Stereo and Epipolar geometry

Jana Kosecka

Previously

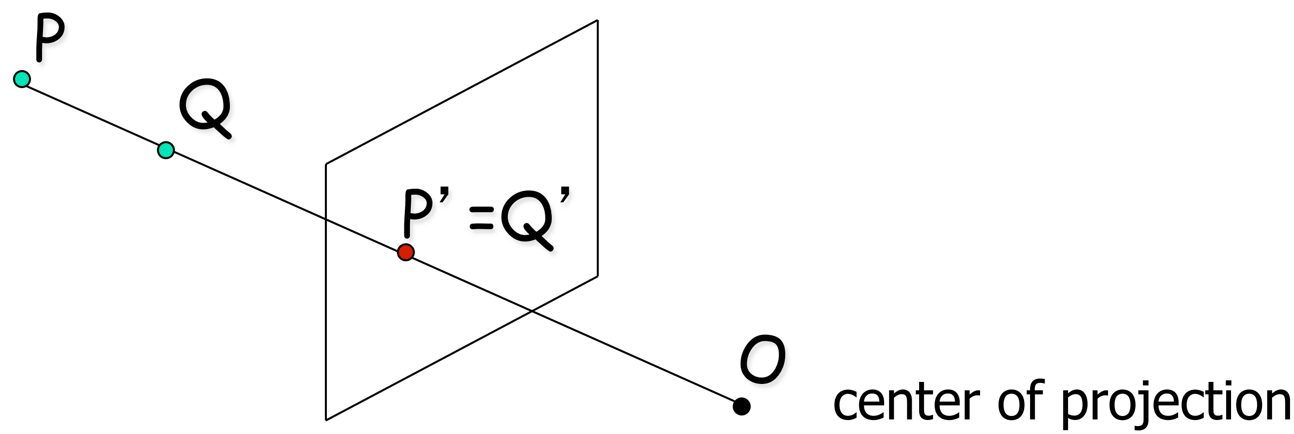
- Image Primitives (feature points, lines, contours)
- Today:

- How to match primitives between two (multiple) views)
- Goals: 3D reconstruction, recognition

- Stereo matching and reconstruction (canonical configuration)
- Epipolar Geometry (general two view setting)

Why Stereo Vision?

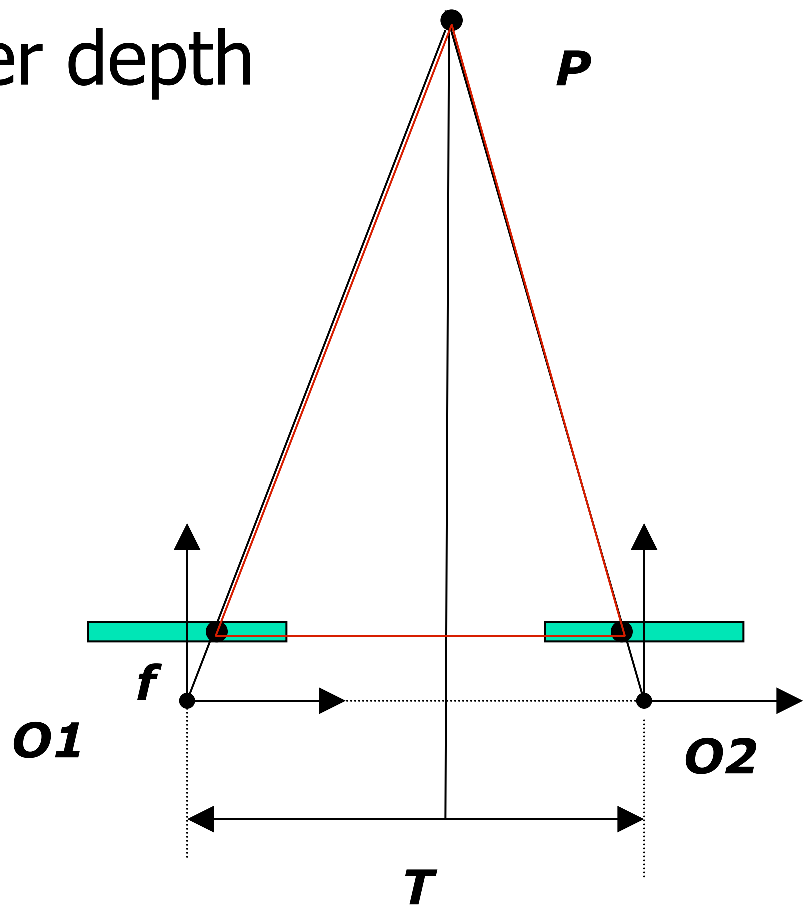
- 2D images project 3D points into 2D:



- 3D points on the same viewing line have the same 2D image:
  - 2D imaging results in depth information loss

Canonical Stereo Configuration

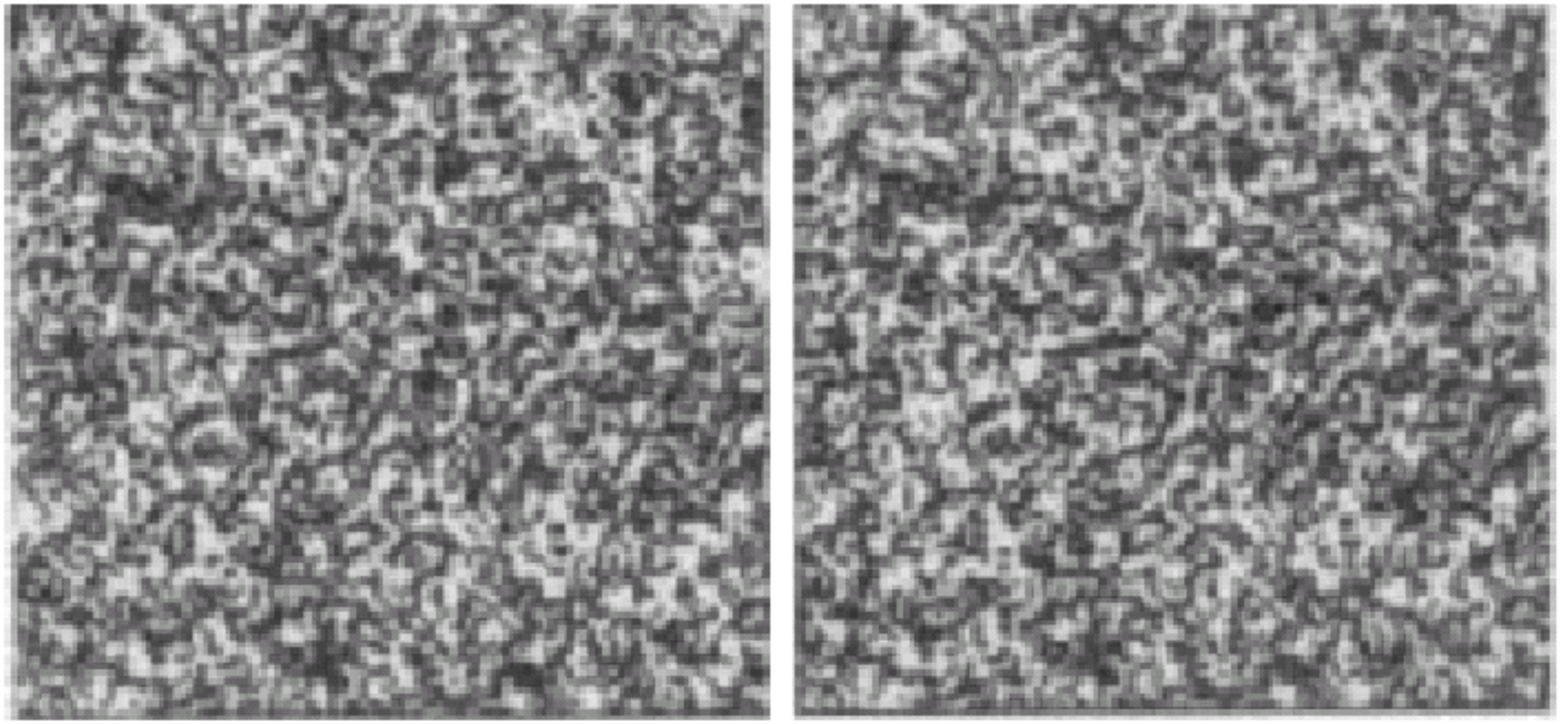
- Assumes (two) cameras
- Known positions and focal lengths
- Recover depth



