Computational Vision

Stereopsis

Szeliski: 11.1 – 11.5

Trucco, chapter 8 (177-198)

Stereopsis

- Recovering 3D information (depth) from two images.
 - The correspondence problem.
 - The reconstruction problem.
 - Epipolar constraint.
 - The 8-point algorithm.

Stereo photography and stereo viewers

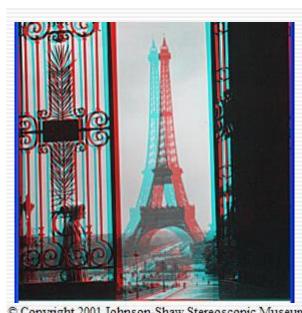
Take two pictures of the same subject from two slightly different viewpoints and display so that each eye sees only one of the images.



Invented by Sir Charles Wheatstone, 1838



Image from fisher-price.com





© Copyright 2001 Johnson-Shaw Stereoscopic Museum

http://www.johnsonshawmuseum.org

Check this out!



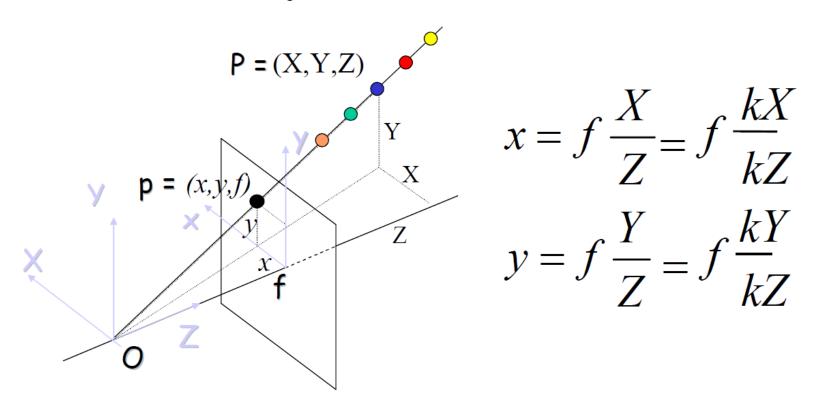
http://www.well.com/user/jimg/stereo/stereo list.html

CSc83029 3-D Computer Vision / Ioannis Stamos

VR headsets and 360 degree videos

- Oculus Facebook
- Google VR Jump [discontinued]
- Microsoft Hololens
- Meta glasses

Why Stereo Vision?

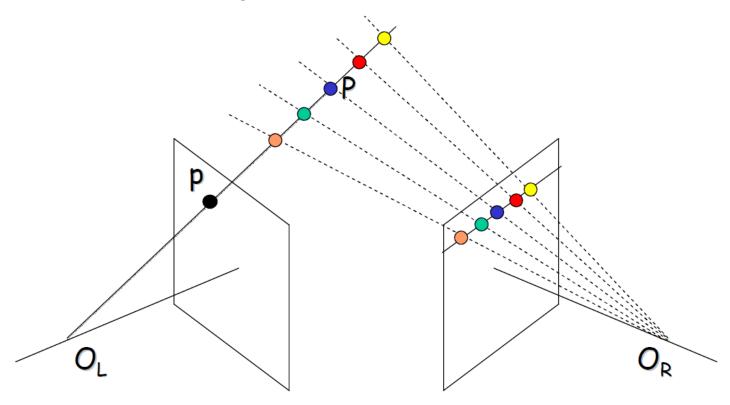


Fundamental Ambiguity:

Any point on the ray OP has image p

Robert Collins CSE486, Penn State

Why Stereo Vision?



A second camera can resolve the ambiguity, enabling measurement of depth via triangulation.

The 2 problems of Stereo

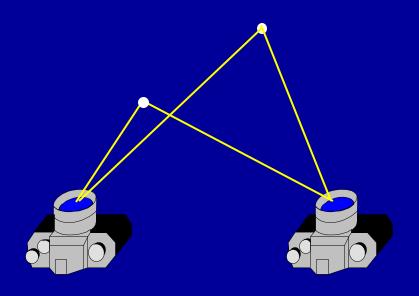
The setting: Simultaneous acquisition of 2 images (left, right) of a static scene.

- Correspondence: Which parts of the left and right images are projections of the same scene element?
- Reconstruction: Given:
 - A number of corresponding points between the left and right image,
 - Information on the geometry of the stereo system,

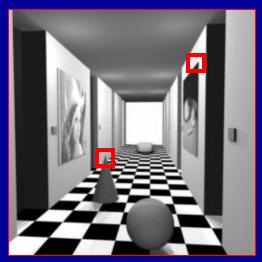
Find:

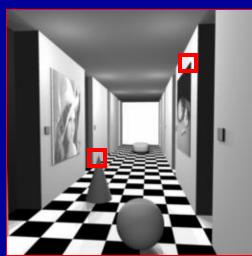
3-D structure of observed objects.

Stereo Vision



depth map

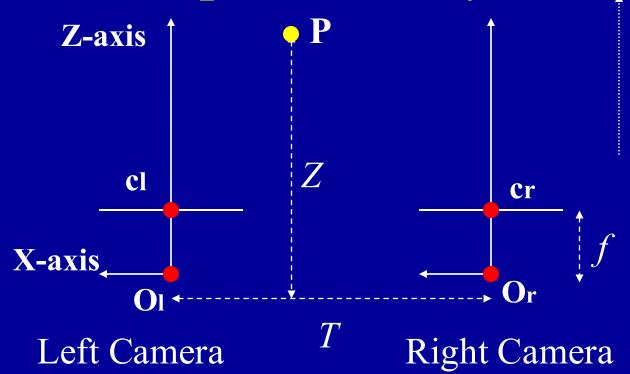




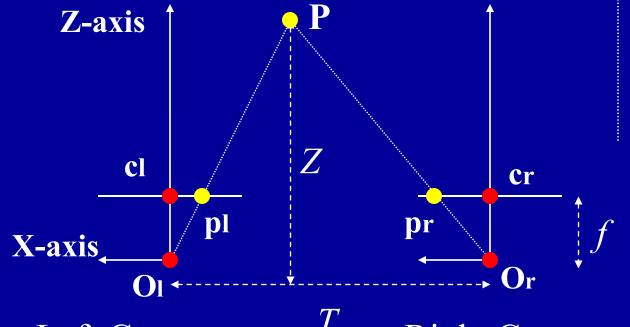




A simple stereo system



Fixation
Point:Infinity.
Parallel
optical axes.



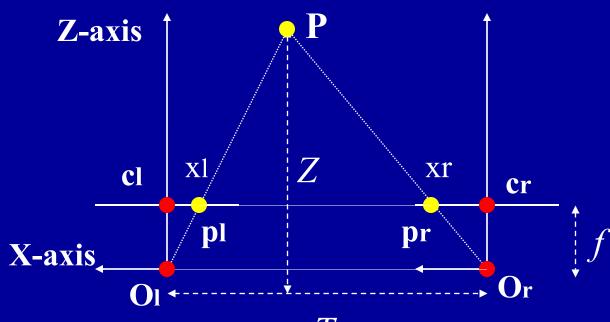
Left Camera

Right Camera

Calibrated Cameras

Fixation
Point:Infinity.
Parallel
optical axes.





Fixation
Point:Infinity.
Parallel
optical axes.

Left Camera

Right Camera

Calibrated Cameras

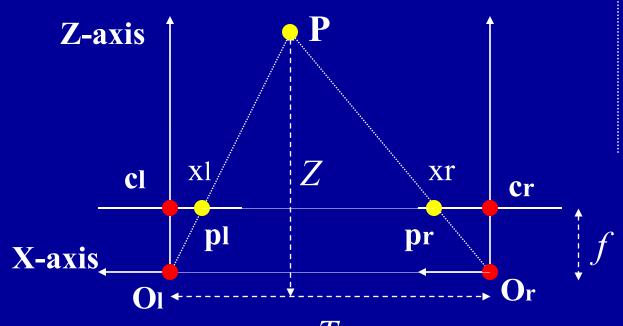
Similar triangles:

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

d:disparity (difference in retinal positions).

T:baseline.

Depth (Z) is inversely proportional to d (fixation at infinity)



Fixation
Point:Infinity.
Parallel
optical axes.

