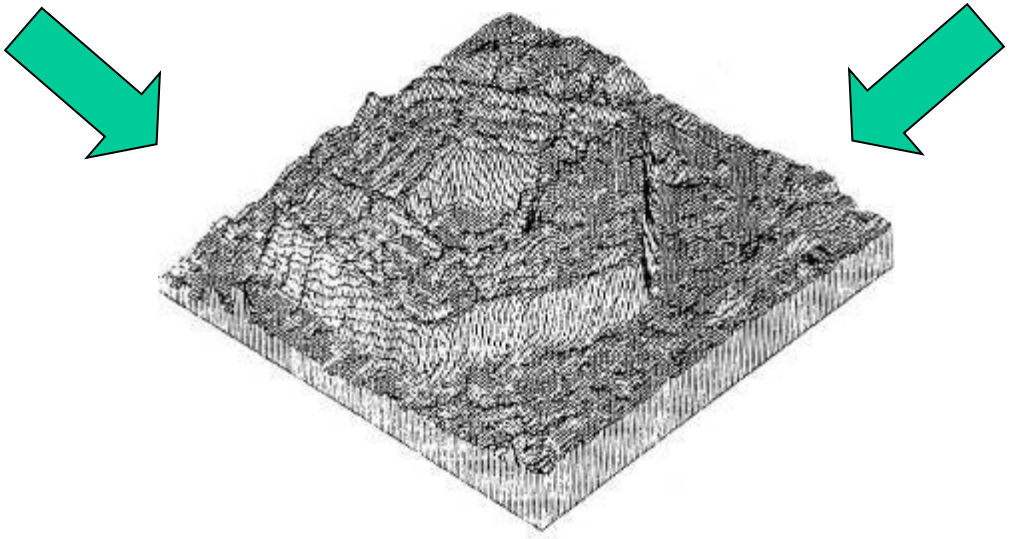


Constraints
- epipolar
- ordering
- uniqueness
- disparity limit
- disparity gradient limit

Trade-off
- Matching cost (data)
- Discontinuities (prior)

(Cox et al. CVGIP'96; Koch'96; Falkenhagen´97;
Van Meerbergen,Vergauwen,Pollefeys,VanGool IJCV'02)

Dynamic Programming (Ohta and Kanade, 1985)

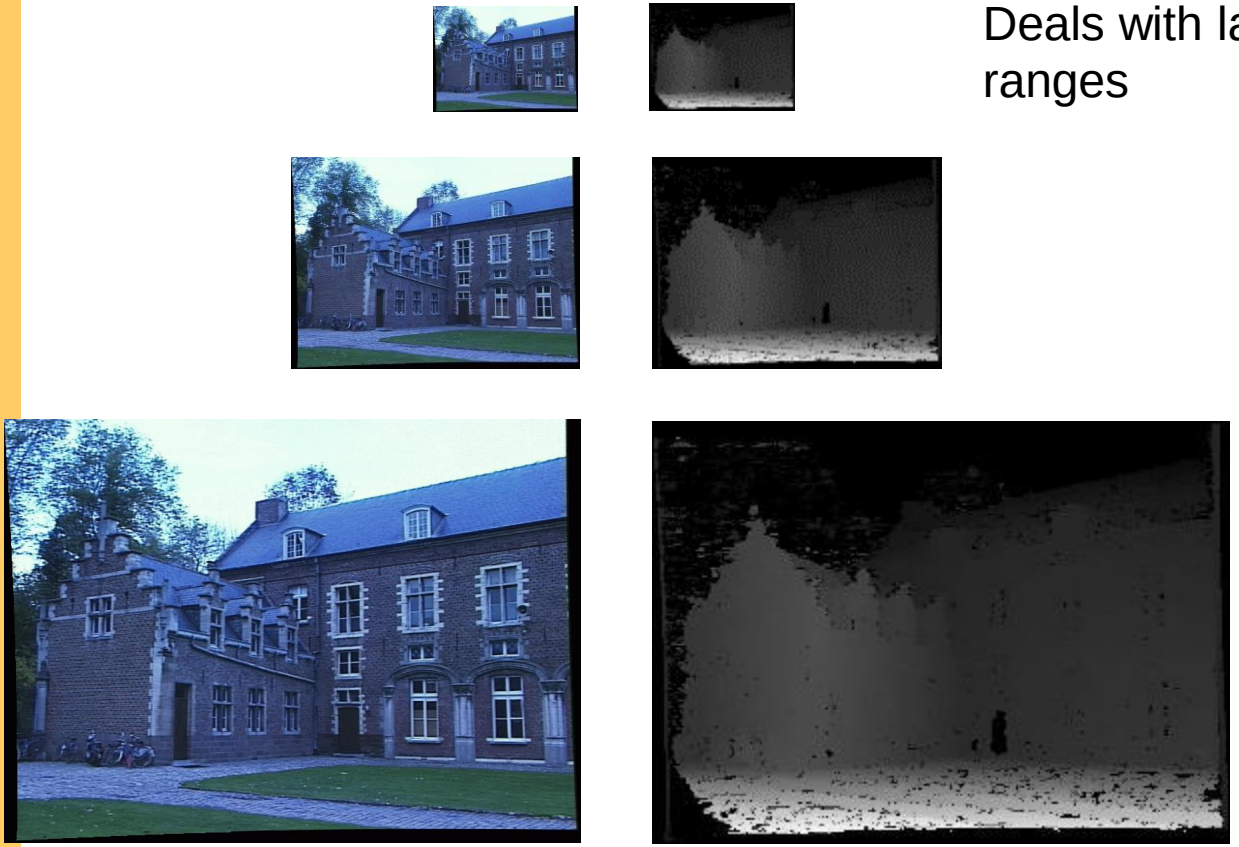


Reprinted from "Stereo by Intra- and Intet-Scanline Search," by Y. Ohta and T. Kanade, IEEE Trans. on Pattern Analysis and Machine Intelligence, 7(2):139-154 (1985). © 1985 IEEE.

Hierarchical stereo matching

Allows faster computation

Deals with large disparity ranges



Downsampling
(Gaussian pyramid)

Disparity propagation

(Falkenhagen´97;Van Meerbergen,Vergauwen,Pollefeys,VanGool IJCV‘02)

Disparity map

image I(x,y)

Disparity map D(x,y)

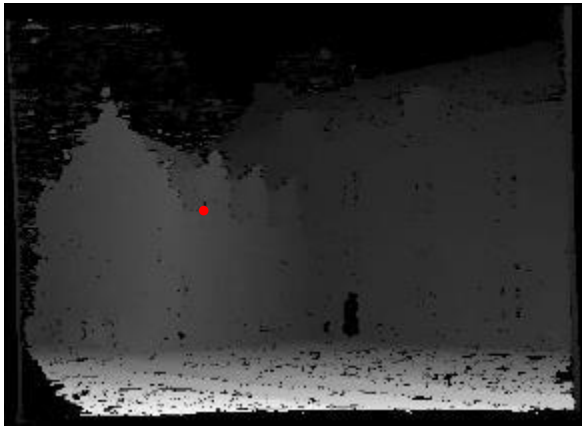
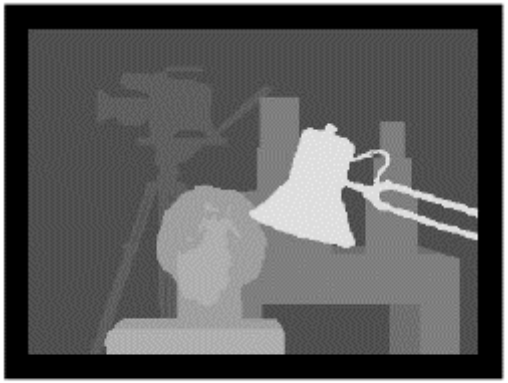


image I´(x´,y´)

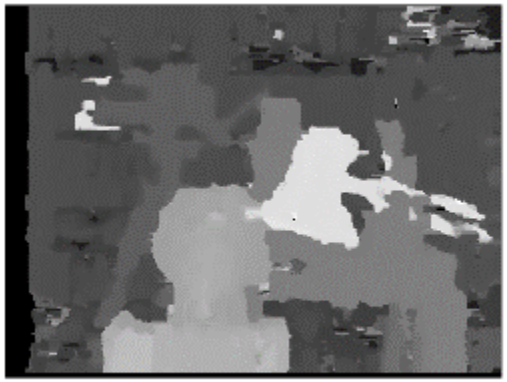
$(x´,y´)=(x+D(x,y),y)$

Example: reconstruct image from neighboring images



True disparities

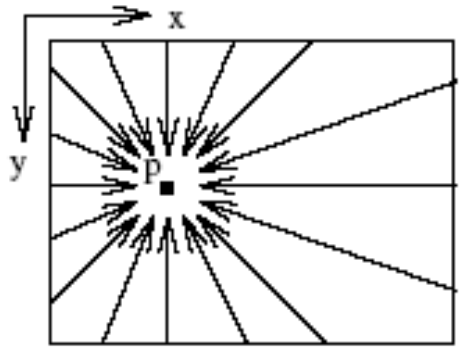
*2 – Dynamic progr.



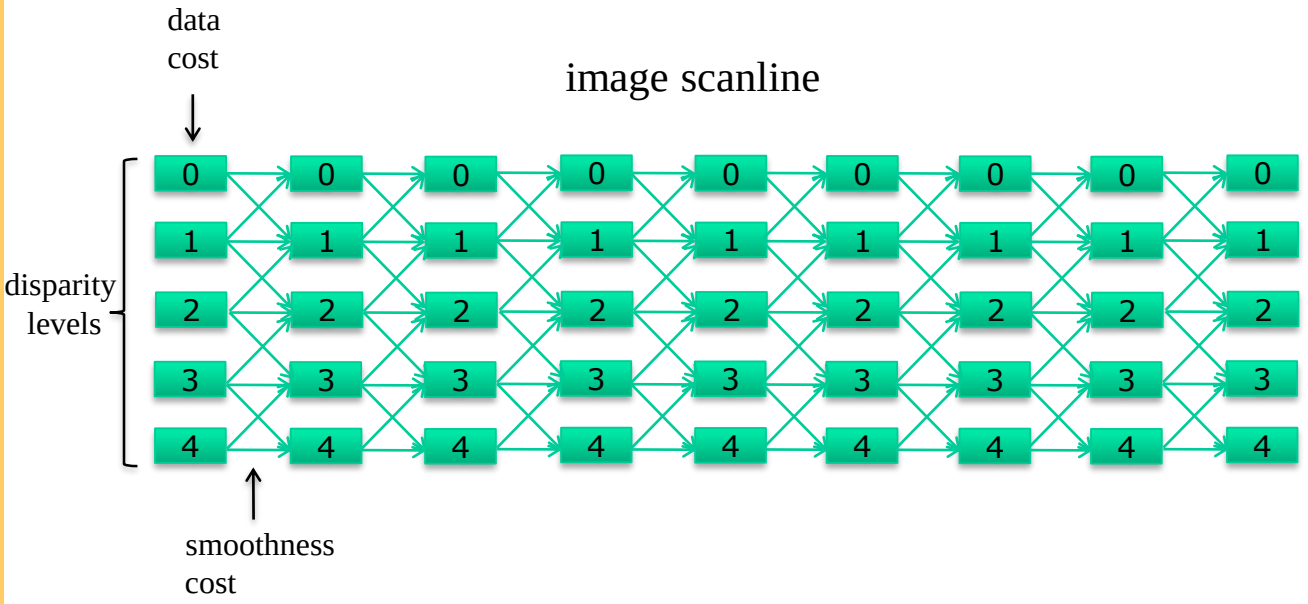
16 – Fast Correlation

Semi-global optimization

- Optimize: $E=E_{data}+E(|D_p-D_q|=1)+E(|D_p-D_q|>1)$ [Hirshmüller CVPR05]
  - Use mutual information as cost
- NP-hard using graph cuts or belief propagation (2-D optimization)
- Instead do dynamic programming along many directions
  - Don't use visibility or ordering constraints
  - Enforce uniqueness
  - Add costs



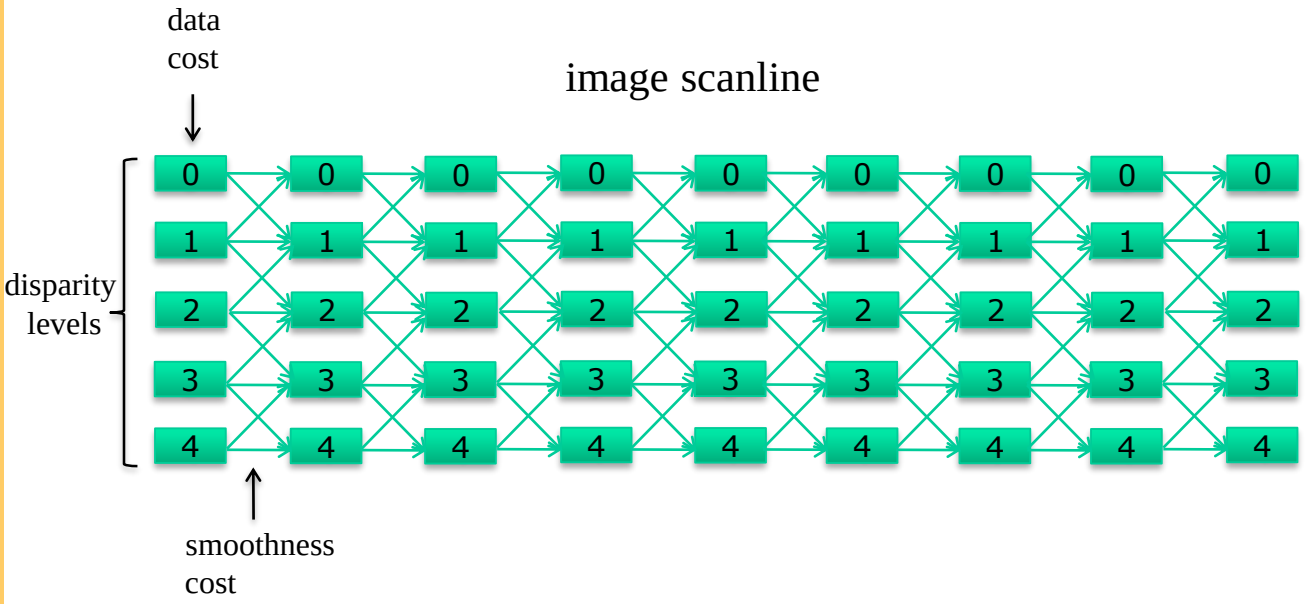
Dynamic programming



Step 1 path-cost propagation →

Step 2 back-tracking best path ←

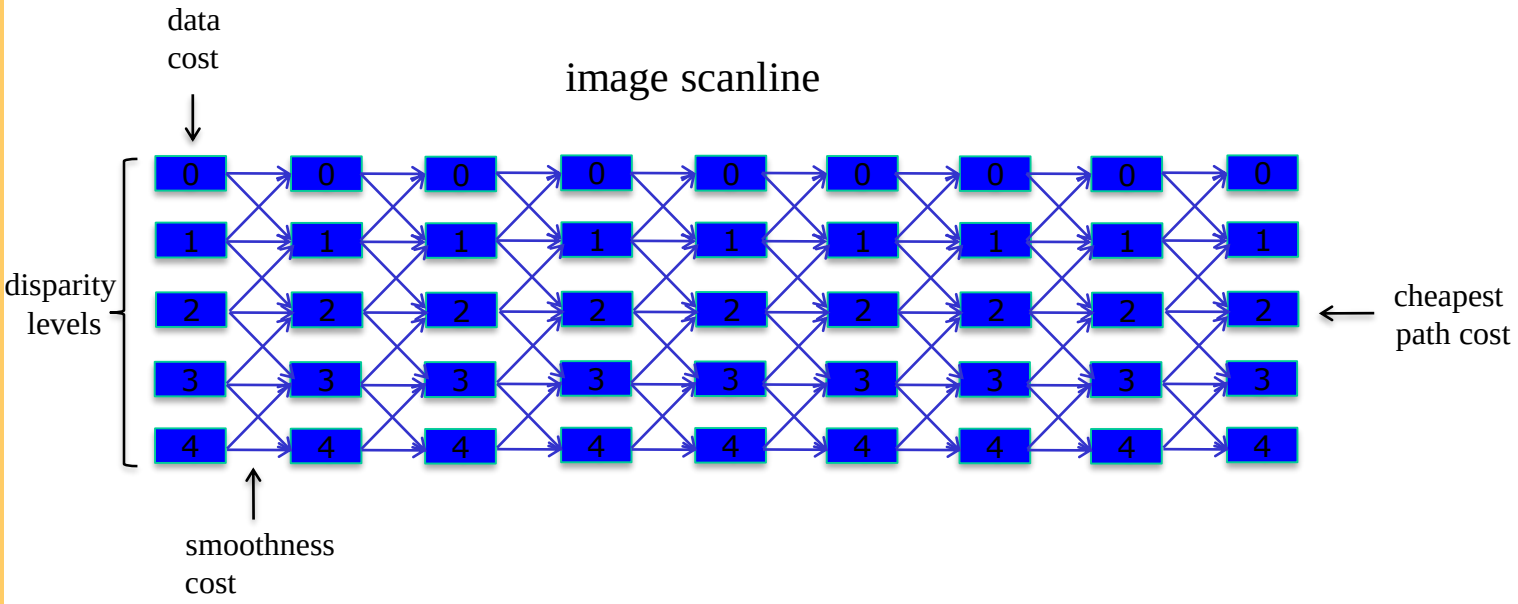
Dynamic programming



Step 1 path-cost propagation →

Step 2 back-tracking best path ←

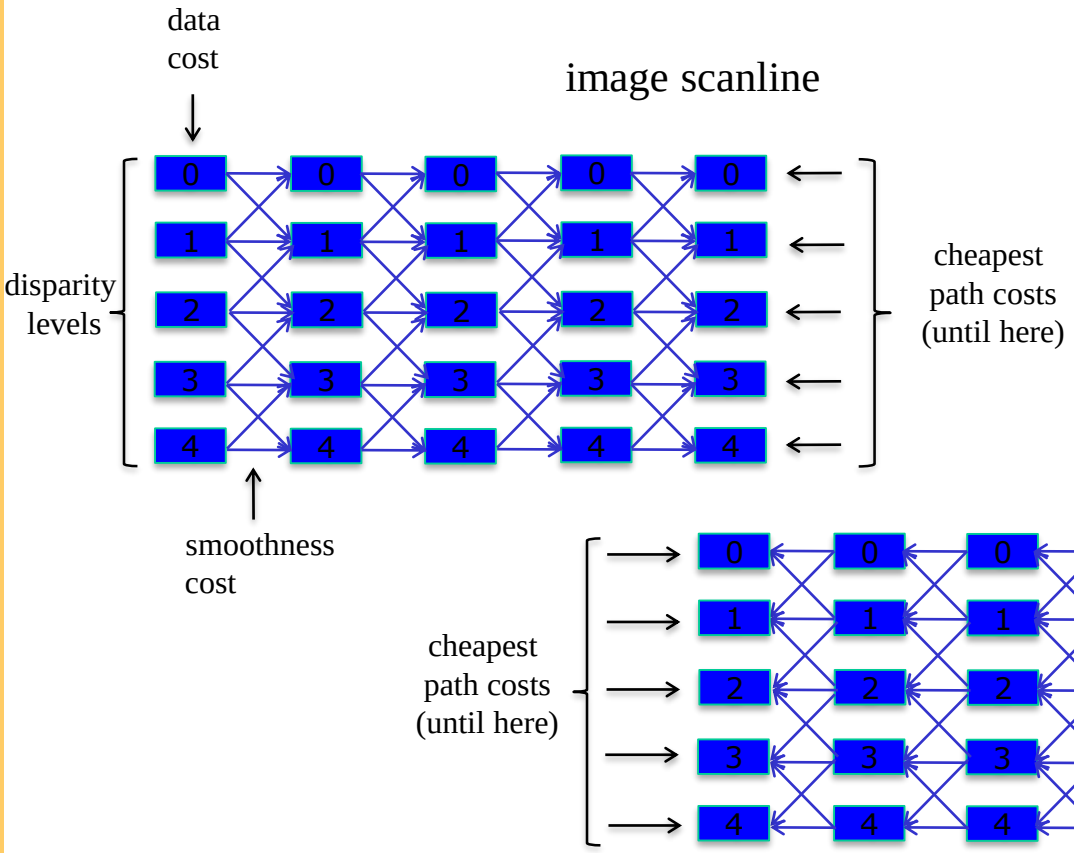
Dynamic programming



Step 1 path-cost propagation →

Step 2 back-tracking best path ←

Semi-Global Matching



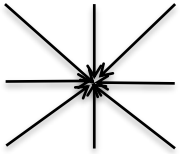
Step 1 path-cost propagation →

Step 2 path-cost propagation ←

Step 3 path-cost propagation ↘

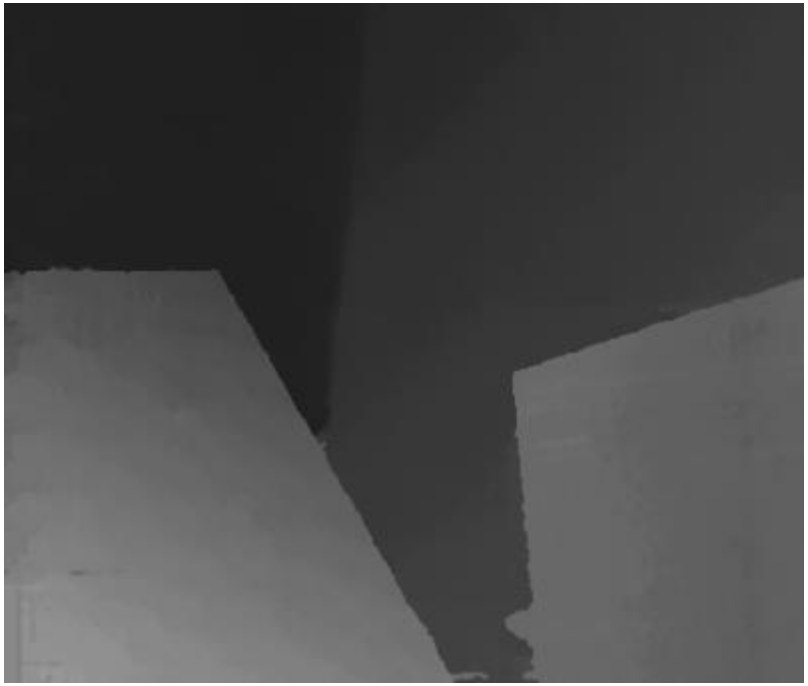
...