$$\frac{Z}{T} = \frac{Z-f}{T-\mathbf{x}_l-\mathbf{x}_r}$$

$$Z = \frac{fT}{\text{disparity}}$$

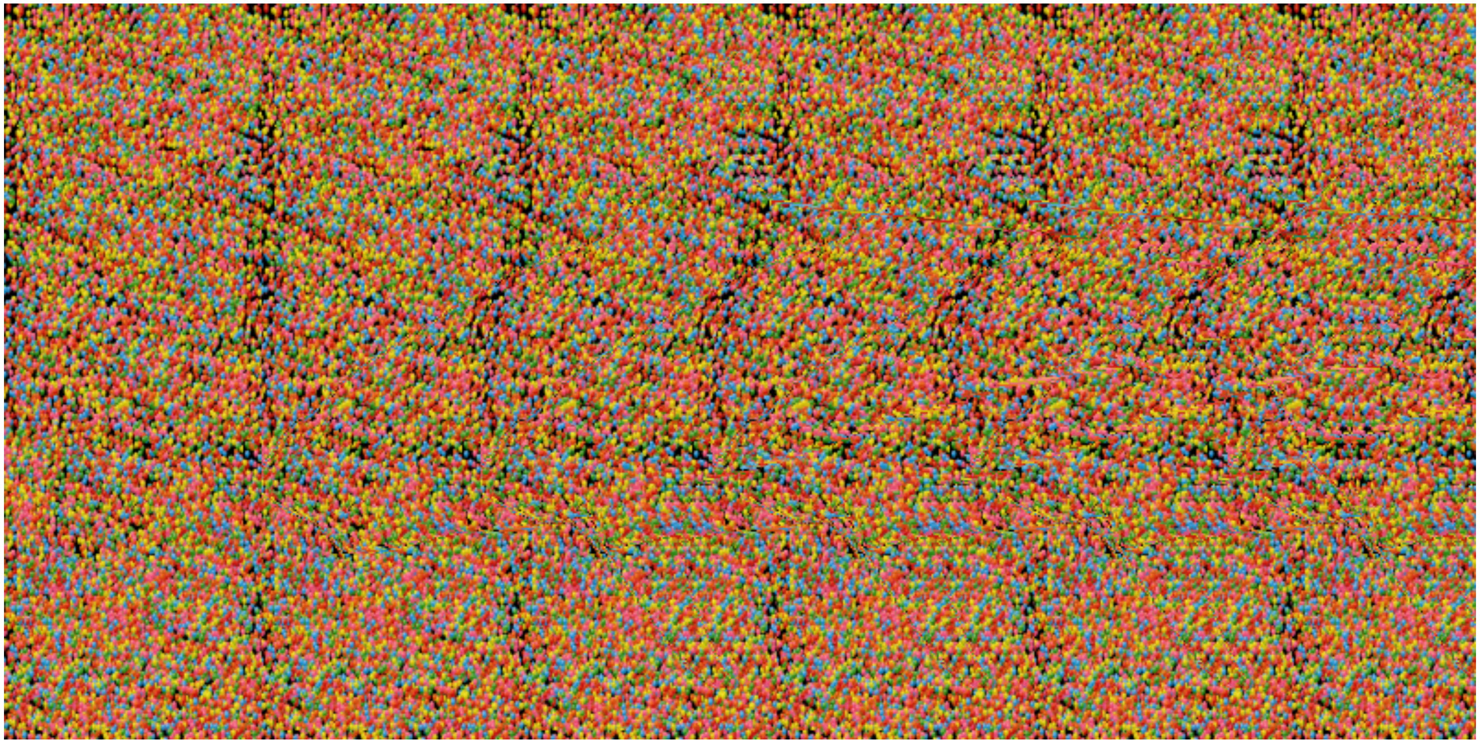
Random Dot Stereo-grams



B. Julesz: showed that the depth can be perceived in the absence of any identifiable objects in correspondence

Autostereograms

- Depth perception from one image



- Viewing trick the brain by focusing at the plane behind - match can be established perception of 3D

Correspondence Problem

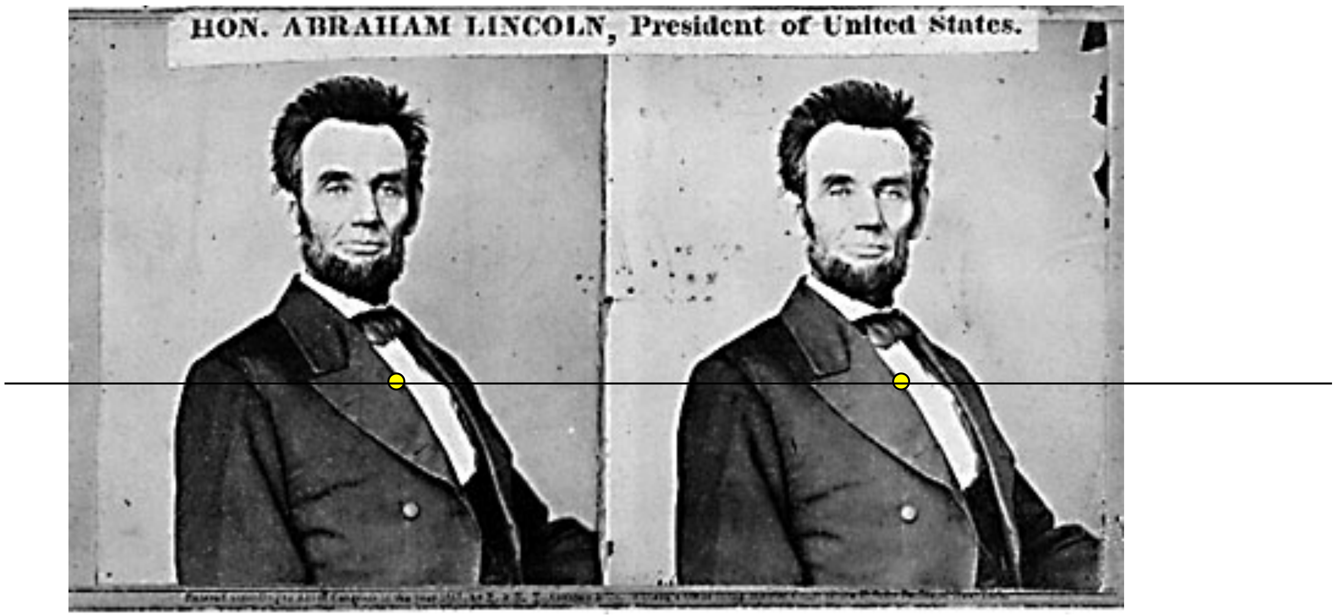
- Two classes of algorithms:
  - Correlation-based algorithms
    - Produce a DENSE set of correspondences
  - Feature-based algorithms
    - Produce a SPARSE set of correspondences

Stereo – Photometric Constraint

- Same world point has same intensity in both images.
  - Lambertian fronto-parallel
  - Issues (noise, specularities, foreshortening)

- Difficulties – ambiguities, large changes of appearance, due to change Of viewpoint, non-uniquess

Stereo Matching



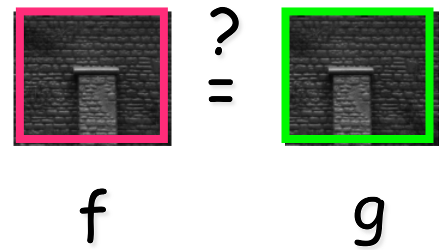
What if ?

For each scanline , for each pixel in the left image

- compare with every pixel on same epipolar line in right image
- pick pixel with minimum match cost
- This will never work, so: **improvement match windows**

(slides O. Camps)

Comparing Windows:



$$SSD = \sum_{[i,j] \in R} (f(i,j) - g(i,j))^2$$

$$C_{fg} = \sum_{[i,j] \in R} f(i,j)g(i,j)$$

Most popular

For each window, match to closest window on epipolar line in other image.

Comparing Windows:

Minimize $$\sum_{[i,j]\in R} (f(i,j) - g(i,j))^2$$ Sum of Squared Differences

Maximize $$C_{fg} = \sum_{[i,j]\in R} f(i,j)g(i,j)$$ Cross correlation

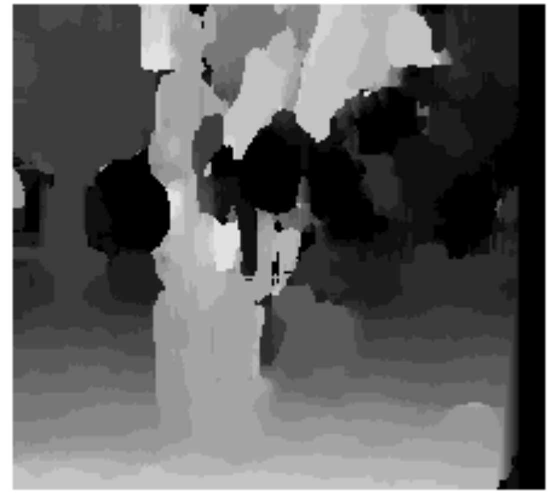
It is closely related to the SSD:

$$SSD = \sum_{[i,j]\in R} (f-g)^2 =$$

$$= \sum_{[i,j]\in R} f^2 + \sum_{[i,j]\in R} g^2 - 2 \sum_{[i,j]\in R} fg$$

Window size

W = 3



W = 20

- Effect of window size

Better results with *adaptive window*

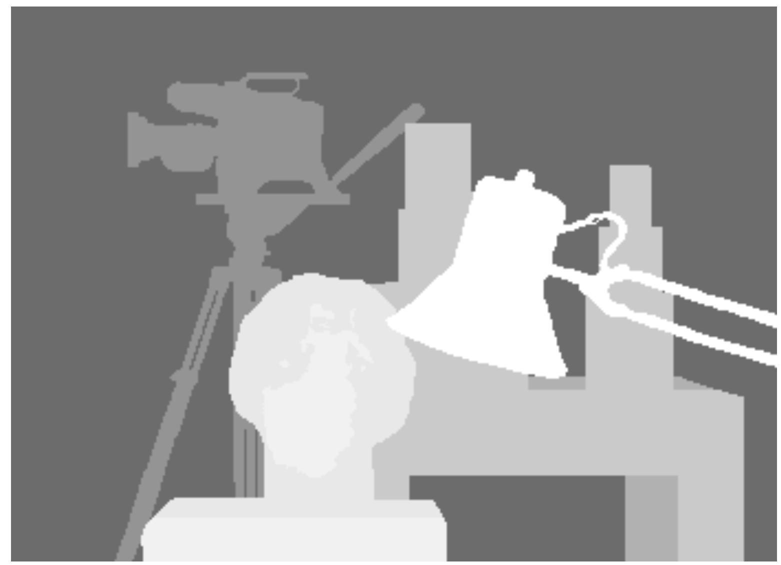
- T. Kanade and M. Okutomi, *A Stereo Matching Algorithm with an Adaptive Window: Theory and Experiment*,, Proc. International Conference on Robotics and Automation, 1991.
- D. Scharstein and R. Szeliski. Stereo matching with nonlinear diffusion. International Journal of Computer Vision, 28(2):155-174, July 1998

(S. Seitz)

Stereo results

- Data from University of Tsukuba

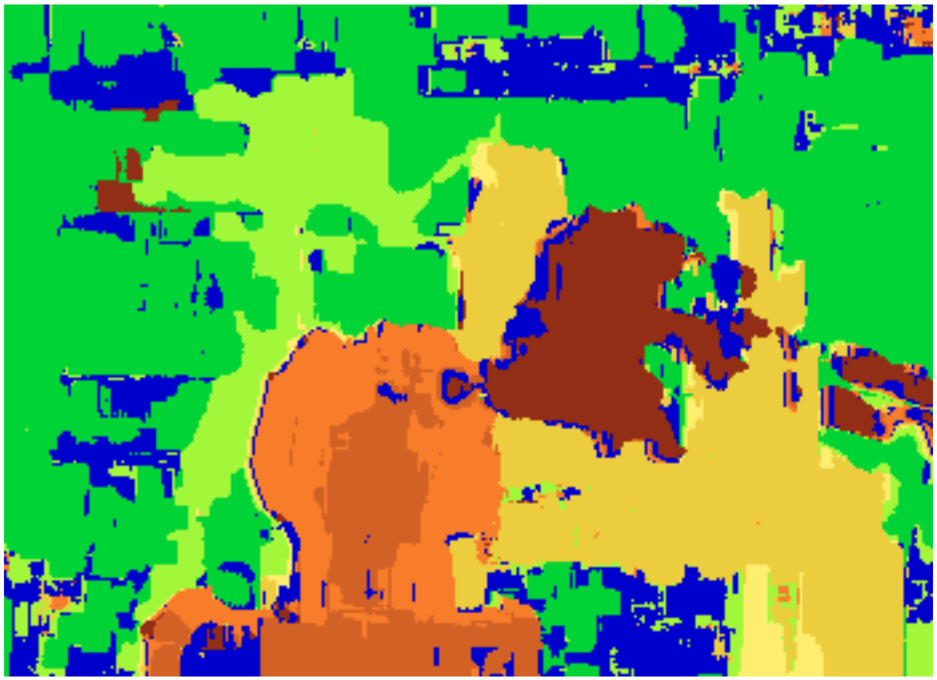
Scene



Ground truth

(Seitz)

Results with window correlation



Window-based matching
(best window size)

Ground truth

(Seitz)

Results with better method

State of the art

Ground truth

Boykov et al., Fast Approximate Energy Minimization via Graph Cuts, International Conference on Computer Vision, September 1999.

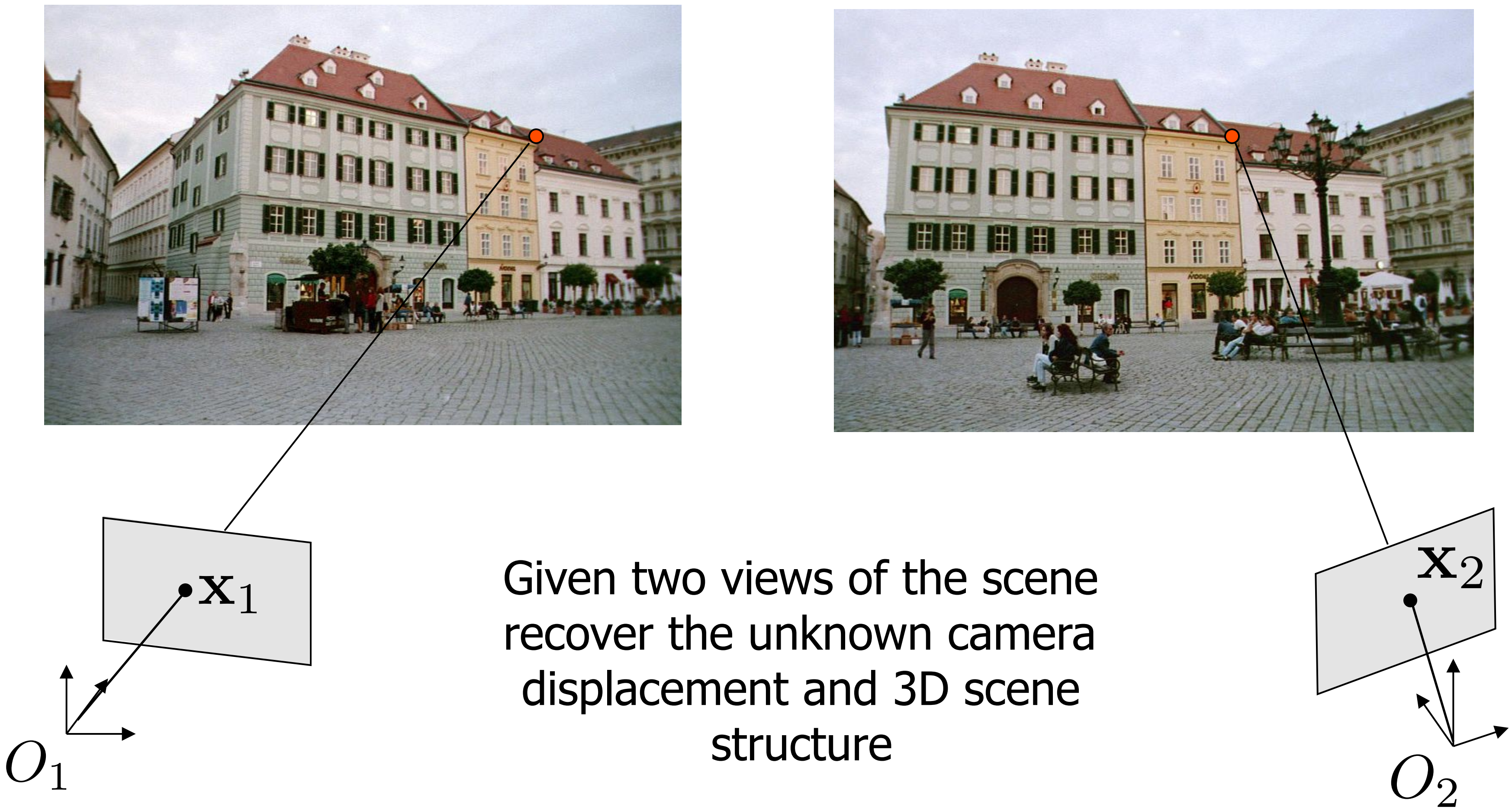
(Seitz)

More of advanced stereo (later)

- Ordering constraint
- Dynamic programming
- Global optimization

Two view – General Configuration

- Motion between the two views is not known



Given two views of the scene recover the unknown camera displacement and 3D scene structure