Left Camera

Right Camera

Calibrated Cameras

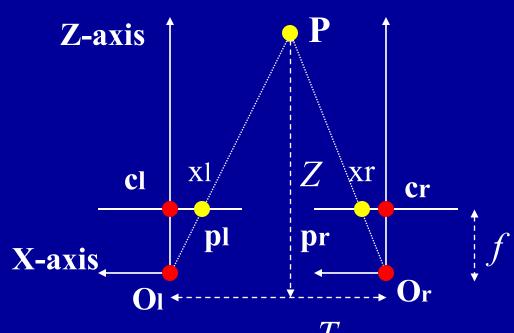
Similar triangles:

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

d:disparity (difference in retinal positions).

T:baseline.

Baseline T: accuracy/robustness of depth calculation.



Fixation
Point:Infinity.
Parallel
optical axes.

Left Camera

Right Camera

Calibrated Cameras

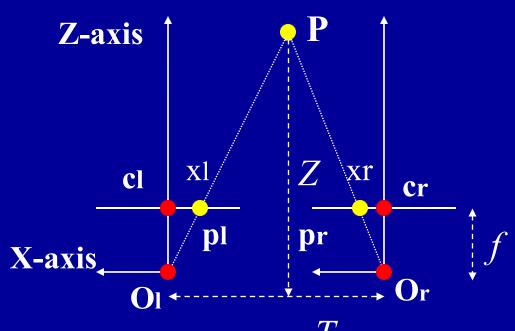
Similar triangles:

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

d:disparity (difference in retinal positions).

T:baseline.

Small baselines: less accurate measurements.



Fixation
Point:Infinity.
Parallel
optical axes.

Left Camera

Right Camera

Calibrated Cameras

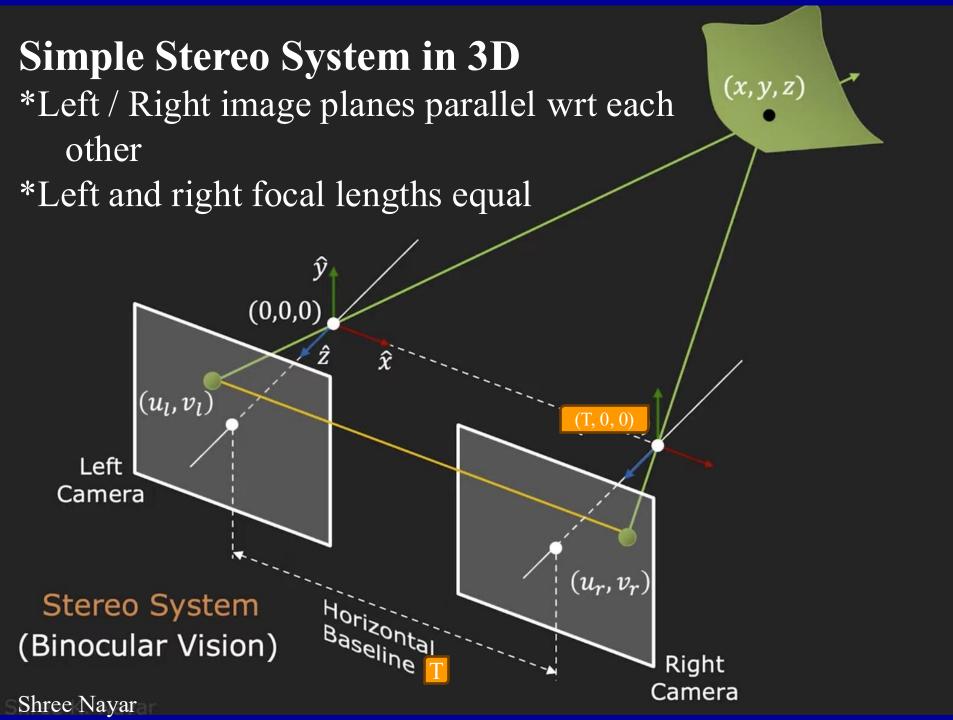
Similar triangles:

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

d:disparity (difference in retinal positions).

T:baseline.

Large baselines: occlusions/foreshortening.



From perspective projection:

$$(u_l, v_l) = \left(f_x \frac{x}{z} + o_x, f_y \frac{y}{z} + o_y\right) \qquad (u_r, v_r) = \left(f_x \frac{x - T}{z} + o_x, f_y \frac{y}{z} + o_y\right)$$

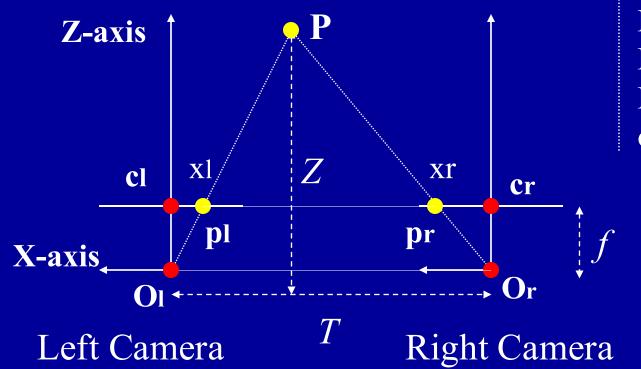
Solving for (x, y, z):

$$x = \frac{T(u_l - o_x)}{(u_l - u_r)} \qquad y = \frac{Tf_x(v_l - o_y)}{f_y(u_l - u_r)} \qquad z = \frac{Tf_x}{(u_l - u_r)}$$

where $(u_l - u_r)$ is called Disparity.

Depth z is inversely proportional to Disparity.

Parameters of Stereo System



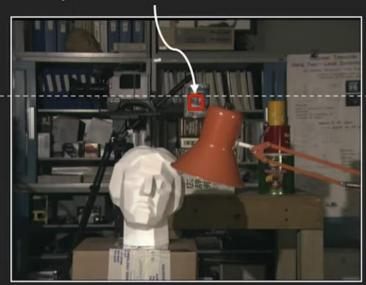
Fixation
Point:Infinity.
Parallel
optical axes.

- 1) Intrinsic parameters (i.e. f, cl, cr)
- 2) Extrinsic parameters: relative position and orientation of the 2 cameras.

STEREO CALIBRATION PROBLEM

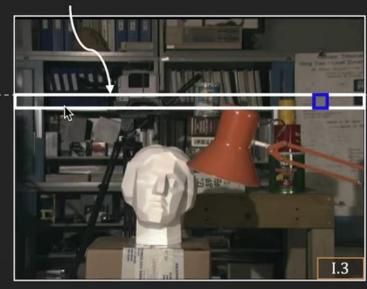
Depth from disparity

Template Window T



Left Camera Image E_l

Search Scan Line L



Right Camera Image E_r

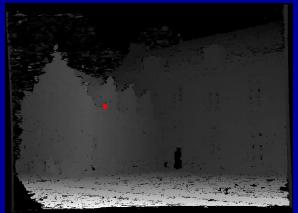
Depth from disparity

image I(x,y)

Disparity map D(x,y)

image I´(x´,y´)

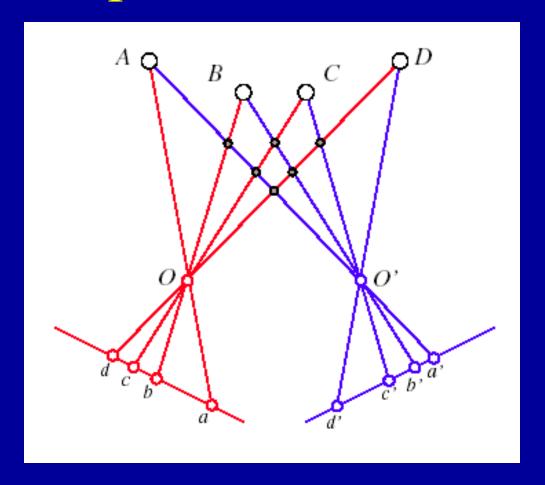




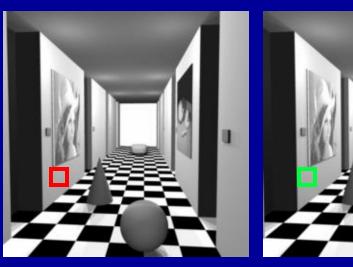


$$(x',y')=(x+D(x,y), y)$$

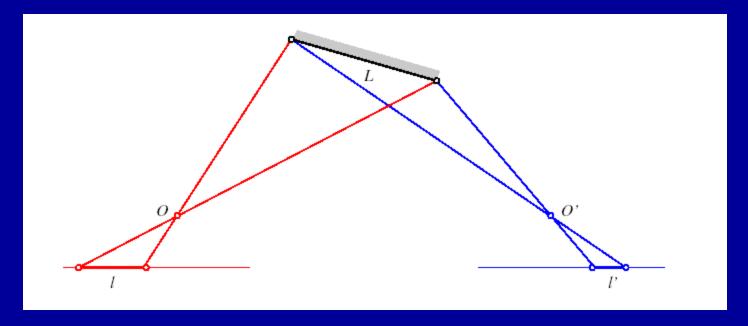
So if we could find the **corresponding points** in two images, we could **estimate relative depth**...



