

CS231A Midterm Review

May 2nd 2025

Agenda

- Exam logistics
- Preparation tips
- Core topics

Midterm logistics

- Format
 - 8 True/False questions, 6 multiple choice questions, and 3 short answer questions
- 80 Minutes during class time (1:30 PM - 2:50 PM, May 5)
- Gates B1- Basement floor of the Gates Building
- Practice exam
- SCPD students - 24 hours window
- *Open notes but closed Internet*
- No electronic devices are allowed (calculators are allowed)

Preparing for the midterm

Resources:

- Lectures 1 - 10
- Problem Sets 0 - 2
- Course notes
- Recommended textbooks

Again: open notes!

- Focus on foundations & high-level understanding; you will have time to look up details.

Core topics (1/2)

- General background
 - Necessary linear algebra
 - Homogeneous coordinates
 - Transformations
 - Formulating & solving least squares problems (when do we use an SVD?)
- Camera models
 - Perspective & non-perspective
 - Degrees of freedom
 - Distortion
 - Calibration
- Single view metrology
 - Vanishing points, vanishing lines

Core topics (2/2)

- Multiview geometry
 - Epipolar geometry; essential and fundamental matrices; 8-point algorithm
 - Structure from motion
 - Stereo
 - Perspective, affine, similarity ambiguities
- Active and volumetric stereo
 - Structured lighting
 - Space carving & Shadow carving & Voxel coloring
- Fitting & Matching
 - Least squares
 - RANSAC
 - Hough transforms
- Representations & Representation Learning (High Level Questions)

Necessary Linear Algebra

- 4 Basic spaces of a matrix: Null space, column space, row space
- Invertibility; Rank; Determinant
- Special matrices: identity matrix, orthogonal matrix, etc.
- QR decomposition: Decomposition of a matrix into orthogonal and upper triangular matrices.
- SVD:
 - Data Compression: Vectors corresponding to k largest singular values
 - Solve a (non-zero) vector in the null space of a matrix approximately: The vector corresponding to the smallest singular value

Homogeneous Coordinates

- Augmented space for writing coordinates:

$$\text{2D:} \quad \begin{bmatrix} x \\ y \end{bmatrix} \iff \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \iff \begin{bmatrix} wx \\ wy \\ w \end{bmatrix}$$

$$\text{3D:} \quad \begin{bmatrix} x \\ y \\ z \end{bmatrix} \iff \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \iff \begin{bmatrix} wx \\ wy \\ wz \\ w \end{bmatrix}$$

2D Lines

Homogeneous coordinates give us a neat way of representing 2D lines as vectors/orthogonality constraints:

$$ax + by + c = 0$$

$$\begin{bmatrix} a & b & c \end{bmatrix} \begin{bmatrix} x & y & 1 \end{bmatrix}^T = 0$$

=> symmetry between lines and points

=> cross products suddenly becomes very useful!

2D Lines

How can we get the line connecting two points?

Given:

$$\begin{bmatrix} x_1 & y_1 & 1 \end{bmatrix}$$
$$\begin{bmatrix} x_2 & y_2 & 1 \end{bmatrix}$$

Unknown:

$$\begin{bmatrix} a & b & c \end{bmatrix}$$

Subject to:

$$\begin{bmatrix} a & b & c \end{bmatrix} \begin{bmatrix} x_1 & y_1 & 1 \end{bmatrix}^T = 0$$
$$\begin{bmatrix} a & b & c \end{bmatrix} \begin{bmatrix} x_2 & y_2 & 1 \end{bmatrix}^T = 0$$

Solution

$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix} \times \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix}$$

2D Lines

How can we get the intersection of two lines?

Given:

$$\begin{bmatrix} a_1 & b_1 & c_1 \\ a_2 & b_2 & c_2 \end{bmatrix}$$

Unknown:

$$\begin{bmatrix} x & y & 1 \end{bmatrix}$$

Subject to:

$$\begin{bmatrix} a_1 & b_1 & c_1 \end{bmatrix} \begin{bmatrix} x & y & 1 \end{bmatrix}^T = 0$$
$$\begin{bmatrix} a_2 & b_2 & c_2 \end{bmatrix} \begin{bmatrix} x & y & 1 \end{bmatrix}^T = 0$$

Solution:

$$\begin{bmatrix} wx \\ wy \\ w \end{bmatrix} = \begin{bmatrix} a_1 \\ b_1 \\ c_1 \end{bmatrix} \times \begin{bmatrix} a_2 \\ b_2 \\ c_2 \end{bmatrix}$$

Transformations

Isometric transformations:

Distances preserved

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$



Similarity transformations:

Shapes preserved

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} SR & t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}, \quad S = \begin{bmatrix} s & 0 \\ 0 & s \end{bmatrix}$$



Affine transformations:

Parallelism preserved

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} A & t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$



