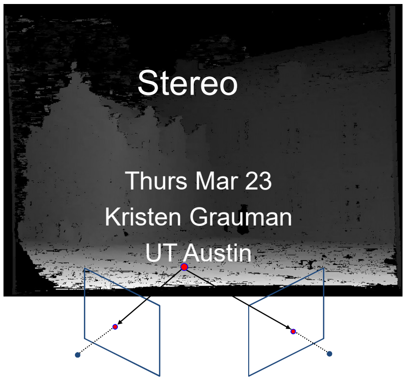


Stereo

Thurs Mar 23

Kristen Grauman

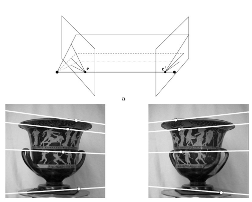
UT Austin

Previously

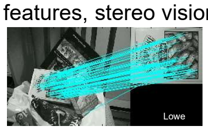
- Write **2d transformations** as matrix-vector multiplication
- Perform **image warping** (forward, inverse)
- **Fitting transformations**: solve for unknown parameters given corresponding points from two views (affine, projective (homography)).
- **Mosaics**: uses homography and image warping to merge views taken from same center of projection.

Multiple views

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



Hartley and Zisserman



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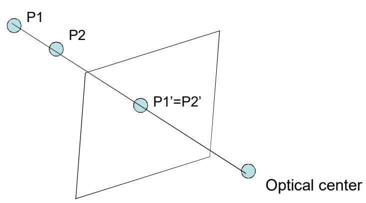
Why multiple views?

- Structure and depth are inherently ambiguous from single views.

Images from Lana Lazebnik

Why multiple views?

- Structure and depth are inherently ambiguous from single views.



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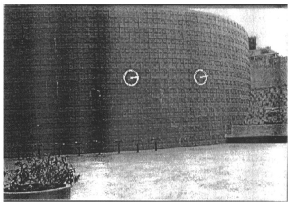
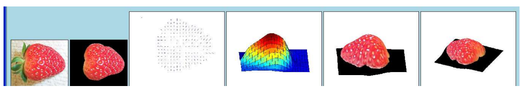
- What cues help us to perceive 3d shape and depth?

Texture



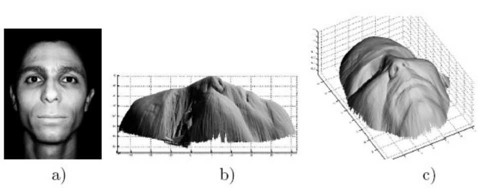


[From A.M. Loh. The recovery of 3-D structure using visual texture patterns. PhD thesis]

Perspective effects

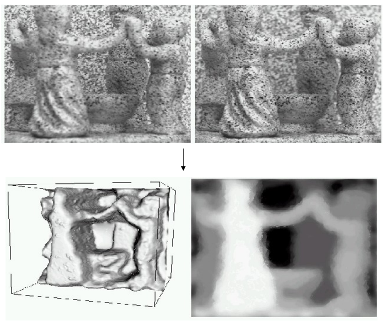
Image credit: S. Seitz

Shading



[Figure from Prados & Faugeras 2006]

Focus/defocus



Images from same point of view, different camera parameters

3d shape / depth estimates

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

Motion

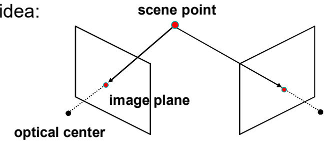
Figures from L. Zhang

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

Estimating scene shape

- "Shape from X": Shading, Texture, Focus, Motion…
- **Stereo**:
  - shape from "motion" between two views
  - infer 3d shape of scene from two (multiple) images from different viewpoints

Main idea:



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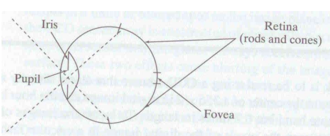
Outline

- Human stereopsis
- Epipolar geometry and the epipolar constraint
  - Case example with parallel optical axes
  - General case with calibrated cameras
- Stereo solutions
  - Correspondences
  - Additional constraints