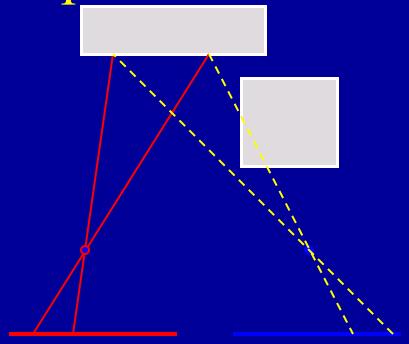
Ambiguity: there may be many possible 3D reconstructions.



No texture: difficult to find a unique match.

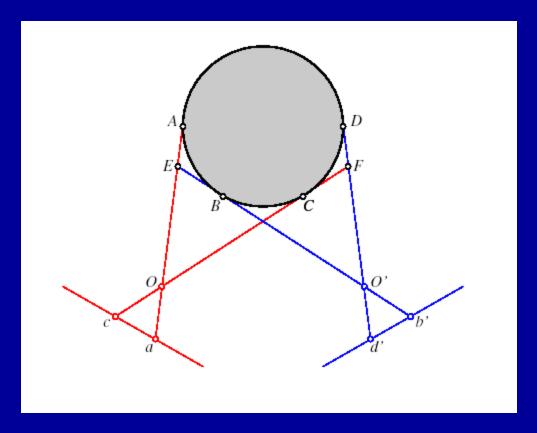


Foreshortening: the projection in each image is different



Occlusions: there may not be a correspondence.

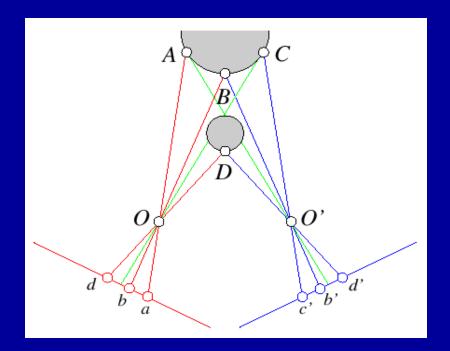
- Assumptions: 1) Most scene points are visible from both views.
 - 2) Corresponding image regions are similar.



Curved surfaces: triangulation produces incorrect position.

Ordering Constraint

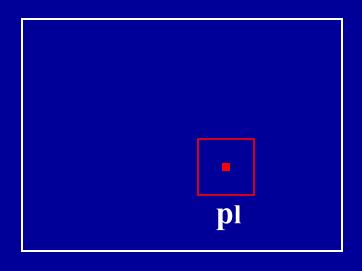
- Order of matching features usually the same in both images
- But not always: occlusion

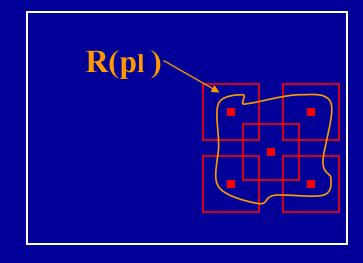


Methods For Correspondence

- Correlation based (dense correspondences).
- Feature based (such as edges/lines/corners).

Correlation-Based Methods





Left Image

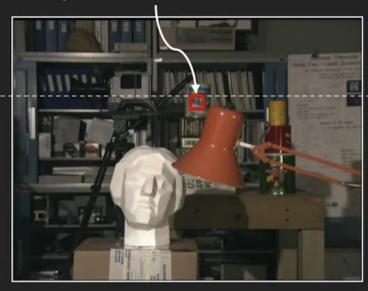
Right Image

- 1)For each pixel pl in the left image **search** in a region R(pl) in the right image for corresponding pixel pr.
- 2)Use image windows of size (2W+1)x(2W+1).
- 3)Select the pixel pr that maximizes a correlation function.

HAVE TO SPECIFY: Region R, size W, and correlation function ψ.

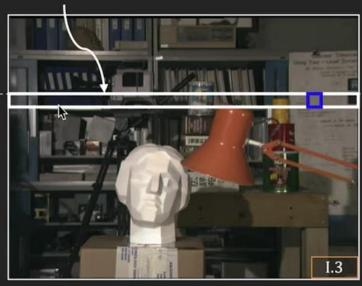
Correlation-based

Template Window T



Left Camera Image E_l

Search Scan Line L



Right Camera Image E_r

Special camera setup (image planes parallel to each other)

Similarity Metrics

Find pixel $(k, l) \in L$ with Minimum Sum of Absolute Differences:

$$SAD(k,l) = \sum_{(i,j) \in T} |E_l(i,j) - E_r(i+k,j+l)|$$

Find pixel $(k, l) \in L$ with Minimum Sum of Squared Differences:

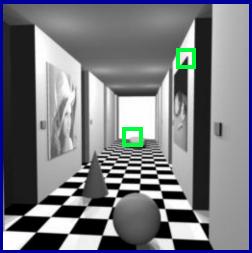
$$SSD(k,l) = \sum_{(i,j) \in T} |E_l(i,j) - E_r(i+k,j+l)|^2$$

Find pixel $(k, l) \in L$ with Maximum Normalized Cross-Correlation

$$NCC(k, l) = \frac{\sum_{(i,j) \in T} E_l(i,j) E_r(i+k,j+l)}{\sqrt{\sum_{(i,j) \in T} E_l(i,j)^2 \sum_{(i,j) \in T} E_r(i+k,j+l)^2}}$$