Step N+1 sum up costs for total tree cost

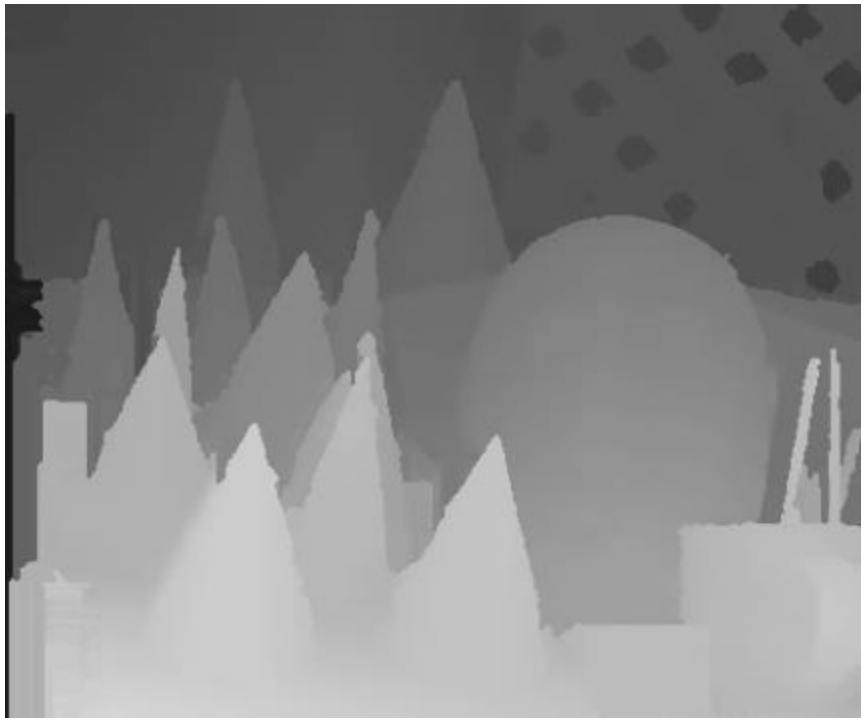


guarantees optimal solution
for combined path
(BUT other pixels have different paths)

Results of Semi-global optimization



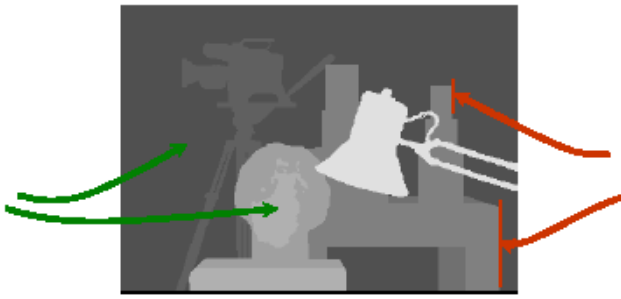
Results of Semi-global optimization



No. 1 overall in Middlebury evaluation
(at 0.5 error threshold as of Sep. 2006)

Energy minimization

Disparity continuous in most places,



except at depth discontinuities

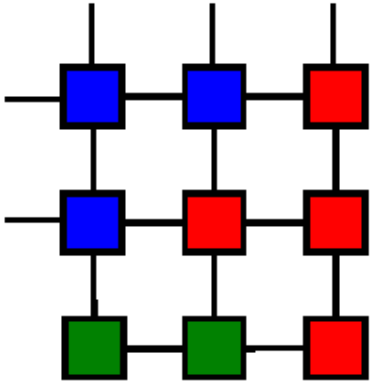
1. Matching pixels should have similar intensities.
2. Most nearby pixels should have similar disparities

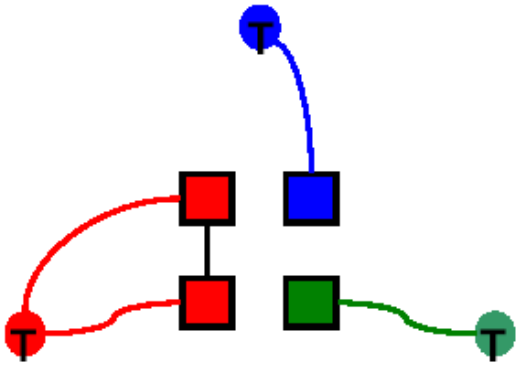
→ Minimize

$$\sum [I_1(x + D(x,y), y) - I_2(x,y)]^2$$
$$+ \lambda \sum [D(x+1,y) - D(x,y)]^2$$
$$+ \mu \sum [D(x,y+1) - D(x,y)]^2$$

(Slide from Pascal Fua)

Graph Cut





1. Stereo is a labeling problem
2. Graph cut corresponds to a labeling.

→ **Assign edge weights cleverly so that the min-weight cut gives the minimum energy!**

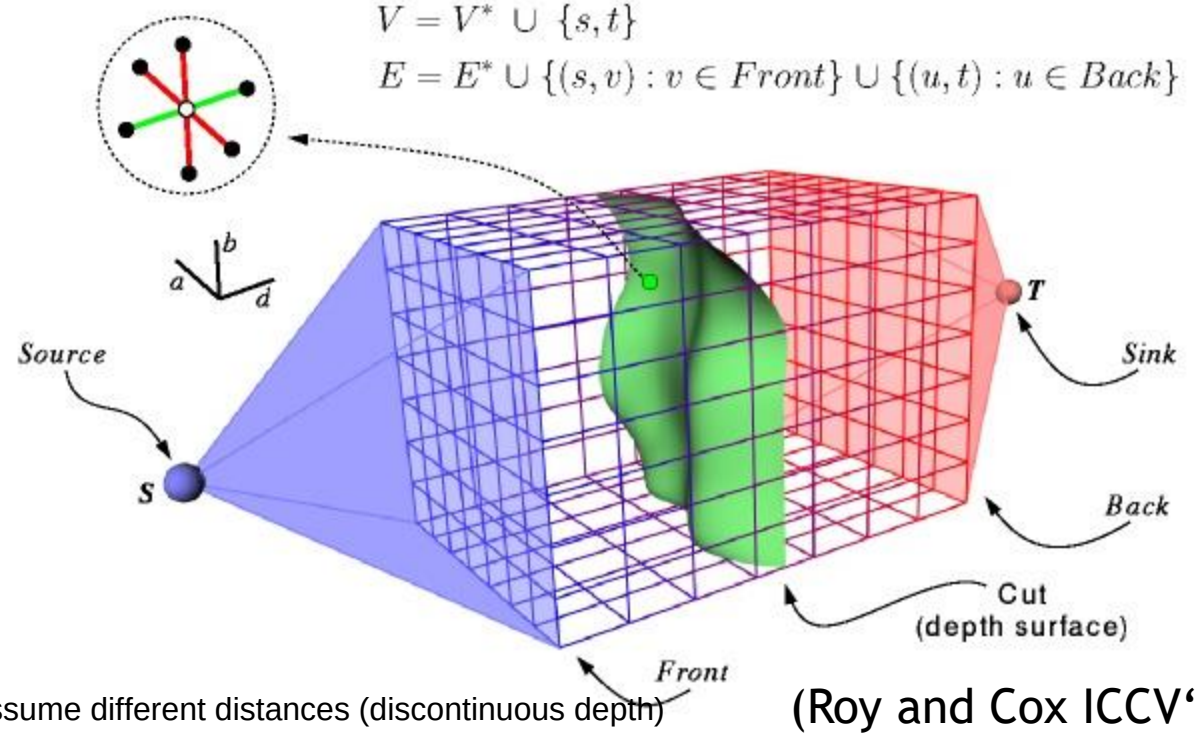
(general formulation requires multi-way cut!)

(Slide from Pascal Fua)

Simplified graph cut

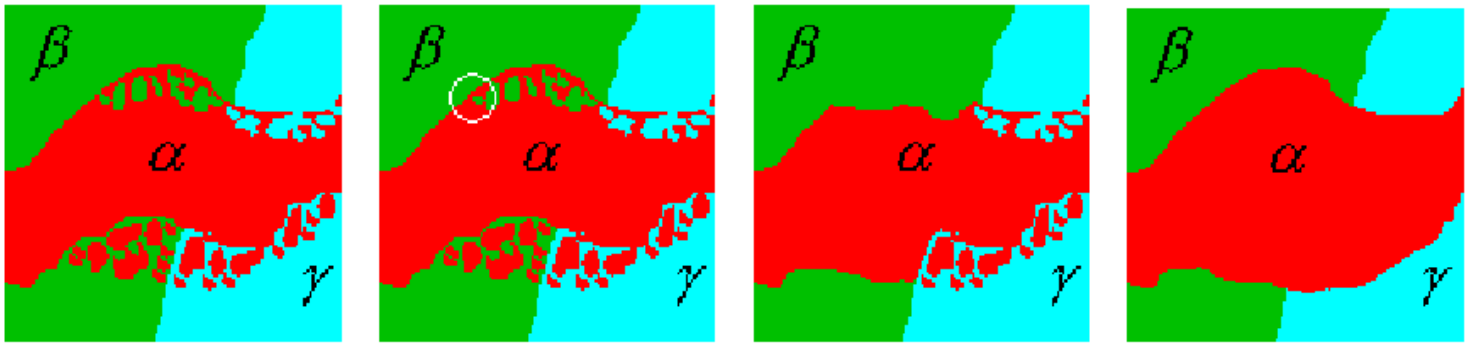
$$V = V^* \cup \{s,t\}$$

$$E = E^* \cup \{(s,v) : v \in Front\} \cup \{(u,t) : u \in Back\}$$



doesnt' assume different distances (discontinuous depth)

(Roy and Cox ICCV'98)



(a) initial labeling (b) standard move (c) α-β-swap (d) α-expansion

(Boykov et al ICCV'99)

Belief Propagation

Belief of one node about another gets propagated through messages (full pdf, not just most likely state)

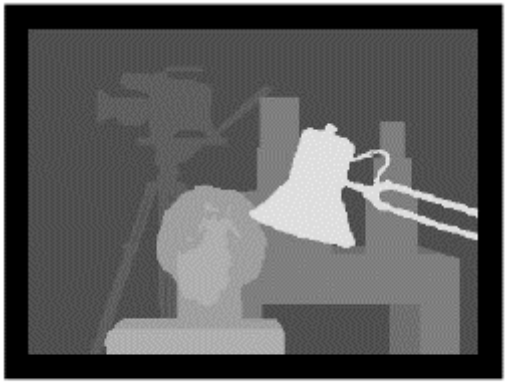
first iteration

per pixel +left +right +up +down

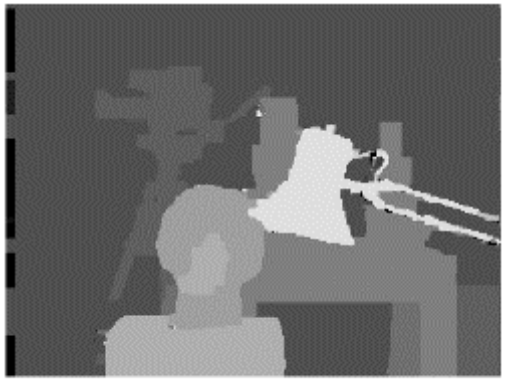
subsequent iterations

2 3 4 5 ... 20

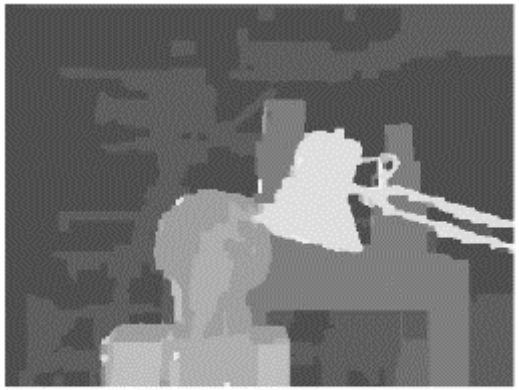
(adapted from J. Coughlan slides)



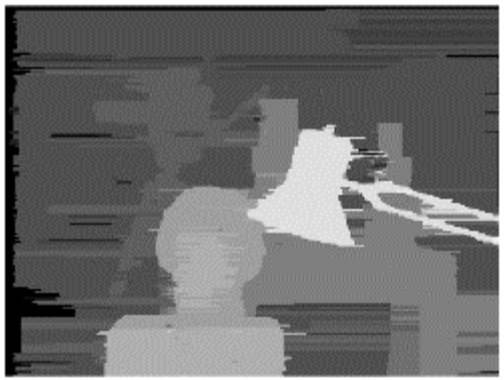
True disparities



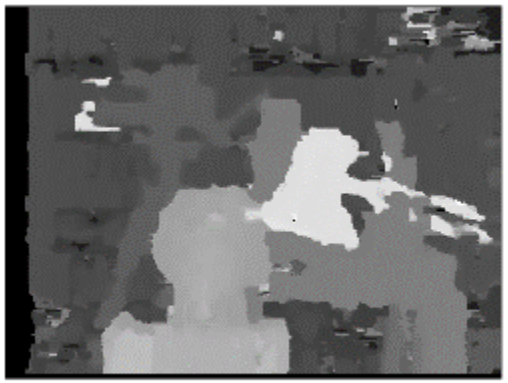
11 – GC + occlusions



19 – Belief propagation

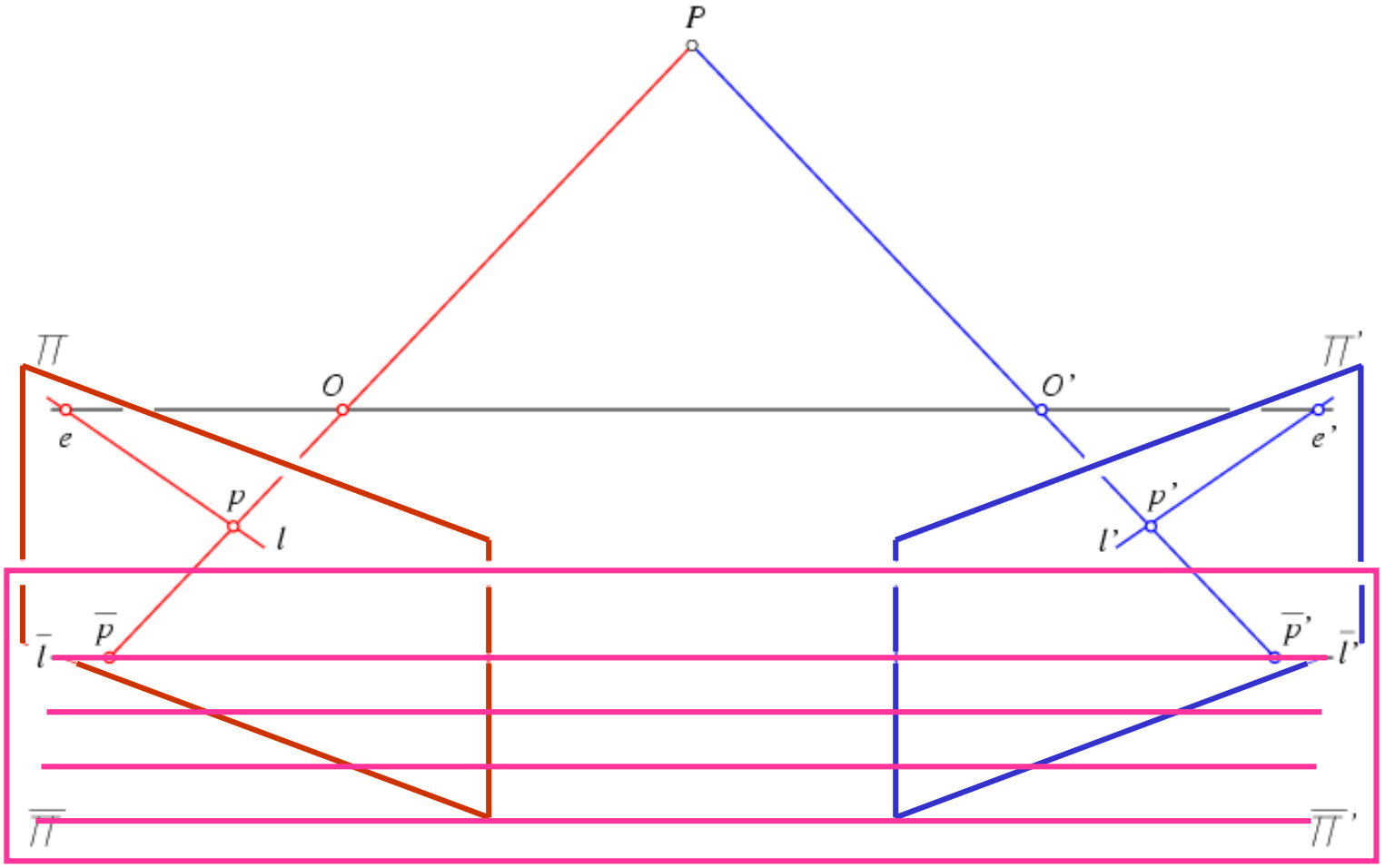


*2 – Dynamic progr.



16 – Fast Correlation

Rectification

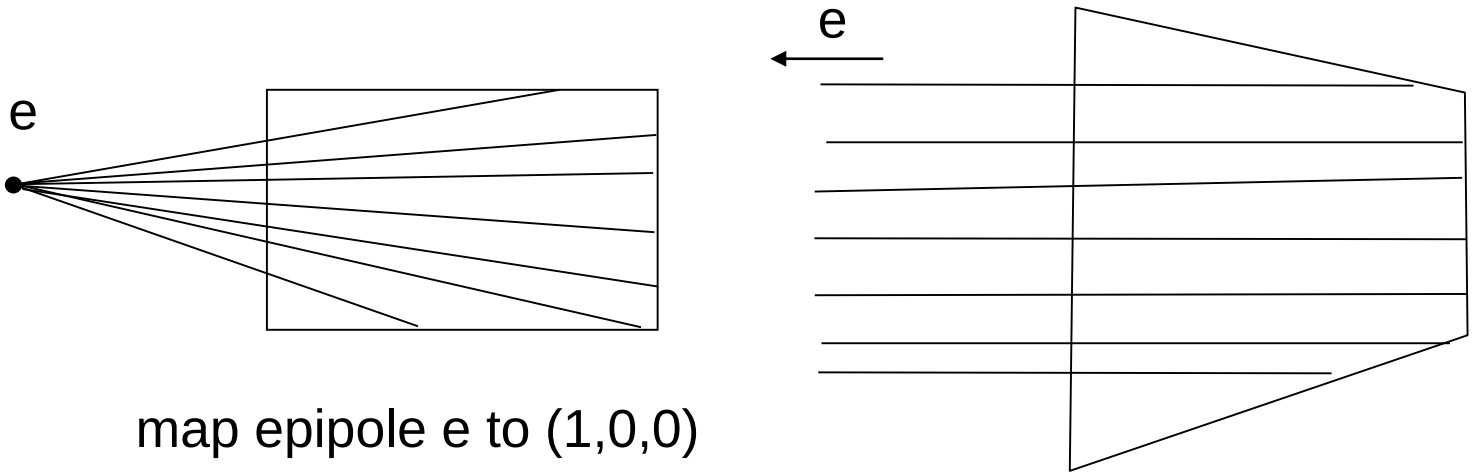


All epipolar lines are parallel in the rectified image plane.