Human eye



Pupil/Iris – control amount of light passing through lens

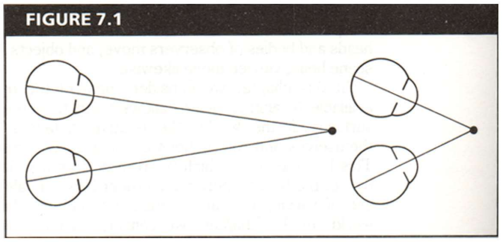
Retina - contains sensor cells, where image is formed

Fovea – highest concentration of cones

Fig from Shapiro and Stockman

Human stereopsis: disparity

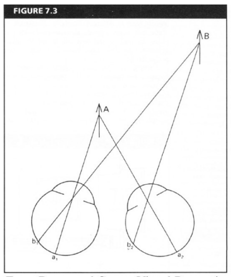
FIGURE 7.1



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

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

Human stereopsis: disparity

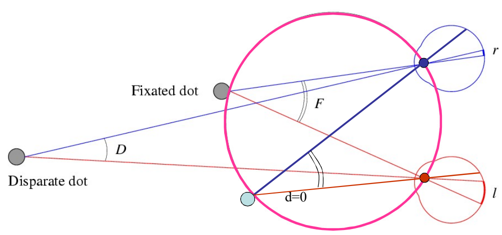


From Bruce and Green, Visual Perception, Physiology, Psychology and Ecology

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

Adapted from David Forsyth, UC Berkeley

Human stereopsis: disparity



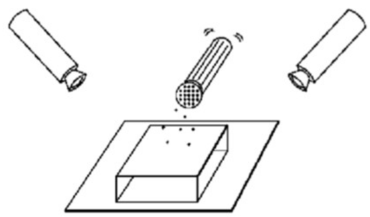
Disparity: $d = r\text{-}l = D\text{-}F.$

Forsyth & Ponce

Random dot stereograms

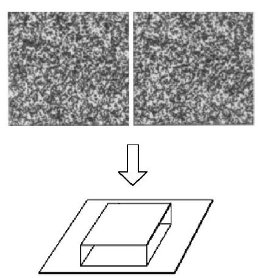
- Julesz 1960: Do we identify local brightness patterns before fusion (monocular process) or after (binocular)?
- To test: pair of synthetic images obtained by randomly spraying black dots on white objects

Random dot stereograms



Forsyth & Ponce

Random dot stereograms



Random dot stereograms

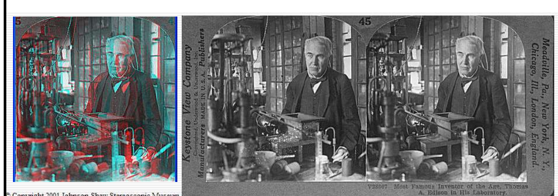
- When viewed monocularly, they appear random; when viewed stereoscopically, see 3d structure.
- Conclusion: human binocular fusion not directly associated with the physical retinas; must involve the central nervous system
- Imaginary "*cyclopean retina*" that combines the left and right image stimuli as a single unit

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

Image from fisher-price.com



http://www.johnsonshawmuseum.org

http://www.johnsonshawmuseum.org

Public Library, Stereoscopic Looking Room, Chicago, by Phillips, 1923

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

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Autostereograms

Exploit disparity as depth cue using single image.

(Single image random dot stereogram, Single image stereogram)

Images from magiceye.com

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Autostereograms

Images from magiceye.com

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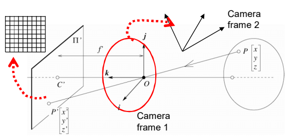
Camera parameters



Extrinsic parameters:
Camera frame 1 ←→ Camera frame 2

Intrinsic parameters:
Image coordinates relative to camera ←→ Pixel coordinates

- *Extrinsic* params: rotation matrix and translation vector
- *Intrinsic* params: focal length, pixel sizes (mm), image center point, radial distortion parameters

We'll assume for now that these parameters are given and fixed.

