

ECE 1390/2390

Image Processing and Computer Vision – Fall 2021

Stereo geometry

Ahmed Dallal

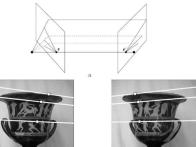
Assistant Professor of ECE University of Pittsburgh

Reading

• FP chapter 7

Stereo geometry

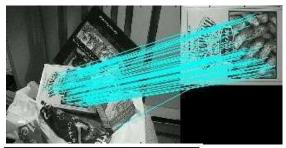
Stereo: A Special case of Multiple views



Hartley and Zisserman



Multi-view geometry, matching, invariant features, stereo vision





Why multiple views?

• Structure and depth are inherently ambiguous from single views.

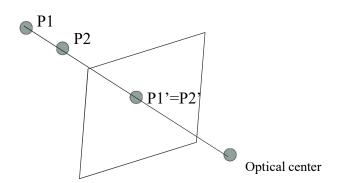




Images from S. Lazebnik

Why multiple views?

 Structure and depth are inherently ambiguous from single views.



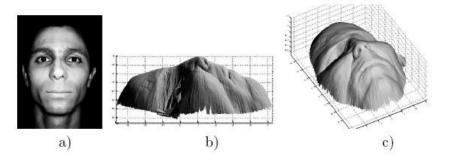
Perspective effects



- What cues help us to perceive 3d shape and depth?What about one eye first?

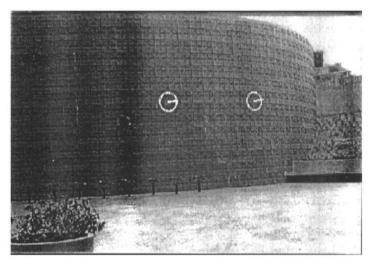
S. Seitz

Shading



K. Grauman

Texture

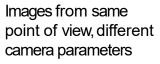


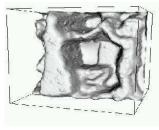
A.M. Loh. The recovery of 3-D structure using visual texture patterns.

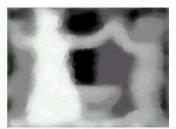
Focus/defocus











3d shape / depth estimates

Figures from H. Jin and P.Favaro, 2002

Motion







Figures from L. Zhang

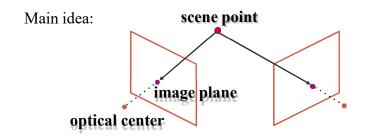
But we (and lots of creatures) have two eyes!

Stereo:

- The image from one eye is a little different than the image form he other eye.
- Think of shape from "motion" between two views
- Infer 3d shape of scene from two (multiple) images from different viewpoints

But we (and lots of creatures) have two eyes!

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

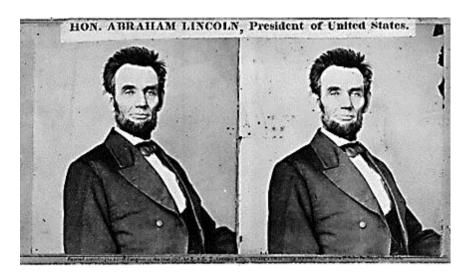


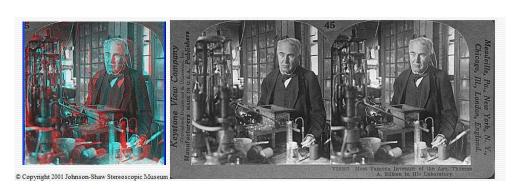
Stereo photography and stereo viewers

Take two pictures of the same subject from two slightly different viewpoints and display so that each eye sees only one of the images.