Image pair rectification

simplify stereo matching
by warping the images

Apply projective transformation so that epipolar lines correspond to horizontal scanlines



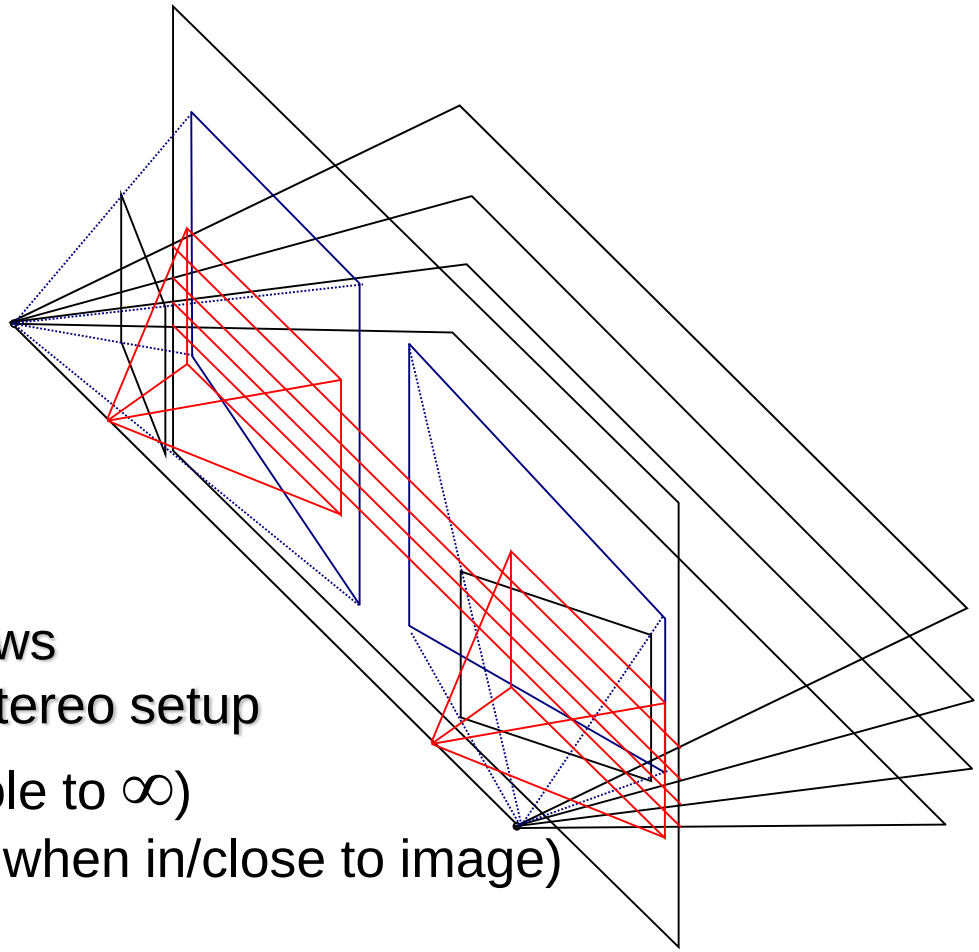
map epipole e to (1,0,0)

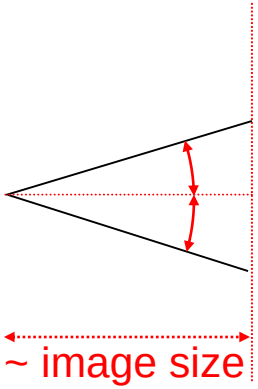
try to minimize image distortion

problem when epipole in (or close to) the image

Planar rectification

(standard approach)



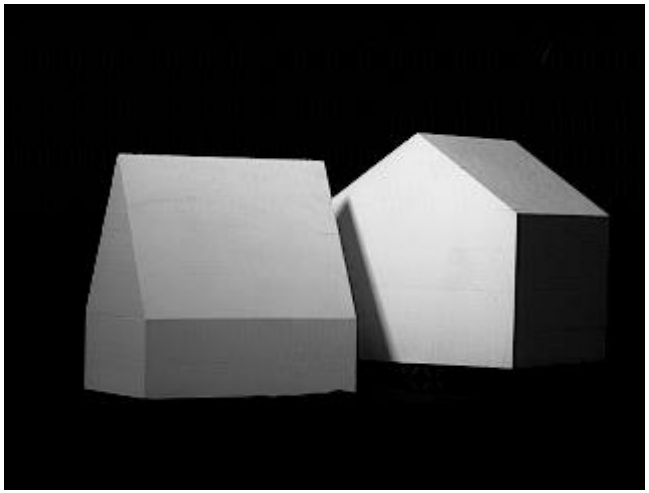


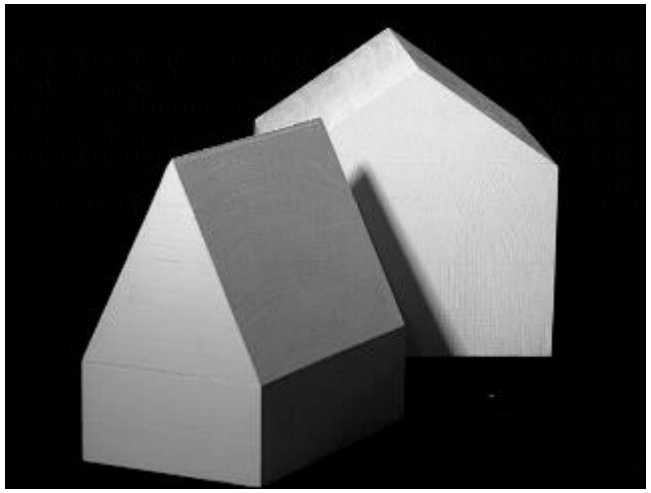
(calibrated)

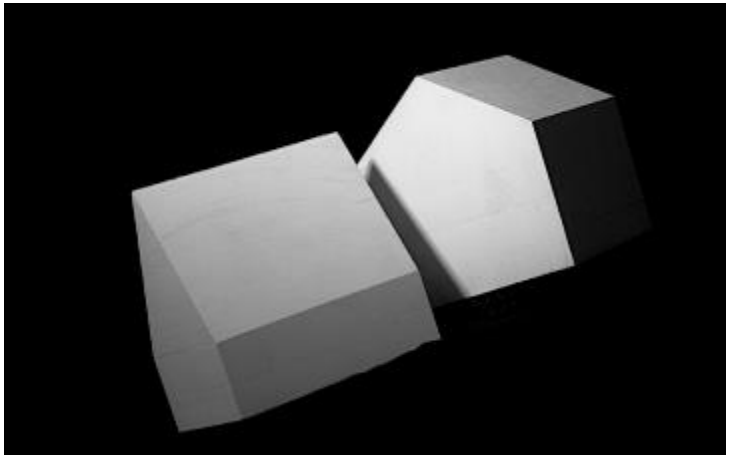
Distortion minimization
(uncalibrated)

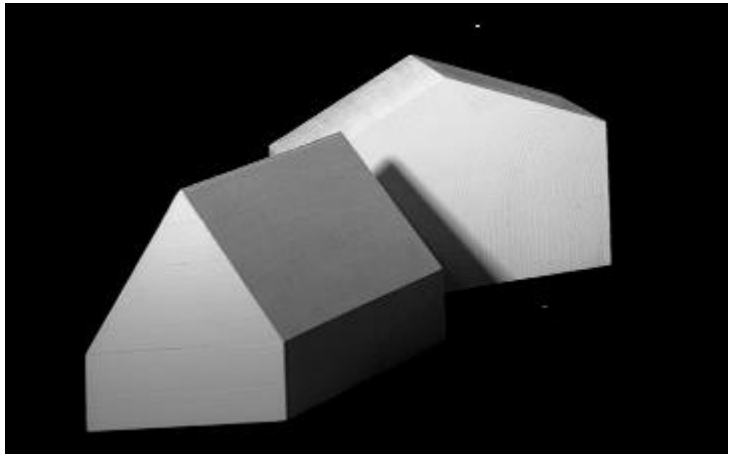
Bring two views
to standard stereo setup

(moves epipole to ∞)
(not possible when in/close to image)





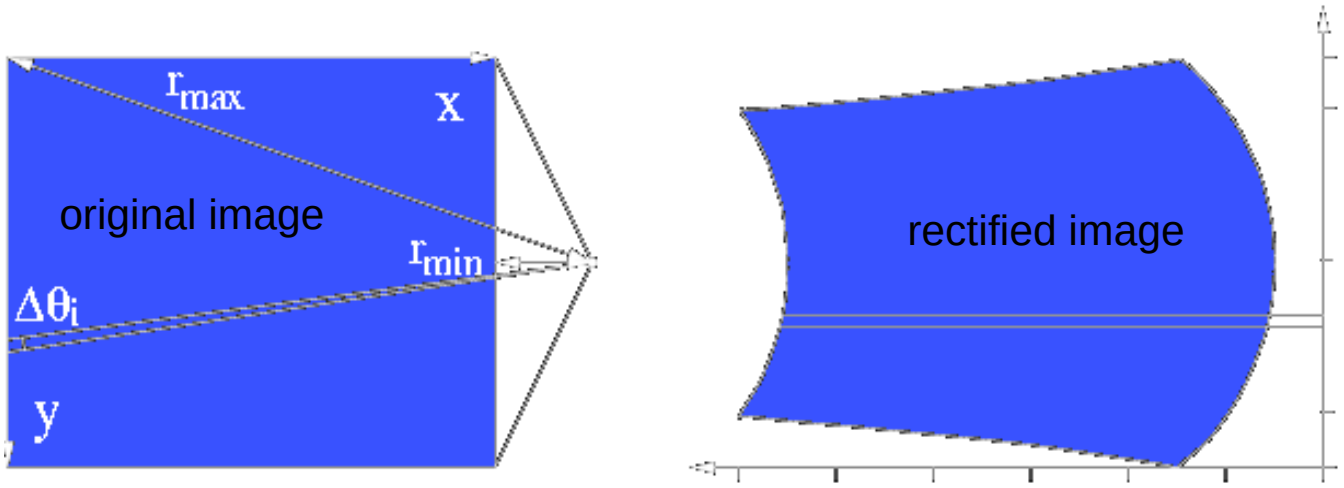




Polar rectification

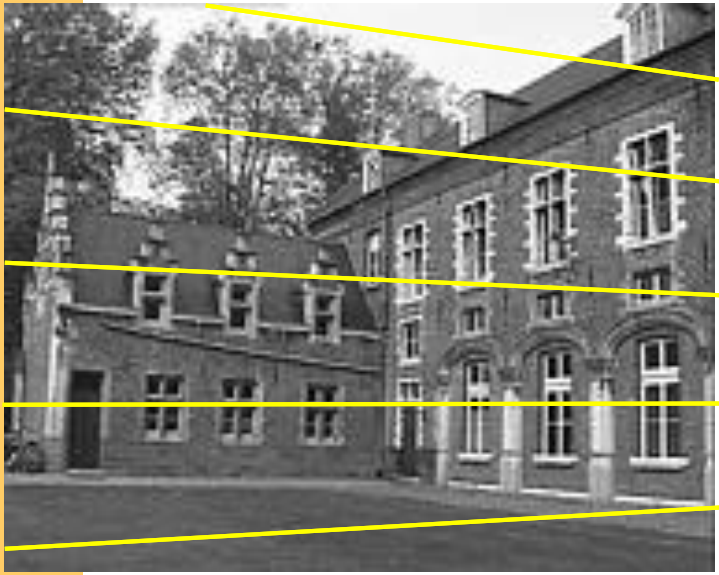
(Pollefeys et al. ICCV' 99)

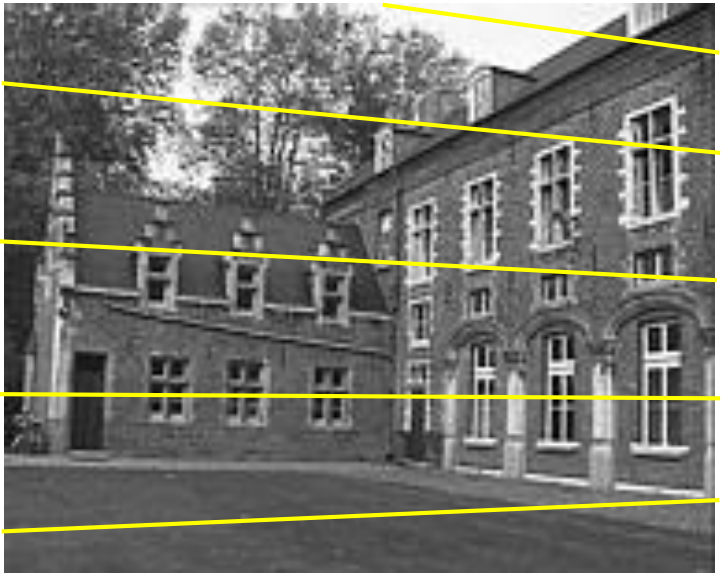
Polar re-parameterization around epipoles
Requires only (oriented) epipolar geometry
Preserve length of epipolar lines
Choose $\Delta\theta$ so that no pixels are compressed



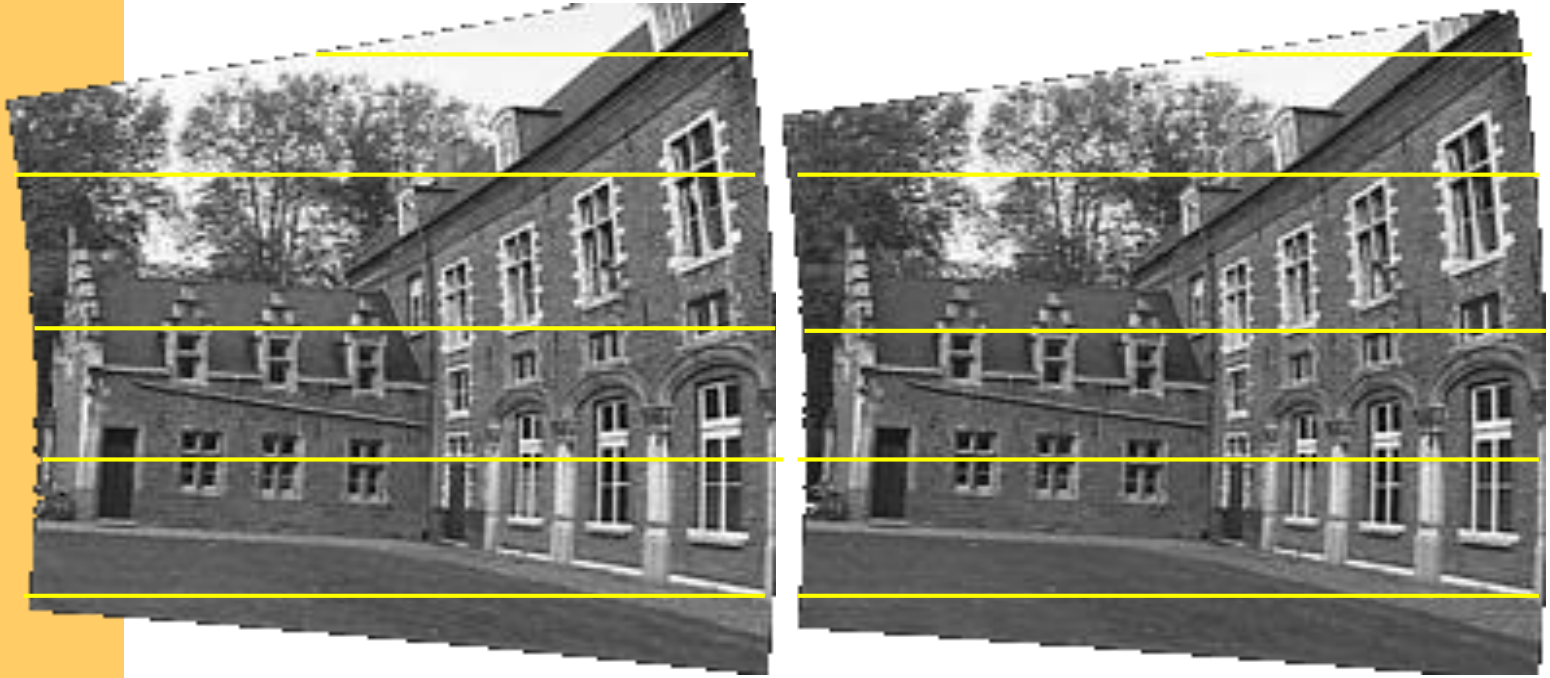
Works for all relative motions
Guarantees minimal image size

polar rectification: example





polar rectification: example



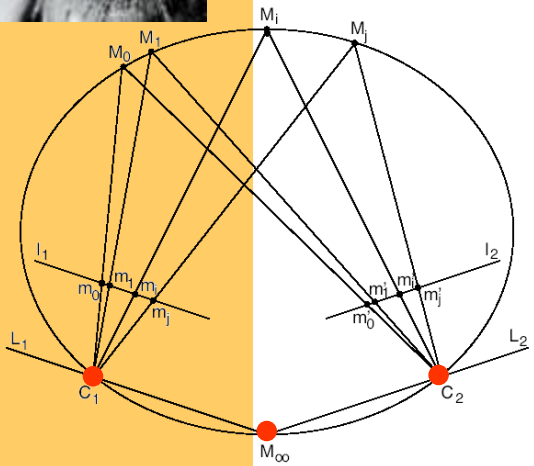
Example: Béguinage of Leuven

Does not work with standard
Homography-based approaches

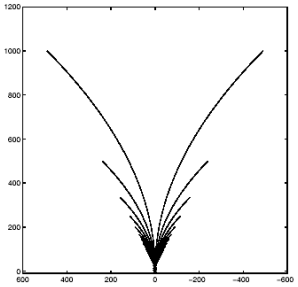
Example: Béguinage of Leuven

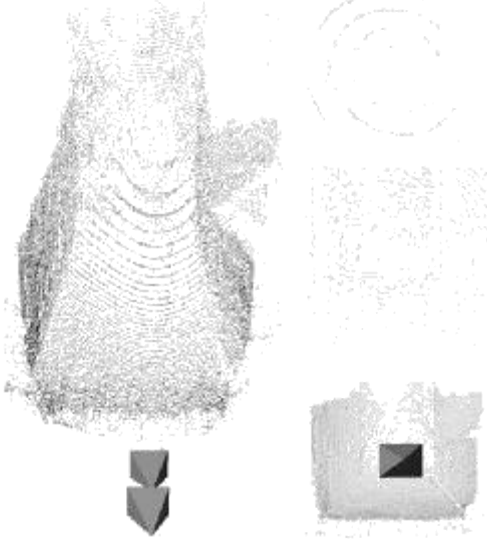
General iso-disparity surfaces

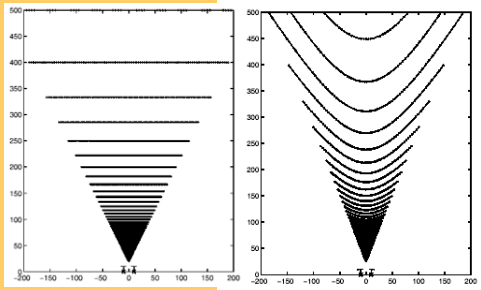
(Pollefeys and Sinha, ECCV' 04)

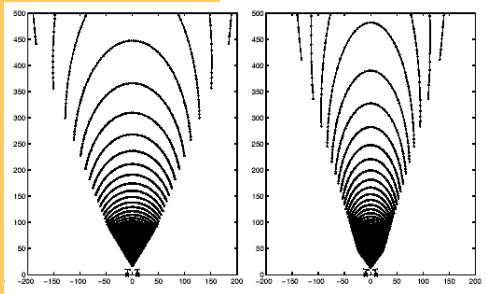


Example: polar rectification preserves disp.