Pinhole Camera Imaging Model

- 3D points $\mathbf{X} = [X, Y, Z, W]^T \in \Re^4, \quad (W = 1)$
- Image points $\mathbf{x} = [x, y, z]^T \in \Re^3, \quad (z = 1)$
- Perspective Projection $\lambda \mathbf{x} = \mathbf{X}$

$$\lambda = Z \;\; x = \frac{X}{Z} \;\; y = \frac{Y}{Z}$$

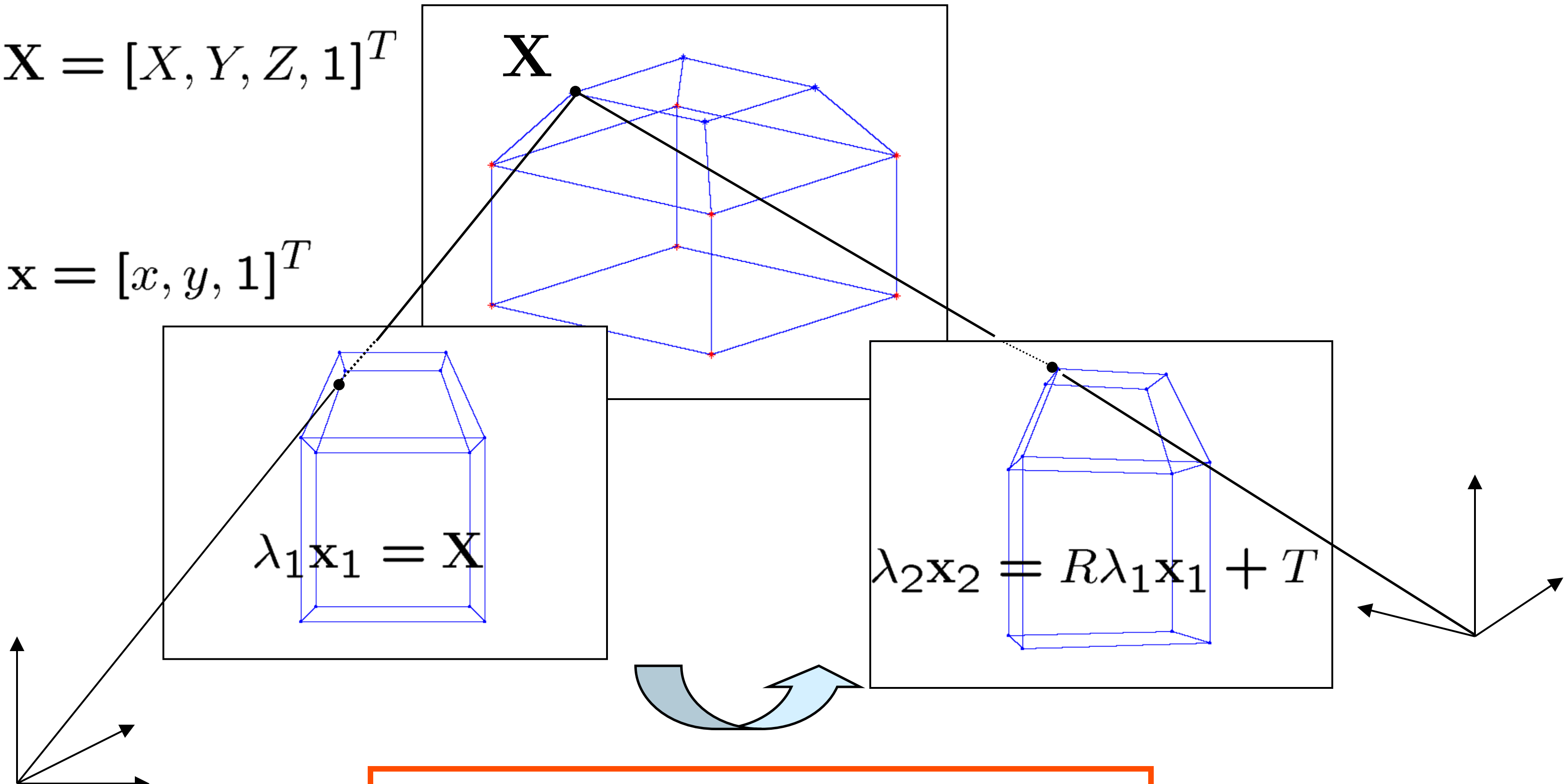
- Rigid Body Motion $\Pi = [R, T] \in \Re^{3\times 4}$
- Rigid Body Motion + Persp. projection $\lambda \mathbf{x} = \Pi \mathbf{X} = [R, T]\mathbf{X}$

$$\lambda \boldsymbol{x}' = K \Pi_0 \mathbf{X} = \begin{bmatrix} f s_x & f s_\theta & o_x \\ 0 & f s_y & o_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} R & T \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

Rigid Body Motion – Two Views

$$\mathbf{X} = [X, Y, Z, 1]^T$$

$$\mathbf{x} = [x, y, 1]^T$$



$$\boxed{\lambda_2 \mathbf{x}_2 = R\lambda_1 \mathbf{x}_1 + T}$$

$$\lambda \mathbf{x} = \Pi \mathbf{X} = [R, T]\mathbf{X} \qquad \Pi = [R, T] \in \Re^{3\times 4}$$

3D Structure and Motion Recovery

Euclidean transformation

$$\lambda_2 \mathbf{x}_2 = R \lambda_1 \mathbf{x}_1 + T$$

Measurements
Corresponding points

unknowns

$$\sum_{j=1}^{n} \|\mathbf{x}_1^j - \pi(R_1, T_1, \mathbf{X})\|^2 + \|\mathbf{x}_2^j - \pi(R_2, T_2, \mathbf{X})\|^2$$

Find such Rotation and Translation and Depth that the reprojection error is minimized

Two views ~ 200 points
6 unknowns – Motion 3 Rotation, 3 Translation
- Structure 200x3 coordinates
- (-) universal scale

Difficult optimization problem

Notation

- Cross product between two vectors in

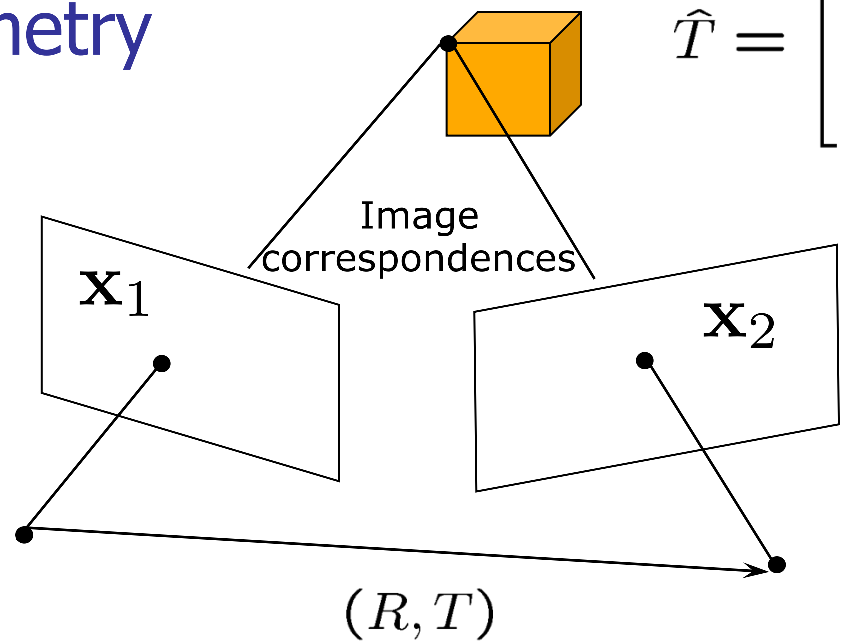
$$c = a \times b \qquad c = \left[\begin{array}{c} -a_3 b_2 + a_2 b_3 \\ a_3 b_1 - a_1 b_3 \\ -a_2 b_1 + a_1 b_2 \end{array} \right]$$

where

$$\hat{a} = \left[\begin{array}{ccc} 0 & -a_3 & a_2 \\ a_3 & 0 & -a_1 \\ -a_2 & a_1 & 0 \end{array} \right]$$

Epipolar Geometry

$$\hat{T} = \begin{bmatrix} 0 & -t_z & t_y \\ t_z & 0 & -t_x \\ -t_y & t_x & 0 \end{bmatrix}$$



$$\lambda_2 \mathbf{x}_2 = R\lambda_1 \mathbf{x}_1 + T \quad / \widehat{\mathbf{x}_2} T$$