Invented by Sir Charles Wheatstone 1838

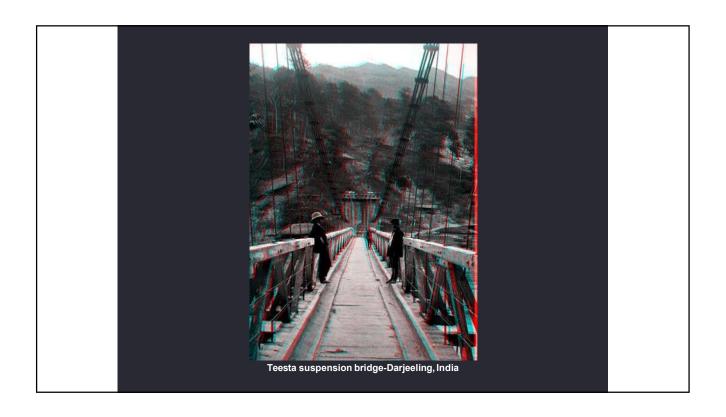
People fascinated by 3D

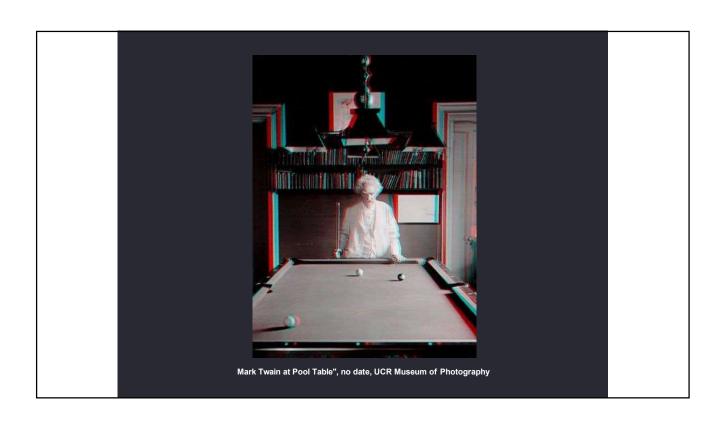


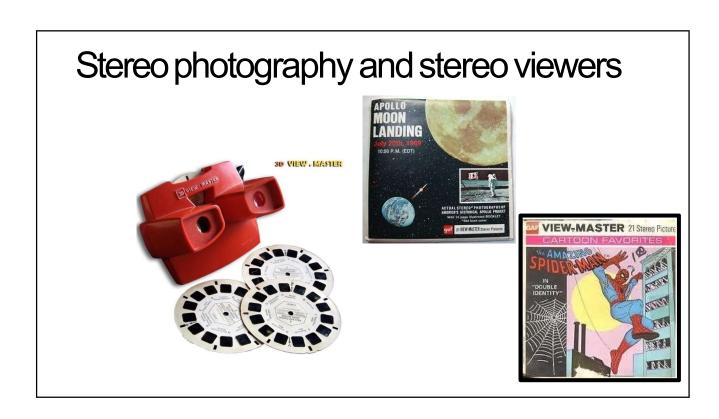


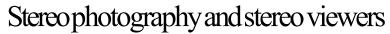
http://www.johnsonshawmuseum.org





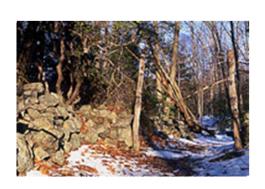






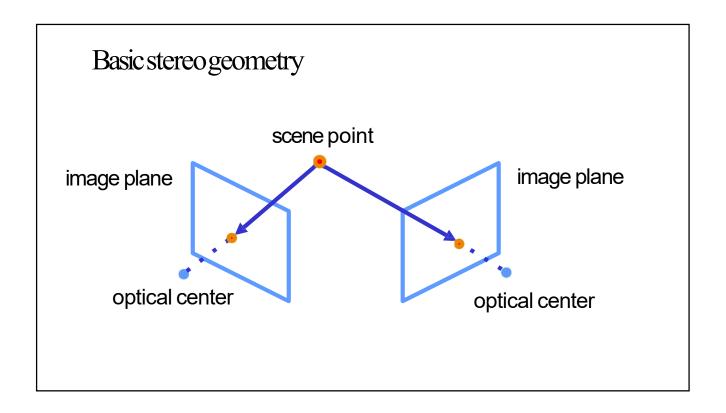


The Basic Idea: Two slightly different images





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

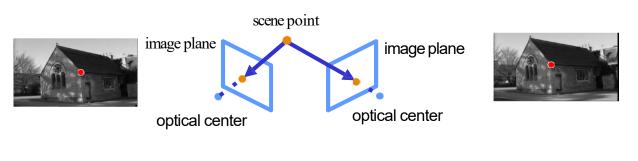


Estimating depth with stereo

Stereo: shape from "motion" between two views

We'll need to consider:

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



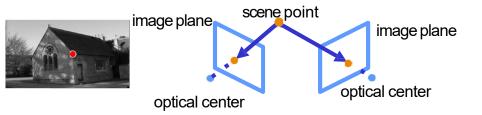
Estimating depth with stereo

Stereo: shape from "motion" between two views

We'll need to consider:

Info on camera pose ("calibration")