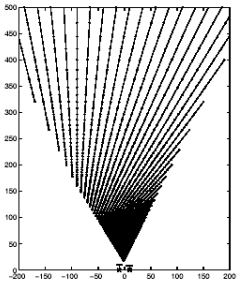






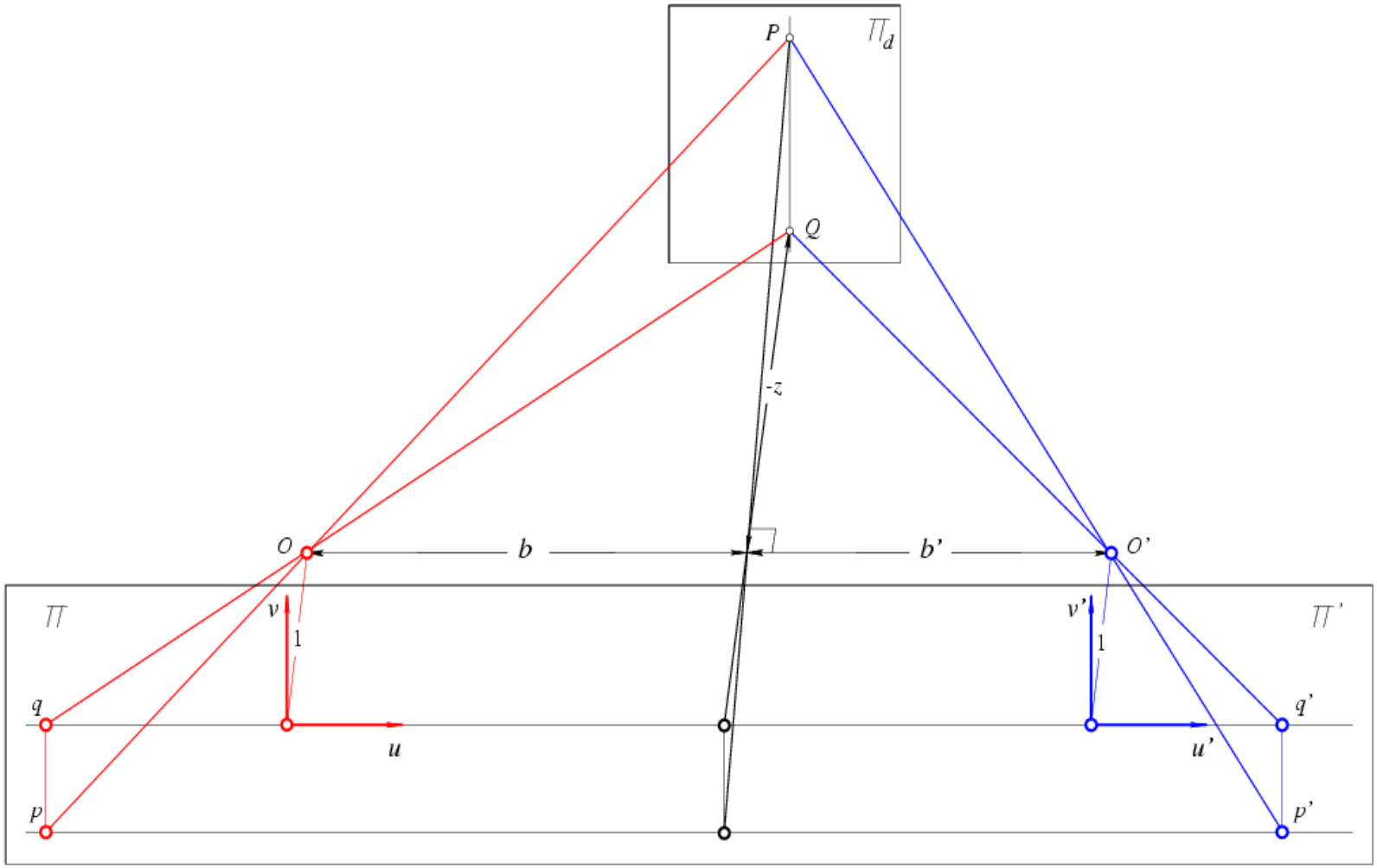


Application: Active vision



Also interesting relation to human horopter

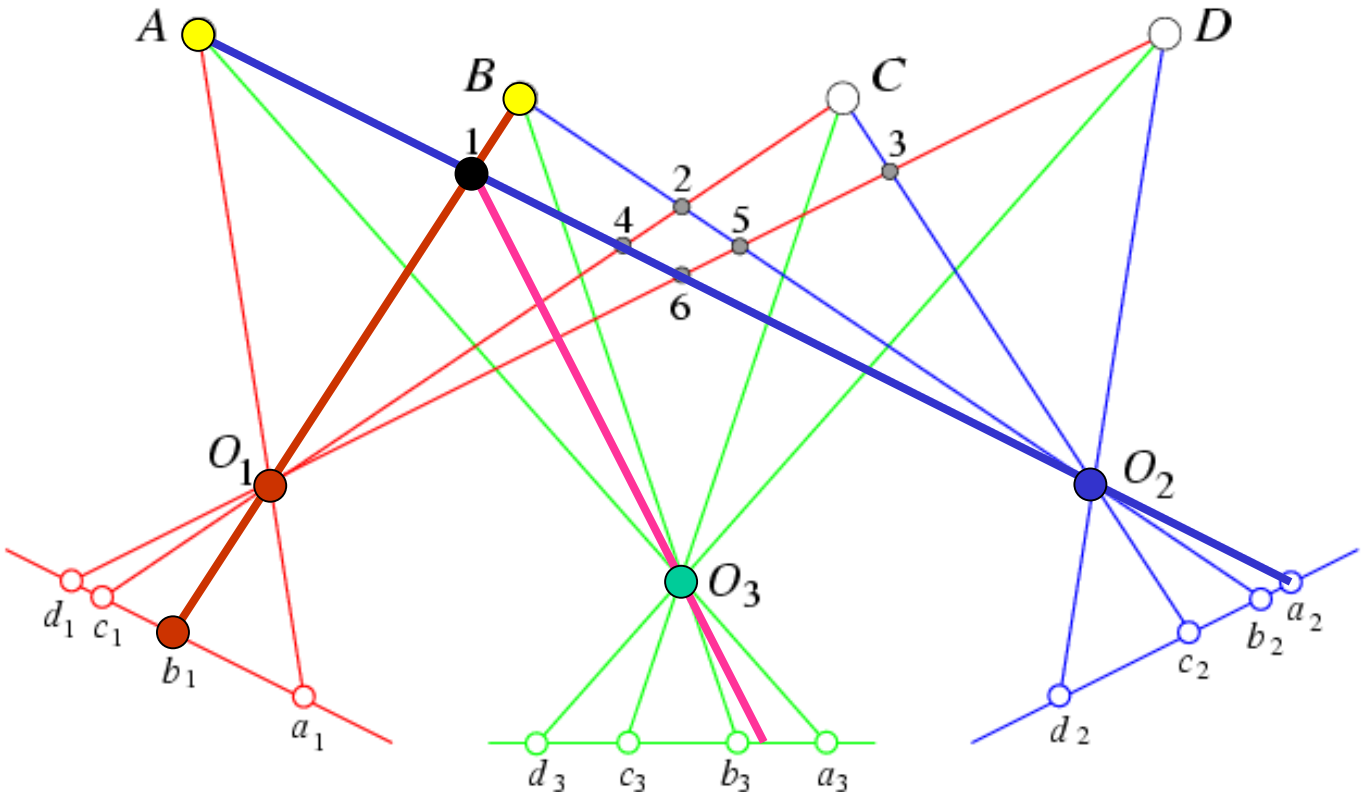
Reconstruction from Rectified Images



Disparity: $d = u' - u$.

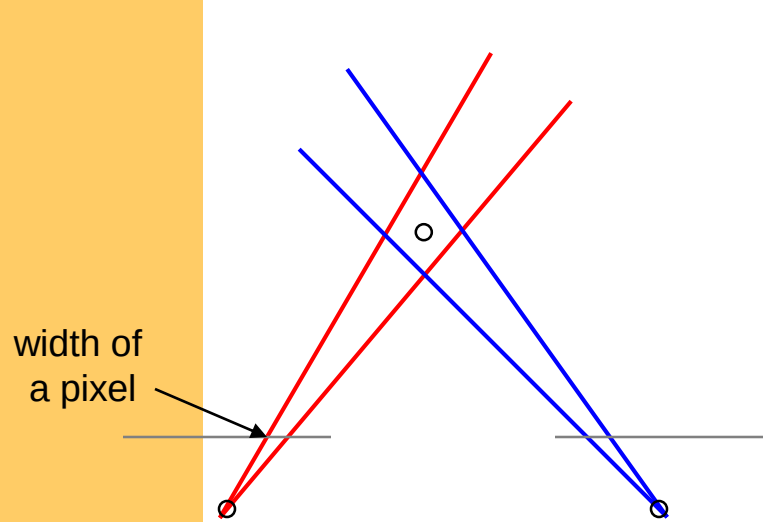
Depth: $z = -B/d$.

Three Views

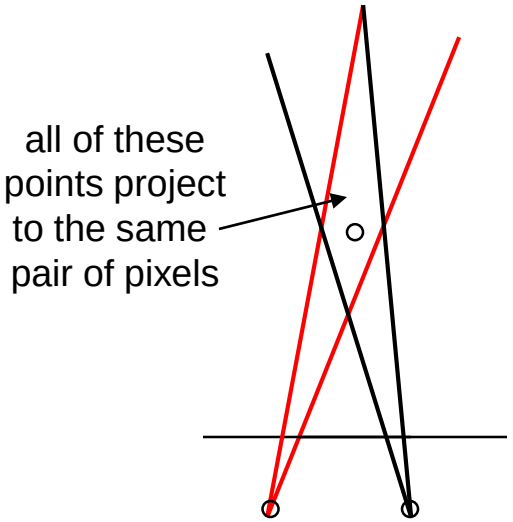


The third eye can be used for verification..

Choosing the stereo baseline



Large Baseline

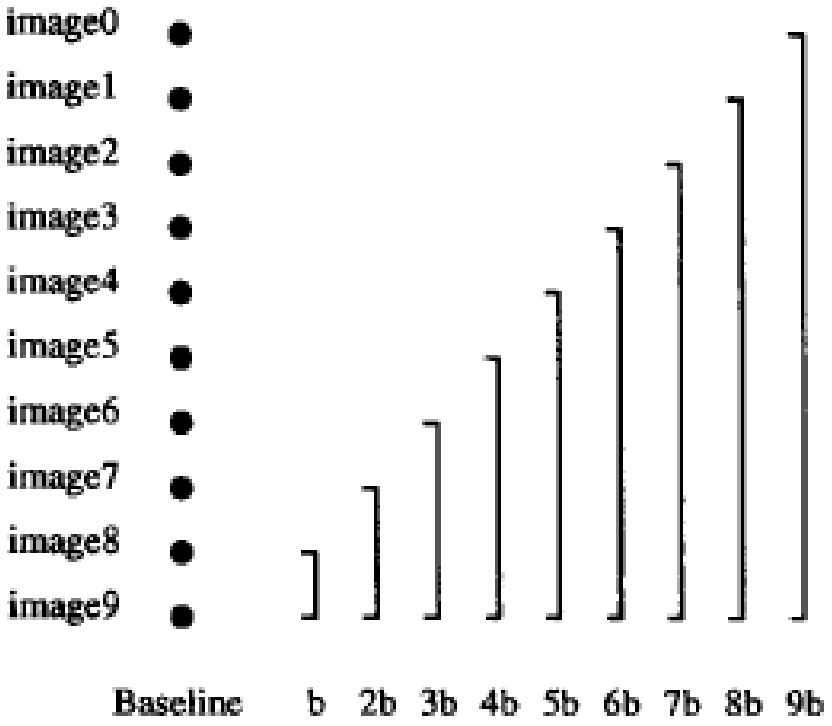


Small Baseline

- What's the optimal baseline?
  - Too small: large depth error
  - Too large: difficult search problem, more occlusions

The Effect of Baseline on Depth Estimation

Figure 2: An example scene. The grid pattern in the background has ambiguity of matching.



(Okutami and Kanade PAMI'93)

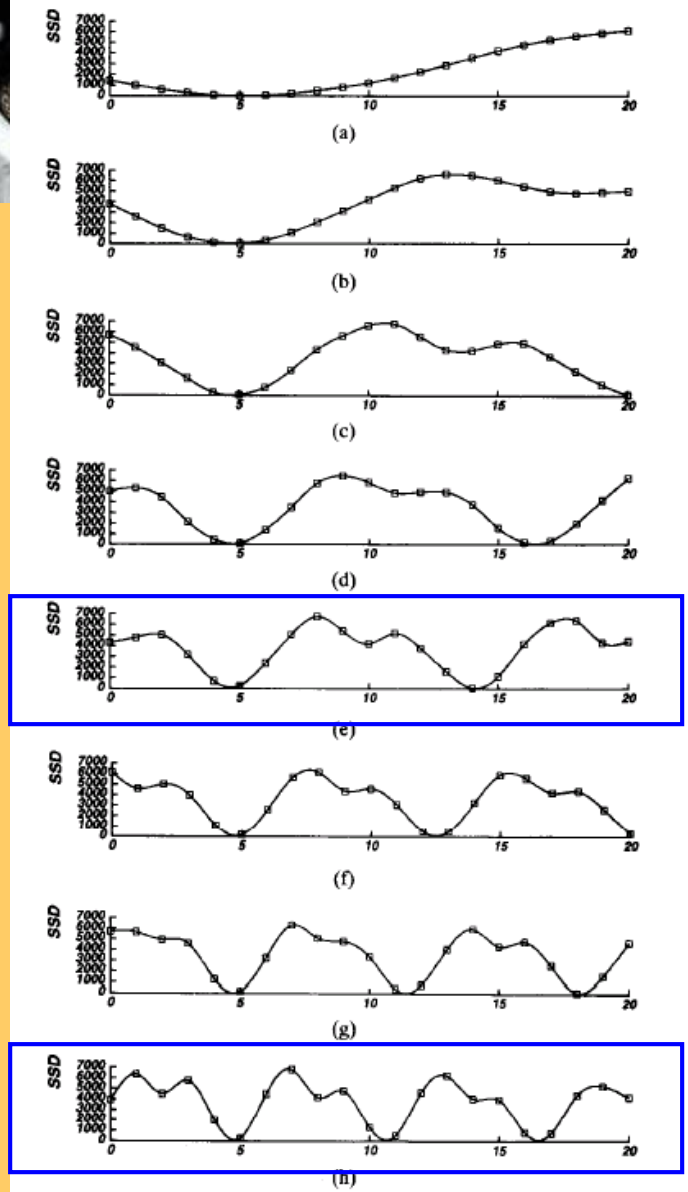


Fig. 5. SSD values versus inverse distance: (a) $B = b$; (b) $B = 2b$; (c) $B = 3b$; (d) $B = 4b$; (e) $B = 5b$; (f) $B = 6b$; (g) $B = 7b$; (h) $B = 8b$. The horizontal axis is normalized such that $8bF = 1$.

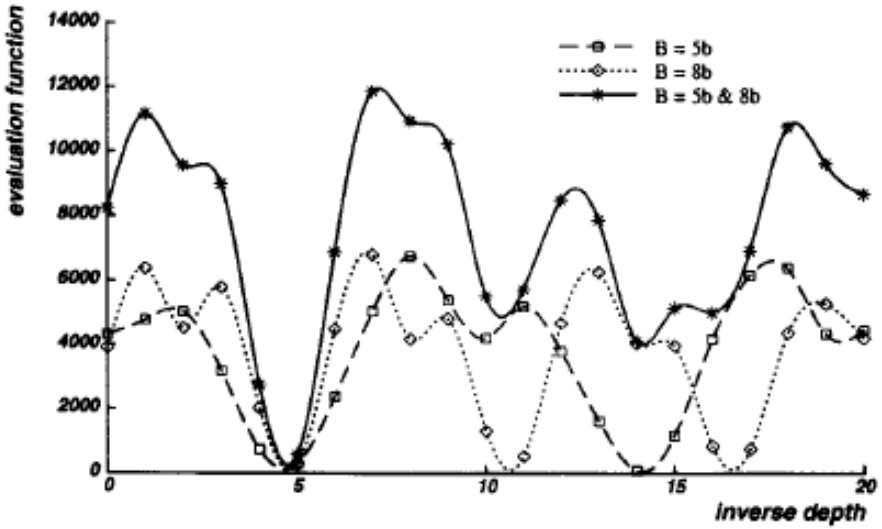


Fig. 6. Combining two stereo pairs with different baselines.

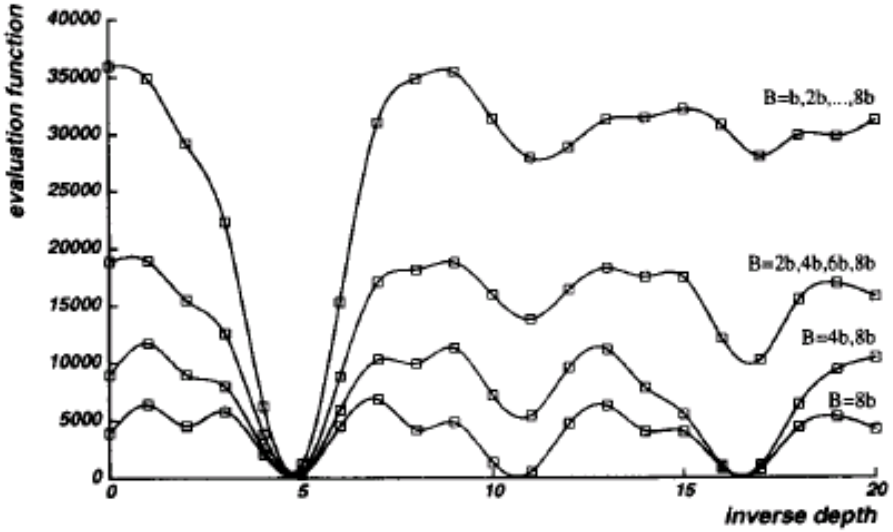
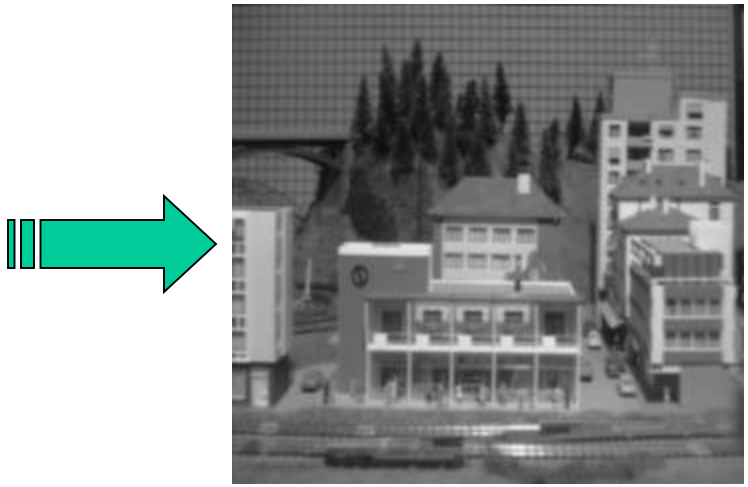


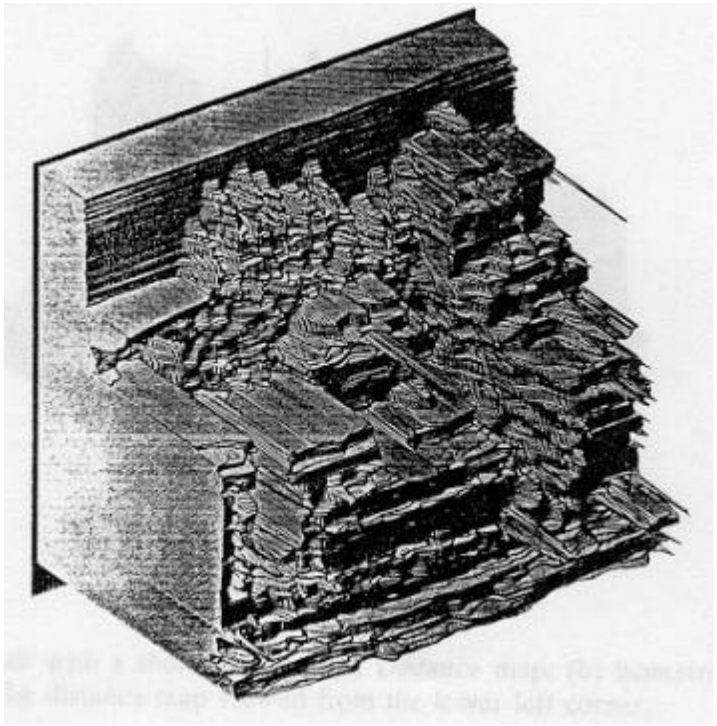
Fig. 7. Combining multiple baseline stereo pairs.

I1

I2



I10



Reprinted from "A Multiple-Baseline Stereo System," by M. Okutami and T. Kanade, IEEE Trans. on Pattern Analysis and Machine Intelligence, 15(4):353-363 (1993). \copyright 1993 IEEE.