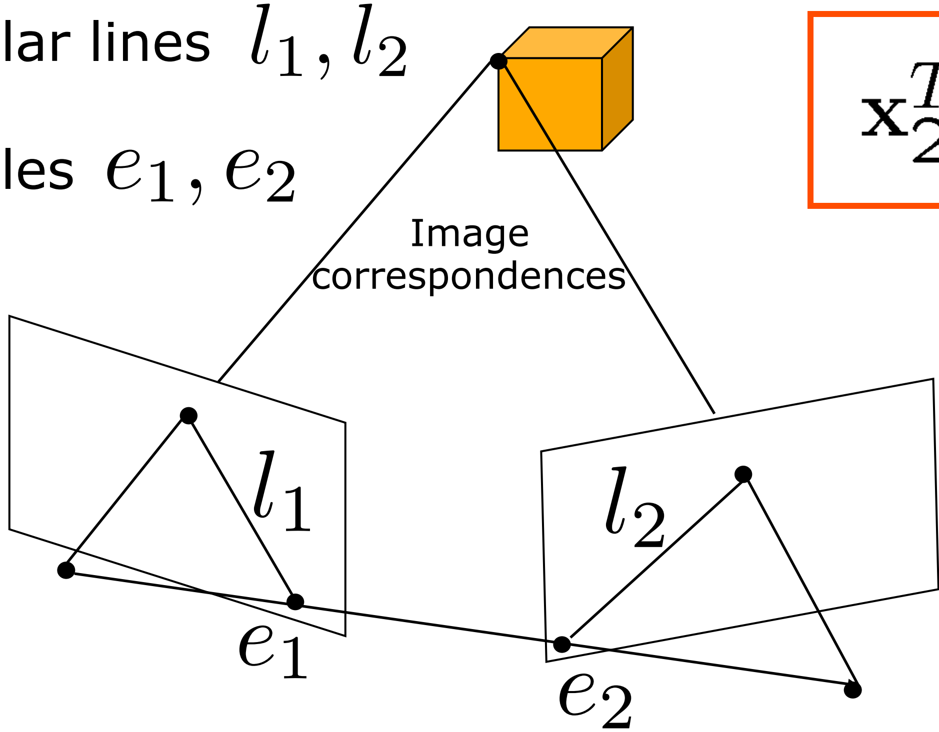
- Algebraic Elimination of Depth [Longuet-Higgins ’81]:

$$\mathbf{x}_2^T \underbrace{\hat{T} R}_{E} \mathbf{x}_1 = 0$$

- Essential matrix $E = \hat{T} R$

Epipolar Geometry

- Epipolar lines l_1, l_2
- Epipoles e_1, e_2



$$\boxed{\mathbf{x}_2^T E \mathbf{x}_1 = 0}$$

$$E = \hat{T} R$$

Epipolar transfer

- Additional constraints

$$l_1 \sim E^T \mathbf{x}_2 \qquad l_i^T \mathbf{x}_i = 0 \qquad l_2 \sim E \mathbf{x}_1$$

$$E \mathbf{e}_1 = 0 \qquad l_i^T \mathbf{e}_i = 0 \qquad \mathbf{e}_2 E^T = 0$$

Characterization of Essential Matrix

$$\mathbf{x}_2^T \widehat{T} R \mathbf{x}_1 = 0$$

Essential matrix $E = \widehat{T} R$ special 3x3 matrix

$$\mathbf{x}_2^T \begin{bmatrix} e_1 & e_2 & e_3 \\ e_4 & e_5 & e_6 \\ e_7 & e_8 & e_9 \end{bmatrix} \mathbf{x}_1 = 0$$

(Essential Matrix Characterization)
A non-zero matrix E is an essential matrix iff its SVD: $E = U \Sigma V^T$
satisfies: $\Sigma = diag([\sigma_1, \sigma_2, \sigma_3])$ with $\sigma_1 = \sigma_2 \neq 0$ and $\sigma_3 = 0$
and $U, V \in SO(3)$

Estimating Essential Matrix

- Find such Rotation and Translation that the epipolar error is minimized

$$min_E \sum_{j=1}^{n} (\mathbf{x}_2^{jT} E \mathbf{x}_1^j)^2$$

- Space of all Essential Matrices is 5 dimensional
- 3 DOF Rotation, 2 DOF – Translation (up to scale !)
- Denote $\mathbf{a} = \mathbf{x}_1 \otimes \mathbf{x}_2$

$$\mathbf{a} = [x_1x_2, x_1y_2, x_1z_2, y_1x_2, y_1y_2, y_1z_2, z_1x_2, z_1y_2, z_1z_2]^T$$

$$E^s = [e_1, e_4, e_7, e_2, e_5, e_8, e_3, e_6, e_9]^T$$

- Rewrite

$$\mathbf{a}^T E^s = 0$$

- Collect constraints from all points

$$\chi E^s = 0$$

$$min_E \sum_{j=1}^{n} \mathbf{x}_2^{jT} E \mathbf{x}_1^j \Rightarrow min_{E^s} \|\chi E^s\|^2$$

Estimating Essential Matrix

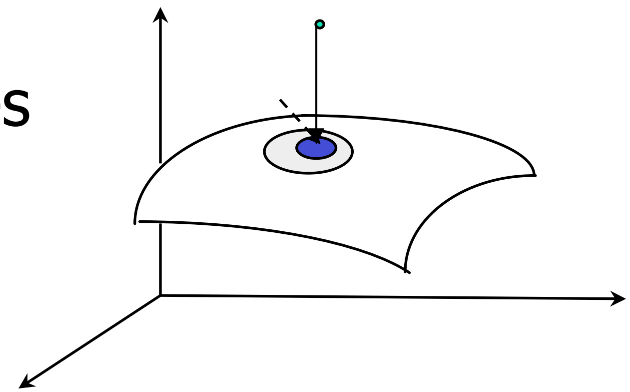
$$min_E \sum_{j=1}^{n} \mathbf{x}_2^{jT} E \mathbf{x}_1^j \quad \Rightarrow \quad min_{E^s} \|\chi E^s\|^2$$

Solution is

- Eigenvector associated with the smallest eigenvalue of $\chi^T \chi$
- If $rank(\chi^T \chi) < 8$ degenerate configuration

E_s estimated using linear least squares

unstack E_s -> F



Projection on to Essential Space

(Project onto a space of Essential Matrices)

If the SVD of a matrix $F \in \mathcal{R}^{3\times3}$ is given by $F = Udiag(\sigma_1, \sigma_2, \sigma_3)V^T$ then the essential matrix which minimizes the Frobenius distance $\|E - F\|_f^2$ is given by $E = Udiag(\sigma, \sigma, 0)V^T$ with $\sigma = \frac{\sigma_1 + \sigma_2}{2}$

Pose Recovery from Essential Matrix

Essential matrix $E = \widehat{T}R$

(Pose Recovery)
There are two relative poses (R, T) with $T \in \mathcal{R}^3$ and $R \in SO(3)$ corresponding to a non-zero matrix essential matrix.

$$E = U\Sigma V^T$$

$$\begin{aligned}(\widehat{T}_1, R_1) &= (UR_Z(+\tfrac{\pi}{2})\Sigma U^T, UR_Z^T(+\tfrac{\pi}{2})V^T)\\(\widehat{T}_2, R_2) &= (UR_Z(-\tfrac{\pi}{2})\Sigma U^T, UR_Z^T(-\tfrac{\pi}{2})V^T)\end{aligned}$$

$$\Sigma = diag([1,1,0]) \qquad R_z(+\tfrac{\pi}{2}) = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

- Twisted pair ambiguity $(R_2, T_2) = (e^{\widehat{u}\pi}R_1, -T_1)$

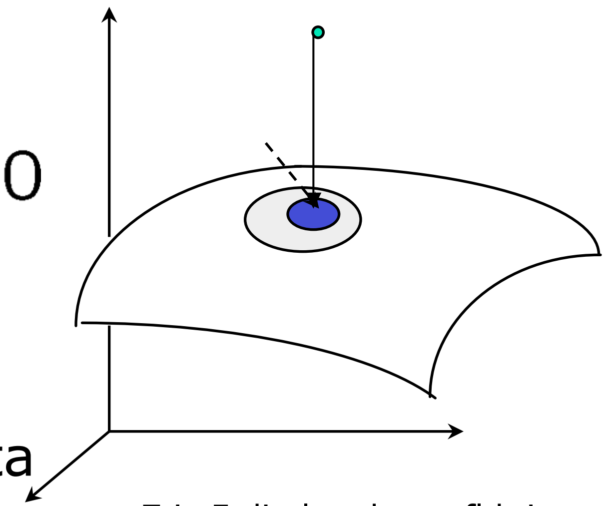
Two view linear algorithm - summary

$$E = \{\hat{T}R | R \in SO(2), T \in S^2\}$$

- Solve the LLSE problem:

$$min_E \sum_{j=1}^{n} (\mathbf{x}_2^{jT} E \mathbf{x}_1^j)^2 \Rightarrow \chi E^s = 0$$

- Solution eigenvector associated with smallest eigenvalue of $\chi^T \chi$



E is 5 diml. sub. mnfld. in

- Compute SVD of F recovered from data

$$E^s \longrightarrow F \qquad F = U \Sigma V^T$$

- Project onto the essential manifold:

$$\Sigma' = diag(1, 1, 0) \quad E = U \Sigma' V^T$$

- 8-point linear algorithm

- Recover the unknown pose:

$$\boxed{(\hat{T}, R) = (U R_Z(\pm\tfrac{\pi}{2}) \Sigma U^T, U R_Z^T(\pm\tfrac{\pi}{2}) V^T)}$$

Pose Recovery

- There are two pairs (R, T) corresponding to essential matrix .
- There are two pairs (R, T) corresponding to essential matrix .
- Positive depth constraint disambiguates the impossible solutions
- Translation has to be non-zero
- Points have to be in general position
  - degenerate configurations – planar points
  - quadratic surface
- Linear 8-point algorithm
- Nonlinear 5-point algorithms yields up to 10 solutions

3D Structure Recovery

$$\underline{\lambda_2}\mathbf{x}_2 = R\underline{\lambda_1}\mathbf{x}_1 + \underline{\gamma}T$$

unknowns

- Eliminate one of the scale's

$$\lambda_1^j \widehat{\mathbf{x}_2^j} R \mathbf{x}_1^j + \gamma \widehat{\mathbf{x}_2^j} T = 0, \qquad j = 1, 2, \ldots, n$$

- Solve LLSE problem

$$M^j \bar{\lambda}^j \doteq \left[\widehat{\mathbf{x}_2^j} R \mathbf{x}_1^j, \ \widehat{\mathbf{x}_2^j} T \right] \begin{bmatrix} \lambda_1^j \\ \gamma \end{bmatrix} = 0$$

If the configuration is non-critical, the Euclidean structure of the points and motion of the camera can be reconstructed up to a universal scale.