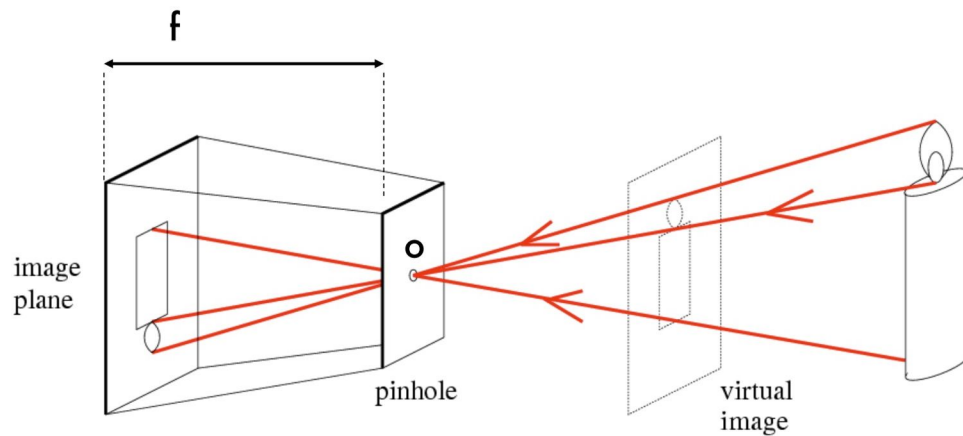
Projective transformations:

Lines preserved

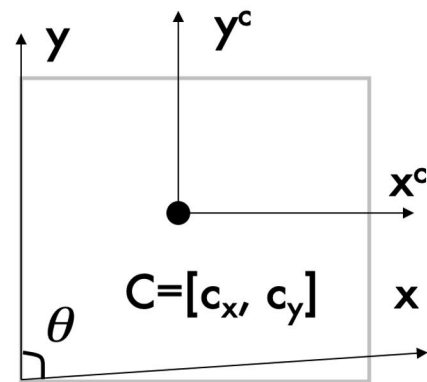
$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} A & t \\ v & b \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$



Pinhole Cameras

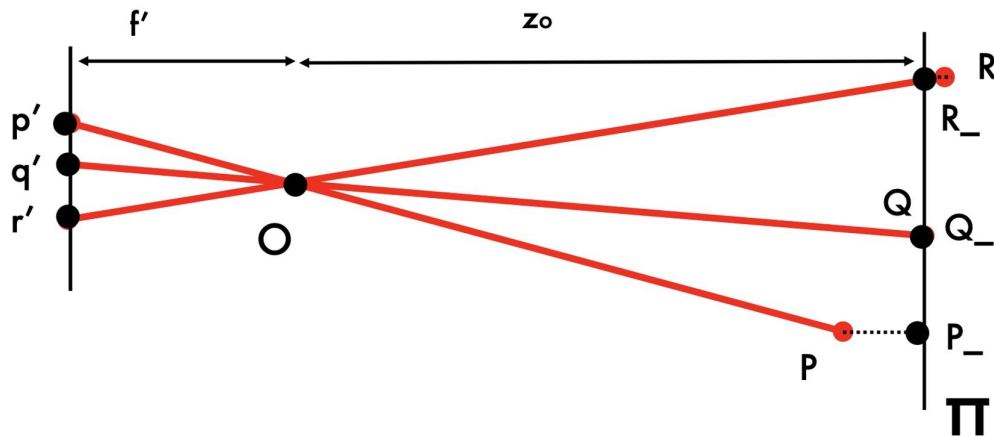


$$P' = \begin{bmatrix} \alpha & -\alpha \cot \theta & c_x & 0 \\ 0 & \frac{\beta}{\sin \theta} & c_y & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$



Camera Models

- Weak perspective projection
 - Useful when relative depth of the scene is **small** and **distant**
 - Magnification m is the ratio of the depth of the scene to camera focal length f'
 - Under what cases is the weak perspective accurate and why?



$$\begin{cases} x' = \frac{f'}{z} x \\ y' = \frac{f'}{z} y \end{cases} \rightarrow \begin{cases} x' = \frac{f'}{z_0} x \\ y' = \frac{f'}{z_0} y \end{cases}$$

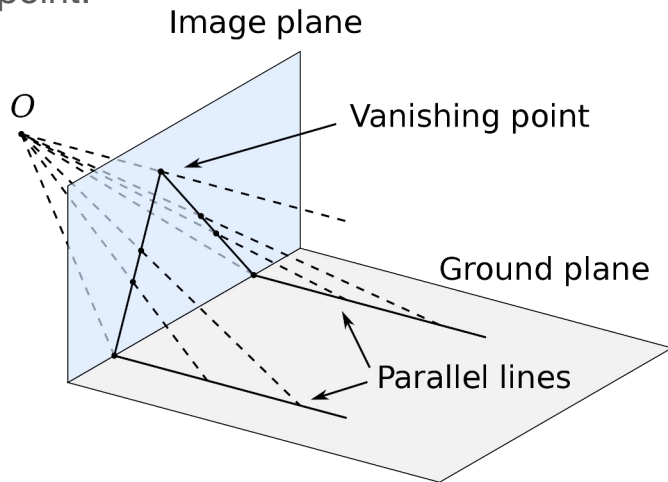
Camera Calibration

- Intrinsic Parameters: K
- Extrinsic Parameters: R, T
- 11 DOF
 - 5 from K
 - 3 from R
 - 3 from T
- Degenerate cases
- Know how to construct the homogeneous linear system

$$P' = M P_w = \underbrace{K}_{\text{Internal parameters}} \underbrace{[R \ T]}_{\text{External parameters}} P_w$$

Single View Metrology

Under projective transformation, parallel lines converge to a vanishing point:



We used this for camera calibration in PSET 1!