Correspondence





$$\sum$$
 (



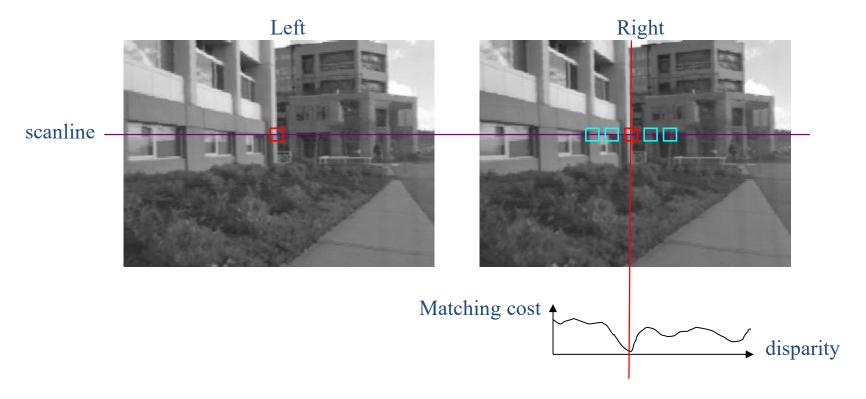
$$)^2 = ssd$$

$$\sum_{i}$$



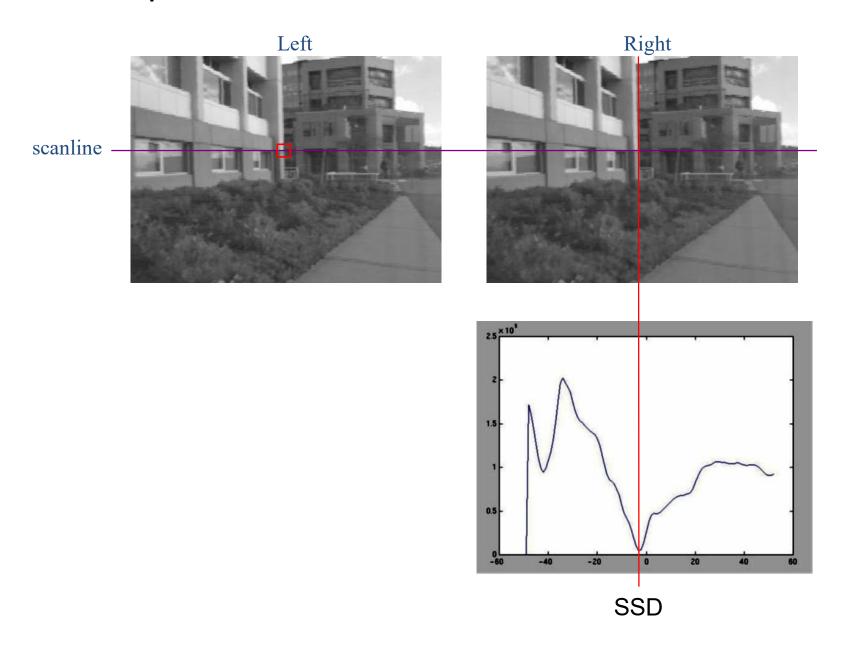
$$)^2 = ssd$$

Correspondence search

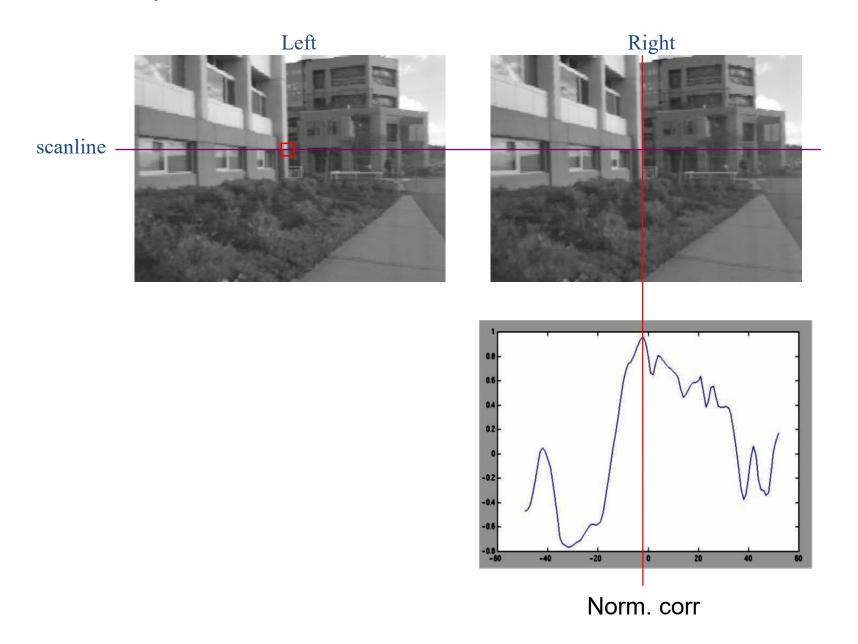


- Slide a window along the right scanline and compare contents of that window with the reference window in the left image
- Matching cost: SSD or normalized correlation

Correspondence search



Correspondence search

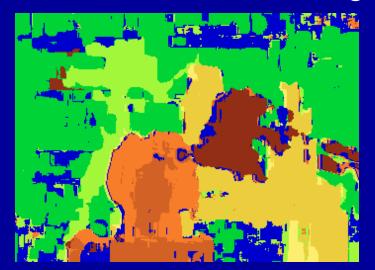


Results with window search

Data



Window-based matching



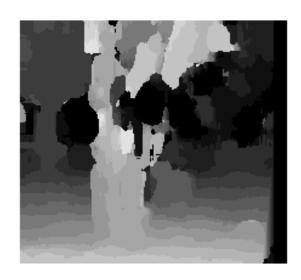
Ground truth



Effect of window size







W = 3

W = 20

- Smaller window
 - + More detail
 - More noise
- Larger window
 - + Smoother disparity maps
 - Less detail

http://vision.middlebury.edu/stereo



Left Image



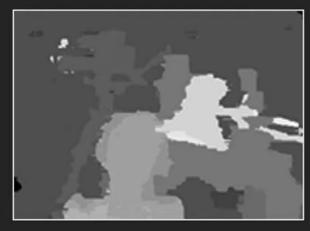
Right Image



Ground Truth



SSD (Window size=21)



SSD - Adaptive Window



State of the Art

http://vision.middlebury.edu/stereo

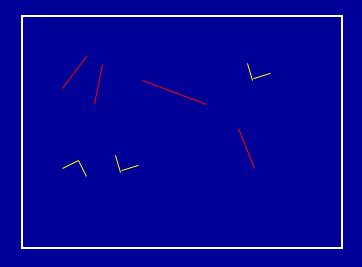
More recent methods

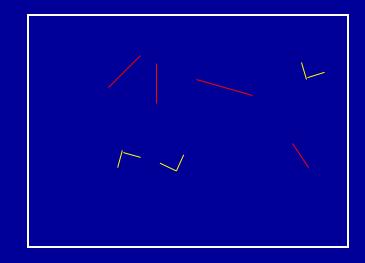
• Learn correspondences:

Paper link:

https://arxiv.org/pdf/1512.02134.pdf

Feature-Based Methods





Left Image

Right Image

Match sparse sets of extracted features.

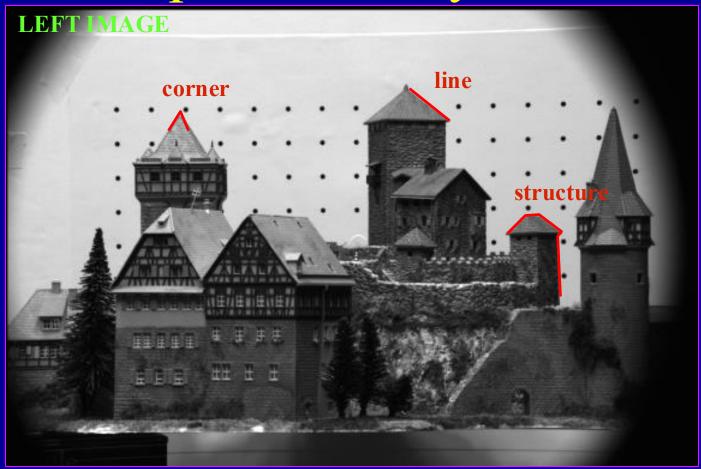
A feature descriptor for a line could contain:

length I, orientation o, midpoint (x,y), average contrast c

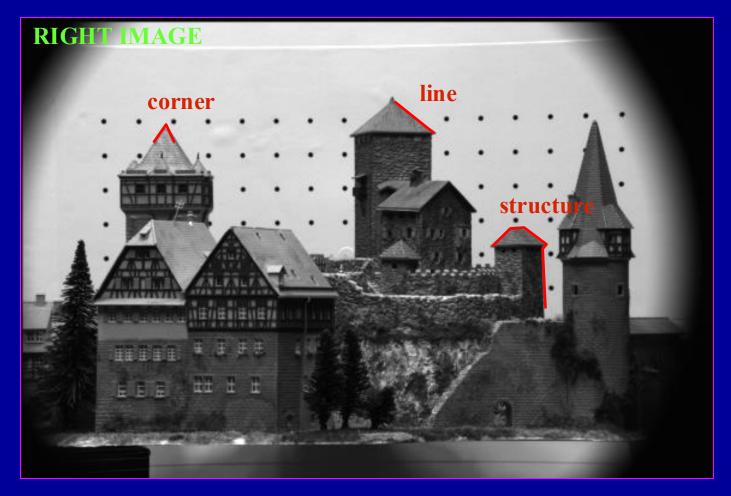
An example similarity measure (w's are weights):

$$S = \frac{1}{w_0(l_l - l_r)^2 + w_1(\theta_1 - \theta_2)^2 + w_2(m_l - m_r)^2 + w_3(c_l - c_r)^2}$$

Correspondence By Features



Correspondence By Features



Search in the right image... the disparity (dx, dy) is the displacement when the similarity measure is maximum

Comparison

Correlation-Based

- Dense depth maps.
- Need textured images
- Sensitive to foreshorening/illumination changes
- Need close views

Feature-Based

- Sparse depth maps.
- Insensitive to illumination changes.
- A-priori info used.
- Faster.