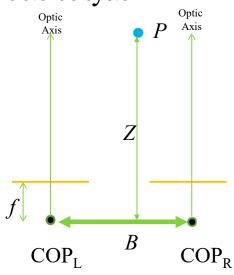
Image point correspondences





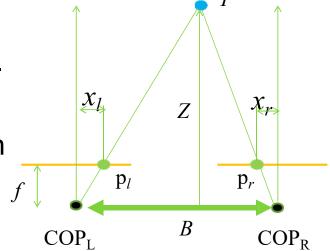
Geometry for a simple stereo system

- First, assuming parallel optical axes, known camera parameters (i.e., calibrated cameras)
- Figure is looking down on the cameras and image planes
- Baseline B, focal length f
- Point P is distance Z in camera coordinate systems



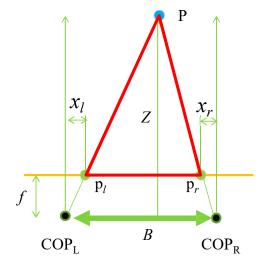
Geometry for a simple stereo system

- Point Pprojects into left and right images.
- Distance is positive in left image, and negative in right



Geometry for a simple stereo system

- What is the expression for Z?
- Similar triangles (p_I, P_ip_r) and (C_L,P, C_r):

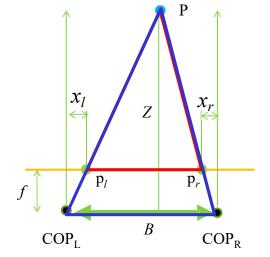


Geometry for a simple stereo system

- What is the expression for Z?
- Similar triangles (p_I, P,p_r) and (C_L,P, C_r):

$$\frac{B - x_l + x_r}{Z - f} = \frac{B}{Z}$$

$$Z = f \frac{B}{x_l - x_r}$$

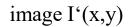


Disparity ... is inversely

proportional to depth

Depth from disparity

image I(x,y)





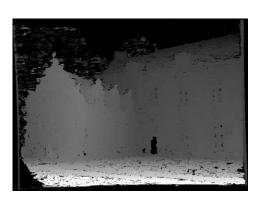


Depth from disparity

image I(x,y)



Disparity map D(x,y)



Depth from disparity

$$(x',y')=(x+D(x,y), y)$$

image I'(x',y')

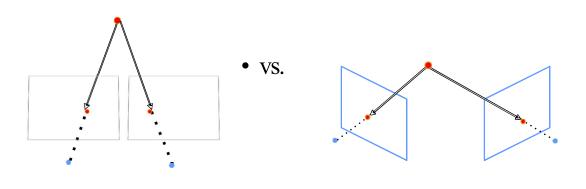


So if we could find the **corresponding points** in two images, we could **estimate relative depth...**

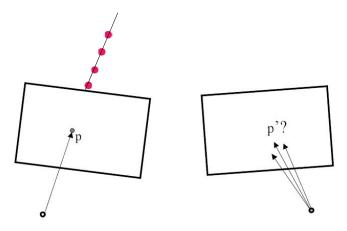
Epipolar geometry

General case, with calibrated cameras

• The two cameras need not have parallel optical axes and image planes.



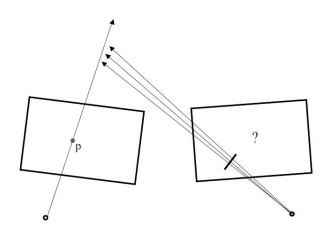
Stereo correspondenceconstraints



Given p in left image, where can corresponding point p' be?

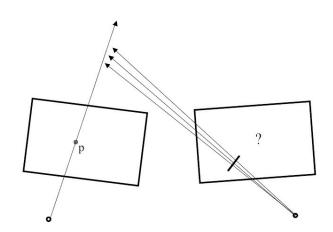
Stereo correspondenceconstraints

Remember: in perspective projection, lines project into lines.

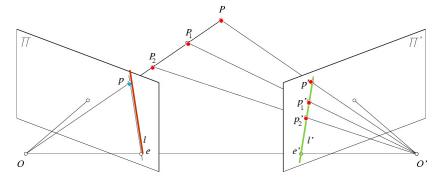


Stereo correspondenceconstraints

So the *line* containing the center of projection and the point P in the left image must project to a *line* in the right image.

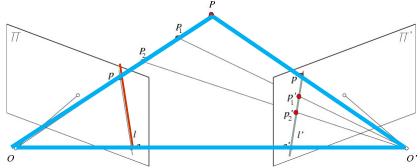


Epipolarconstraint



Geometry of two views constrains where the corresponding pixel for some image point in the first view must occur in the second view.

Epipolar constraint

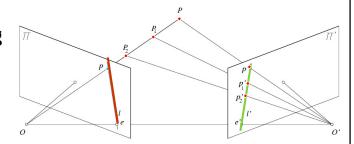


Geometry of two views constrains where the corresponding pixel for some image point in the first view must occur in the second view.