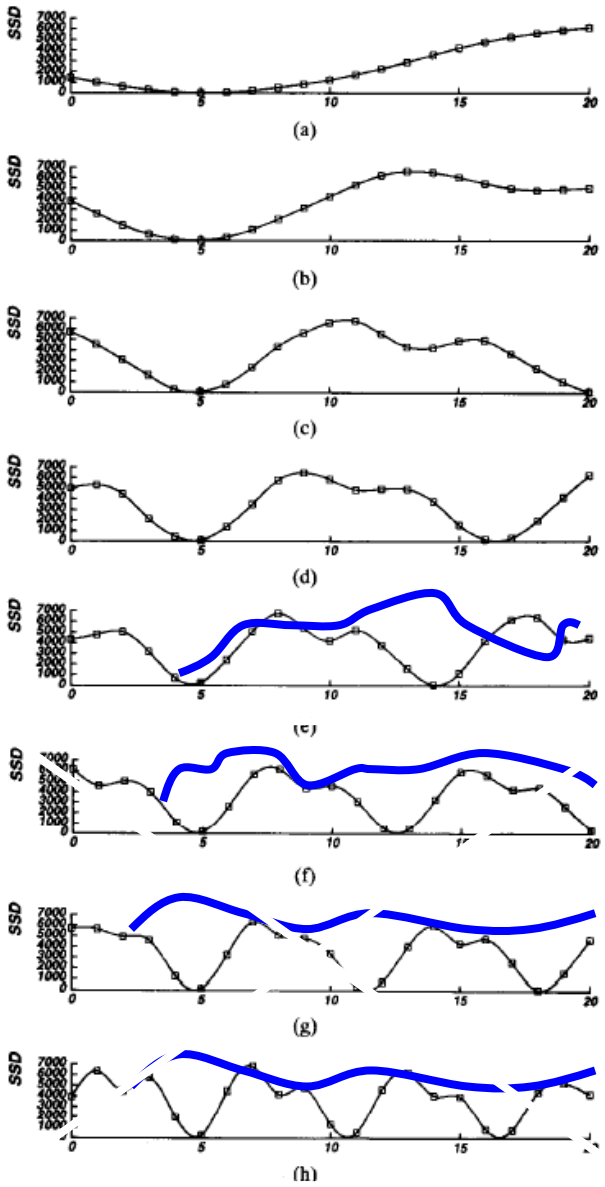


Fig. 5. SSD values versus inverse distance: (a) $B = b$; (b) $B = 2b$; (c) $B = 3b$; (d) $B = 4b$; (e) $B = 5b$; (f) $B = 6b$; (g) $B = 7b$; (h) $B = 8b$. The horizontal axis is normalized such that $8bF = 1$.

Problem: *visibility*

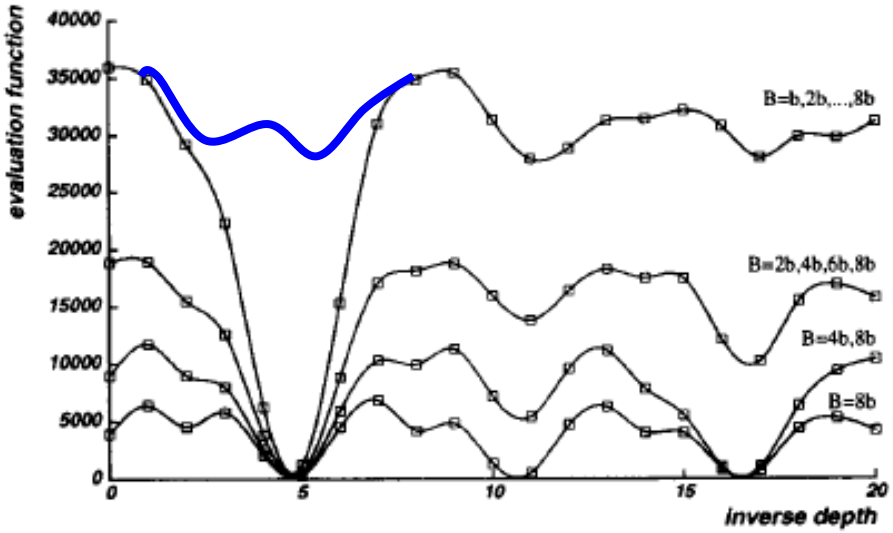


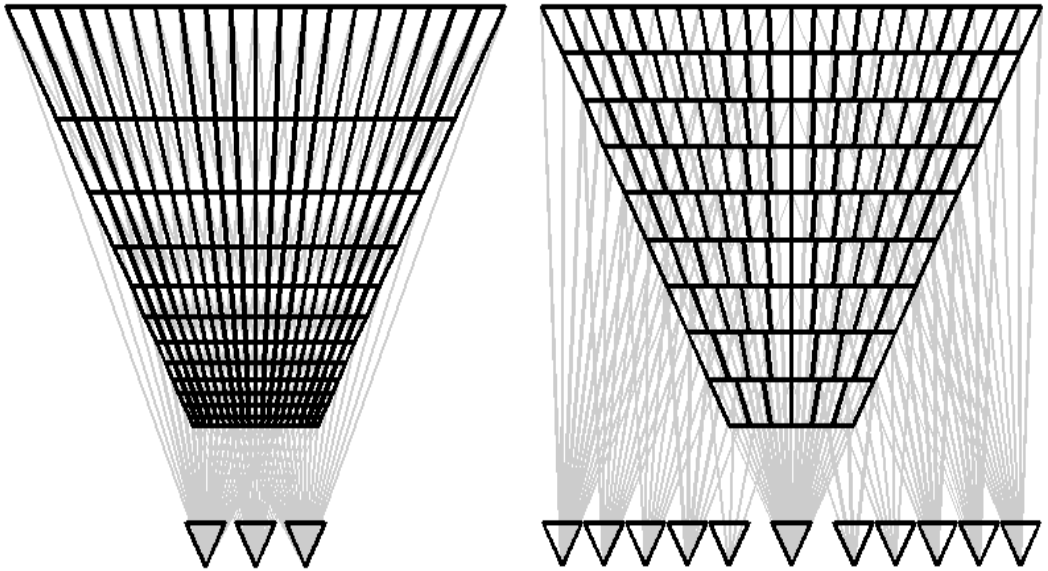
Fig. 7. Combining multiple baseline stereo pairs.

Some Solutions

- Multi-view linking (Koch et al. ECCV98)
- Best of left or right (Kang et al. CVPR01)
- Best *k* out of *n* , ...

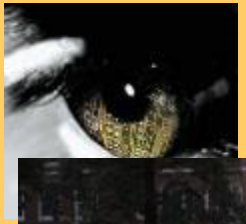
Variable Baseline/Resolution Stereo

(Gallup et al., CVPR08)



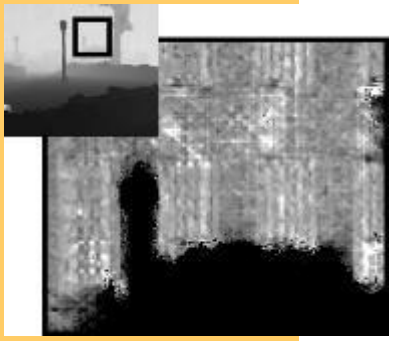
- Multi-baseline, multi-resolution
- At each depth, baseline and resolution selected proportional to that depth
- Allows to keep depth accuracy constant!

Variable Baseline/Resolution Stereo: comparison





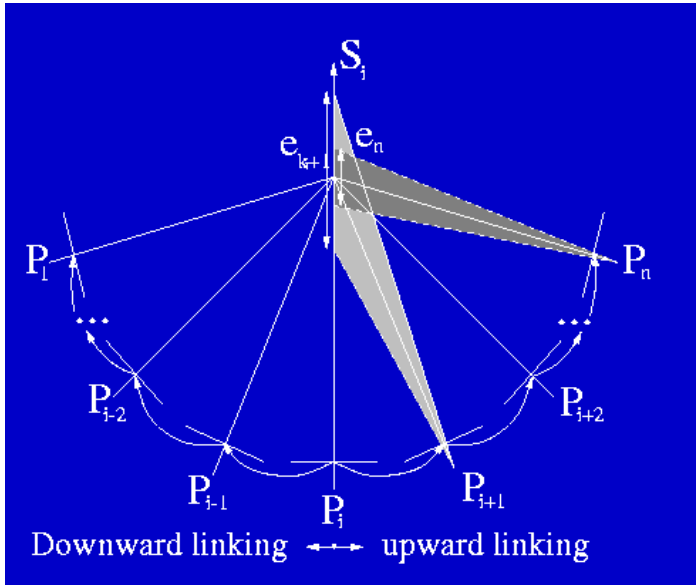


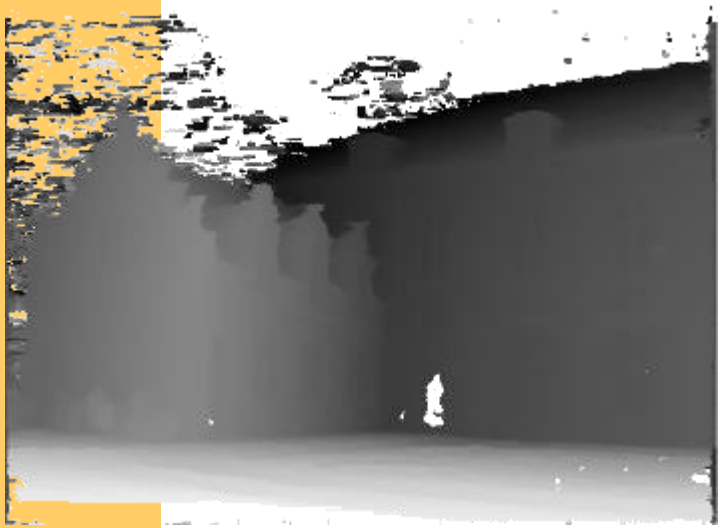



Multi-view depth fusion

(Koch, Pollefeys and Van Gool. ECCV‘98)

- Compute depth for every pixel of reference image
  - Triangulation
  - Use multiple views
  - Up- and down sequence
  - Use Kalman filter



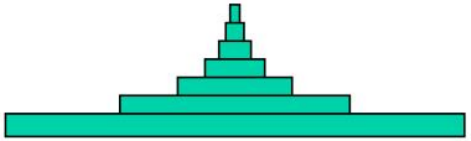


Allows to compute robust texture

Real-time stereo on graphics hardware

Yang and Pollefeys CVPR03

- Computes Sum-of-Square-Differences
- Hardware mip-map generation used to aggregate results over support region
- Trade-off between small and large support window



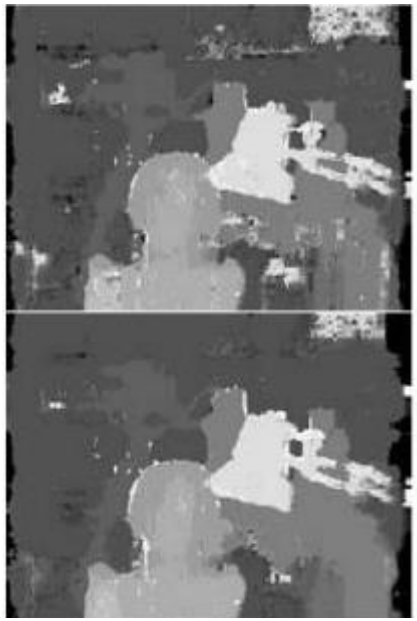
Shape of a kernel
for summing up 6 levels

140M disparity hypothesis/sec on Radeon 9700pro
e.g. 512x512x20disparities at 30Hz

Combine multiple aggregation windows using hardware mipmap and multiple texture units in single pass

(1x1)

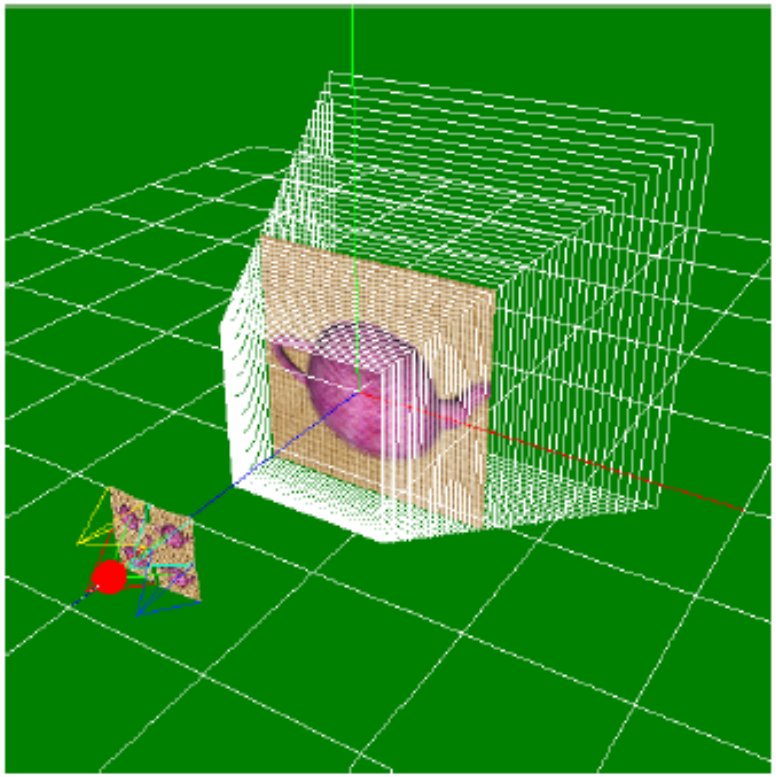
(1x1+2x2)



(1x1+2x2 +4x4+8x8)

(1x1+2x2 +4x4+8x8 +16x16)

Plane-sweep multi-view matching



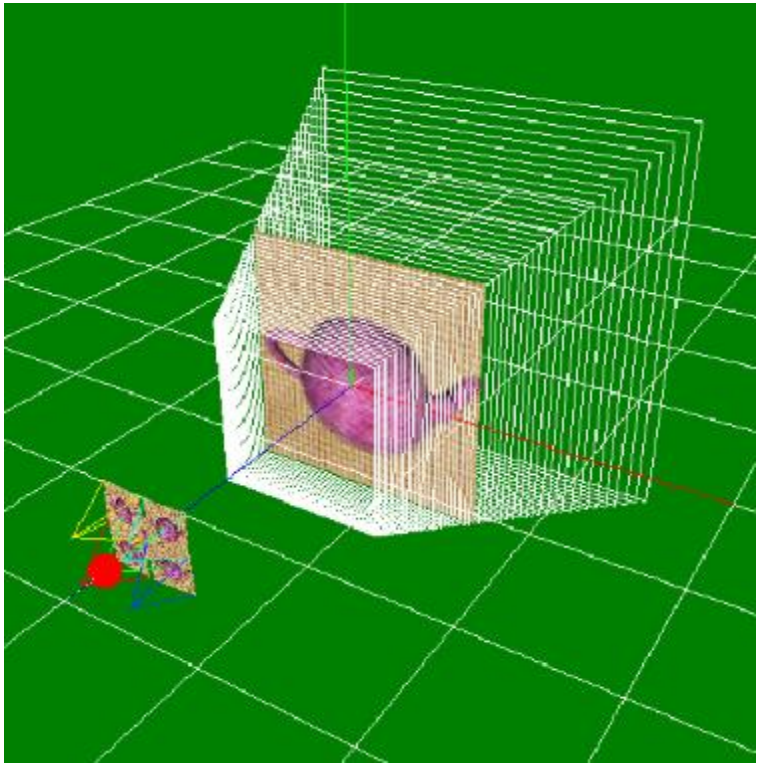
- Simple algorithm for multiple cameras
- no rectification necessary
- doesn't deal with occlusions

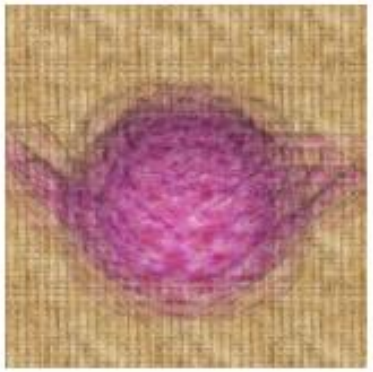
Collins' 96; Roy and Cox' 98 (GC); Yang et al.' 02/' 03 (GPU)

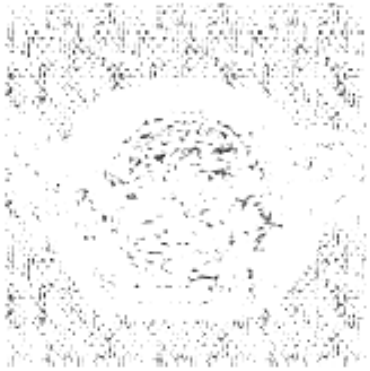
Fast GPU-based plane-sweeping stereo

Plane-sweep multi-view depth estimation

(Yang & Pollefeys, CVPR' 03)