Outline

- Human stereopsis
- Stereograms
- Epipolar geometry and the epipolar constraint
  - Case example with parallel optical axes
  - General case with calibrated cameras

Stereo vision

Two cameras, simultaneous views

Single moving camera and static scene

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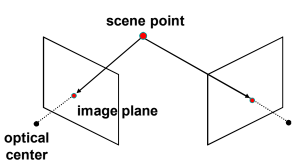
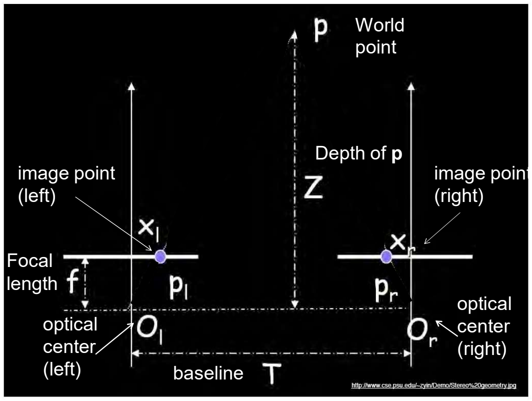
Estimating depth with stereo

- **Stereo**: shape from "motion" between two views
- We'll need to consider:
  - Info on camera pose ("calibration")
  - Image point correspondences



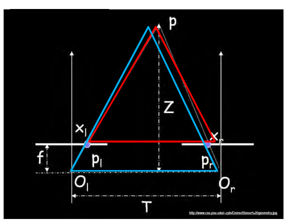
Geometry for a simple stereo system

- First, assuming parallel optical axes, known camera parameters (i.e., calibrated cameras):



Geometry for a simple stereo system

- Assume parallel optical axes, known camera parameters (i.e., calibrated cameras). **What is expression for Z?**



Similar triangles (p_l, P, p_r) and (O_l, P, O_r):

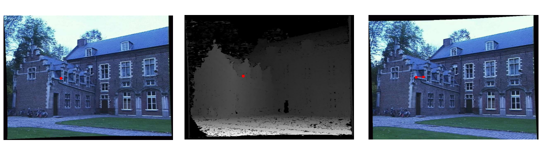
$$\frac{T + x_l - x_r}{Z - f} = \frac{T}{Z}$$

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

disparity

Depth from disparity

image I(x,y) Disparity map D(x,y) image I´(x´,y´)



(x´,y´)=(x+D(x,y), y)

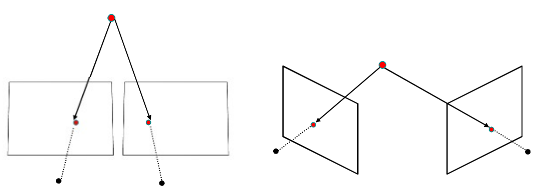
So if we could find the **corresponding points** in two images, we could **estimate relative depth**…

Outline

- Human stereopsis
- Stereograms
- Epipolar geometry and the epipolar constraint
  - Case example with parallel optical axes
  - General case with calibrated cameras

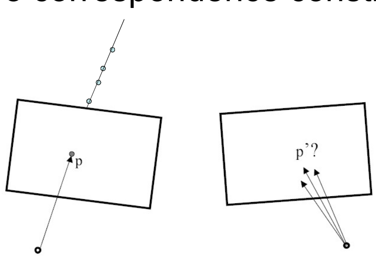
General case, with calibrated cameras

- The two cameras need not have parallel optical axes.



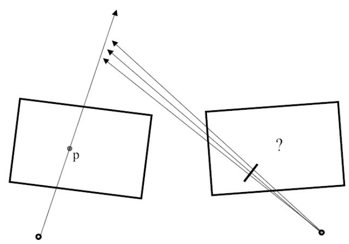
Vs.