•It must be on the line carved out by a plane – *the epipolar plane* – connecting the world point and optical centers.

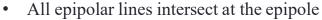
Epipolar geometry: Terms

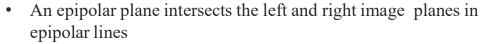
- Baseline: line joining the camera centers
- *Epipolar plane*: plane containing baseline and world point
- Epipolar line: intersection of epipolar plane with the image plane - come in pairs
- *Epipole*: point of intersection of baseline with image plane



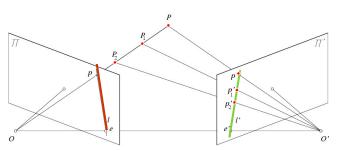
Epipolar geometry: Terms

- Baseline: line joining the camera centers
- Epipolar plane: plane containing baseline and world point
- Epipolar line: intersection of epipolar plane with the image plane - come in pairs
- *Epipole*: point of intersection of baseline with image plane





Why is the epipolar constraint useful?

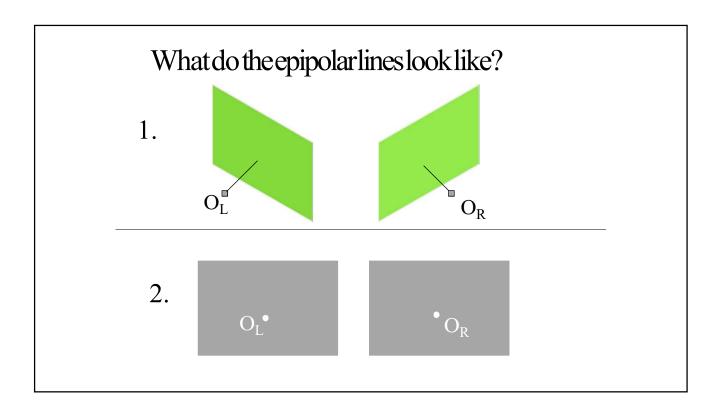


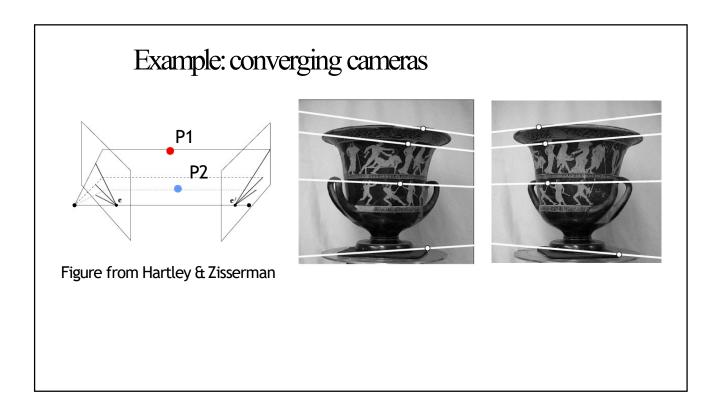
Epipolarconstraint

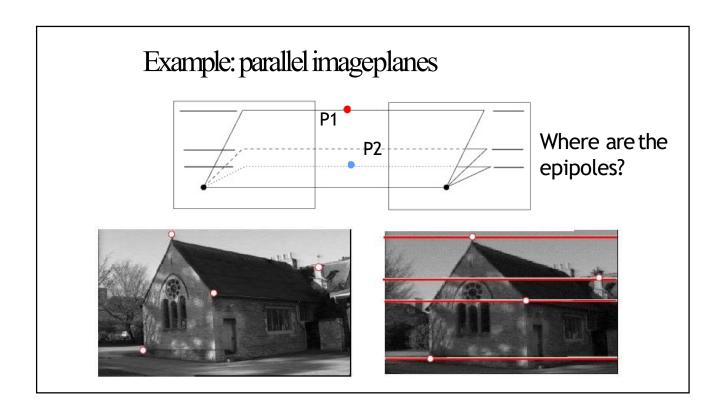


The *epipolar constraint* reduces the correspondence problem to a 1D search along an epipolar line.