$$\mathbf{v} = K \mathbf{d}$$

[Eq. 24]

$$\mathbf{n} = K^T \mathbf{l}_{\text{horiz}}$$

[Eq. 27]

$$\cos \theta = \frac{\mathbf{v}_1^T \boldsymbol{\omega} \mathbf{v}_2}{\sqrt{\mathbf{v}_1^T \boldsymbol{\omega} \mathbf{v}_1} \sqrt{\mathbf{v}_2^T \boldsymbol{\omega} \mathbf{v}_2}}$$

[Eq. 28]

$\theta = 90$

$$\mathbf{v}_1^T \boldsymbol{\omega} \mathbf{v}_2 = 0$$

[Eq. 29]

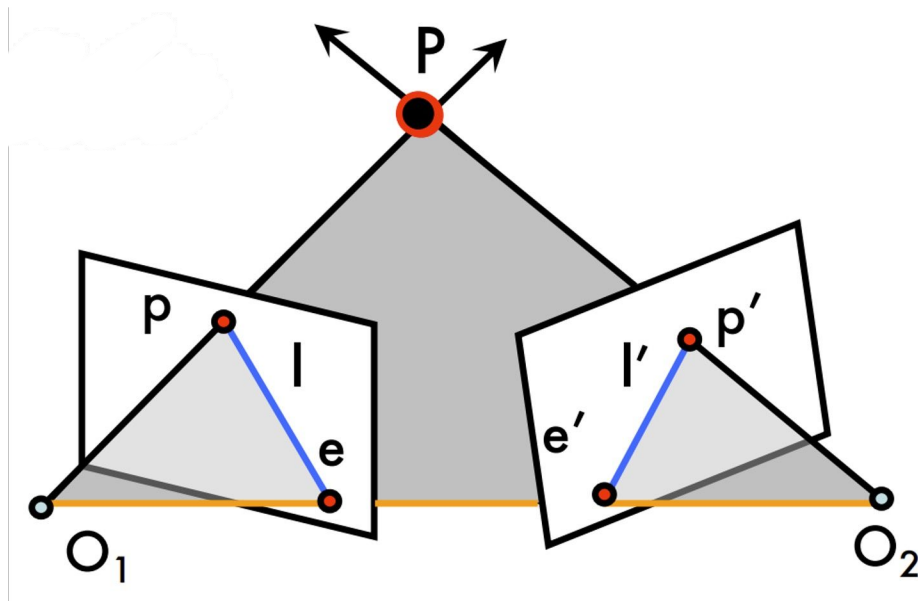
Useful to:

- To calibrate the camera
- To estimate the geometry of the 3D world

$$\boldsymbol{\omega} = (K K^T)^{-1}$$

[Eq. 30]

Epipolar Geometry



Essential matrix:

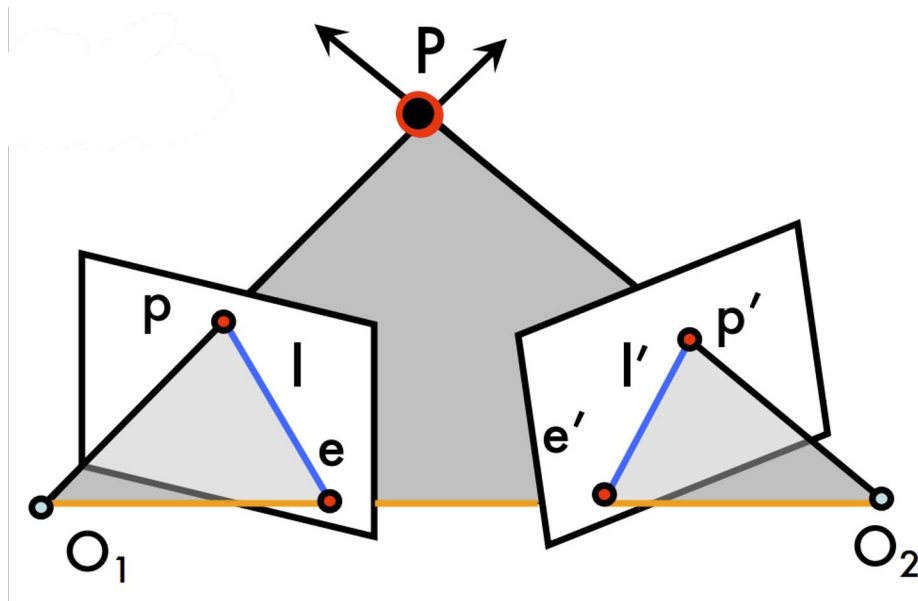
A point \rightarrow epipolar line
mapping for canonical
cameras ($K = I$)

$$l' = E^T p$$

$$l = E p'$$

$$p^T E p' = 0$$

Epipolar Geometry



Given a 2D point in one camera, a correspondence in the other must lie on an epipolar line