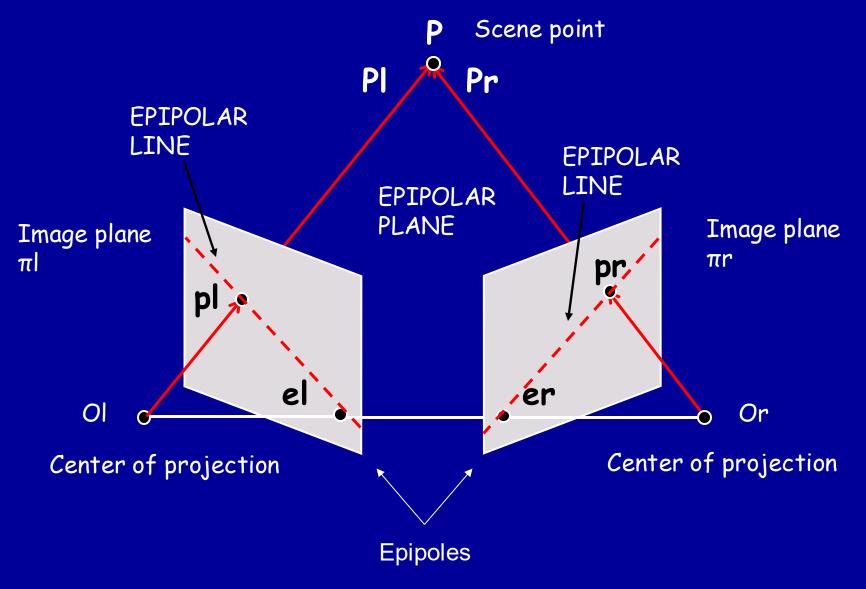
Problems: occlusions/spurious matches:

=>Introduce constraints in matching (i.e. left-right consistency constraint)

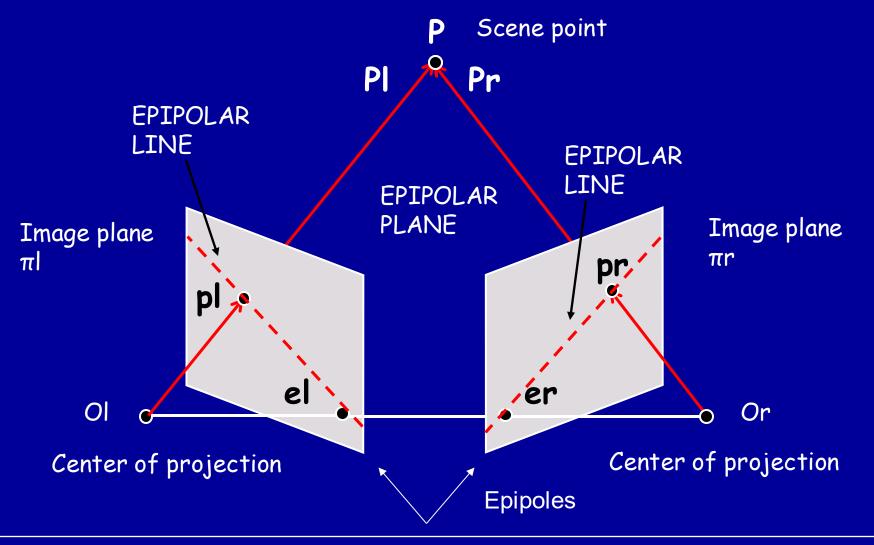
Evaluation Benchmarks

- Middlebury stereo dataset:
 - http://vision.middlebury.edu/stereo/
- KITTI
 - http://www.cvlibs.net/datasets/kitti/

Epipolar Constraint



Epipolar Constraint



Extrinsic parameters: Left/Right Camera Frames: Pr=R(PI-T), T=Or-Ol (1)

Epipolar Constraint Ol, Or, pl => Scene point Enough to define right E.L. Pr **EPIPOLAR** LINE **EPIPOLAR** LINE **EPIPOLAR** PLANE Image plane Image plane pr, π πr pl Center of projection Center of projection **Epipoles**

Given pl, pr is constrained to lie on the Epipolar Line (E.L.). For each left pixel pl, find the corresponding right E.L. Searching for pr reduces to a 1-D problem.

Epipolar Constraint Scene points Image plane Center of projection Center of projection **Epipoles**

All E.L.s go through epipoles.

Parallel image planes => epipoles at infinity.

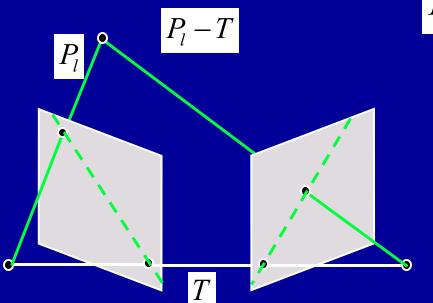
Essential Matrix

Estimate the epipolar geometry: correspondence between points and E.L.s.

 P_l and T are coplanar

Essential Matrix

Estimate the epipolar geometry: correspondence between points and E.L.s.



 P_{I}, P_{I} -T and T are coplanar

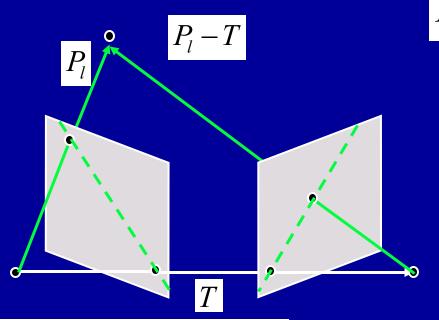
$$(P_l - T)^T T \times P_l = 0$$

$$(1)$$

$$(R^T P_r)^T (T \times P_l) = 0$$

Essential Matrix

Estimate the epipolar geometry: correspondence between points and E.L.s.



 P_l, P_l -T and T are coplanar

$$(P_l - T)^T T \times P_l = 0$$

$$(R^T P_r)^T (T \times P_l) = 0$$



$$P_r^T E P_l = 0$$

Link bw/ epipolar constraint and extrinsic parameters of stereo system.

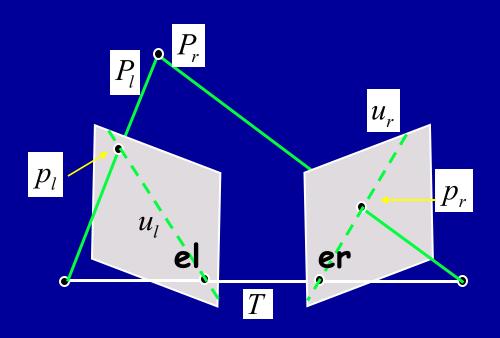
$$T \times P_l = SP_l$$

$$S = \begin{bmatrix} 0 & -T_Z & T_Y \\ T_Z & 0 & -T_X \\ -T_Y & T_X & 0 \end{bmatrix}$$

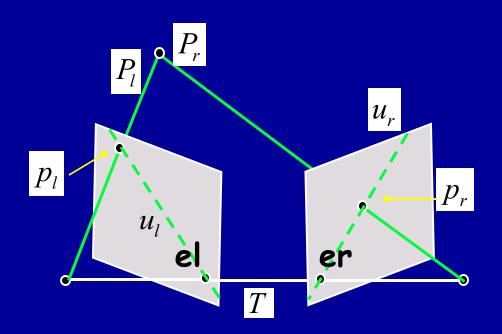
$$P_r^T R (T \times P_l) = 0$$



$$P_r^T(RS)P_l = 0$$



$$P_r^T E P_l = 0$$

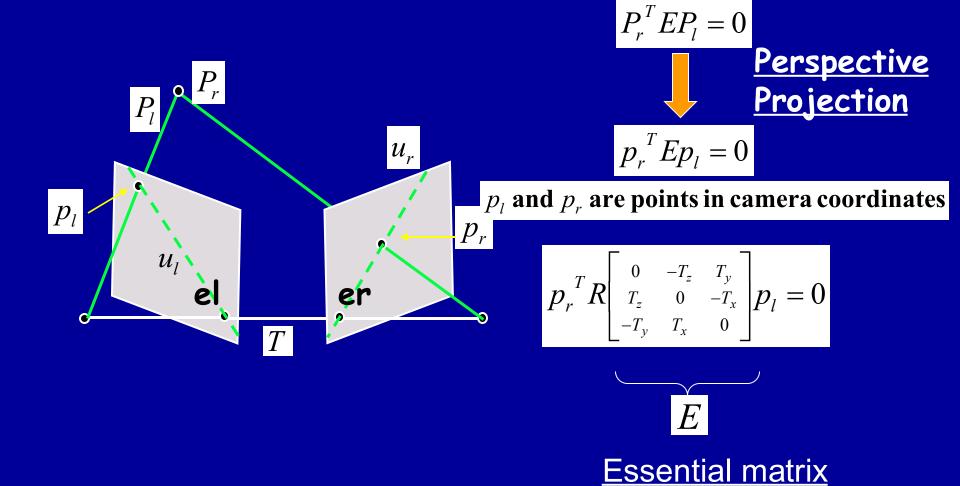


Perspective Projection:

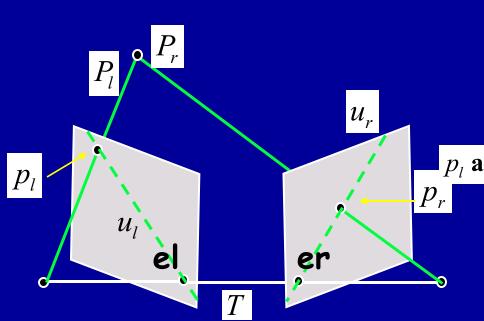
$$P_r^T E P_l = 0$$

$$p_r = \frac{f_r}{Z_r} P_r$$

$$p_l = \frac{f_l}{Z_l} P_l$$



Rank 2



$$p_r^T E p_l = 0$$

 p_l and p_r are points in camera coordinates

$$p_r^T R \begin{bmatrix} 0 & -T_z & T_y \\ T_z & 0 & -T_x \\ -T_y & T_x & 0 \end{bmatrix} p_l = 0$$

Epipolar lines are found by

$$u_r = Ep_l$$
$$u_l = E^T p_r$$

E

Essential matrix Rank 2

Note:

Lines in Projective space

Homogennous Center of projection image points So & & B can be represented by 3-vectors Pa & Ps with any A, 2 \$0 The imperconditate of a for example are: $\left(\begin{array}{c} 2\times\alpha\\ 92\alpha\end{array}\right) = \left(\begin{array}{c} 7\alpha\\ 2\alpha\end{array}\right) = \left(\begin{array}{c} 7\alpha\\ 2\alpha\end{array}\right)$

dine ab is the interection but imper place and plane of Parb (It) with Mount by = + Namo lize (PxxPo) Therefore & line can be represented by & 3-vector My in projective scare! Note:

EVERY POINT 3 on line ab

Lines in

Projective space

product > MJ. P=0.

So for example in MJ = [U2]

and g is a point [Px] in

Projective space, then:

MJ. P=0=> Ux-Px+U2-Py+U3=0

Camera Models (linear versions)

$$M_{int} = \begin{pmatrix} -f/s_x & 0 & o_x \\ 0 & -f/s_y & o_y \\ 0 & 0 & 1 \end{pmatrix}$$

Elegant decomposition. No distortion!

$$M_{ext} = \begin{pmatrix} r_{11} & r_{12} & r_{13} & \mathrm{Tx} \\ r_{21} & r_{22} & r_{23} & \mathrm{Ty} \\ r_{31} & r_{32} & r_{33} & \mathrm{Tz} \end{pmatrix},$$

The Linear Matrix Equation of Perspective Projections

Homogeneous Coordinates

$$\begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = M_{int} M_{ext} \begin{pmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{pmatrix}.$$

Measured Pixel

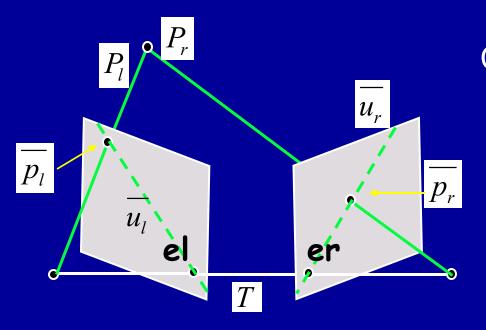
$$(x_{im}=x_1/x_3, y_{im}=x_2/x_3)$$



Fundamental Matrix (F)

Ml (Mr) matrix of intrinsic parameters for left (right) camera.

$$p_r^T E p_l = 0$$



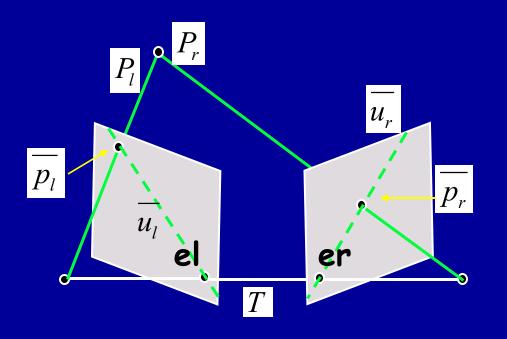
Converting to pixel coordinates

$$\overline{p}_l = M_l p_l$$

$$\overline{p}_r = M_r p_r$$

Fundamental Matrix (F)

Ml (Mr) matrix of intrinsic parameters for left (right) camera.



Fundamental matrix F

$$\overline{p}_r^T F \overline{p}_l = 0$$

$$F = M_r^{-T} E M_l^{-1}$$

F: pixel coordinates!

E: camera coordinates!

Epipolar lines:

$$\frac{\overline{u_r}}{\overline{u_l}} = F\overline{p}_l$$

$$\overline{u_l} = F^T\overline{p}_r$$

Conclusions

Essential Matrix

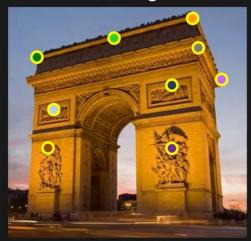
- Encodes information on extrinsic parameters.
- Has rank 2.
- Its 2 non-zero singular values are equal.

Fundamental Matrix

- Encodes information on both the <u>extrinsic</u> and <u>intrinsic</u> parameters.
- Has rank 2.

Find a set of corresponding features in left and right images (e.g. using SIFT or hand-picked)

Left image

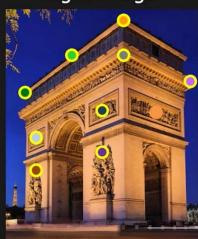


$$(u_l^{(1)}, v_l^{(1)})$$

:

$$\bullet$$
 $(\boldsymbol{u}_l^{(m)}, \boldsymbol{v}_l^{(m)})$

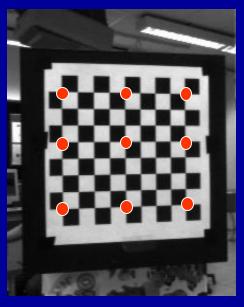
Right image

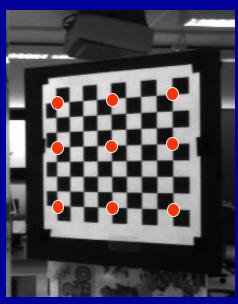


$$(u_r^{(1)}, v_r^{(1)})$$

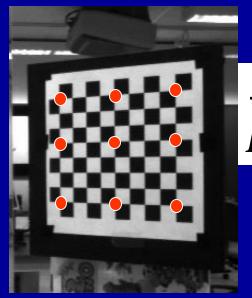
:

$$\bullet$$
 $(\boldsymbol{u}_r^{(m)}, \boldsymbol{v}_r^{(m)})$







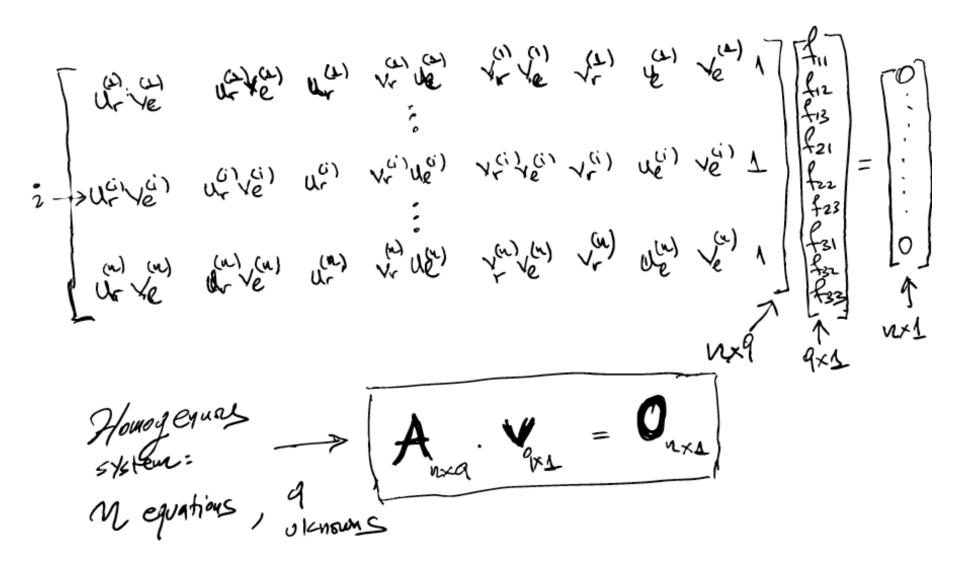


$$\overline{p}_{r}^{i} F \overline{p}_{l}^{i} = 0$$

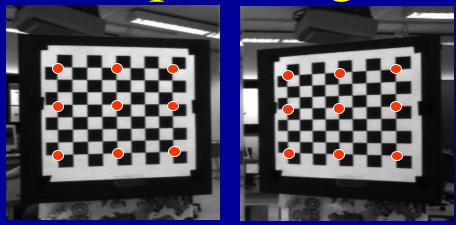
Problem: Find the fundamental matrix from a set of image correspondences

$$\{\!\!\left(\overline{p}_{l}^{i},\overline{p}_{r}^{i}\right)\!\!\},i=1...N$$

Known



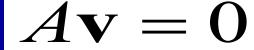
The 8-point algorithm



n>=8 correspondences

$$\overline{p}_{r}^{i_{r}^{T}}F \ \overline{p}_{l}^{i} = 0$$





v: the 9 elements of F (uknown)

A: n x 9 measurement matrix (known).