Image from Andrew Zisserman









Quiz

How do we know that (B) has parallel image planes

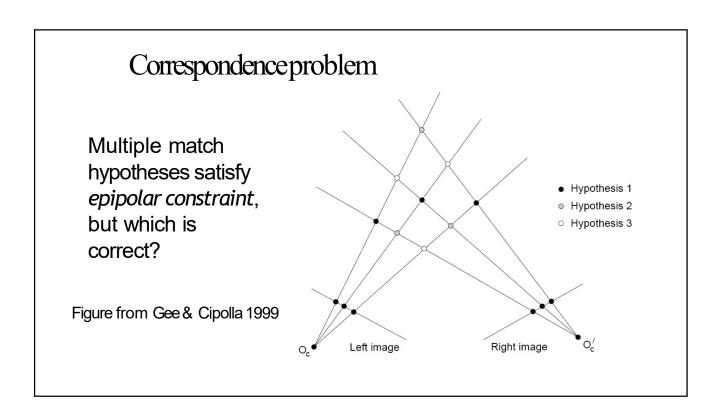
- a) The epipolar lines are horizontal
- b) The epipolar lines are parallel
- c) Because I just said (B) had parallel image planes

Ħ

Stereo correspondence

For now assume parallel image planes...

- Assume parallel (co-planar) image planes...
- Assume same focal lengths...
- Assume epipolar lines are horizontal...
- Assume epipolar lines are at the same y location in the image...
- That's a lot of assuming, but it allows us to move to the correspondence problem – which you will be solving!



Correspondence problem

Beyond the hard constraint of epipolar geometry, there are "soft" constraints to help identify corresponding points

- Similarity
- Uniqueness
- Ordering
- · Disparity gradient is limited
 - Depth doesn't change too quick

Correspondenceproblem

Beyond the hard constraint of epipolar geometry, there are "soft" constraints to help identify corresponding points

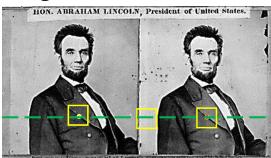
- Similarity
- Uniqueness
- Ordering
- · Disparity gradient is limited

Correspondence problem

Tofind matches in the image pair, we will assume

- Most scene points visible from both views
- Image regions for the matches are similar in appearance

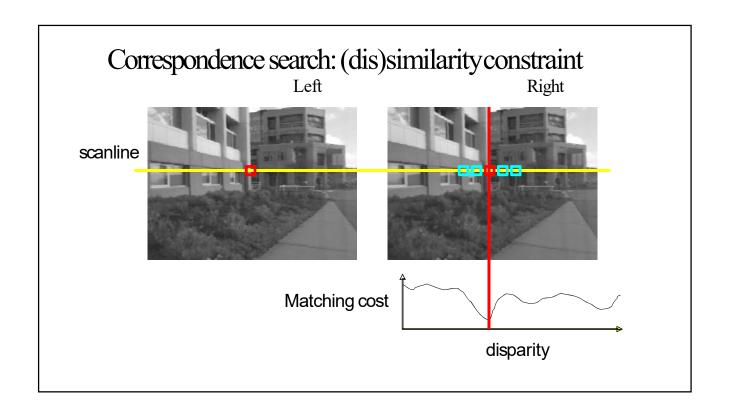
Dense correspondence search

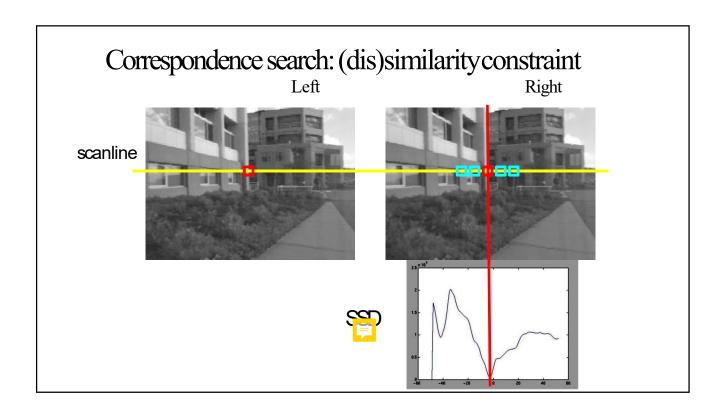


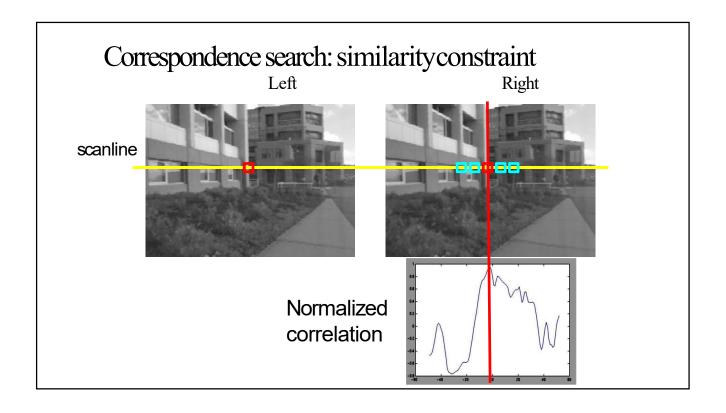
For each pixel / window in the left image