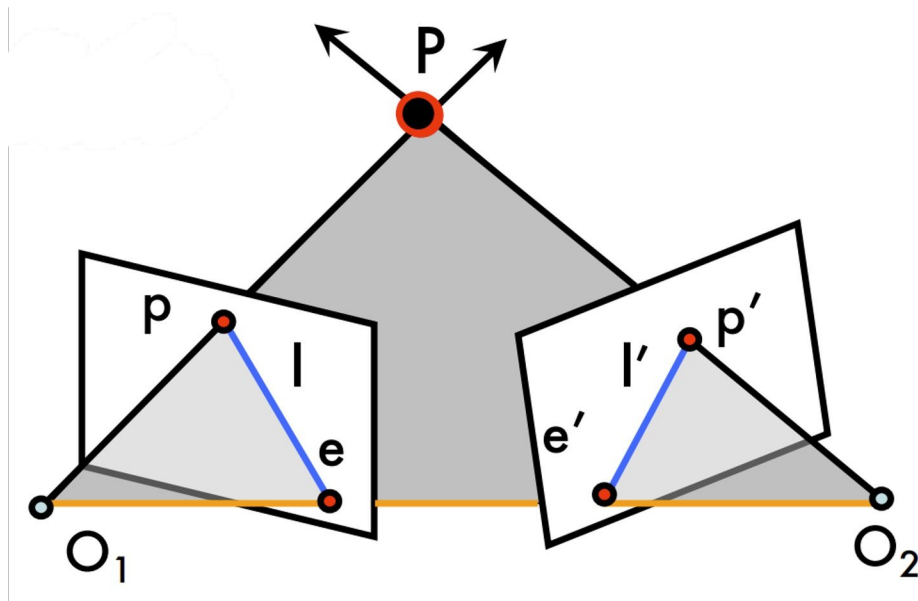
If \mathbf{p}' is known, we can compute \mathbf{l} and search for \mathbf{p} using:

$$\mathbf{l}^T \mathbf{p} = 0$$

If \mathbf{p} is known, we can compute \mathbf{l}' and search for \mathbf{p}' using:

$$\mathbf{l}'^T \mathbf{p}' = 0$$

Epipolar Geometry



Fundamental matrix:

A point \rightarrow epipolar line
mapping for general
projective cameras

$$l' = F^T p$$

$$l = F p'$$

$$p^T F p' = 0$$

Epipolar Geometry

Computing the fundamental matrix with the 8-point algorithm:

$$\mathbf{p}^T \mathbf{F} \mathbf{p}' = 0$$

Estimating F

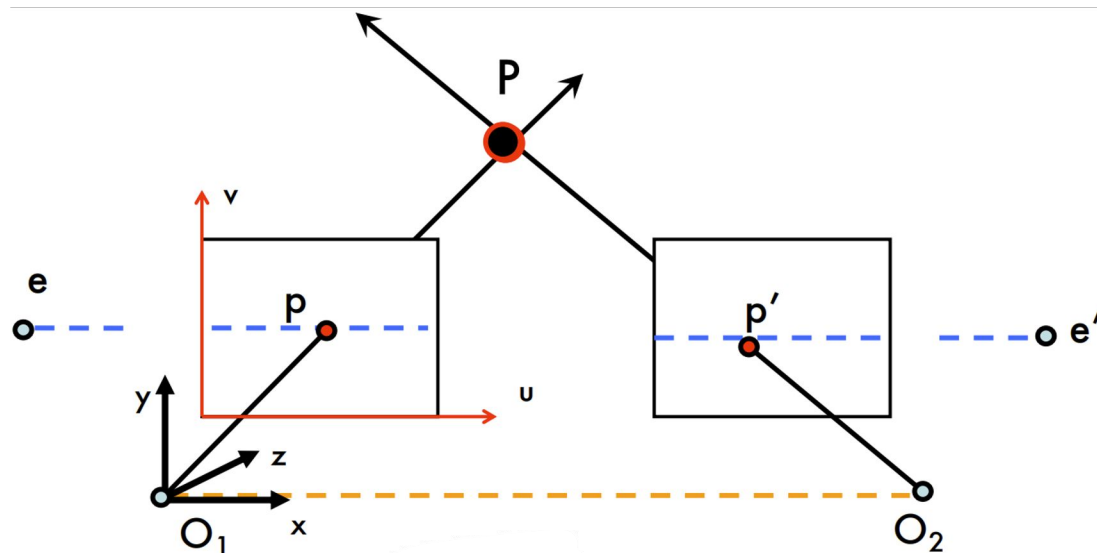
$$\mathbf{W} \begin{pmatrix} u_1 u'_1 & u_1 v'_1 & u_1 & v_1 u'_1 & v_1 v'_1 & v_1 & u'_1 & v'_1 & 1 \\ u_2 u'_2 & u_2 v'_2 & u_2 & v_2 u'_2 & v_2 v'_2 & v_2 & u'_2 & v'_2 & 1 \\ u_3 u'_3 & u_3 v'_3 & u_3 & v_3 u'_3 & v_3 v'_3 & v_3 & u'_3 & v'_3 & 1 \\ u_4 u'_4 & u_4 v'_4 & u_4 & v_4 u'_4 & v_4 v'_4 & v_4 & u'_4 & v'_4 & 1 \\ u_5 u'_5 & u_5 v'_5 & u_5 & v_5 u'_5 & v_5 v'_5 & v_5 & u'_5 & v'_5 & 1 \\ u_6 u'_6 & u_6 v'_6 & u_6 & v_6 u'_6 & v_6 v'_6 & v_6 & u'_6 & v'_6 & 1 \\ u_7 u'_7 & u_7 v'_7 & u_7 & v_7 u'_7 & v_7 v'_7 & v_7 & u'_7 & v'_7 & 1 \\ u_8 u'_8 & u_8 v'_8 & u_8 & v_8 u'_8 & v_8 v'_8 & v_8 & u'_8 & v'_8 & 1 \end{pmatrix} \begin{pmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{pmatrix} = 0 \quad [\text{Eqs. 15}]$$