Stereo correspondence constraints

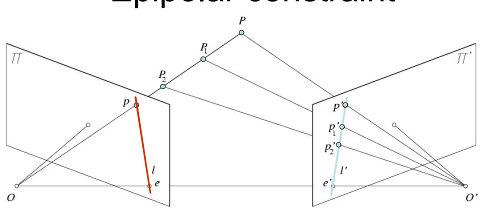


- Given p in left image, where can corresponding point p' be?

Stereo correspondence constraints



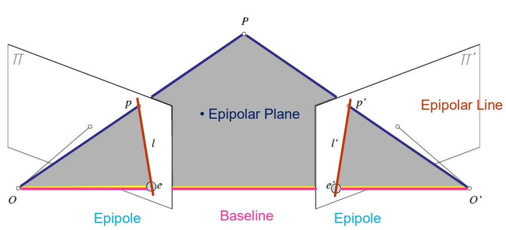
Epipolar constraint



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 connecting the world point and optical centers.

Epipolar geometry



http://www.ai.sri.com/~luong/research/Meta3DViewer/EpipolarGeo.html

Epipolar geometry: terms

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

- All epipolar lines intersect at the epipole
- An epipolar plane intersects the left and right image planes in epipolar lines

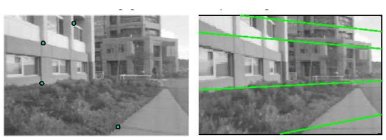
Why is the epipolar constraint useful?

Epipolar constraint

This is useful because it reduces the correspondence problem to a 1D search along an epipolar line.

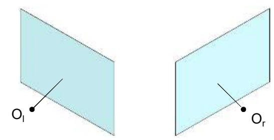
Image from Andrew Zisserman

Example

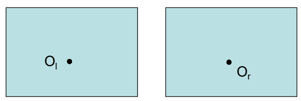


What do the epipolar lines look like?

1.



2.



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Example: converging cameras

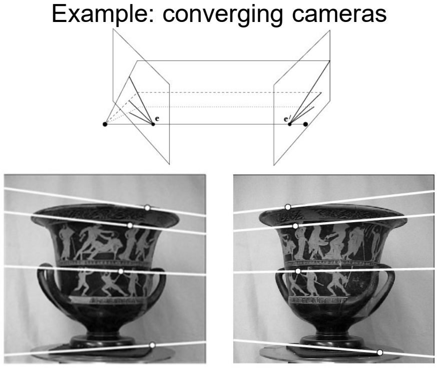
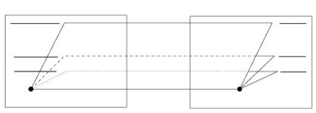


Figure from Hartley & Zisserman

Example: parallel cameras

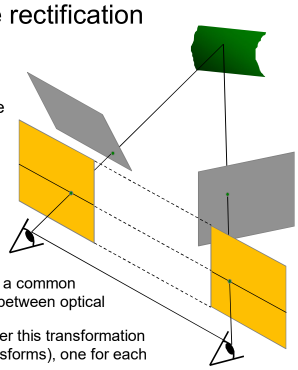


Where are the epipoles?

Figure from Hartley & Zisserman

Stereo image rectification

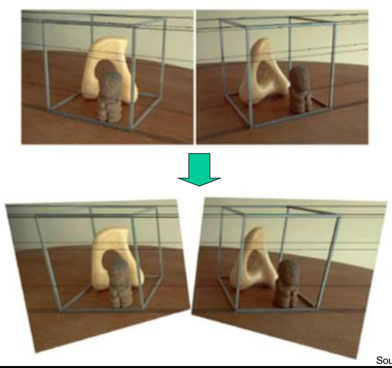
In practice, it is convenient if image scanlines (rows) are the epipolar lines.



