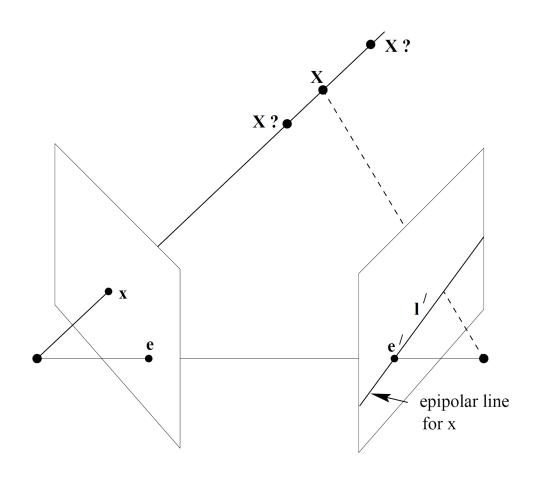


CS 4391 Introduction Computer Vision
Professor Yu Xiang
The University of Texas at Dallas

Recall Fundamental Matrix



• Epipolar line
$$\mathbf{l'} = F\mathbf{x}$$

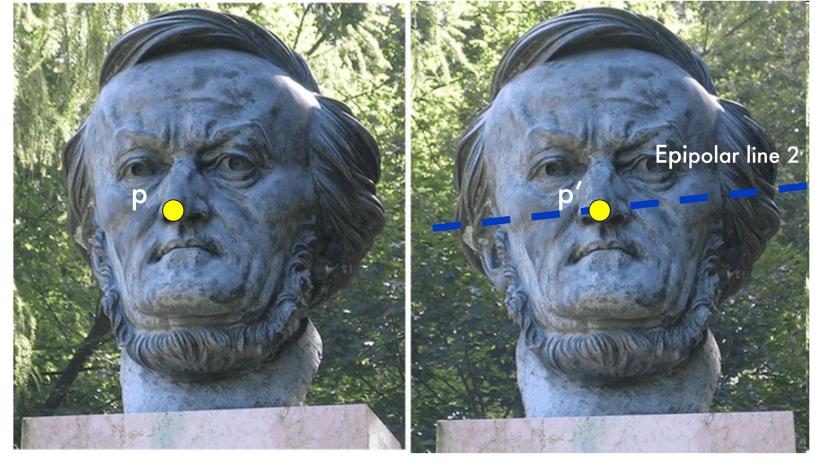
$$\mathbf{l} = F^T\mathbf{x'}$$

Fundamental matrix

$$F=[\mathbf{e}']_{ imes}P'P^+$$
3x3

Epipole $\mathbf{e}'=(P'C)$
 $P^+=P^T(PP^T)^{-1}$

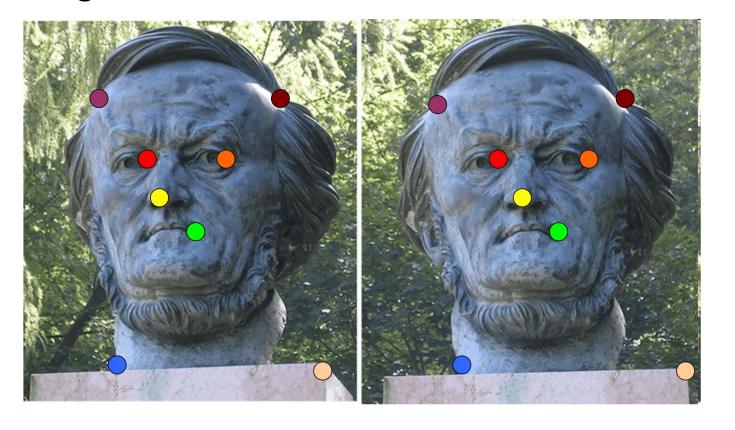
Why the Fundamental Matrix is Useful?



$$\mathbf{l}' = F\mathbf{p}$$

Estimating the Fundamental Matrix

• The 8-point algorithm



$$\mathbf{l}' = F\mathbf{x}$$

 $\mathbf{x}'^\mathsf{T} \mathbf{F} \mathbf{x} = 0$

Estimating the Fundamental Matrix

$$\mathbf{x}'^{\mathsf{T}}\mathbf{F}\mathbf{x} = 0 \quad \mathbf{x} = (x, y, 1)^{\mathsf{T}} \quad \mathbf{x}' = (x', y', 1)^{\mathsf{T}}$$
$$x'xf_{11} + x'yf_{12} + x'f_{13} + y'xf_{21} + y'yf_{22} + y'f_{23} + xf_{31} + yf_{32} + f_{33} = 0$$
$$(x'x, x'y, x', y'x, y'y, y', x, y, 1) \mathbf{f} = 0$$

n correspondences

$$\mathbf{Af} = \begin{bmatrix} x'_1 x_1 & x'_1 y_1 & x'_1 & y'_1 x_1 & y'_1 y_1 & y'_1 & x_1 & y_1 & 1 \\ \vdots & \vdots \\ x'_n x_n & x'_n y_n & x'_n & y'_n x_n & y'_n y_n & y'_n & x_n & y_n & 1 \end{bmatrix} \mathbf{f} = \mathbf{0}$$