- Alternatively recover each point depth separately

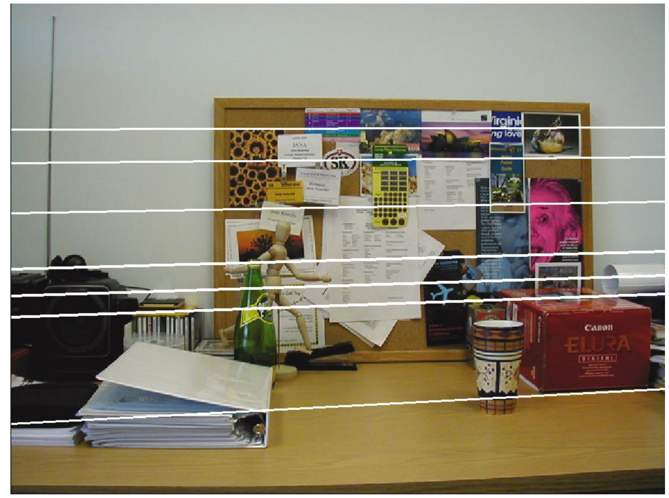
Example

Two views

Point Feature Matching

Example

Epipolar Geometry



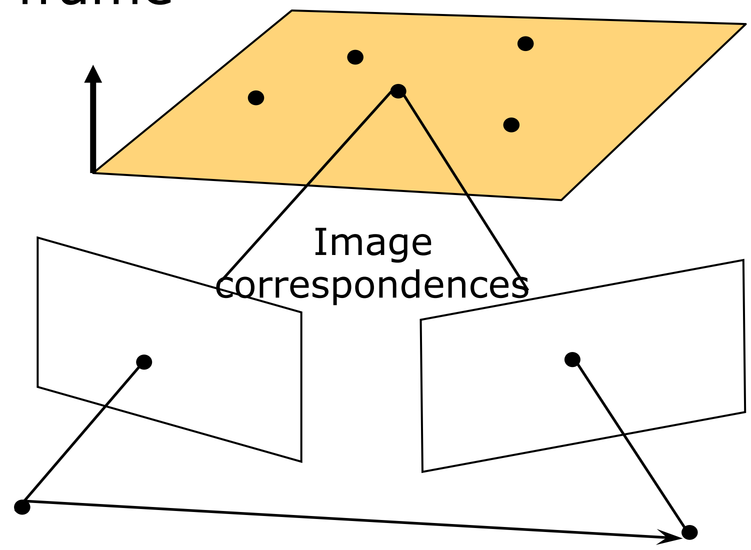
Camera Pose
and
Sparse Structure Recovery

Epipolar Geometry - Planar case

- Plane in first camera coordinate frame

$$aX + bY + cZ + d = 0$$

$$\frac{1}{d}N^T\mathbf{X} = 1$$



$$\lambda_2\mathbf{x}_2 = R\lambda_1\mathbf{x}_1 + T$$

$$\lambda_2\mathbf{x}_2 = (R + \frac{1}{d}TN^T)\lambda_1\mathbf{x}_1$$

$$\mathbf{x}_2 \sim H\mathbf{x}_1$$

$$\boxed{H = (R + \frac{1}{d}TN^T)}$$

Planar homography

Linear mapping relating two corresponding planar points in two views

Decomposition of H (into motion and plane normal)

- Algebraic elimination of depth $\widehat{\mathbf{x}_2} H \mathbf{x}_1 = 0$
- can be estimated linearly $H_L = \lambda H$
- Normalization of $H = H_L / \sigma_3$
- Decomposition of H into 4 solutions $H = (R + \frac{1}{d} T N^T)$

$R_1 = W_1 U_1^T$ $N_1 = \widehat{v_2} u_1$ $\frac{1}{d} T_1 = (H - R_1) N_1$	$R_3 = R_1$ $N_3 = -N_1$ $\frac{1}{d} T_3 = -\frac{1}{d} T_1$	$R_2 = W_2 U_2^T$ $N_2 = \widehat{v_2} u_2$ $\frac{1}{d} T_2 = (H - R_2) N_2$	$R_4 = R_2$ $N_4 = -N_2$ $\frac{1}{d} T_4 = -\frac{1}{d} T_2$

- $H^T H = V \Sigma V^T \quad V = [v_1, v_2, v_3] \quad \Sigma = diag(\sigma_1^2, \sigma_2^2, \sigma_3^2)$

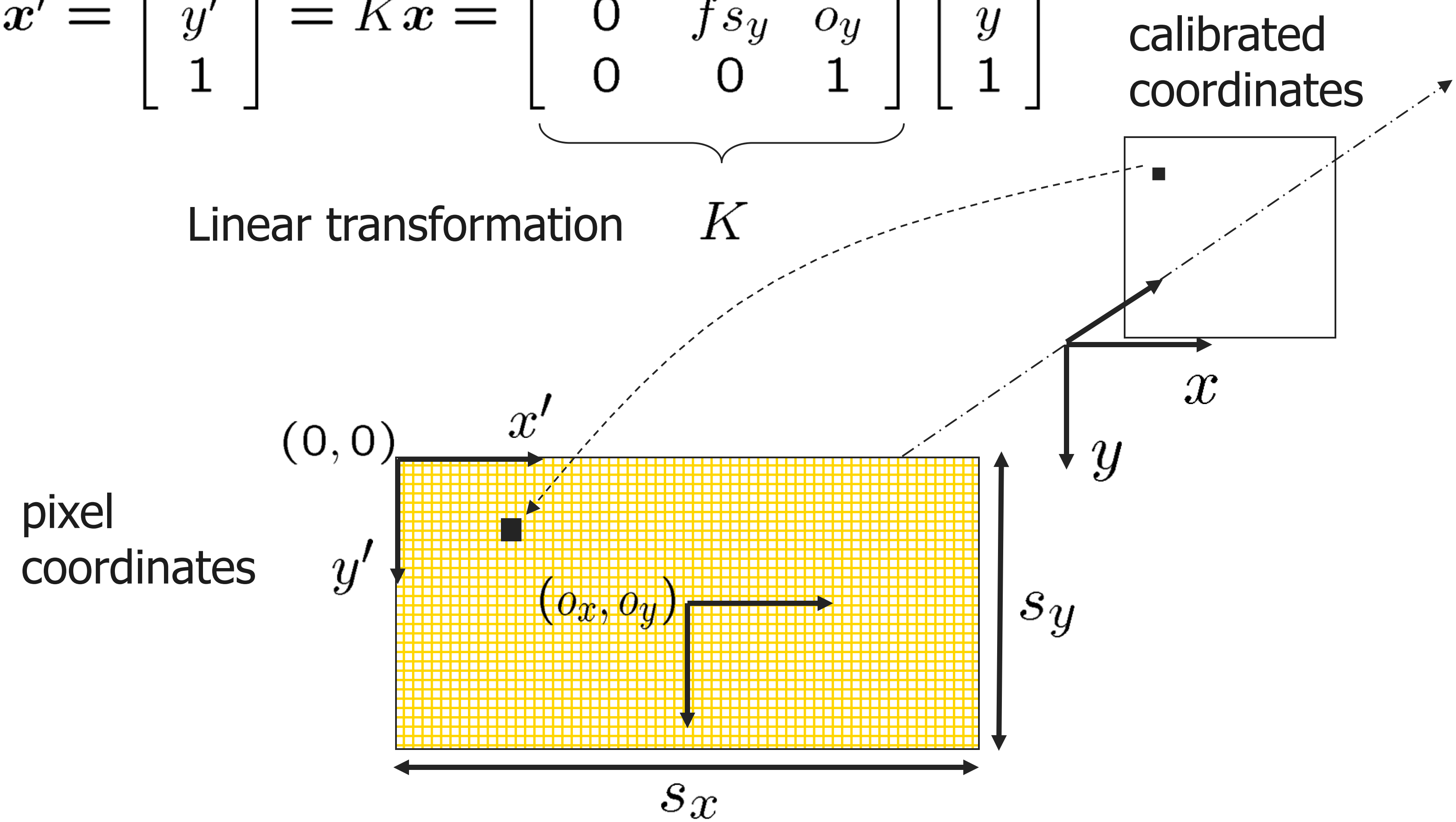
$$u_1 \doteq \frac{\sqrt{1-\sigma_3^2} v_1 + \sqrt{\sigma_1^2 - 1} v_3}{\sqrt{\sigma_1^2 - \sigma_3^2}} \qquad u_2 \doteq \frac{\sqrt{1-\sigma_3^2} v_1 - \sqrt{\sigma_1^2 - 1} v_3}{\sqrt{\sigma_1^2 - \sigma_3^2}}$$

$$U_1 = [v_2, u_1, \widehat{v_2} u_1], \qquad W_1 = [H v_2, H u_1, \widehat{H v_2} H u_1];$$
$$U_2 = [v_2, u_2, \widehat{v_2} u_2], \qquad W_2 = [H v_2, H u_2, \widehat{H v_2} H u_2].$$