- reproject image planes onto a common plane parallel to the line between optical centers
- pixel motion is horizontal after this transformation
- two homographies (3x3 transforms), one for each input image reprojection

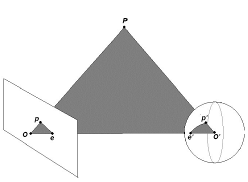
Slide credit: Li Zhang

Stereo image rectification: example



Source: Alyosha Efros

An audio camera & epipolar geometry



Spherical microphone array

Adam O' Donovan, Ramani Duraiswami and Jan Neumann
Microphone Arrays as Generalized Cameras for Integrated Audio Visual Processing, IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Minneapolis, 2007

An audio camera & epipolar geometry

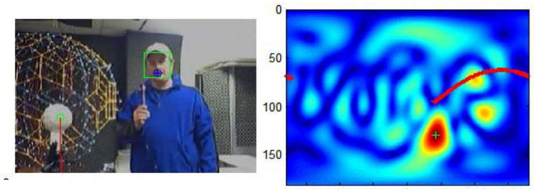


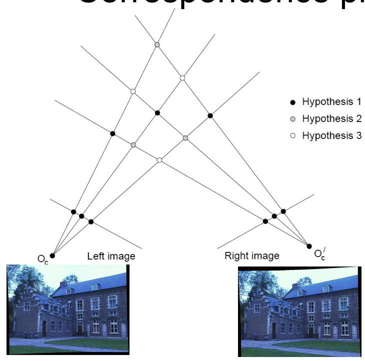
Figure 4. An example of the use of the system in speaker tracking with noise suppression. The bright red spot on the sound image (marked with a +) corresponds to the dominant source. The less dominant source however lies on the epipolar line in the sound image induced by the location of the mouth in the camera image, and this source is beamformed.

An audio camera & epipolar geometry

Summary so far

- Depth from stereo: main idea is to triangulate from corresponding image points.
- Epipolar geometry defined by two cameras
  - We've assumed known extrinsic parameters relating their poses
- Epipolar constraint limits where points from one view will be imaged in the other
  - Makes search for correspondences quicker
- **Terms**: epipole, epipolar plane / lines, disparity, rectification, baseline

Correspondence problem



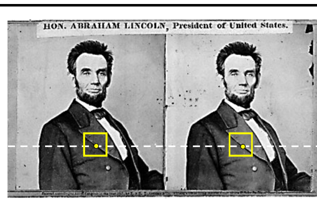
Multiple match hypotheses satisfy epipolar constraint, but which is correct?

Figure from Gee & Cipolla 1999

Correspondence problem

- Beyond the hard constraint of epipolar geometry, there are "soft" constraints to help identify corresponding points
  - Similarity
  - Uniqueness
  - Ordering
  - Disparity gradient
- To find 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 epipolar line

For each pixel / window in the left image

- compare with every pixel / window on same epipolar line in right image
- pick position with minimum match cost (e.g., SSD, correlation)

Adapted from Li Zhang

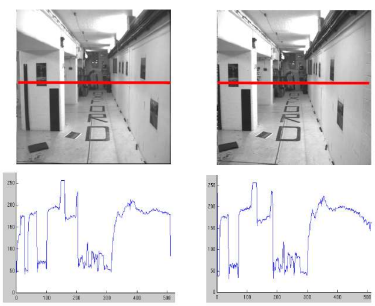
Correspondence problem

Parallel camera example: epipolar lines are corresponding image scanlines

Source: Andrew Zisserman

Correspondence problem

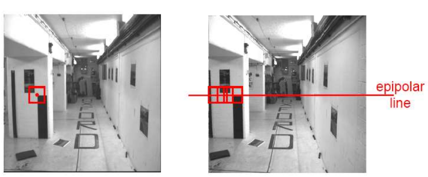
Intensity profiles



- Clear correspondence between intensities, but also noise and ambiguity

Source: Andrew Zisserman

Correspondence problem



Neighborhoods of corresponding points are similar in intensity patterns.