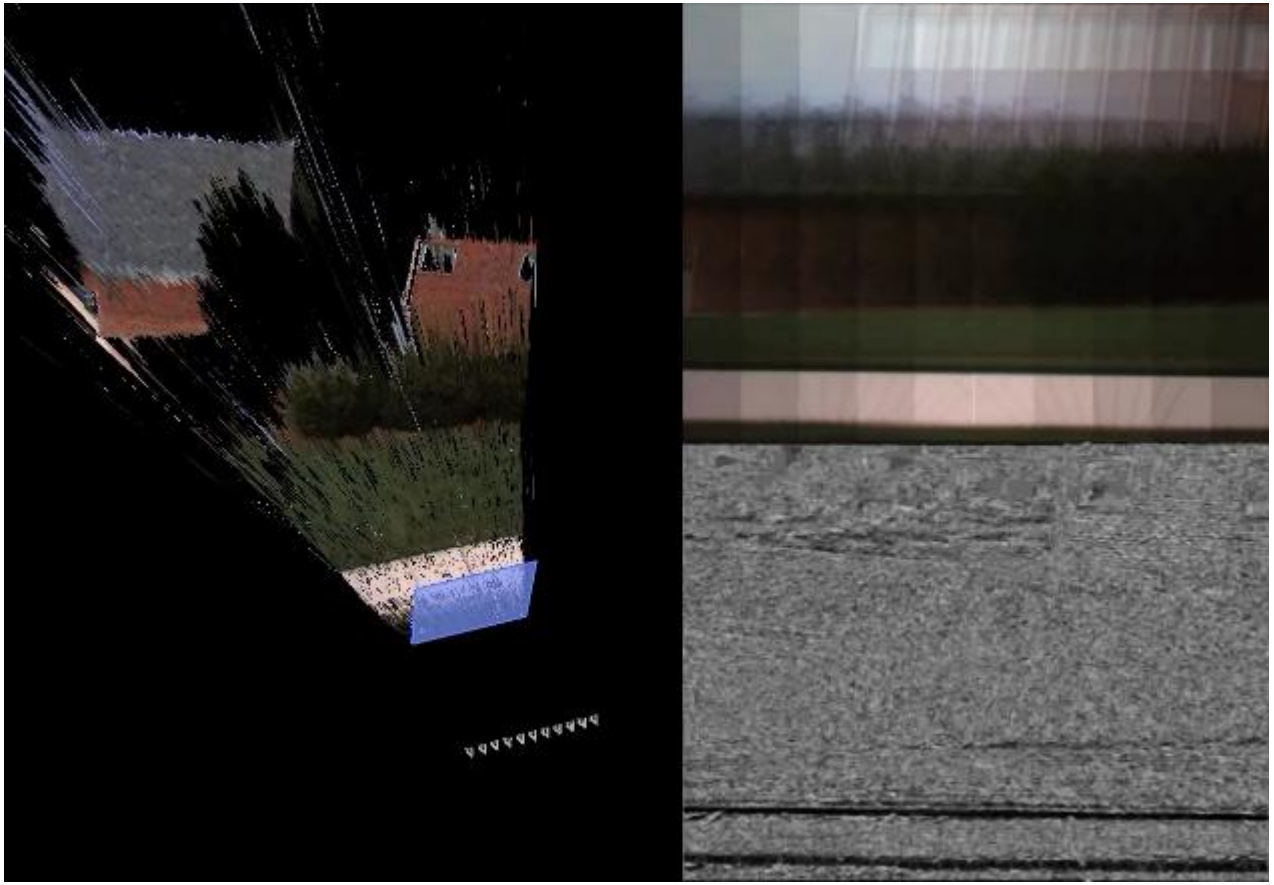






Plane Sweep Stereo

Images Projected on Plane



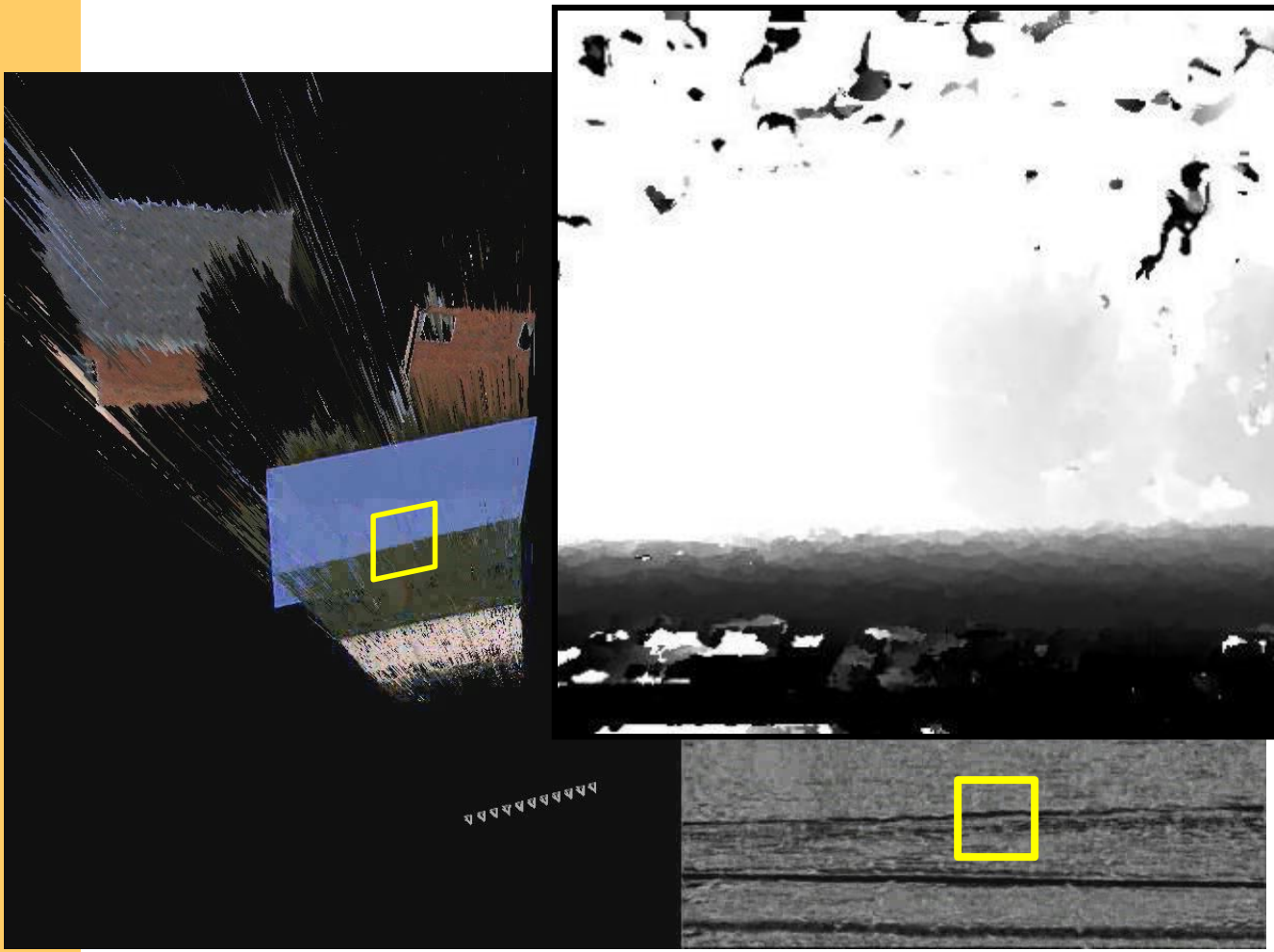
Plane Sweep

Matching Score

Plane Sweep Stereo Result

- Ideal for GPU processing
- 512x384 depthmap, 50 planes, 5 images: 50 Hz

Plane Sweep Stereo

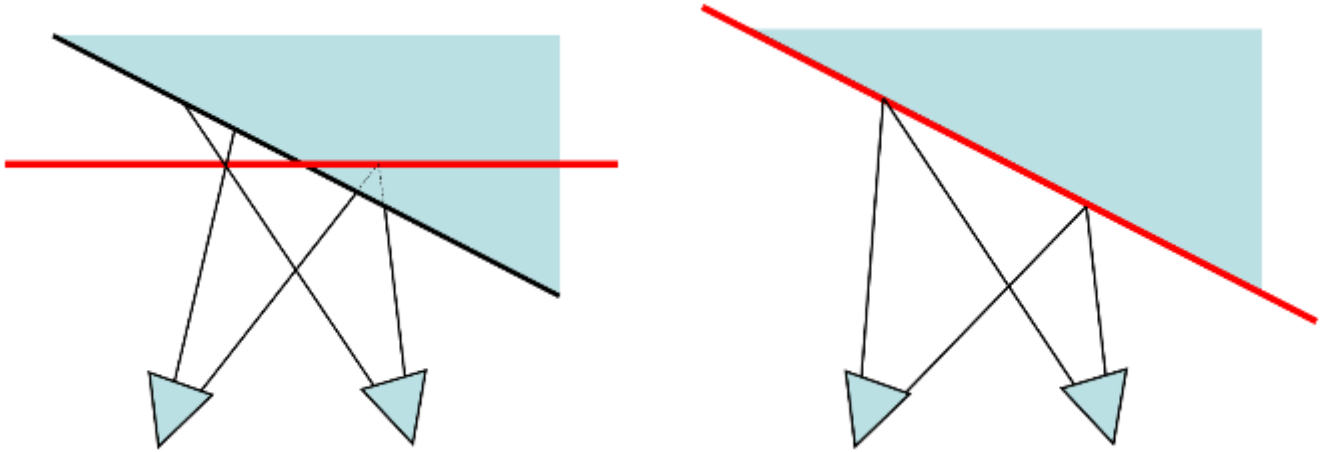


Plane Sweep

Matching Score (SAD)

Window-Based Matching - Local Stereo

- Pixel-to-pixel matching is ambiguous for local stereo
- Use a matching window (SAD/SSD/NCC)

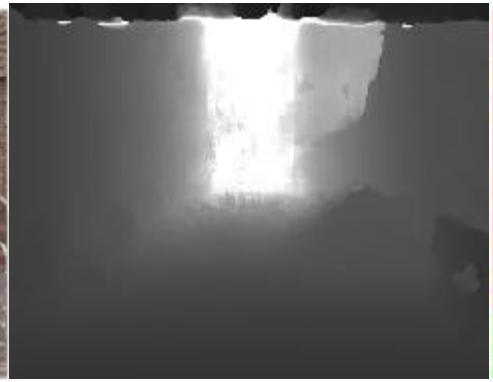
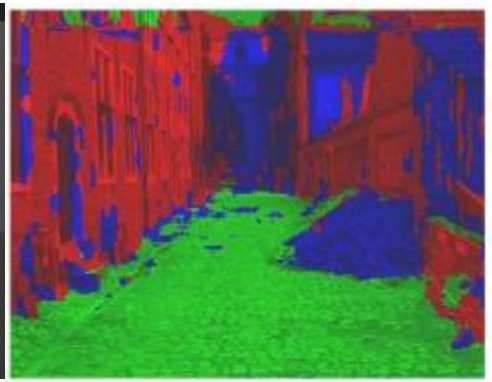
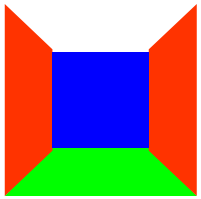


- Assumes all pixels in window are on the plane

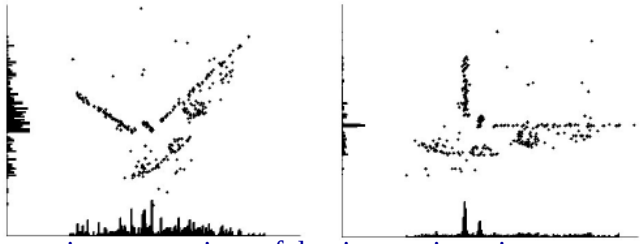
Multi-directional plane-sweeping stereo

(Gallup, Frahm & Pollefeys, CVPR07)

- Select best-cost over depths AND orientation

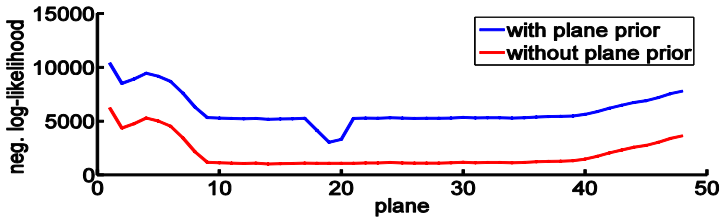
3D model from
11 video frames
(hand-held)



Automatic computations of dominant orientations

Plane Priors and Quicksweep

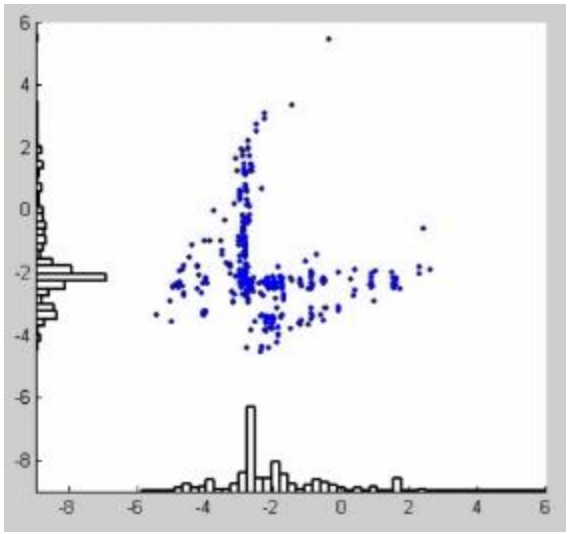
Use SfM points as a prior for stereo



$$P(\pi_i \mid c_i) \propto P(c_i \mid \pi_i) P(\pi_i)$$

without plane prior

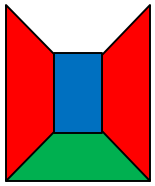
with plane prior

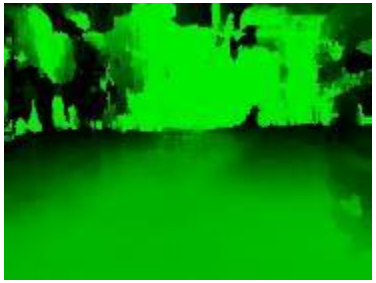


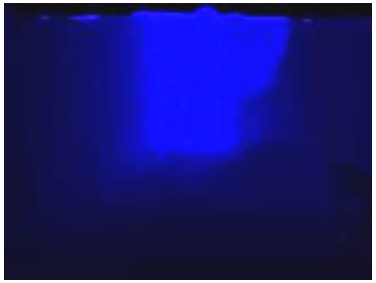
For real-time:
test only the planes with high prior probability

Selecting Best Depth / Surface Normal

- Combining multiple sweeps

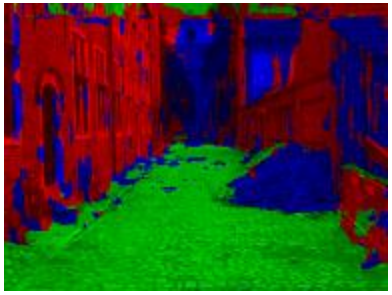




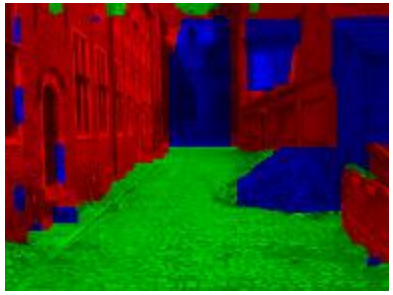


Sweep 1 Sweep 2 Sweep 3

How to combine sweeps?



OR



Graph Cut:
1-2 seconds

Continuous
Formulation: 45 ms

Local best cost

Global labeling

(Zach, Gallup, Frahm, Niethammer VMV 2008)

Results

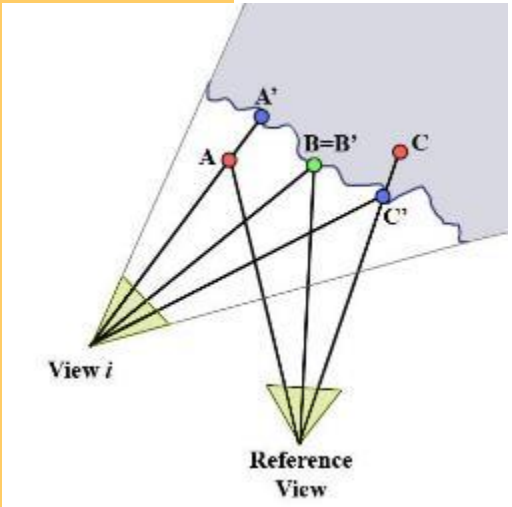
1474 frame reconstruction, 11 images in stereo,
512x384 grayscale, 48 plane hypotheses (quick sweep),
processing rate 20.0 Hz (Nvidia 8800 GTX)

Fast visibility-based fusion of depth-maps

(Merrell , Akbarzadeh, Wang, Mordohai, Frahm, Yang, Nister, Pollefeys ICCV07)

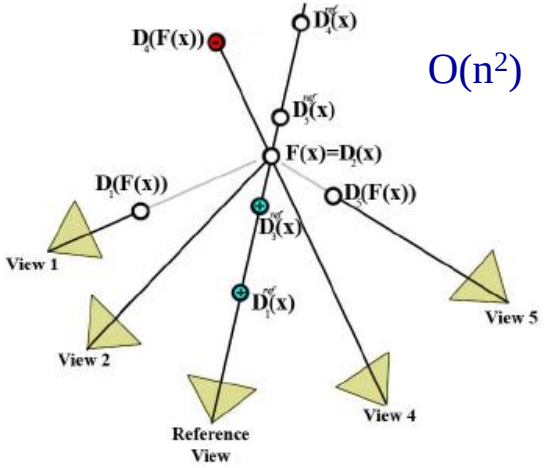
- Complements very fast multi-view stereo

visibility constraints



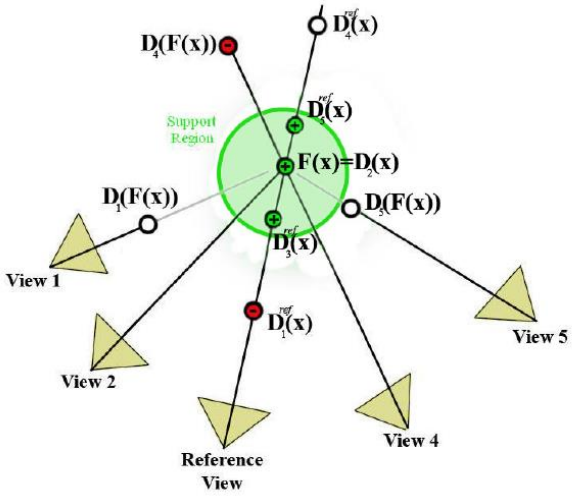
Two fusion approaches

stability-based fusion



$O(n^2)$

confidence-based fusion

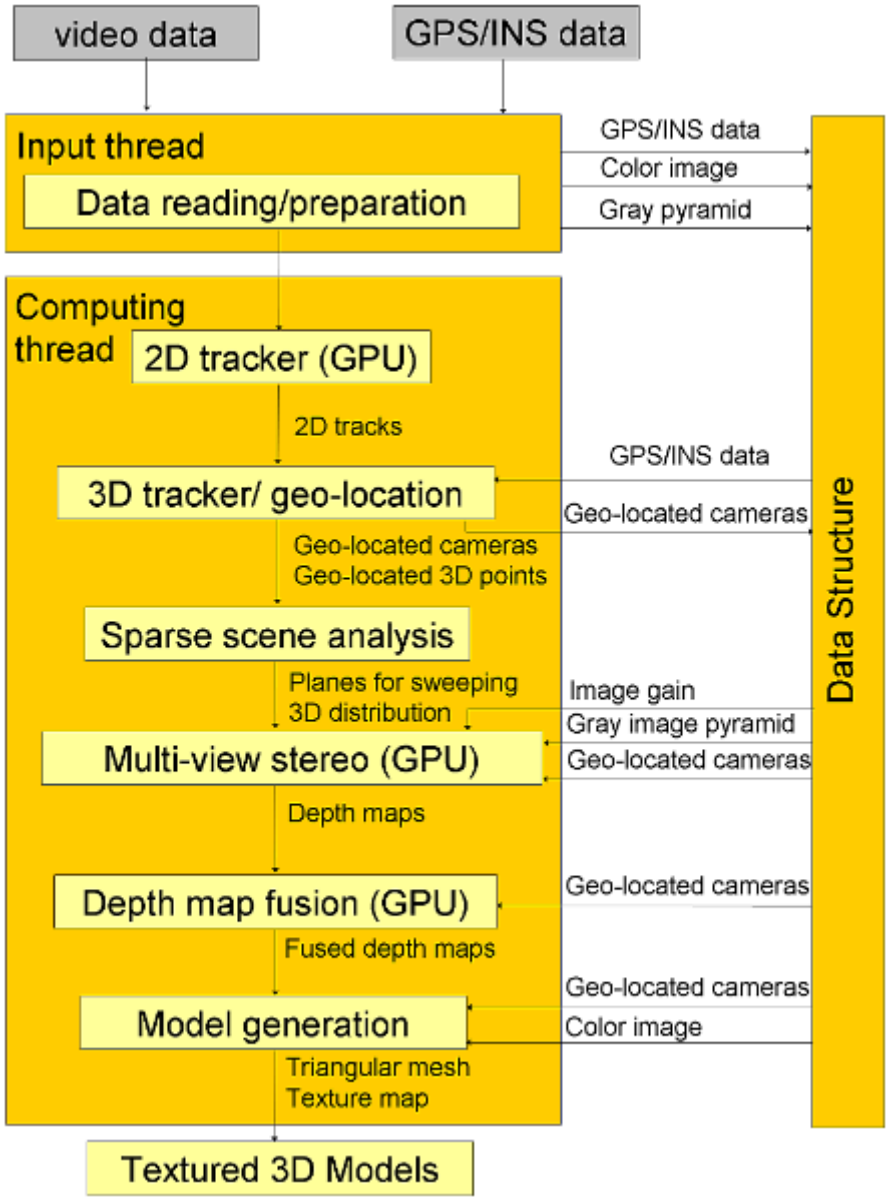


Fast on GPU as key operation is rendering depth-maps into other views

Fast video-based modeling of cities

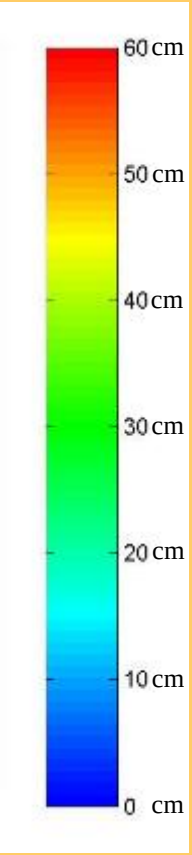
- **Fast video processing pipeline**
- - up to 26Hz on single CPU/GPU
- - Most image processing on GPU
- (x10-x100 faster)
- - Exploits urban structure
- - Generates textured 3D mesh

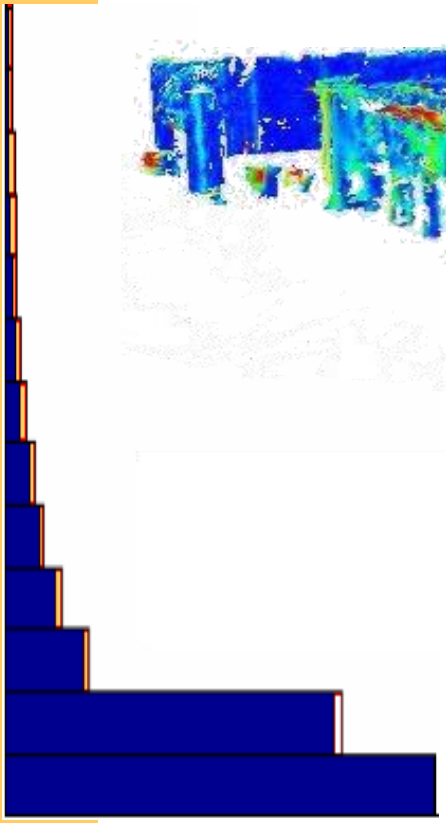
(Pollefeys et al. IJCV, 2008)