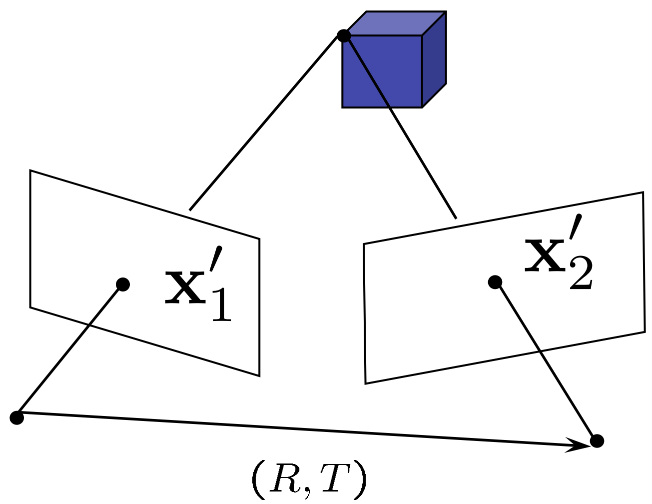
Uncalibrated Camera

$$\boldsymbol{x}' = \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = K\boldsymbol{x} = \underbrace{\begin{bmatrix} fs_x & fs_\theta & o_x \\ 0 & fs_y & o_y \\ 0 & 0 & 1 \end{bmatrix}}_{K} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Linear transformation K



Uncalibrated Epipolar Geometry

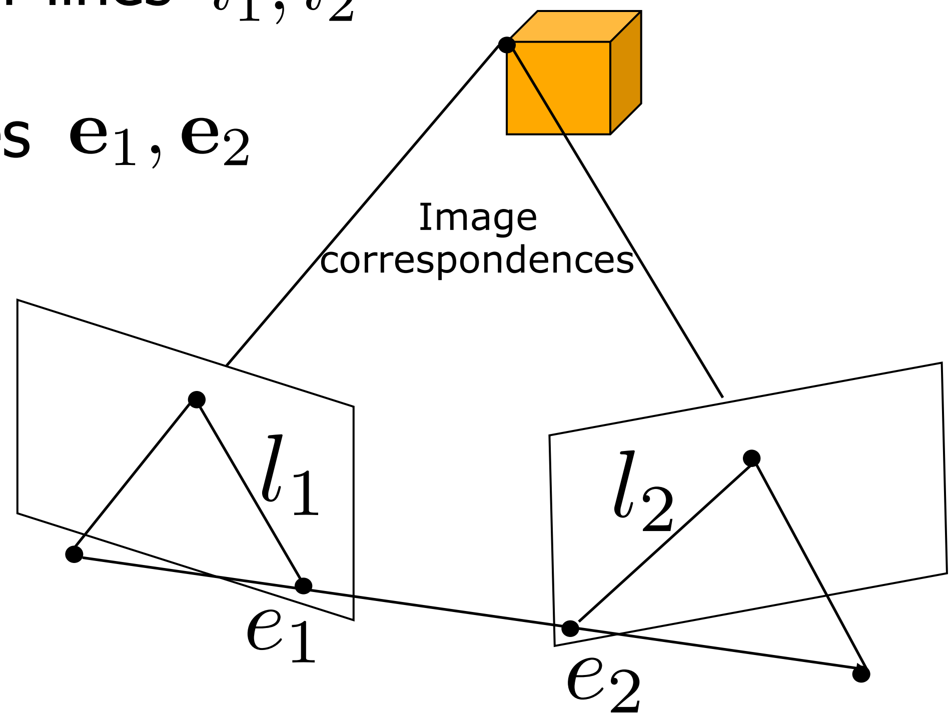


- Epipolar constraint $\mathbf{x'}_2^T \underbrace{K^{-T}\hat{T}RK^{-1}}\mathbf{x'}_1 = 0$
- Fundamental matrix $F = K^{-T}\hat{T}RK^{-1}$

Properties of the Fundamental Matrix

$$\mathbf{x'}_2^T F \mathbf{x'}_1 = 0$$

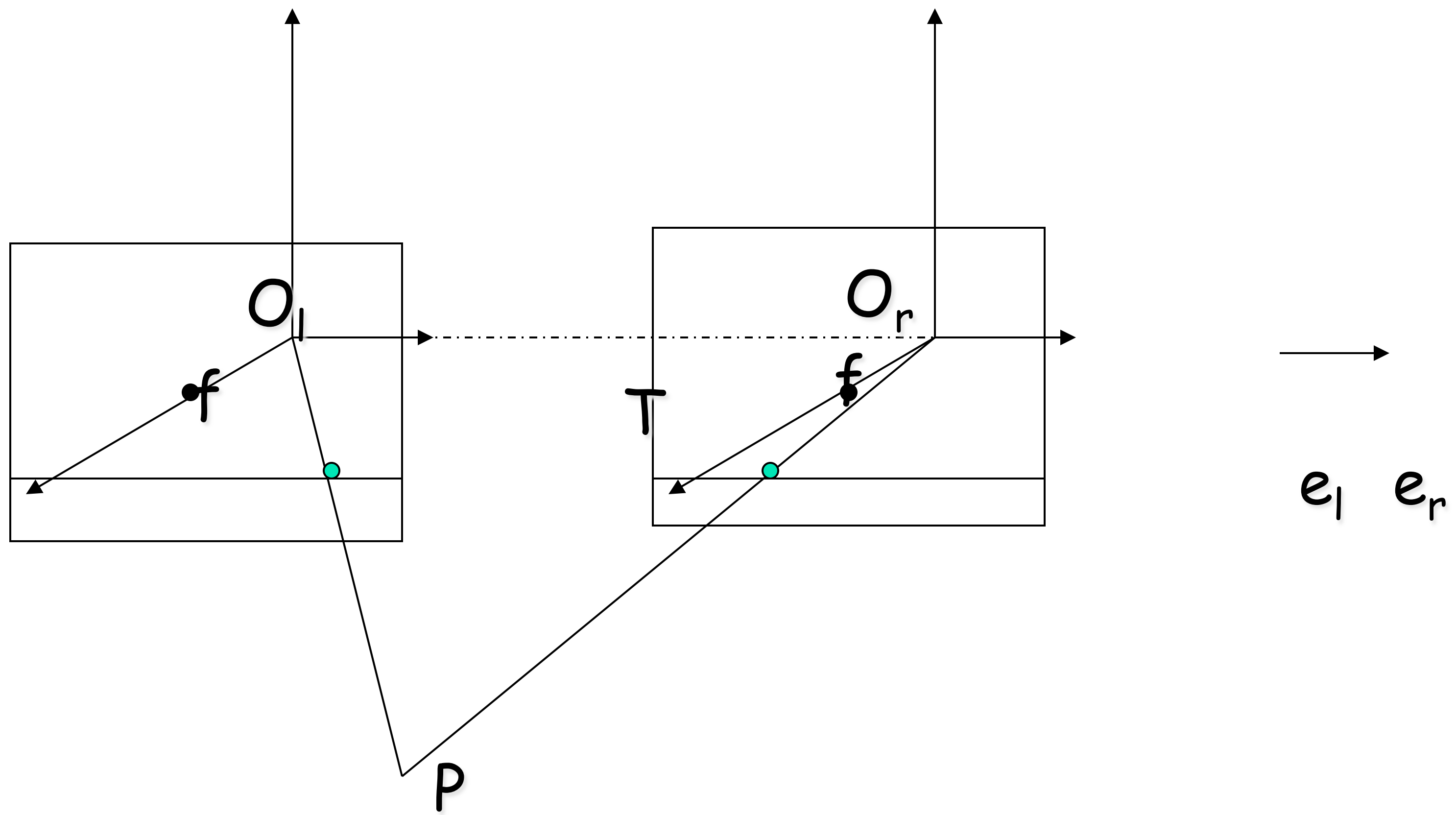
- Epipolar lines l_1, l_2
- Epipoles $\mathbf{e}_1, \mathbf{e}_2$



$l_1 \sim F^T \mathbf{x}'_2$ $\quad$ $l_i^T \mathbf{x}'_i = 0$ $\quad$ $l_2 \sim F \mathbf{x}'_1$

$F \mathbf{e}_1 = 0$ $\quad$ $l_i^T \mathbf{e}_i = 0$ $\quad$ $\mathbf{e}_2^T F = 0$

Epipolar Geometry for Parallel Cameras



Epipoles are at infinite
Epipolar lines are parallel to the baseline

Properties of the Fundamental Matrix

A nonzero matrix $F \in \mathbb{R}^{3\times 3}$ is a fundamental matrix if has a singular value decomposition (SVD) $F = U\Sigma V^T$ with

$$\Sigma = \mathrm{diag}\{\sigma_1, \sigma_2, 0\}$$

for some $\sigma_1, \sigma_2 \in \mathbb{R}_+$.