- Compare with every pixel / window on same epipolar line in rightimage
- Pick position with minimum match cost (e.g., SSD, normalized correlation)

Adapted from Li Zhang







Matlab Implementation

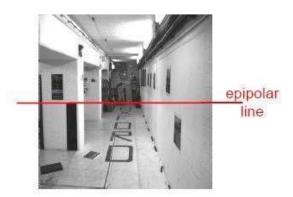
```
function best_x = find_best_match(patch, strip)
    min_diff = Inf;
    best_x = 0; % haven't found it yet
    for x = 1:(size(strip)(2) - size(patch)(2))
        other_patch = strip(:, x:(x + size(patch)(2) - 1));
        diff = sumsq((patch - other_patch)(:));
        if diff < min_diff
            min_diff
            min_diff = diff;
            best_x = x;
        endif|
        endfor
endfunction</pre>
```

Matlab Implementation

- Test code is posted to courseweb
- Feel free to try normalized correlation

Correspondence problem





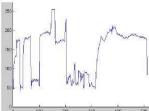
Source: Andrew Zisserman

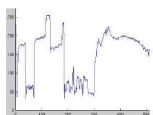
Correspondence problem





Intensity profiles



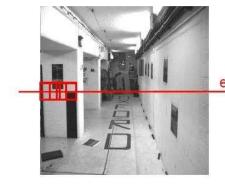


Clear correspondence between intensities, but also noise and ambiguity

Source: Andrew Zisserman

Correspondence problem





epipolar line

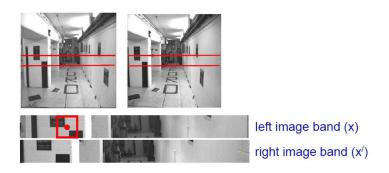
Neighborhoods of corresponding points are similar in intensity patterns.