3D-from-video evaluation: Firestone building

building surveyed to 6mm





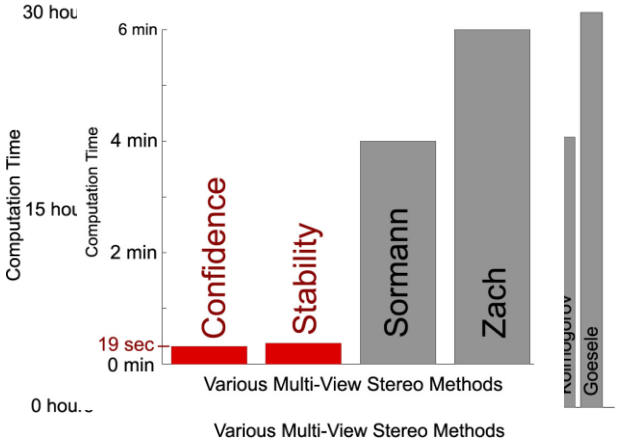
error histogram

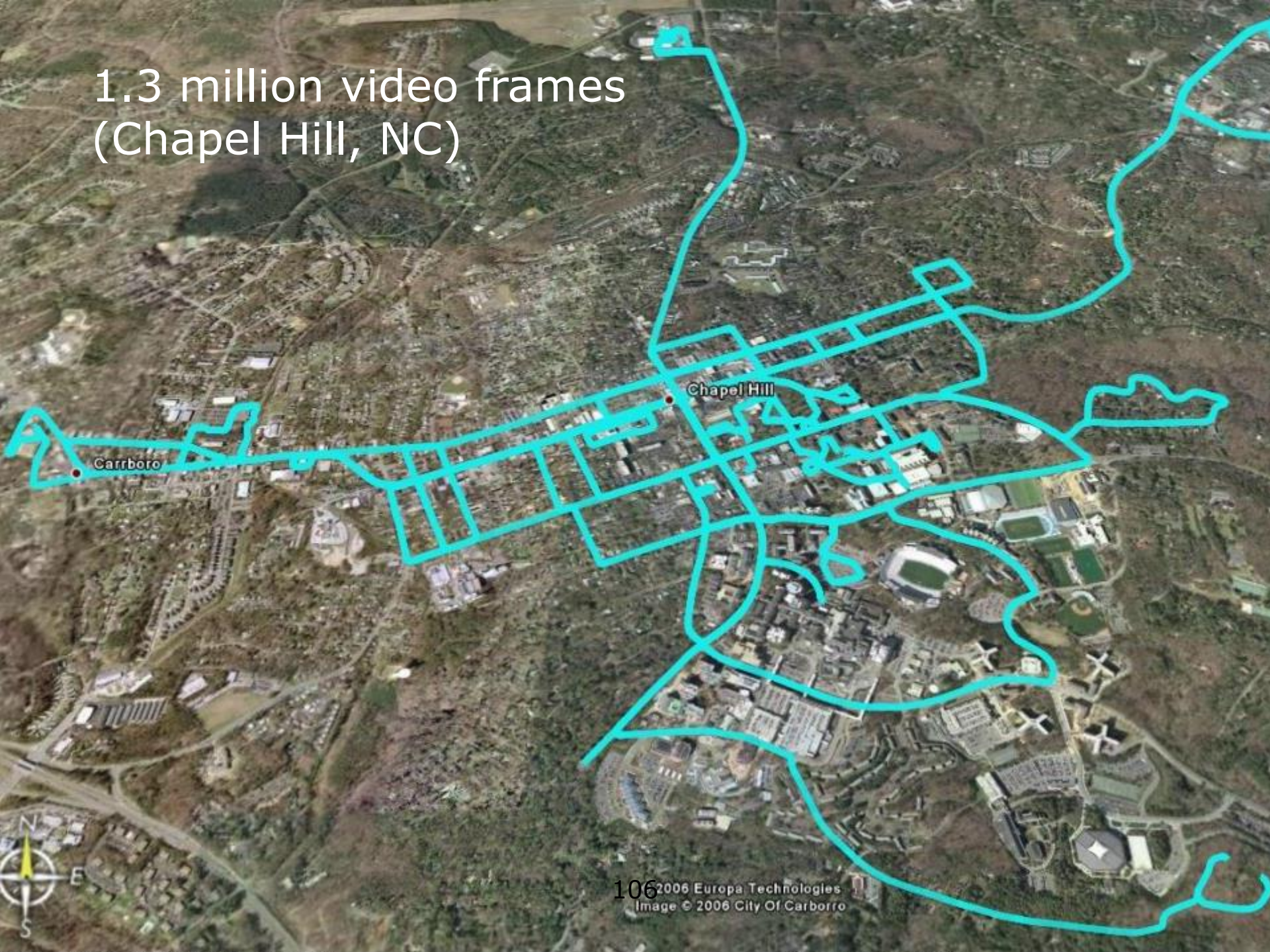
RMS error: 13.4cm
mean error: 6.8cm
median error: 3.0cm

3D-from-video evaluation: Middlebury Multi-View Stereo Evaluation Benchmark

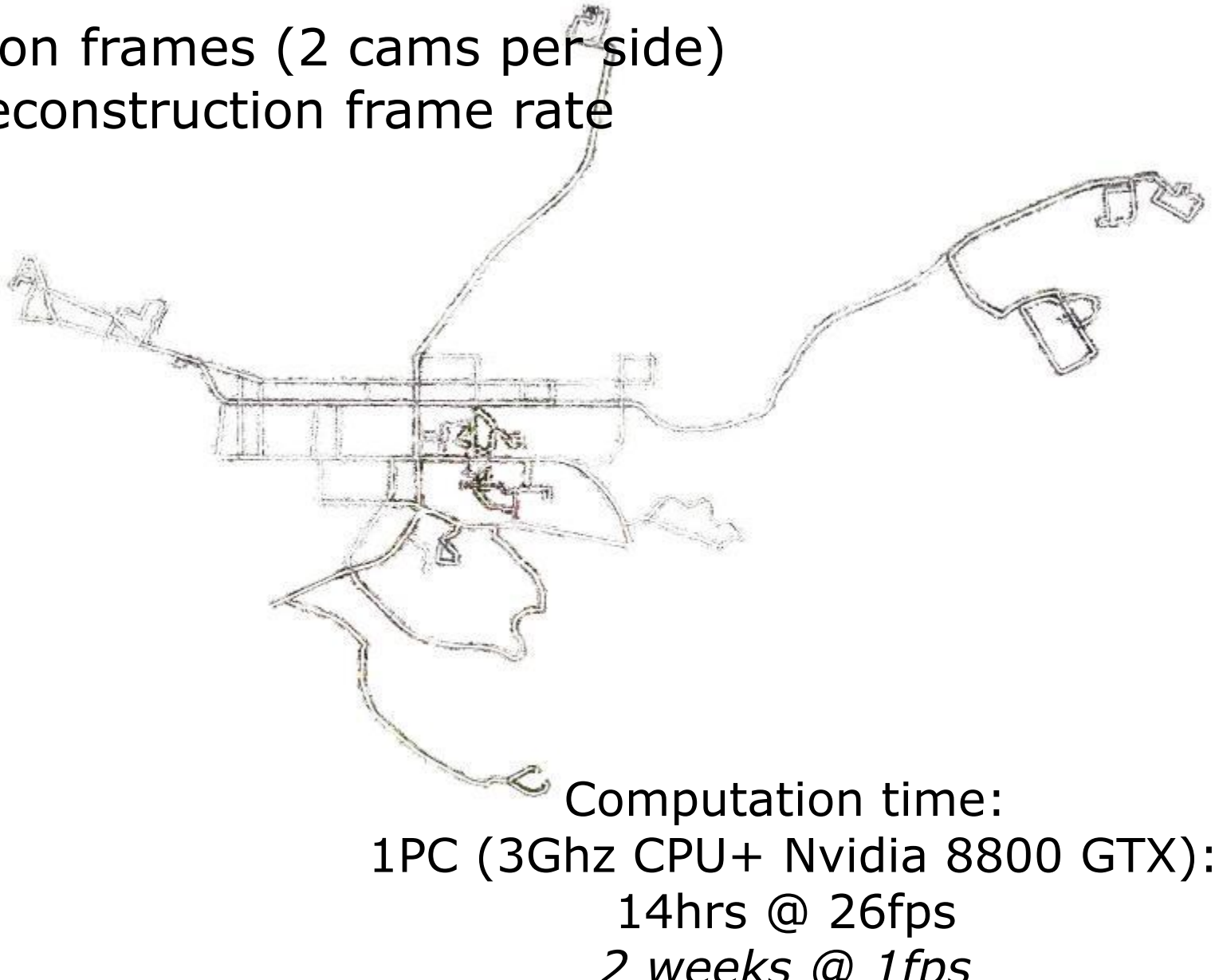
Ring datasets: 47 images

Results competitive
but much, much faster
(30 minutes → 30 seconds)




1.3 million video frames
(Chapel Hill, NC)
Chapel Hill
Carrboro
N
E
S
©2006 Europa Technologies
Image © 2006 City Of Carborro

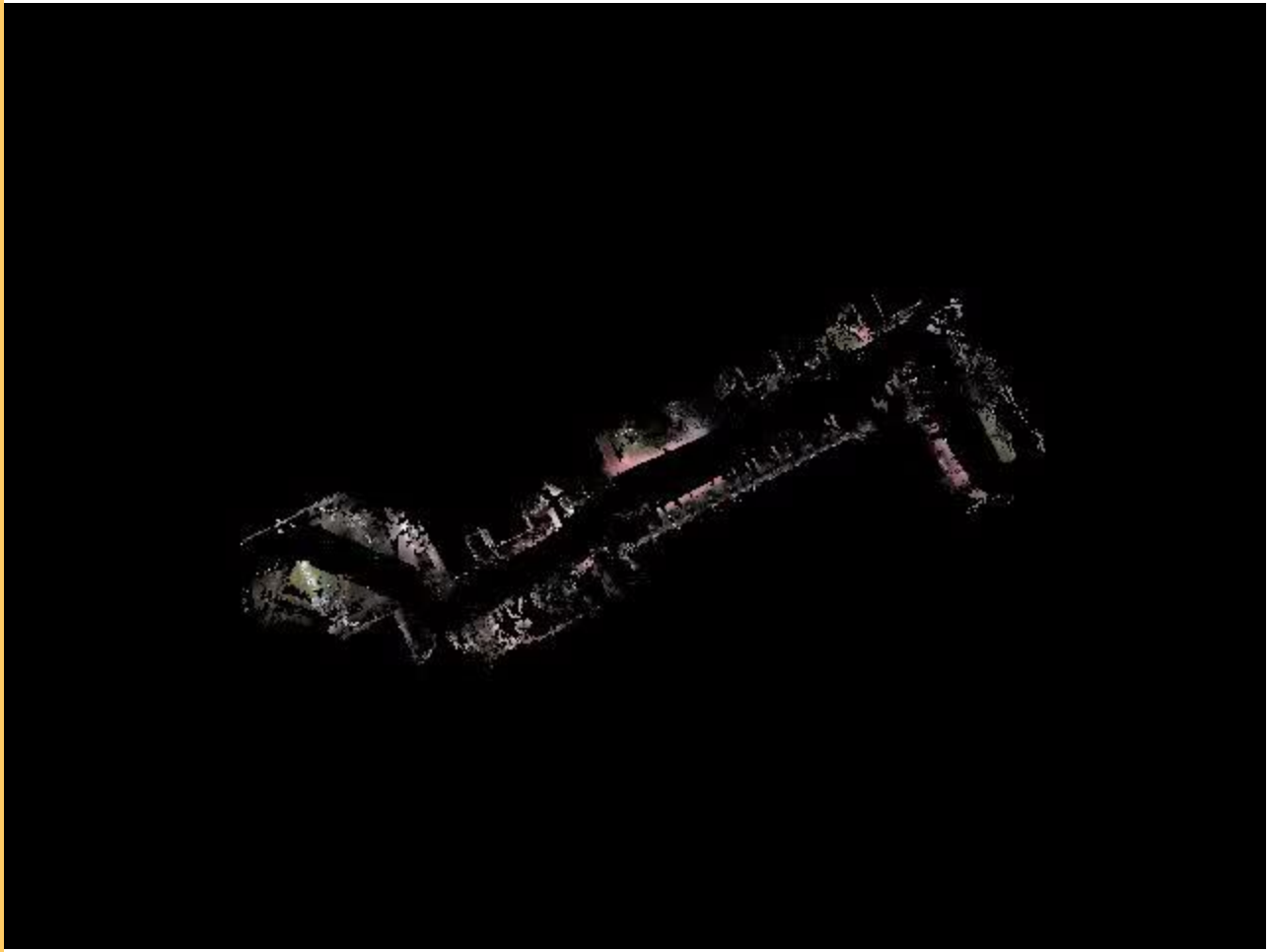
- 1.3 million frames (2 cams per side)
- 26 Hz reconstruction frame rate



Computation time:
1PC (3Ghz CPU+ Nvidia 8800 GTX):
14hrs @ 26fps
2 weeks @ 1fps
2.5 years @ 1fpm

- 1.3 million frames (2 cams per side)
- 26 H

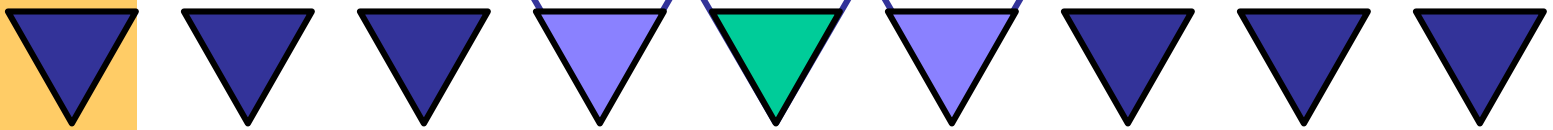
1PC (3Ghz CPU+ Nvidia 8800 GTX):
14hrs @ 26fps



Another Scene

view 1 . . . . . view N

Depthmap



view 1 . . . reference view . . . view N

3D Model: Standard Stereo

3D Model: Standard Stereo

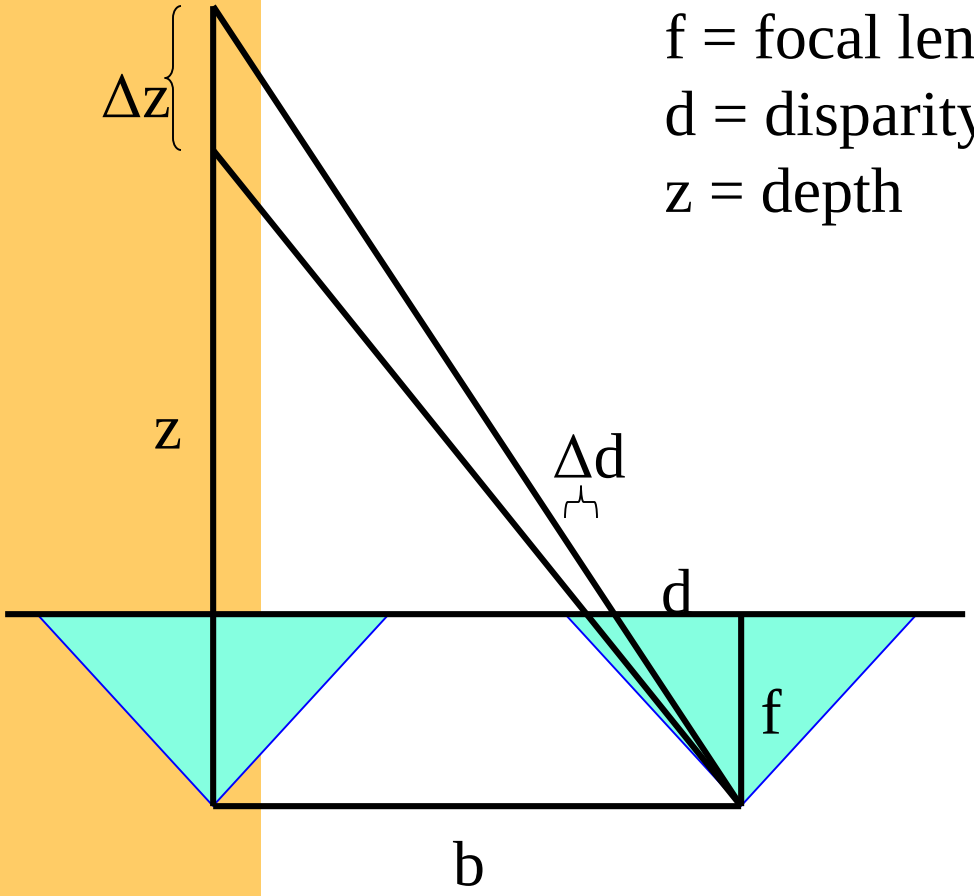
3D Model: Standard Stereo

3D Model: Standard Stereo

How Accurate Is Stereo?

b = baseline
f = focal length
d = disparity
z = depth

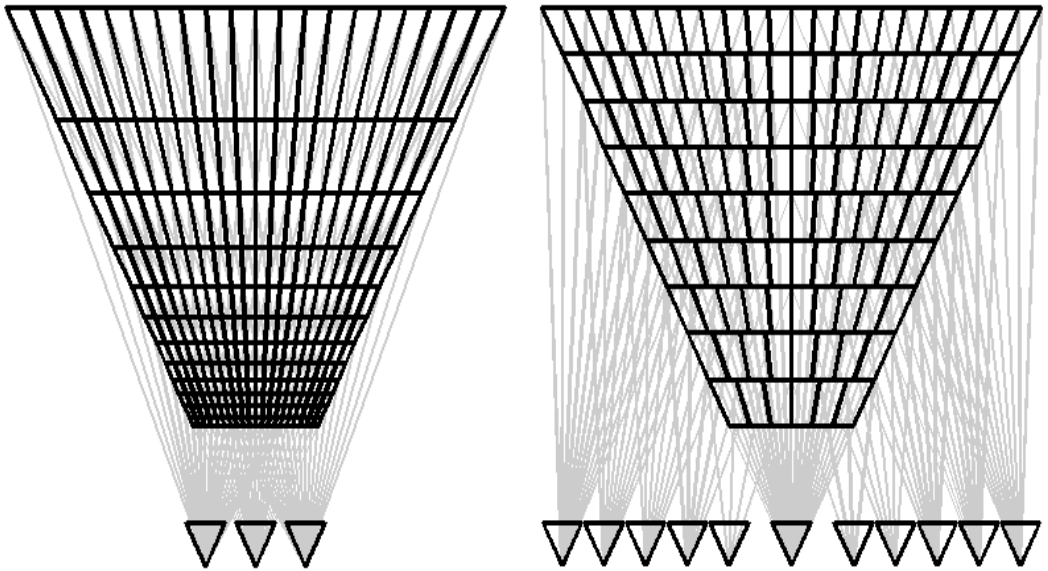
$$z = -\frac{bf}{d}$$



$$\Delta z \approx z' \Delta d = \frac{bf}{d^2} \Delta d$$

$$\Delta z \approx \frac{z^2}{bf} \Delta d$$

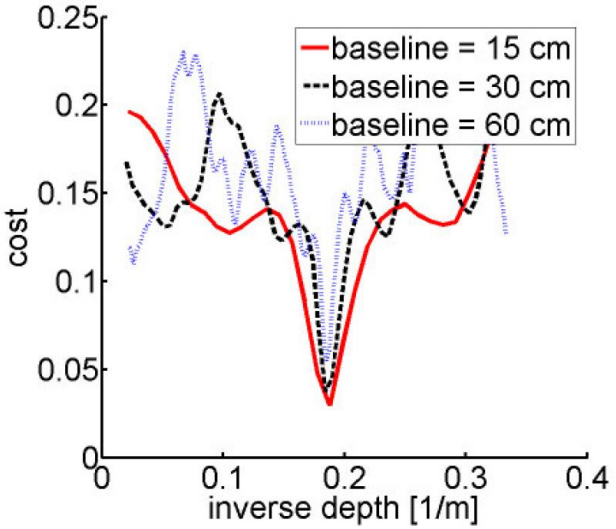
Variable Baseline/Resolution Stereo (Gallup et al., CVPR08

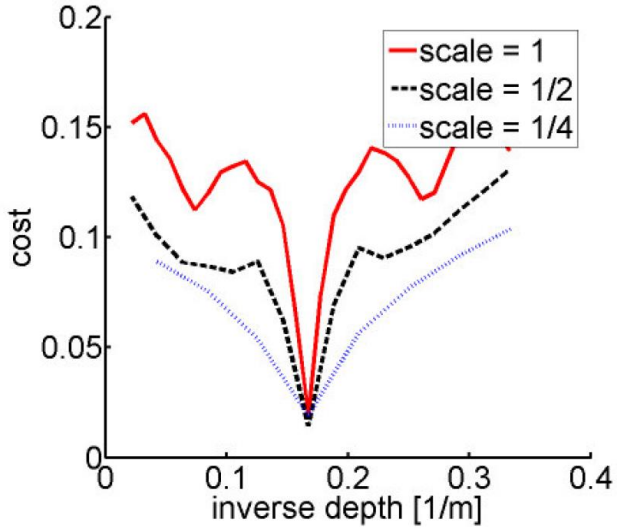


- Multi-baseline, multi-resolution
- At each depth, baseline and resolution selected proportional to that depth
- Allows to keep depth accuracy constant!