Source: Andrew Zisserman

Normalized cross correlation

subtract mean: $A \leftarrow A - \langle A \rangle, B \leftarrow B - \langle B \rangle$

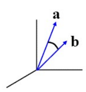
$$\text{NCC} = \frac{\sum_i \sum_j A(i,j) B(i,j)}{\sqrt{\sum_i \sum_j A(i,j)^2} \sqrt{\sum_i \sum_j B(i,j)^2}}$$

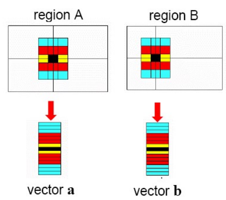
Write regions as vectors

$\mathtt{A} \rightarrow \mathbf{a},\ \mathtt{B} \rightarrow \mathbf{b}$

$$\text{NCC} = \frac{\mathbf{a}.\mathbf{b}}{|\mathbf{a}||\mathbf{b}|}$$

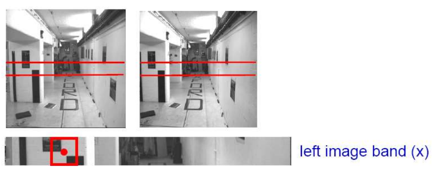
$-1 \leq \text{NCC} \leq 1$





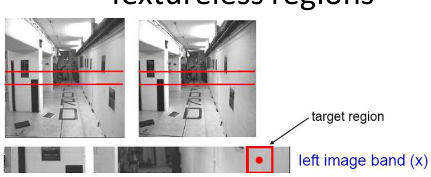
Source: Andrew Zisserman

Correlation-based window matching



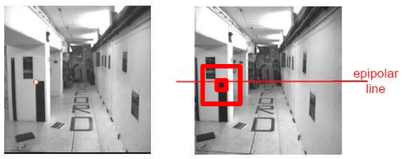
Source: Andrew Zisserman

Textureless regions



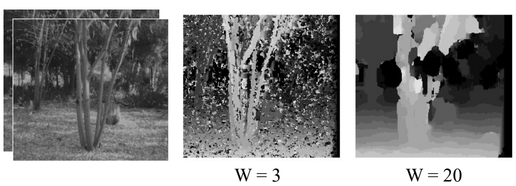
Source: Andrew Zisserman

Effect of window size?



Source: Andrew Zisserman

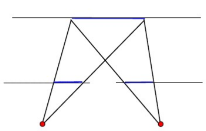
Effect of window size



Want window large enough to have sufficient intensity variation, yet small enough to contain only pixels with about the same disparity.

Figures from Li Zhang

Foreshortening effects

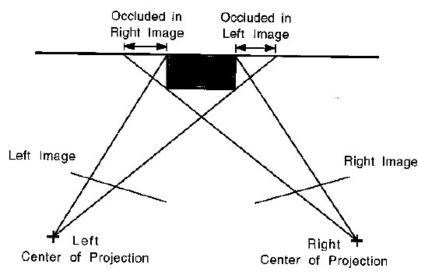


fronto-parallel surface

imaged length the same

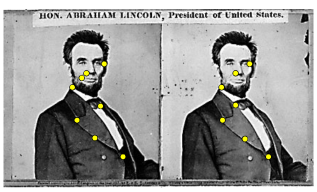
Source: Andrew Zisserman

Occlusion



Slide credit: David Kriegman

Sparse correspondence search



- Restrict search to sparse set of **detected features** (e.g., corners)
- Rather than pixel values (or lists of pixel values) use *feature descriptor* and an associated *feature distance*
- Still narrow search further by epipolar geometry

Tradeoffs between dense and sparse search?

Correspondence problem

- Beyond the hard constraint of epipolar geometry, there are "soft" constraints to help identify corresponding points
  - Similarity
  - Uniqueness
  - Disparity gradient
  - Ordering

Uniqueness constraint

- Up to one match in right image for every point in left image

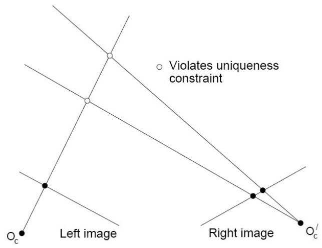
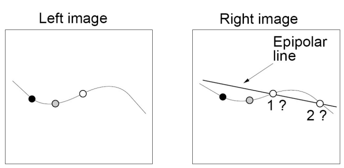


Figure from Gee & Cipolla 1999

Disparity gradient constraint

- Assume piecewise continuous surface, so want disparity estimates to be locally smooth



Given matches ● and ◎, point ○ in the left image must match point 1 in the right image. Point 2 would exceed the disparity gradient limit.