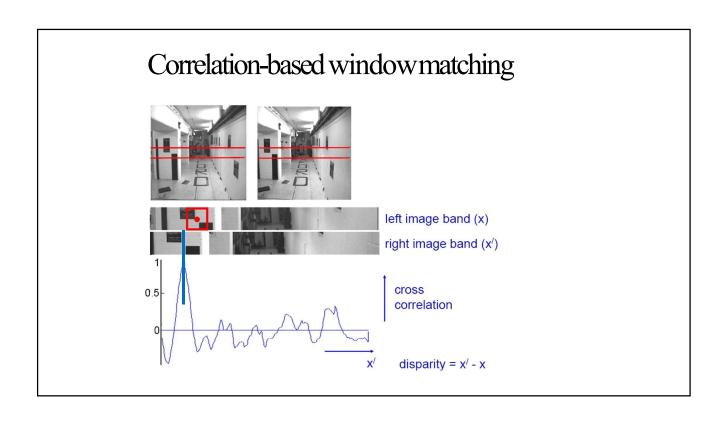
Source: Andrew Zisserman

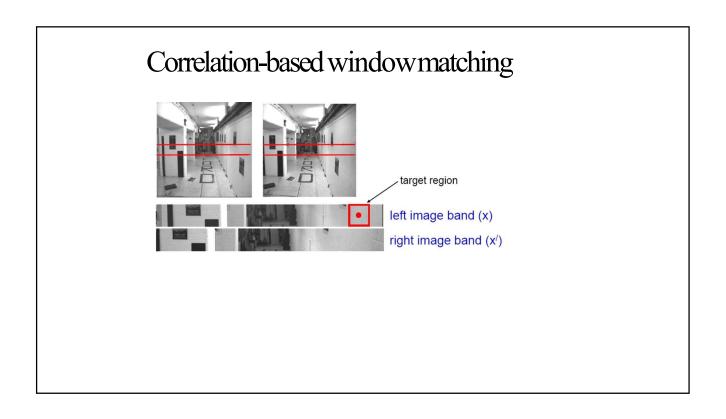
Correlation-based window matching

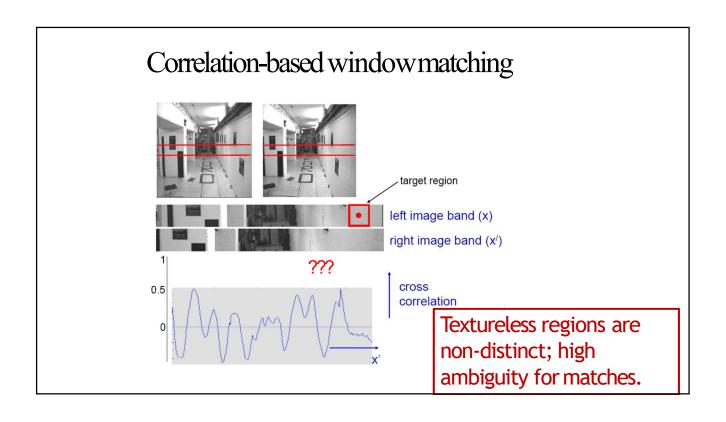


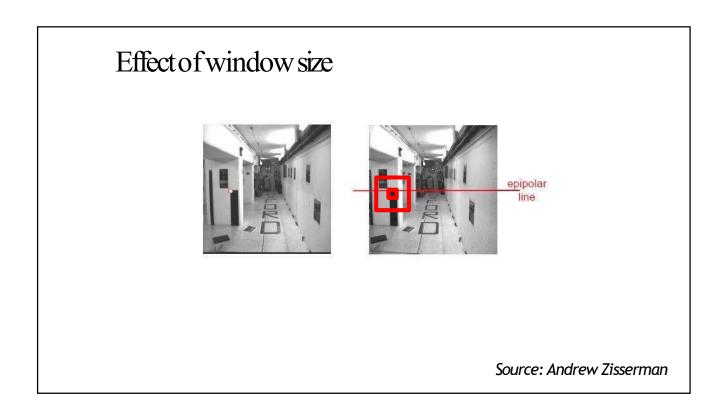
Correlation-based window matching







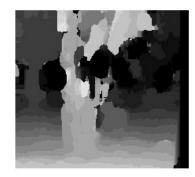




Effect of window size







W = 3

W = 20

Figures from Li Zhang

Correspondence problem

Beyond the hard constraint of epipolar geometry, there are "soft" constraints to help identify corresponding points

- Similarity
- Uniqueness
- Ordering
- Disparity gradient is limited

Uniqueness constraint

No more than one match in right image for every point in left image

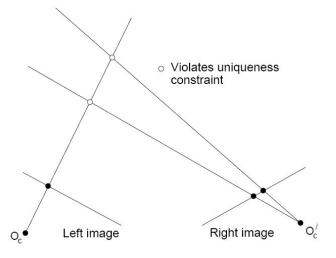
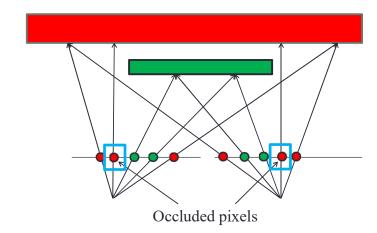


Figure from Gee & Cipolla 1999

Problem: Occlusion

- Uniqueness says "up to match" per pixel
- · When is there no match?



Ordering constraint

 Points on same surface (opaque object) will be in same order in both views

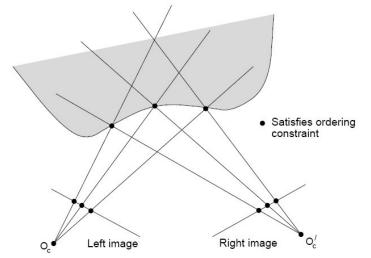
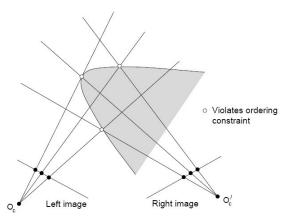


Figure from Gee & Cipolla 1999

Ordering constraint

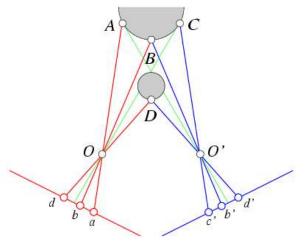
Won't always hold, e.g. consider transparent object...



Figures from Forsyth & Ponce

Ordering constraint

...ora narrow occluding surface



Figures from Forsyth & Ponce

Stereoresults

Image data from University of Tsukuba

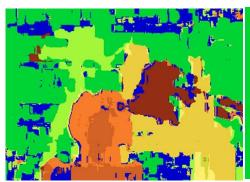






Ground truth

Results with window search





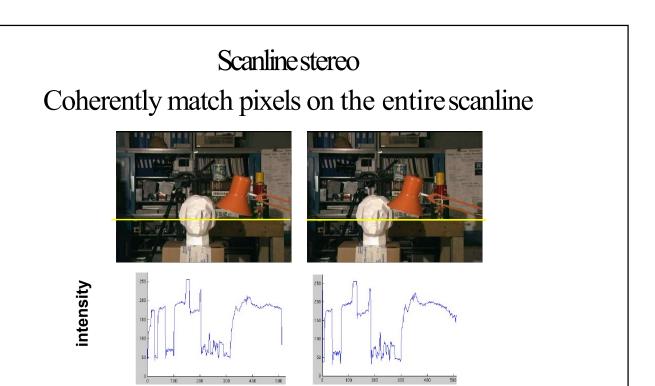
Window-based matching (best window size)