Solve using SVD (solution up to a scale factor).

Enforce rank(F)=2 (SVD on the computed F). Be careful: numerical instabilities.

The 8-point algorithm

n>=8 correspondences

$$\overline{p}_{r}^{i} F \overline{p}_{l}^{i} = 0$$



$$A\mathbf{v} = 0$$

1) SVD:
$$A = UDV^T$$

=> v is column V: smaller singular value

- 2) Construct F using values of v
- 3) Apply SVD to F (again!): $F = U'D'V'^T$
- 4) Enforce rank(F) = 2 by setting D' smaller sing. value to 0.
- 5) So $F' = U'D''V'^T$ fundamental matrix element set to 0).

is the estimate of the (D'' is D' with smaller

Find R, T from Fundamental Matrix

• If cameras are calibrated (internals known)

$$F = M_r^{-T} E M_l^{-1} \longrightarrow E = M_r^{T} F M_l$$

• But, $E = R S_{[T]}$ Solve for R, T (SVD)

Epipolar Lines – Example





Left Image





Epipolar Lines – Example



Left Epipolar Lines

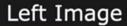
Right E. L.

Example

Finding Epipolar Lines: Example

Given the Fundamental matrix,

$$F = \begin{bmatrix} -.003 & -.028 & 13.19 \\ -.003 & -.008 & -29.2 \\ 2.97 & 56.38 & -9999 \end{bmatrix}$$





Right Image



Finding Epipolar Lines: Example

Given the Fundamental matrix,

$$F = \begin{bmatrix} -.003 & -.028 & 13.19 \\ -.003 & -.008 & -29.2 \\ 2.97 & 56.38 & -9999 \end{bmatrix}$$

and the left image point

$$\widetilde{\boldsymbol{u}}_l = \begin{bmatrix} 343 \\ 221 \\ 1 \end{bmatrix}$$

Left Image



Right Image

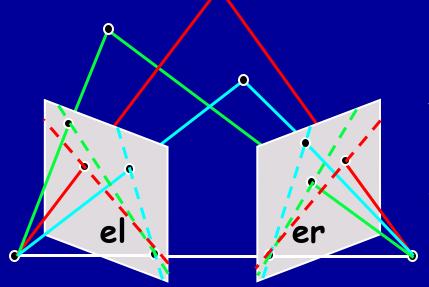


Epipolar Line

The equation for the epipolar line in the right image is

$$.03u_r + .99v_r - 265 = 0$$

Locating the Epipoles from E & F



Accurate epipole localization:

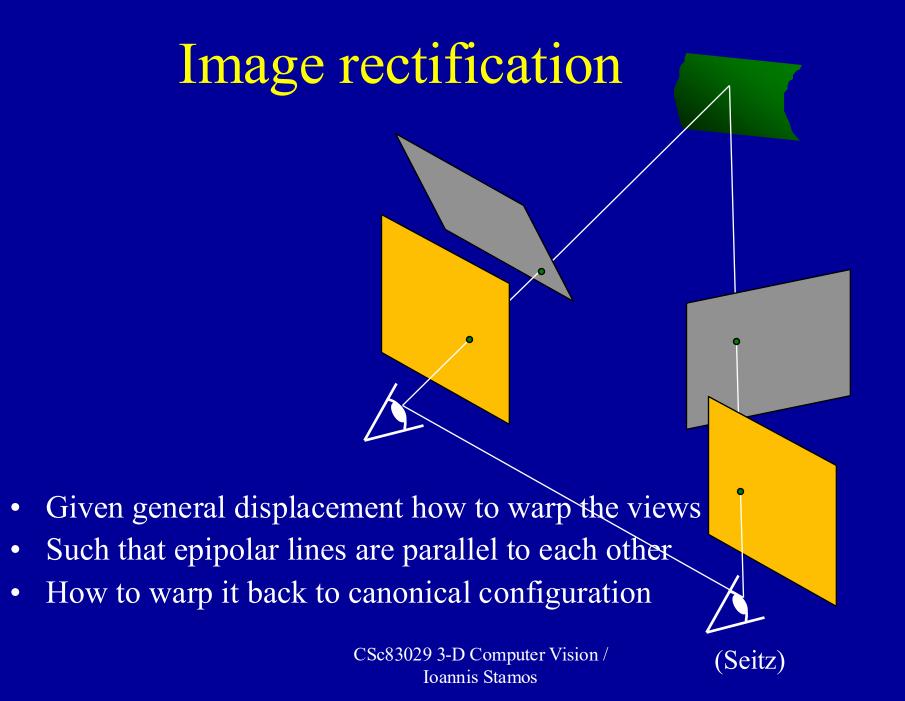
- 1) Refining epipolar lines.
- 2) Checking for consistency.
- 3) Uncalibrated stereo.

 $F \Rightarrow el$, er in pixel coordinates.

E => el, er in camera coordinates.

Fact: All epipolar lines pass through epipoles.

$$\overline{p}_r^T F \overline{e}_l = 0, \forall \overline{p}_r$$



Epipolar rectification





- Rectified Image Pair
- Corresponding epipolar lines are aligned with the scan-lines
- Search for dense correspondence is a 1D search

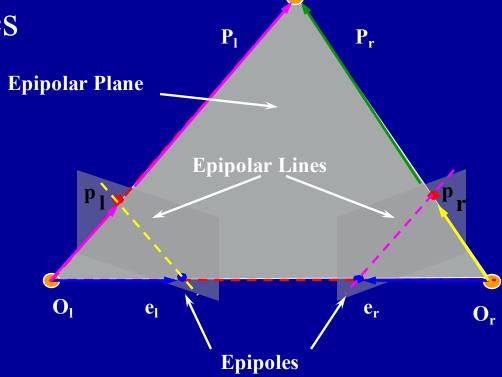
Epipolar rectification



Rectified Image Pair

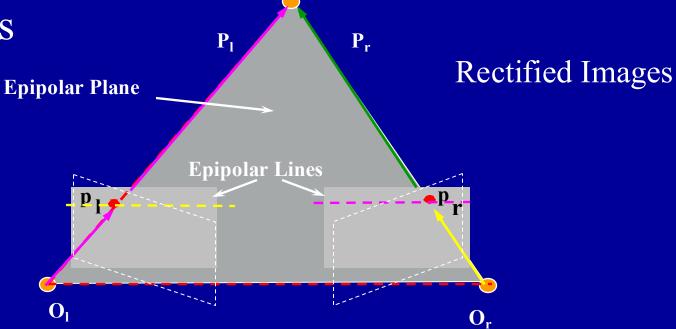
Rectification

• Problem: Epipolar lines not parallel to scan lines



Rectification

• Problem: Epipolar lines not parallel to scan lines



Epipoles at infinity

Image Rectification (cont.)

- Perform by rotating the cameras
- *Not* equivalent to rotating the images
- The lines through the centers become parallel to each other, and the epipoles move to infinity

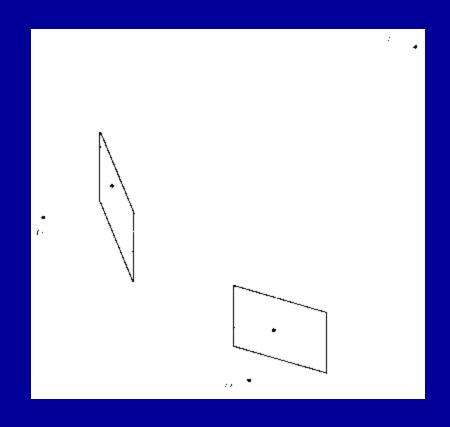


Image Rectification (cont.)

- Given extrinsic parameters T and R (relative position and orientation of the two cameras)
 - Rotate the left camera about the projection center so that the epipolar lines become parallel to the horizontal axis
 - Apply the same rotation to the right camera
 - Rotate the right camera by R
 - Adjust the scale in both camera reference frames

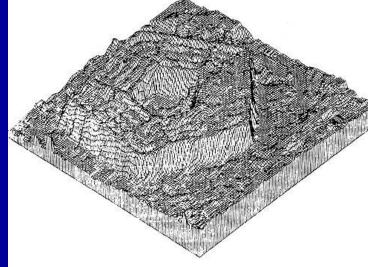
3-D Reconstruction

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.