\mathbf{f}

- Homogeneous system $\mathbf{W} \mathbf{f} = 0$

=> Solve with SVD,
then project to rank
2

Epipolar Geometry



Parallel images planes or rectification:
simplifies correspondence problem, moves epipoles to
infinity

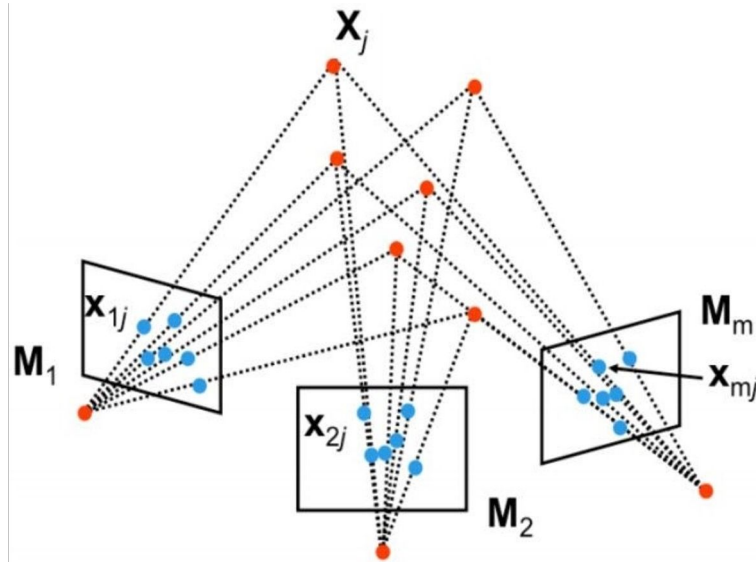
Structure from Motion

Determining *structure* and *motion*

- Structure: n 3D points
- Motion: m projection matrices

You've implemented a few algorithms for this!

- Factorization
- Triangulation



Factorization Method

$$\mathbf{D} = \begin{bmatrix} \hat{\mathbf{x}}_{11} & \hat{\mathbf{x}}_{12} & \cdots & \hat{\mathbf{x}}_{1n} \\ \hat{\mathbf{x}}_{21} & \hat{\mathbf{x}}_{22} & \cdots & \hat{\mathbf{x}}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\mathbf{x}}_{m1} & \hat{\mathbf{x}}_{m2} & \cdots & \hat{\mathbf{x}}_{mn} \end{bmatrix} = \begin{bmatrix} \mathbf{A}_1 \\ \mathbf{A}_2 \\ \vdots \\ \mathbf{A}_m \end{bmatrix} \begin{bmatrix} \mathbf{X}_1 & \mathbf{X}_2 & \cdots & \mathbf{X}_n \end{bmatrix} \quad [\text{Eq. 10}]$$

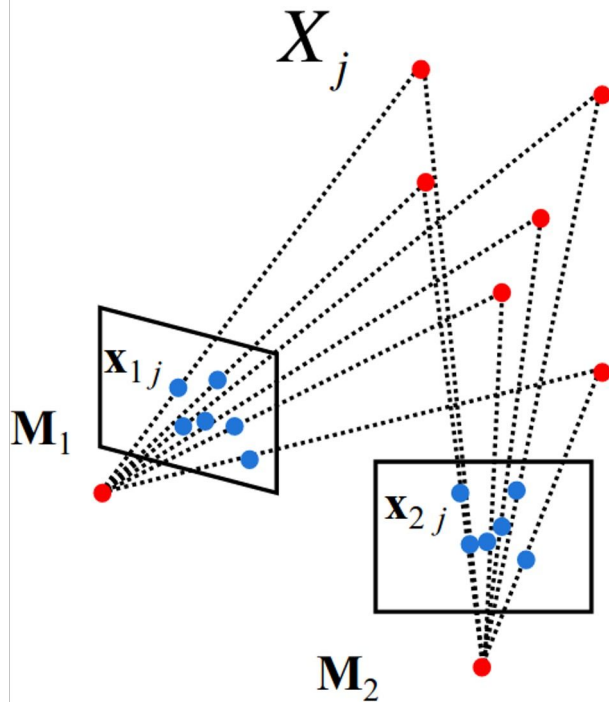
(2m × n)
cameras (2m × 3)
points (3 × n)
S

M

- Affine Structure from Motion
- Assume all points are visible
- SVD - solution not unique
- Ambiguities
 - Affine Ambiguity
 - Similarity Ambiguity

Algebraic approach

- Compute fundamental matrix F
- Use F to estimate projective cameras
- Use these cameras to triangulate and estimate points in 3D
- Works with 2 views