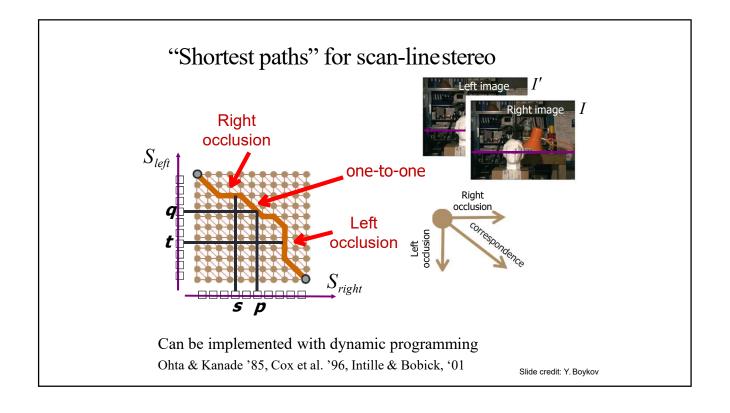
Ground truth

Better solutions

Beyond individual correspondences to estimate disparities:

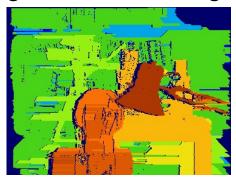
- Optimize correspondence assignments jointly
 - Scanline at a time (DP)
 - Full 2D grid (graph cuts)





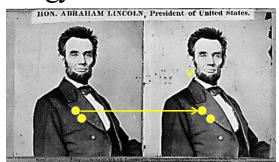
Coherent stereo on 2D grid

Scanline stereo generates streaking artifacts



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

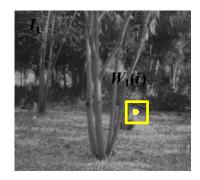
Stereo as energy minimization

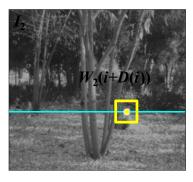


What defines a good stereo correspondence?

- Match quality Want each pixel to find a good appearance match in the other image
- 2. **Smoothness** of two pixels are adjacent, they should (usually) move about the same amount

Stereo matching as energyminimization







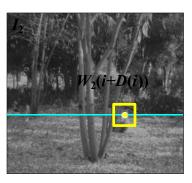
Data term:

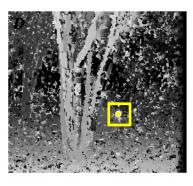
$$E_{\text{\tiny data}} = \sum_{i} \left(W_{\text{\tiny I}}(i) - W_{\text{\tiny 2}}(i + D(i)) \right)^{2}$$

Source: Steve Seitz

Stereo matching as energyminimization





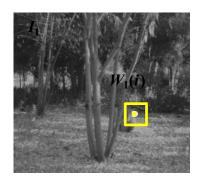


Smoothness term:

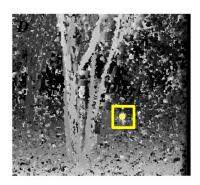
$$E_{\text{smooth}} = \sum_{\text{neighbors } i,j} \rho \left(D(i) - D(j) \right)$$

Source: Steve Seitz

Stereo matching as energyminimization



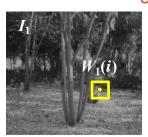


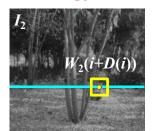


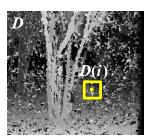
Total energy:
$$E = \alpha E_{\text{data}}(I_1, I_2, D) + \beta E_{\text{smooth}}(D)$$

Source: Steve Seitz

Stereo matching as energyminimization







$$E = \alpha E_{\text{data}}(I_1, I_2, D) + \beta E_{\text{smooth}}(D)$$

$$E_{\text{data}} = \sum_{i} (W_1(i) - W_2(i + D(i)))^2$$

$$E_{\text{smooth}} = \sum_{\text{neighbors } i,j} \rho (D(i) - D(j))$$

· 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

Betterresults...





State of the art method

Ground truth

For the latest and greatest: http://www.middlebury.edu/stereo

Challenges

- Low-contrast; textureless image regions
- Occlusions
- Violations of brightness constancy (e.g., specular reflections)
- Really large baselines (foreshortening and appearance change)
- Camera calibration errors