Figure from Gee & Cipolla 1999

Ordering constraint

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

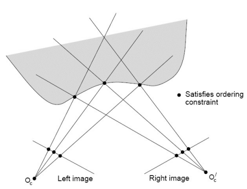
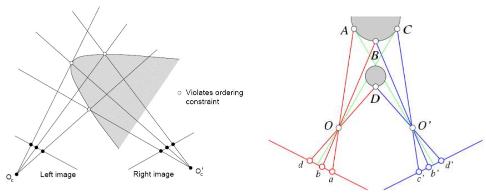


Figure from Gee & Cipolla 1999

Ordering constraint

- Won't always hold, e.g. consider transparent object, or an occluding surface

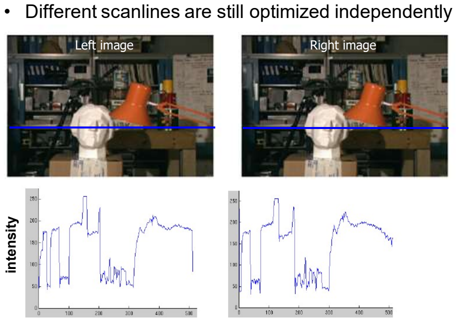


Figures from Forsyth & Ponce

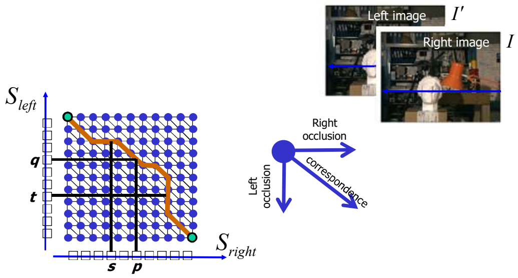
- Beyond individual correspondences to estimate disparities:
- Optimize correspondence assignments jointly
  - Scanline at a time (DP)
  - Full 2D grid (graph cuts)

Scanline stereo

- Try to coherently match pixels on the entire scanline
- Different scanlines are still optimized independently



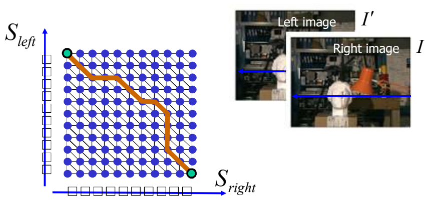
"Shortest paths" for scan-line stereo



Can be implemented with dynamic programming
Ohta & Kanade '85, Cox et al. '96

Slide credit: Y. Boykov

"Shortest paths" for scan-line stereo



Can be implemented with dynamic programming
Ohta & Kanade '85, Cox et al. '96

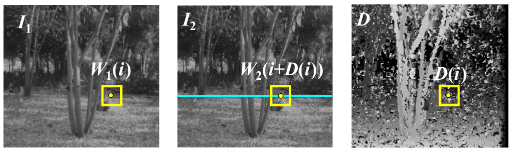
Slide credit: Y. Boykov

Coherent stereo on 2D grid

- Scanline stereo generates streaking artifacts

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

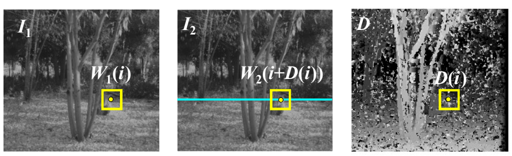
Stereo matching as energy minimization



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

$$E_{\text{data}} = \sum_i \left(W_1(i) - W_2(i + D(i))\right)^2 \qquad E_{\text{smooth}} = \sum_{\text{neighbors } i,j} \rho\left(D(i) - D(j)\right)$$