Bundle Adjustment

Non-linear method for refining structure and motion

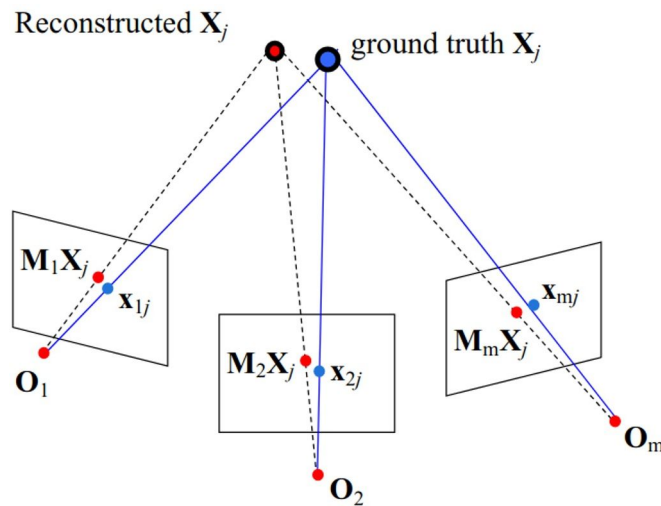
Goal: minimize reprojection error

Advantages

- Handle large number of views
- Handle missing data

Limitations

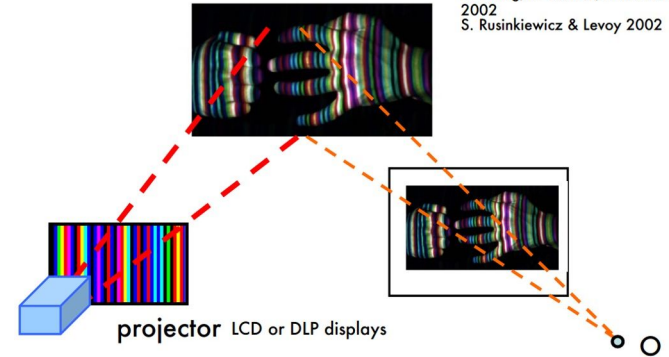
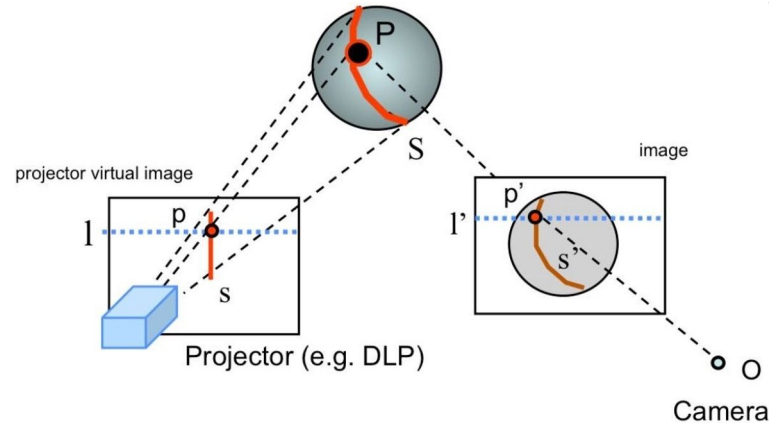
- Large minimization problem
- Require good initialization



Active Stereo

Active Stereo

- Replaces one camera with a projector
- Solves matching problem

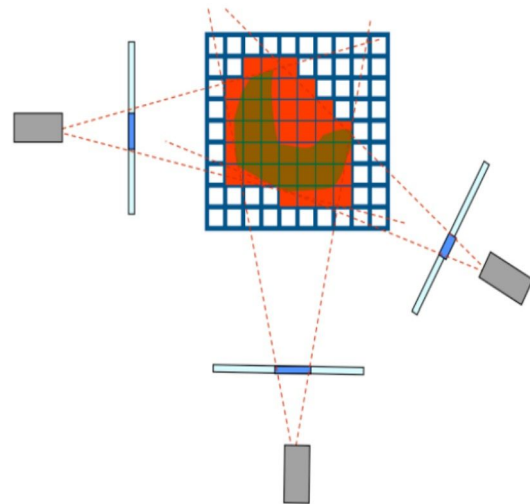
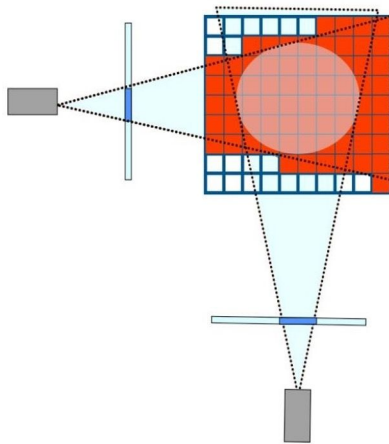