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Linear System

$$\begin{array}{c}
A\mathbf{f} = 0 \\
n \times 9 & 9 \times 1
\end{array}$$

- Find non-zero solutions
- If f is a solution, k×f is also a solution for $k \in \mathcal{R}$
- If the rank of A is 8, unique solution (up to scale)
- Otherwise, we can seek a solution $\|\mathbf{f}\| = 1$

$$\min \|A\mathbf{f}\| \qquad \qquad \sum_{1}^{\text{Solution: } A} \underbrace{UDV^T}_{\text{SVD decomposition of A}} \text{Subject to } \|\mathbf{f}\| = 1 \qquad \qquad n \times n \quad n \times 9 \quad 9 \times 9$$

f is the last column of V

A5.3 in HZ

Estimating the Fundamental Matrix

• The singularity constraint $\det {\sf F} = 0$

$$\min \|F - F'\|$$
 Subject to $\det F' = 0$

$$F = UDV^T$$

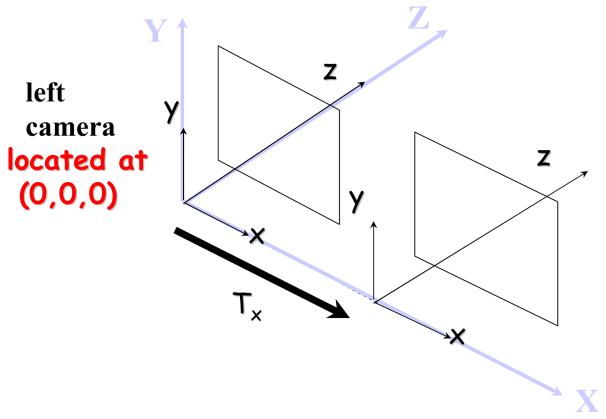
$$D = diag(r, s, t)$$

$$r \geq s \geq t$$

Solution:

$$\mathbf{F}' = \mathbf{U}\mathbf{diag}(r, s, 0)\mathbf{V}^\mathsf{T}$$

Special Case: A Stereo System

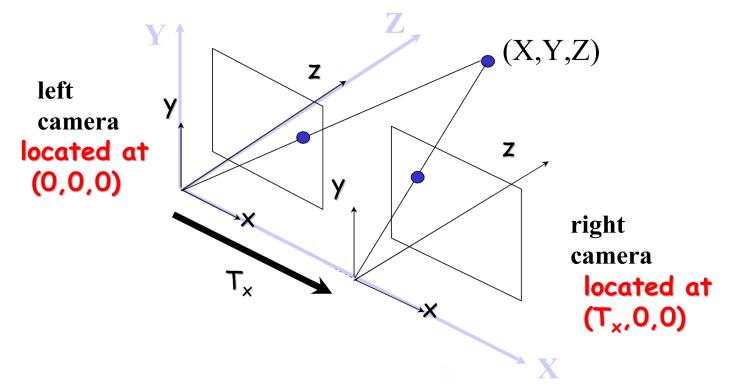


• The right camera is shifted by T_{x} (the stereo baseline)