Stereo matching as energy minimization



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

$$E_{\text{data}} = \sum_i \left(W_1(i) - W_2(i + D(i))\right)^2 \qquad E_{\text{smooth}} = \sum_{\text{neighbors } i,j} \rho\left(D(i) - D(j)\right)$$

- Energy functions of this form can be minimized using *graph cuts*

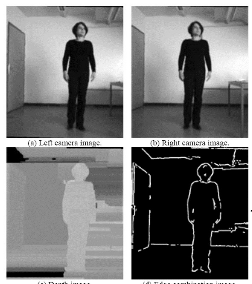
Y. Boykov, O. Veksler, and R. Zabih, Fast Approximate Energy Minimization via Graph Cuts, PAMI 2001

Source: Steve Seitz

Error sources

- Low-contrast ; textureless image regions
- Occlusions
- Camera calibration errors
- Violations of *brightness constancy* (e.g., specular reflections)
- Large motions

Depth for segmentation



(a) Left camera image. (b) Right camera image.

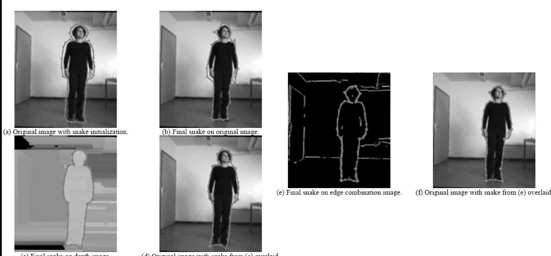
(c) Depth image. (d) Edge combination image.

Edges in disparity in conjunction with image edges enhances contours found

Figure 3 Stereo video frames with computed depth map and edge combination result.

Danijela Markovic and Margrit Gelautz, Interactive Media Systems Group, Vienna University of Technology

Depth for segmentation



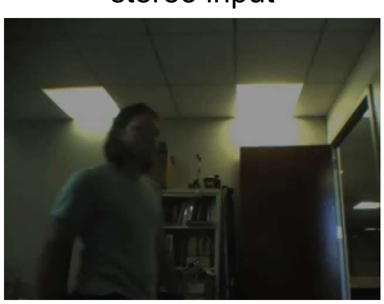
(a) Original image with snake initialization. (b) Final snake on original image.

(c) Final snake on depth image. (d) Original image with snake from (c) overlaid.

(e) Final snake on edge combination image. (f) Original image with snake from (e) overlaid.

Danijela Markovic and Margrit Gelautz, Interactive Media Systems Group, Vienna University of Technology

Model-based body tracking, stereo input



David Demirdjian, MIT Vision Interface Group
http://people.csail.mit.edu/demirdji/movie/artic-tracker/turn-around.m1v

Virtual viewpoint video

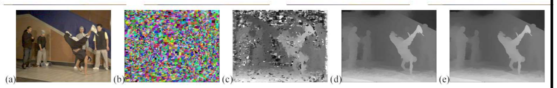


Figure 6: *Sample results from stereo reconstruction stage: (a) input color image; (b) color-based segmentation; (c) initial disparity estimates $\hat{d}_{ij}$; (d) refined disparity estimates; (e) smoothed disparity estimates $d_i(x)$.*

d) A depth-matted object from earlier in the sequence is inserted into the video.

C. Zitnick et al, High-quality video view interpolation using a layered representation, SIGGRAPH 2004.

Virtual viewpoint video

C. Larry Zitnick et al, High-quality video view interpolation using a layered representation, SIGGRAPH 2004.

http://research.microsoft.com/IVM/VVV/

Summary

- Depth from stereo: main idea is to triangulate from corresponding image points.
- Epipolar geometry defined by two cameras
  - We've assumed known extrinsic parameters relating their poses
- Epipolar constraint limits where points from one view will be imaged in the other
  - Makes search for correspondences quicker
- To estimate depth
  - Limit search by epipolar constraint
  - Compute correspondences, incorporate matching preferences

Coming up

- Instance recognition
  - Indexing local features efficiently
  - Spatial verification models