L. Zhang, B. Curless, and S. M. Seitz
2002
S. Rusinkiewicz & Levoy 2002

Volumetric Stereo

Space carving

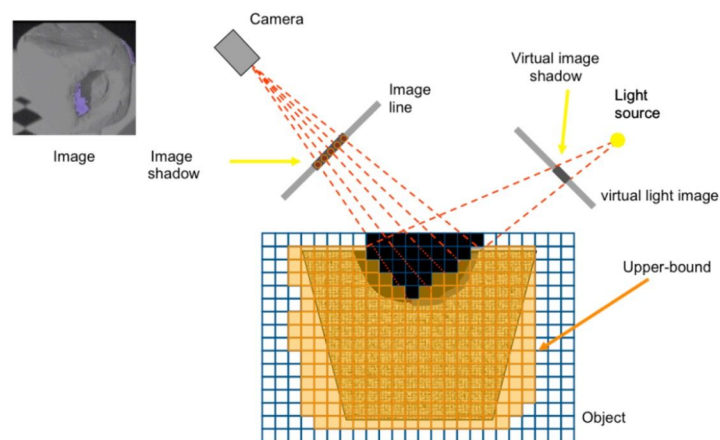
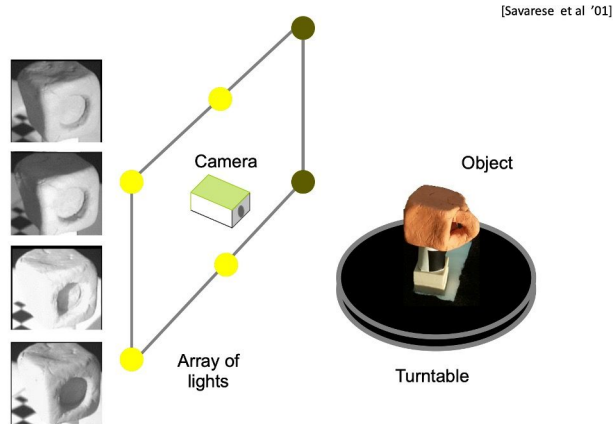
- Use contours and silhouettes
- Complexity: $O(N^3)$
- Octrees
- Conservative estimations
- Cannot carve concavity



Volumetric Stereo

Shadow carving

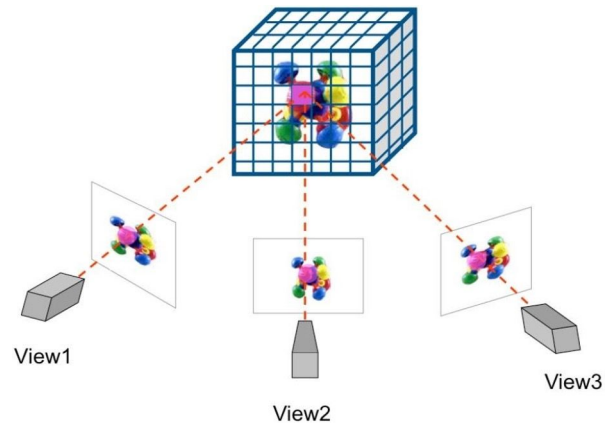
- Use shadows
- Complexity: $O(2N^3)$
- Conservative estimations
- Can carve concavity
- Limitations with reflective & low albedo regions



Volumetric Stereo

Voxel coloring

- Use colors
- Complexity: $O(LN^3)$
- Model intrinsic scene colors and textures



Fitting and Matching

- 3 Techniques:
 - Least Square Methods
 - Normal Equations
 - SVD
 - RANSAC
 - Hough Transform
- Advantages and disadvantages of each technique?

Least square

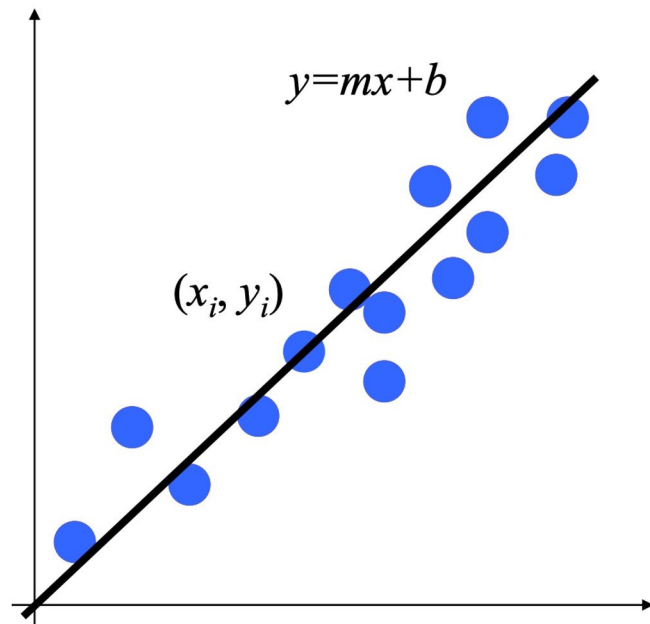
- Find (m, b) to minimize the fitting error (residual):

$$E = \sum_{i=1}^n (y_i - mx_i - b)^2$$

- Normal Equation:

$$h = (X^T X)^{-1} X^T Y$$

- Fail for vertical lines

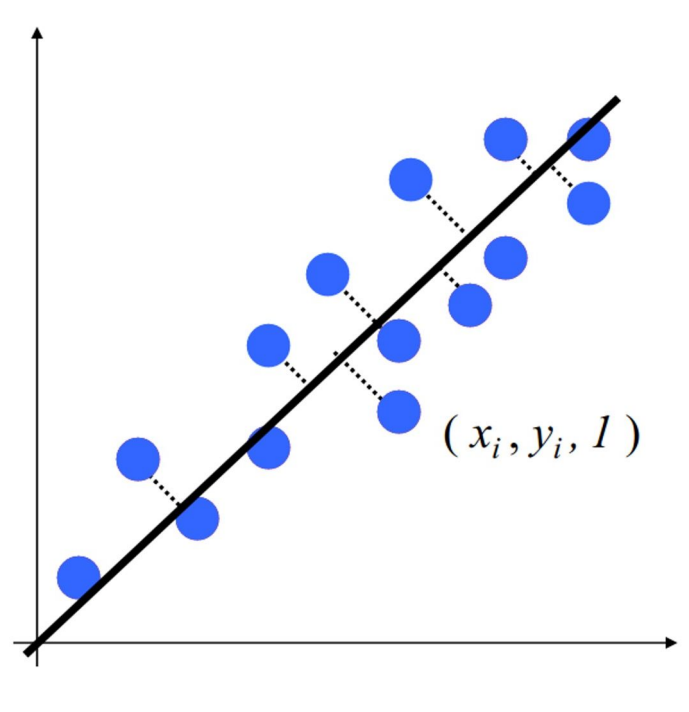


Least square

- Find a line to minimize the sum of squared distance to the points

$$E = \sum_{i=1}^n (ax_i + by_i + d)^2$$

- Can be solved by SVD
- However, **susceptible to outliers!**

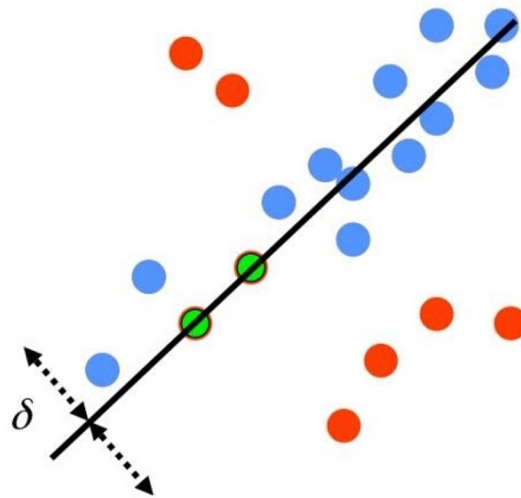


RANSAC

Random sample consensus

For fitting a model to noisy data! Iterative approach:

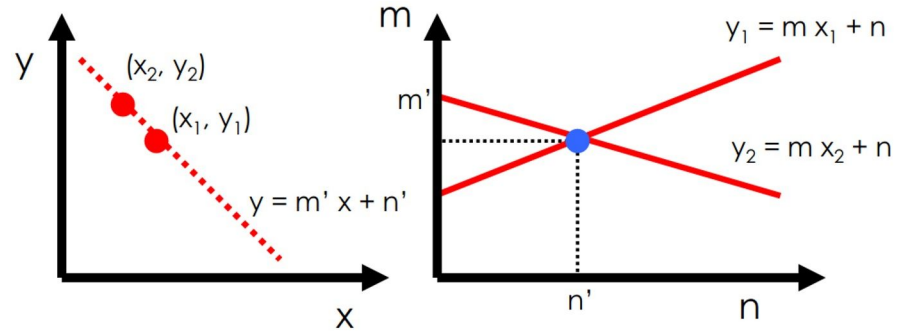
- Sample a subset of points
- Fit our model
- Count the total # of inliers that match this model
- Repeat for a finite number of iterations M and keep the set with the maximal number of inliers



Hough Transforms

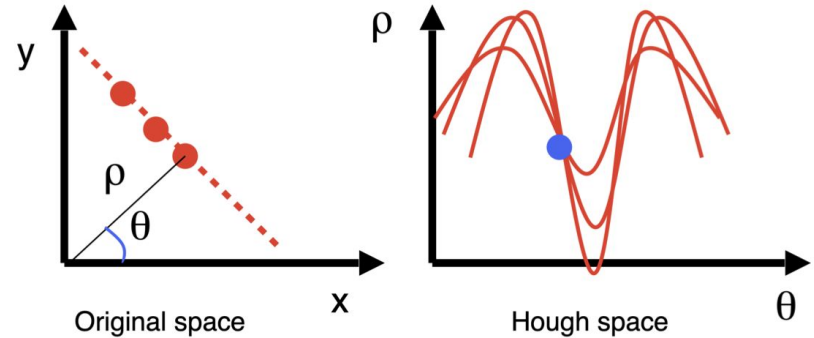
Key idea for line fitting:

- Map points in (x,y) to a line in our Hough space
- Each point in our Hough space represents a line in our (x,y) space
- Intersection of lines in hough space = line
- Polar line representation
- Discretization and voting



Original space where the data points are

Hough space defined by the parameters of the model we want to fit (i.e.,

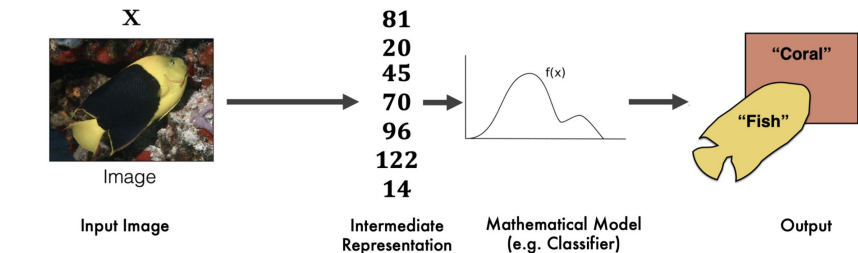


Original space

Hough space

Representation Learning

- What is a representation?
- Input vs. intermediate vs. output representation
- What makes a good representation?
- Supervised vs. Unsupervised vs. Self-supervised learning



Good Luck!

Questions