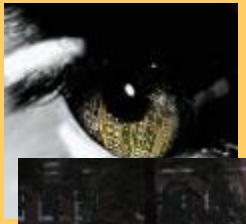
Verification of consistent results

- Analysis of matching scores at various baselines and scales
  - Location of global minimum unchanged
  - Value of global minimum preserved



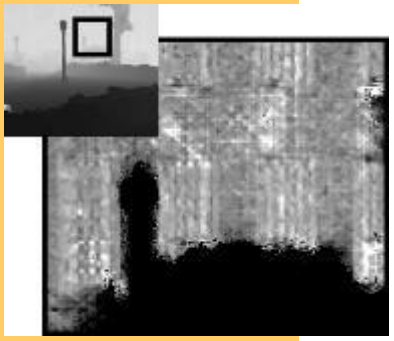


Variable Baseline/Resolution Stereo: comparison

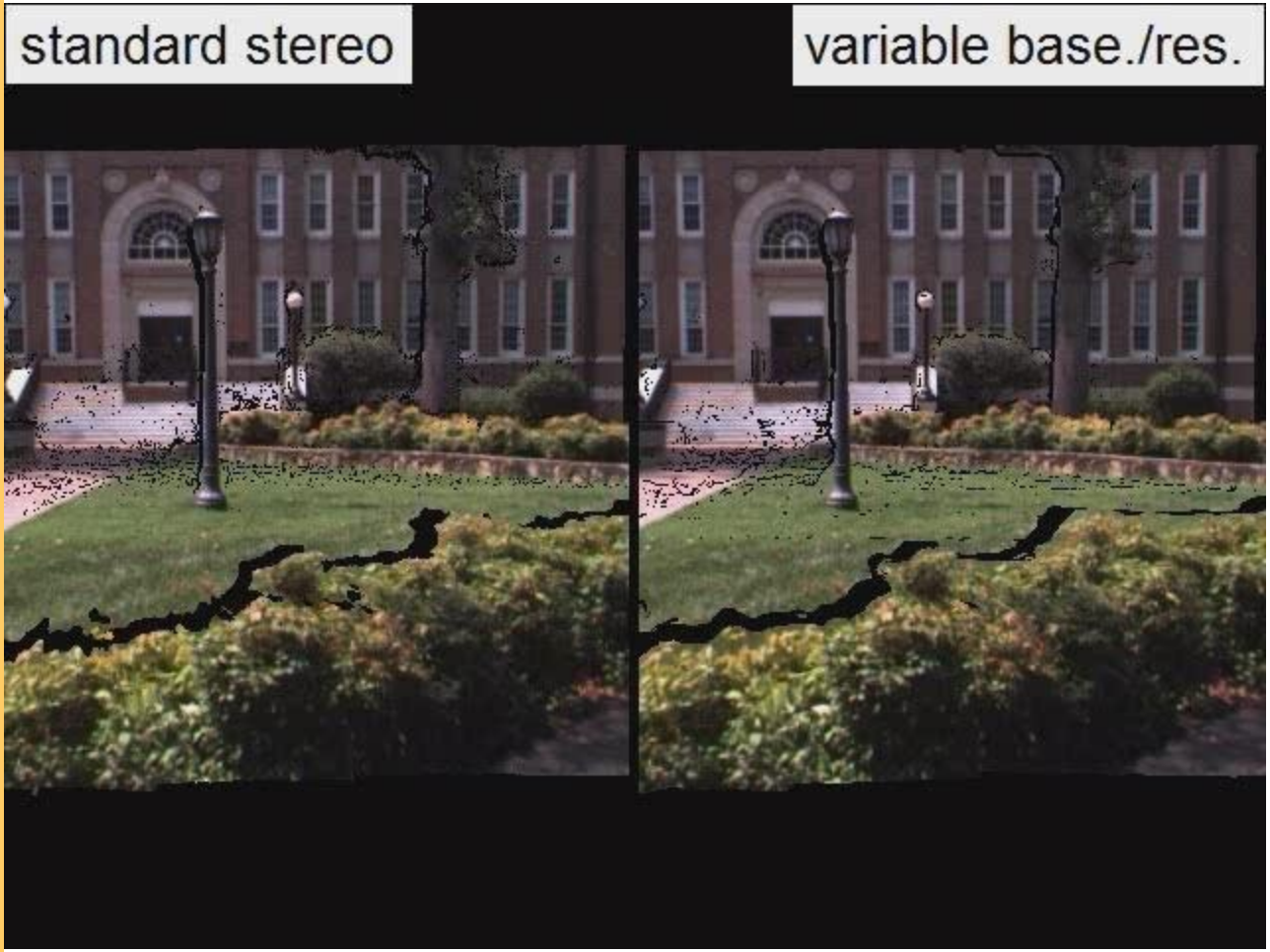









Results



Depth Resolution Limits

Piecewise Planar Stereo

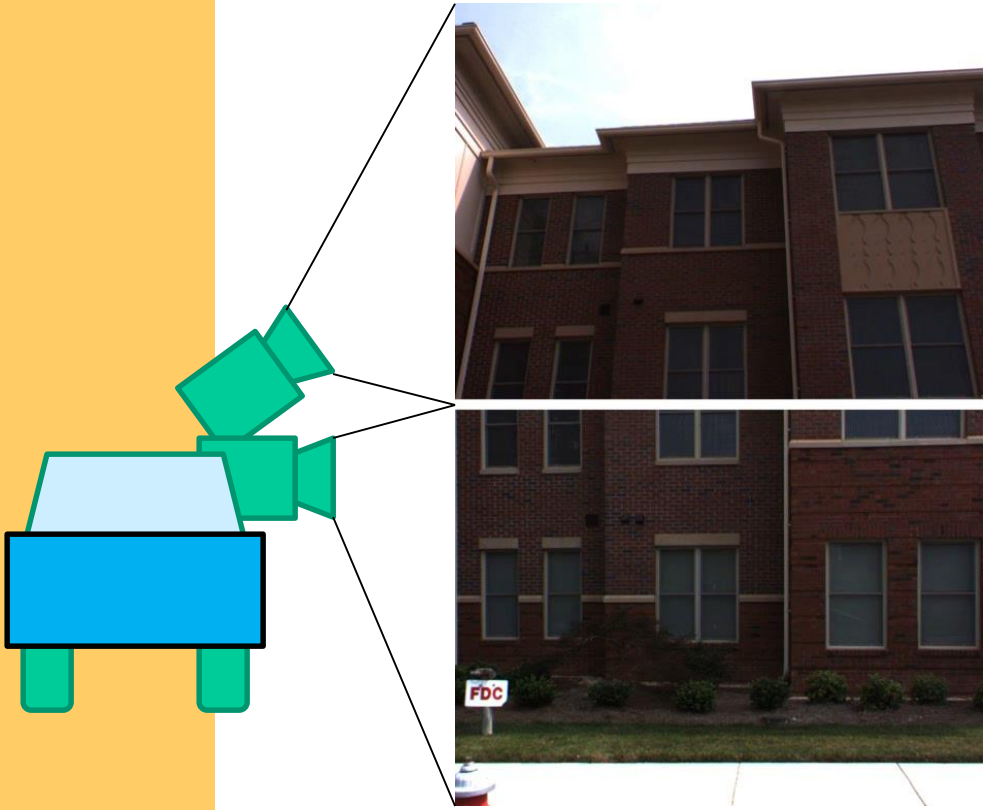
- Fit planes to scene
- But also handle non-planar regions
- Use planar appearance
- Ensure consistency over video sequences

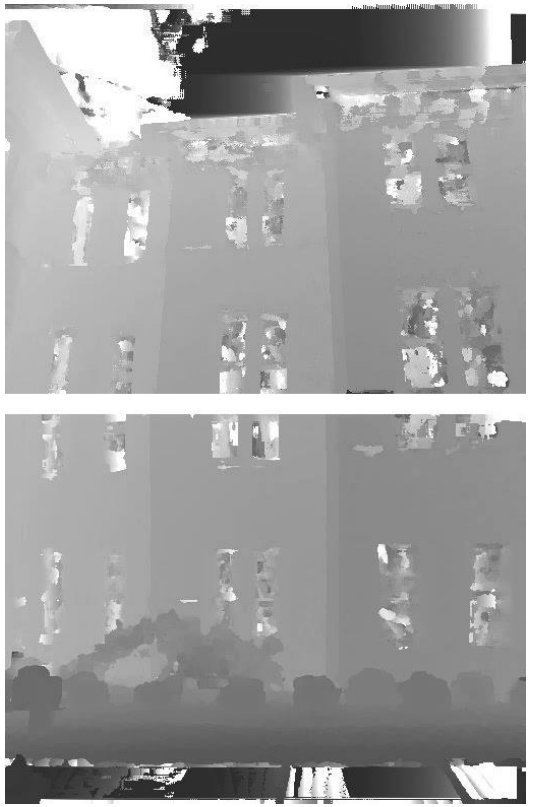


3D Reconstruction from Video

Street-Side Video

Real-Time Stereo

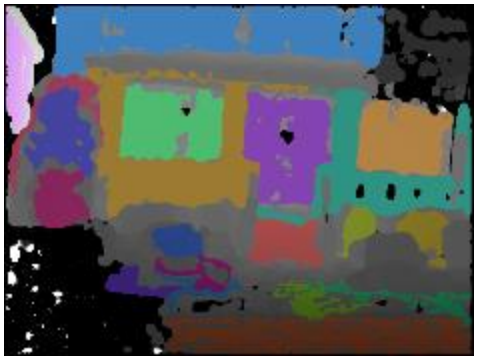




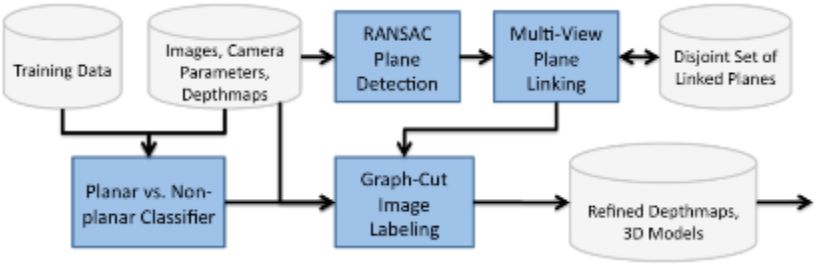
Method

(Gallup et al. CVPR 2010)

Video Frame



Depthmap with RANSAC planes

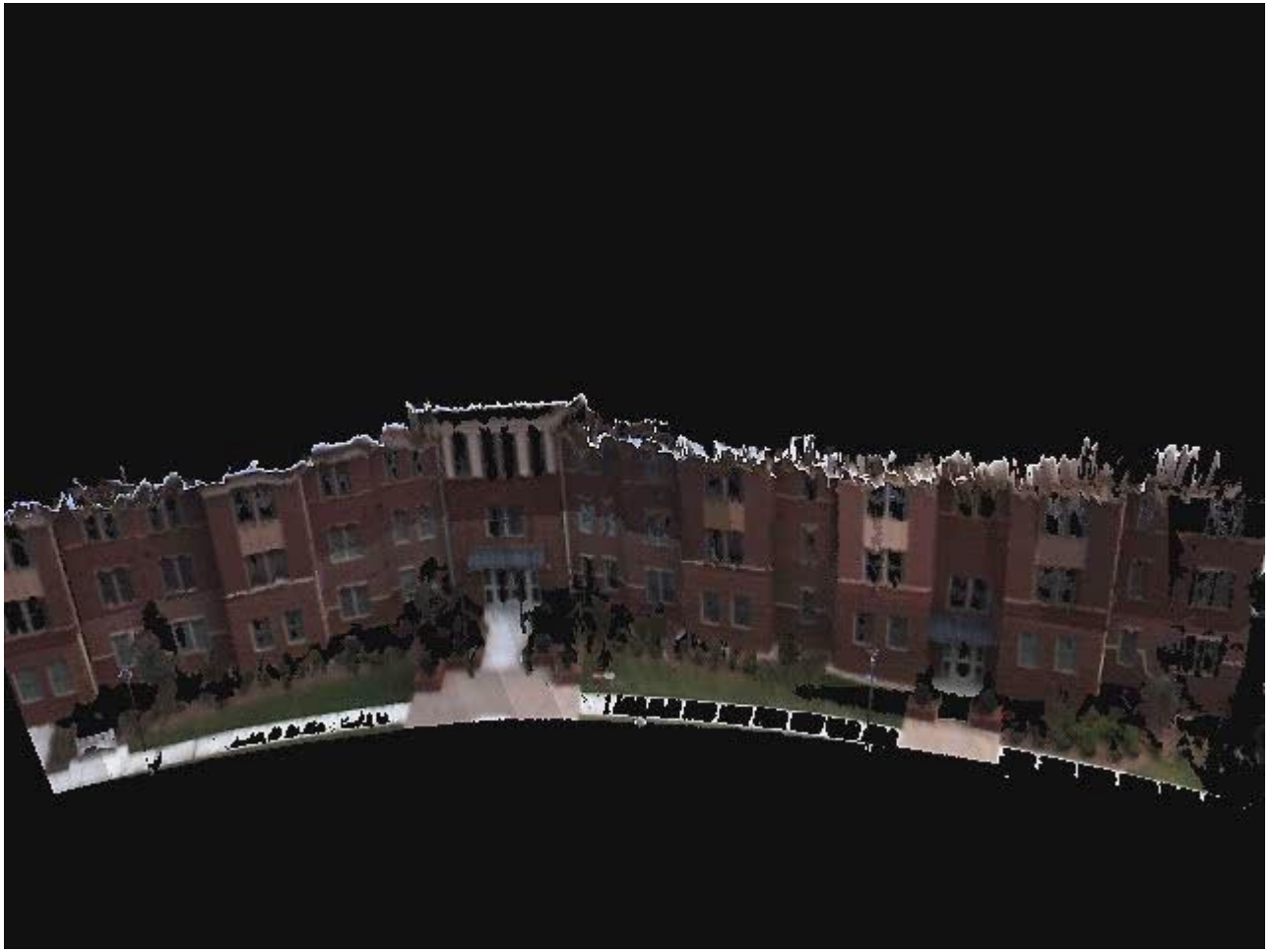


Flowchart

Planar Class Probability Map

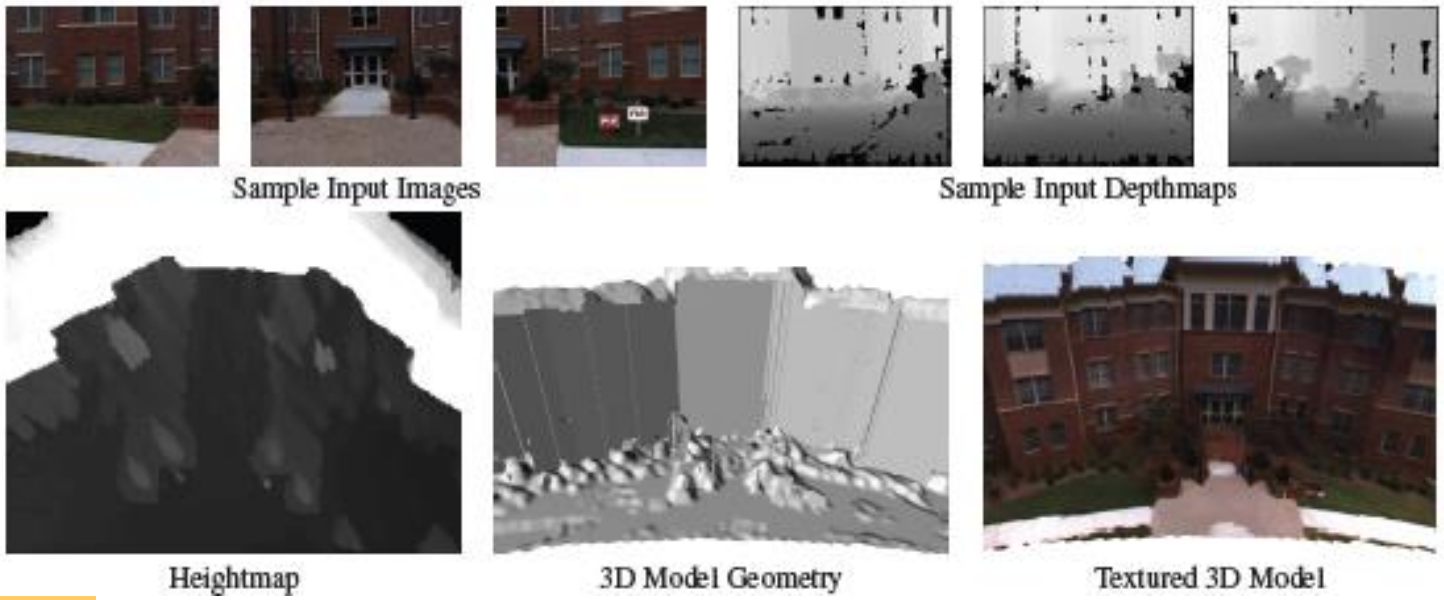
Graph-Cut Labeling

3D Model



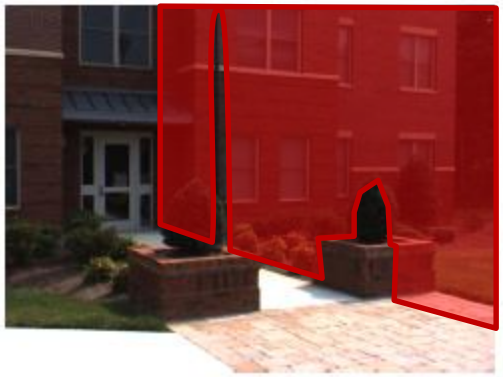
Heightmap Model

(Gallup et al. 3DPVT 2010)



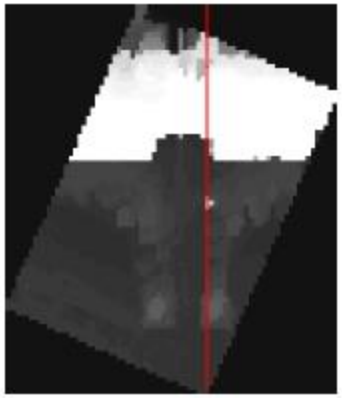
- Enforces vertical facades
- One continuous surface, no holes
- 2.5D: Fast to compute, easy to store

Occupancy Voting

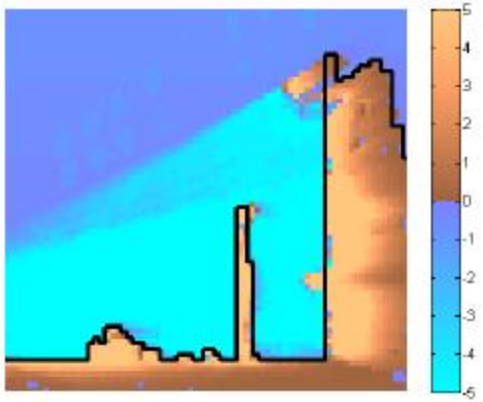


(a)

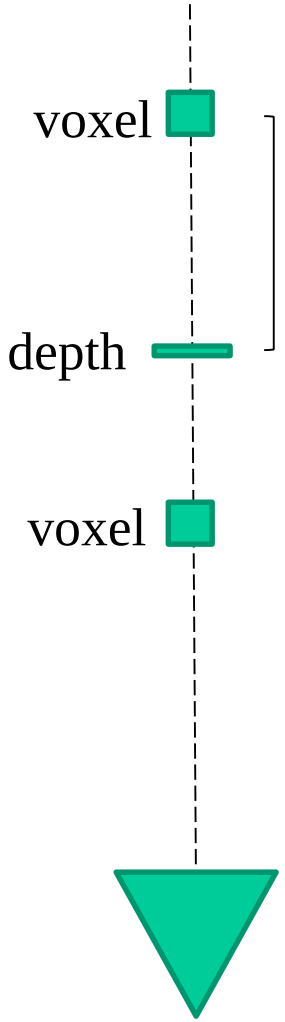
(b)



(c)



(d)



$V = \exp(-d / \sigma)$

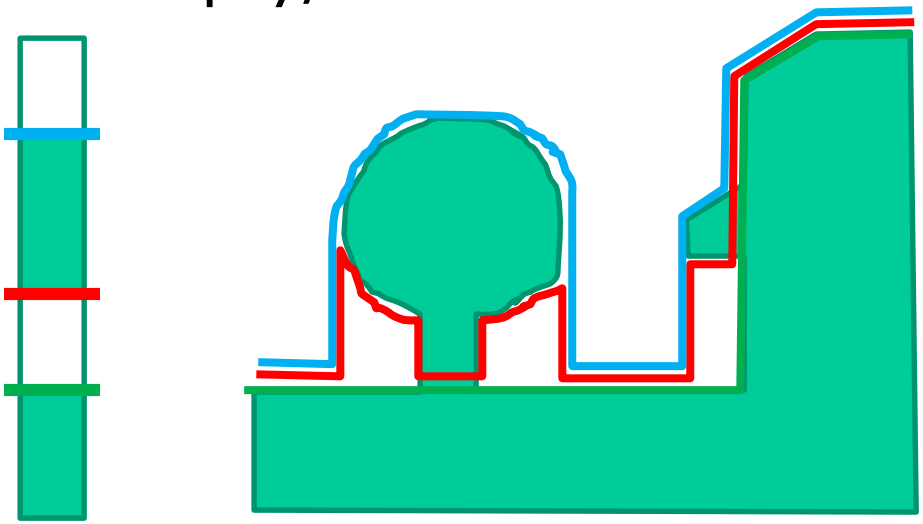
$V = -\lambda_{empty}$

This is a *log-odds* likelihood

n-layer heightmap fusion

(Gallup et al. DAGM'10)

- Generalize to n-layer heightmap
- Each layer is a transition from full/empty or empty/full



- Compute layer positions with dynamic programming
- Use model selection (BIC) to determine number of layers

n-layer heightmap fusion

1 Layer

3 Layer

1 Layer

3 Layer

Reconstruction from Photo Collections

- Millions of images download from Flickr
- Camera poses computed using (Li et al. ECCV'08)
- Depthmaps from GPU planesweep

Results

More on stereo

The Middleburry Stereo Vision Research Page

http://cat.middlebury.edu/stereo/

Recommended reading:

D. Scharstein and R. Szeliski.

A Taxonomy and Evaluation of Dense Two-Frame Stereo Correspondence Algorithms. IJCV 47(1/2/3):7-42, April-June 2002. PDF file (1.15 MB) - includes current evaluation. Microsoft Research Technical Report MSR-TR-2001-81, November 2001. PDF file (1.27 MB)

Next week:
Structure from Motion