3-D Reconstruction

A Priori Knowledge

- **3-D Reconstruction from two views**
- Intrinsic and extrinsic
- Intrinsic only
- No information

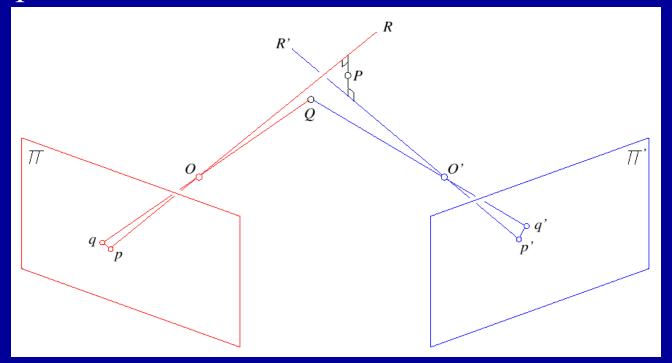
- Unambiguous (triangulation)
- Up to unknown scaling factor
- Up to unknown projective transformation

Reconstruction

- Given pair of image points p and p', and focal points O and O', find preimage P
- In theory: find P by intersecting the rays R=Op and R'=Op'
- In practice: R and R' won't actually intersect due to calibration and feature localization errors

Reconstruction Approaches

- Geometric
 - Construct the line segment perpendicular to R and R' that intersects both rays and take its midpoint



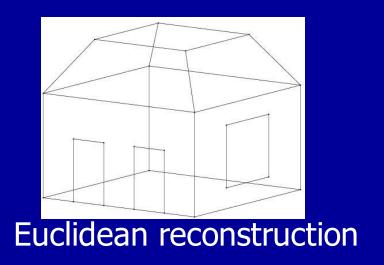
2. Pl 3. (Rpr) H | Goord. System OF T RIGHT So wis _ to both lines & V : «Pe + c (7exx pr) = T+ b (2pr) => $\Rightarrow \alpha pl - b(p^{T}pr) + c(p_{e} \times p^{T}pr) = T \Rightarrow$ 3×3 system: compute 0, b & C.

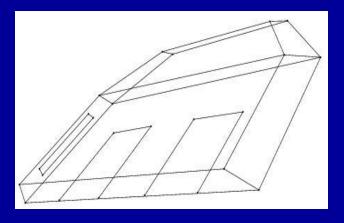
Check this out!



http://www.well.com/user/jimg/stereo/stereo list.html

Projective Reconstruction





Projective reconstruction

Euclidean vs Projective reconstruction

- Euclidean reconstruction true metric properties of objects lengths (distances), angles, parallelism are preserved
- Unchanged under rigid body transformations
- => Euclidean Geometry properties of rigid bodies under rigid body transformations, similarity transformation
- Projective reconstruction lengths, angles, parallelism are NOT preserved we get distorted images of objects their distorted
 3D counterparts --> 3D projective reconstruction
- => Projective Geometry

How can We Improve Stereo?



Space-time stereo scanner uses unstructured light to aid in correspondence



Result: Dense 3D mesh (noisy)

Active Stereo: Adding Texture to Scene

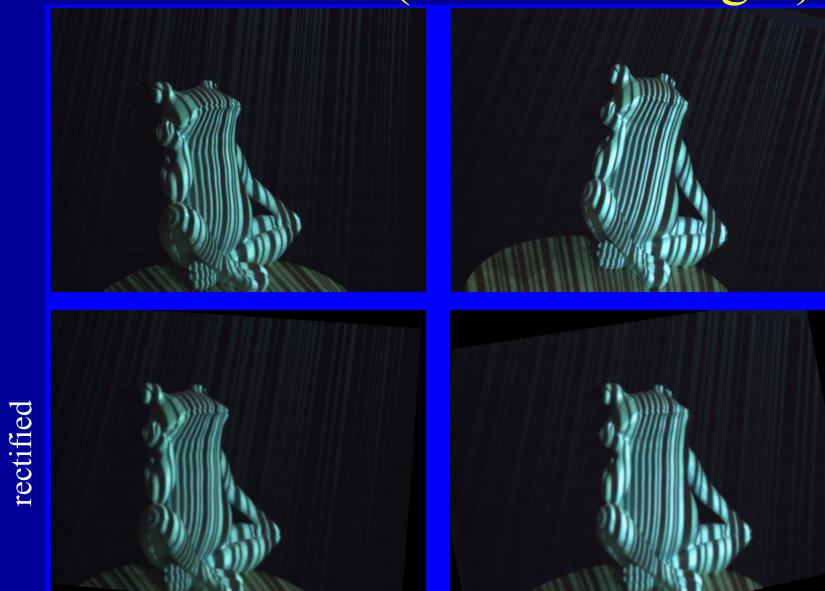


By James Davis, Honda Research, Now UCSC

CSC83029 3-D Computer Vision /

Ioannis Stamos

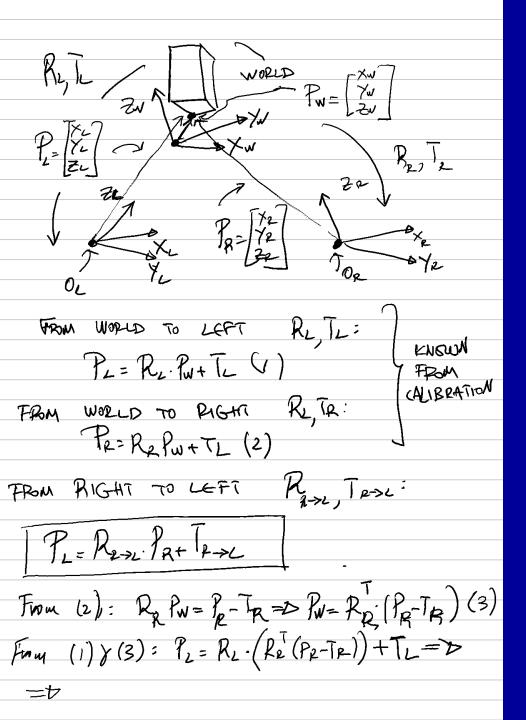
Active Stereo (Structured Light)



From Sebastian Thrun/Jana Kosecka

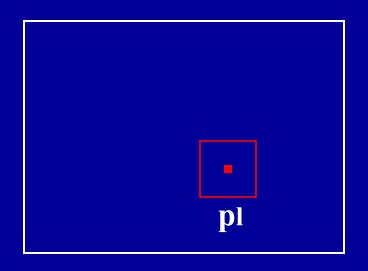
Older slides

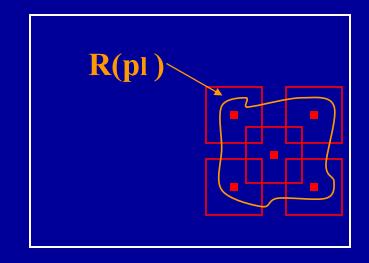
Stereo Calibration
Using
Calibration object



Stereo Calibration
Using
Calibration object

Correlation-Based Methods





Left Image

Right Image

For each pixel pl=[i,j] in the left image

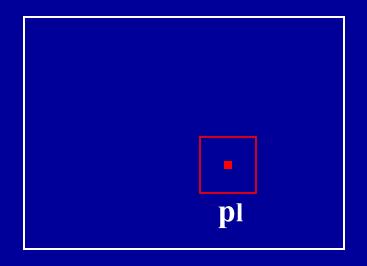
For each displacement d=[d1,d2] in R(p1)

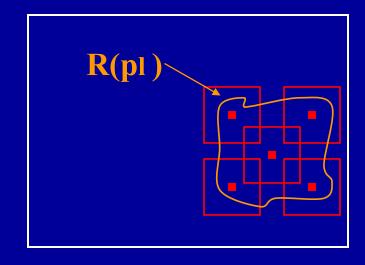
Compute
$$c(\mathbf{d}) = \sum_{k=-W}^{W} \sum_{l=-W}^{W} \psi(I_l(i+k,j+l), Ir(i+k-d_1,j+l-d_2))$$

The disparity of pl is the \mathbf{d} that maximizes $\mathbf{c}(\mathbf{d})$

HAVE TO SPECIFY: Region R, size W, and correlation function ψ.

Correlation-Based Methods





Left Image

Right Image

SSD is usually preferred: handles different intensity scales.

Normalized cross-correlation is better (but is more expensive).