The camera intrinsics are the same

right camera located at $(T_x, 0, 0)$

Special Case: A Stereo System



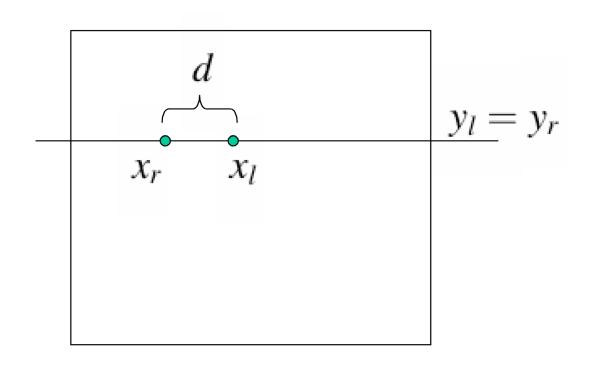
Left camera

$$x_l = f\frac{X}{Z} + p_x \qquad y_l = f\frac{Y}{Z} + p_y$$

• Right camera

$$x_r = f \frac{X - T_x}{Z} + p_x$$
$$y_r = f \frac{Y}{Z} + p_y$$

Stereo Disparity



Disparity

$$d = x_l - x_r$$

$$= (f\frac{X}{Z} + p_x) - (f\frac{X - T_x}{Z} + p_x)$$

$$= f\frac{T_x}{Z}$$

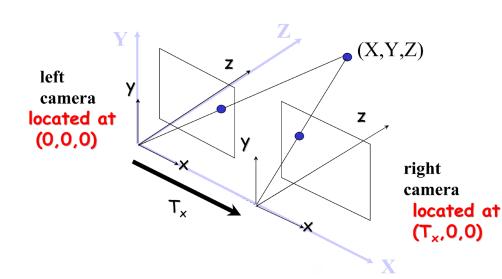
• Depth $Z=frac{T_x}{I}$

Disparity

Baseline

Recall motion parallax: near objects move faster (large disparity)

Special Case: A Stereo System



$$P = K[I \mid 0]$$
 $P' = K[I \mid t]$

$$\mathbf{F} = [\mathbf{e}']_{\times} \mathbf{K}' \mathbf{R} \mathbf{K}^{-1} = \mathbf{K}'^{-\mathsf{T}} [\mathbf{t}]_{\times} \mathbf{R} \mathbf{K}^{-1} = \mathbf{K}'^{-\mathsf{T}} \mathbf{R} [\mathbf{R}^{\mathsf{T}} \mathbf{t}]_{\times} \mathbf{K}^{-1} = \mathbf{K}'^{-\mathsf{T}} \mathbf{R} \mathbf{K}^{\mathsf{T}} [\mathbf{e}]_{\times}$$

$$\mathbf{F} = [\mathbf{e}']_{\times} \mathbf{K} \mathbf{K}^{-1} = [\mathbf{e}']_{\times}$$

$$\mathbf{e}' = (P'C)$$
 $\mathbf{C} = \begin{pmatrix} \mathbf{0} \\ 1 \end{pmatrix}$

$$K = \begin{bmatrix} f_x & 0 & p_x \\ 0 & f_y & p_y \\ 0 & 0 & 1 \end{bmatrix} \quad \mathbf{e}' = \begin{bmatrix} f_x T_x \\ 0 \\ 0 \end{bmatrix} \quad F = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -f_x T_x \\ 0 & f_x T_x & 0 \end{bmatrix} \quad \mathbf{x}'^T F \mathbf{x} = 0$$

$$y = y'$$

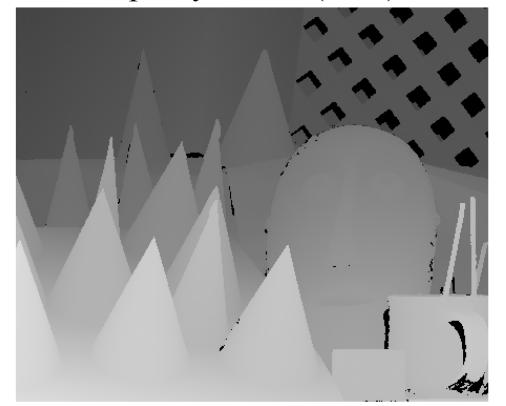
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Stereo Example





Disparity values (0-64)



Note how disparity is larger (brighter) for closer surfaces.

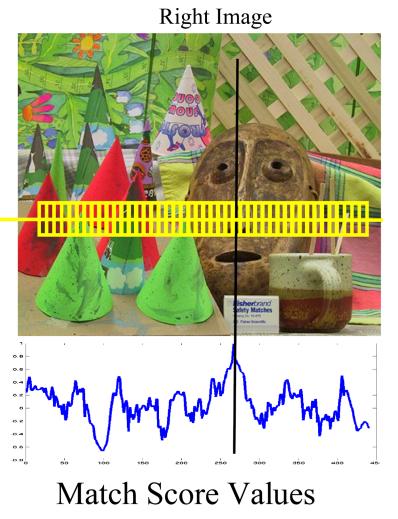
$$d = f \frac{T_x}{Z}$$

Computing Disparity

Left Image

For a patch in left image

Compare with patches along same row in right image



- Eipipolar lines are horizontal lines in stereo
- For general cases, we can find correspondences on eipipolar lines
- Depth from disparity

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

Further Reading

• Stanford CS231A: Computer Vision, From 3D Reconstruction to Recognition, Lecture 5 https://web.stanford.edu/class/cs231a/syllabus.html

Multiview Geometry in Computer Vision, Richard Hartley and Andrew Zisserman,
 Chapter 9, Epipolar Geometry and Fundamental Matrix