There is little structure in the matrix F except that

$$\det(F) = 0$$

Estimating Fundamental Matrix

- Find such F that the epipolar error is minimized

$$min_F \sum_{j=1}^{n} (\mathbf{x}_2^{'jT} F \mathbf{x}_1^{'j})^2 \leftarrow \text{Pixel coordinates}$$

- Fundamental matrix can be estimated up to scale
- Denote $\mathbf{a} = \mathbf{x}_1' \otimes \mathbf{x}_2'$

$$\mathbf{a} = [x_1x_2, x_1y_2, x_1z_2, y_1x_2, y_1y_2, y_1z_2, z_1x_2, z_1y_2, z_1z_2]^T$$

$$F^s = [f_1, f_4, f_7, f_2, f_5, f_8, f_3, f_6, f_9]^T$$

- Rewrite

$$\mathbf{a}^T F^s = 0$$

- Collect constraints from all points

$$\chi F^s = 0$$

$$min_F \sum_{j=1}^{n} (\mathbf{x}_2^{jT} F \mathbf{x}_1^{j})^2 \Rightarrow min_{F^s} \|\chi F^s\|^2$$

Two view linear algorithm – 8-point algorithm

- Solve the LLSE problem:

$$min_F \sum_{j=1}^{n} (\mathbf{x}_2'^{jT} F \mathbf{x}_1'^{j})^2 \Rightarrow min_{F_s} \|\chi F^s\|^2 = 0$$

- Solution eigenvector associated with smallest eigenvalue of $\chi^T \chi$

- Compute SVD of F recovered from data

$$F = U \Sigma V^T \quad \Sigma = diag(\sigma_1, \sigma_2, \sigma_3)$$

- Project onto the essential manifold:

$$\Sigma' = diag(\sigma_1, \sigma_2, 0) \quad F = U \Sigma' V^T$$

- cannot be unambiguously decomposed into pose and calibration

$$F = K^{-T} \hat{T} R K^{-1}$$

Dealing with correspondences

- Previous methods assumed that we have exact correspondences
- Followed by linear least squares estimation
- Correspondences established either by tracking (using affine or translational flow models)
- Or wide-baseline matching (using scale/rotation invariant features and their descriptors)
- In many cases we get incorrect matches/tracks

Robust estimators for dealing with outliers

- Use robust objective function
- The M-estimator and Least Median of Squares (LMedS) Estimator (neither of them can tolerate more than 50% outliers)

- The RANSAC (RANdom SAmple Consensus) algorithm
- Proposed by Fischler and Bolles
- Popular technique used in Computer Vision community (and else where for robust estimation problems)

- It can tolerate more than 50% outliers

The RANSAC algorithm

- Generate M (a predetermined number) model hypotheses, each of them is computed using a minimal subset of points

- Evaluate each hypothesis

- Compute its residuals with respect to all data points.
- Points with residuals less than some threshold are classified as its inliers

- The hypothesis with the maximal number of inliers is chosen. Then re-estimate the model parameter using its identified inliers.

RANSAC – Practice

- The theoretical number of samples needed to ensure 95% confidence that at least one outlier free sample could be obtained.

$$\rho = 1 - (1 - (1 - \epsilon)^k)^s$$

- Probability that a point is an outlier $1 - \epsilon$
- Number of points per sample k
- Probability of at least one outlier free sample ρ

- Then number of samples needed to get an outlier free sample with probability ρ

$$s = \frac{\log(1 - \rho)}{\log(1 - (1 - \epsilon)^k)}$$

RANSAC – Practice

- The theoretical number of samples needed to ensure 95% confidence that at least one outlier free sample could be obtained.
- Example for estimation of essential/fundamental matrix
- Need at least 7 or 8 points in one sample i.e. k = 7, probability is
- 0.95 then the number if samples for different outlier ratio ϵ

Outlier ratio	20%	30%	40%	50%	60%	70%
seven-point algorithm	13	35	106	382	1827	13696
eight-point algorithm	17	51	177	766	4570	45658

- In practice we do not now the outlier ratio
- Solution adaptively adjust number of samples as you go along
- While estimating the outlier ratio

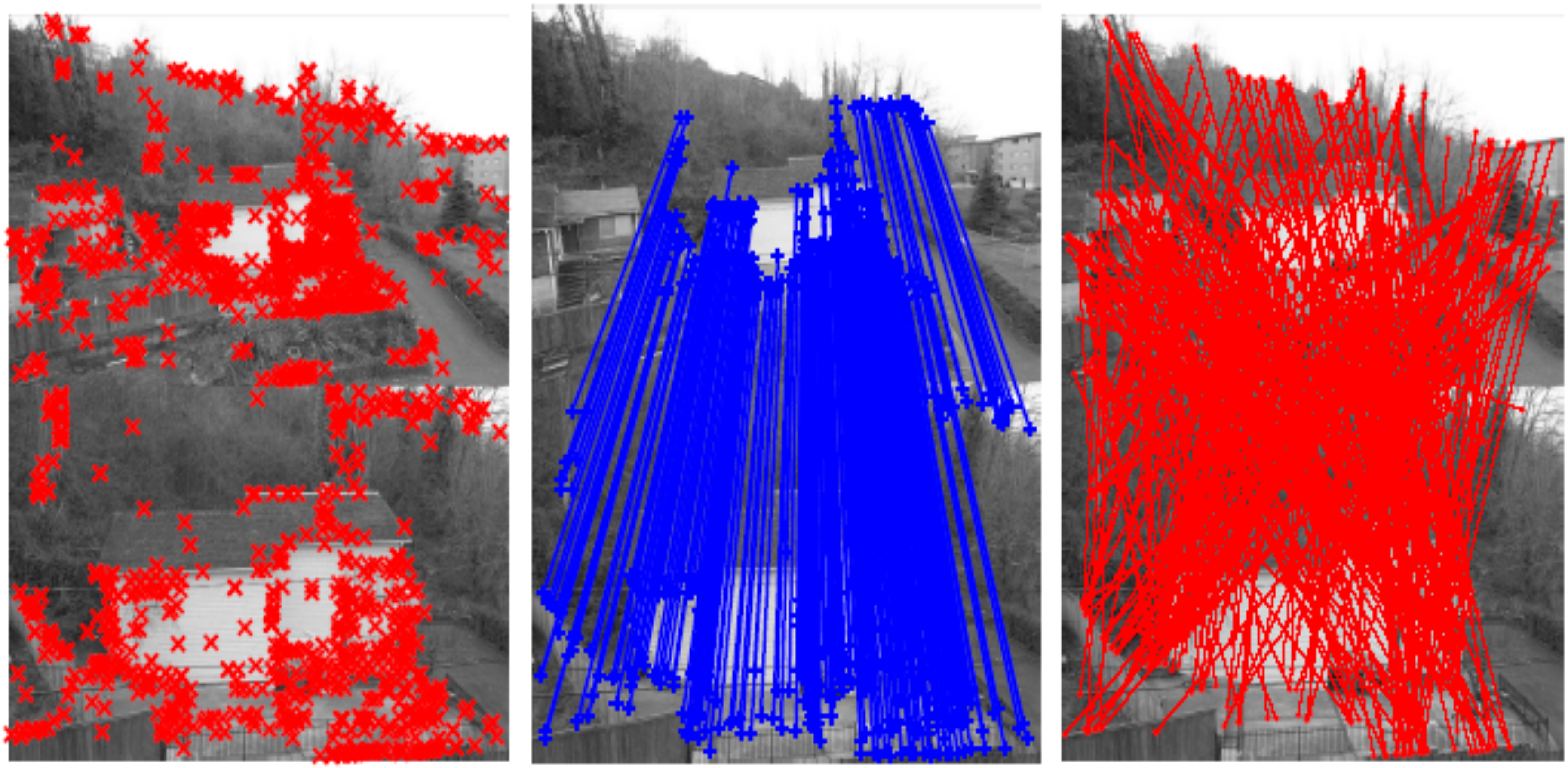
The difficulty in applying RANSAC

- Drawbacks of the standard RANSAC algorithm
  - Requires a large number of samples for data with many outliers (exactly the data that we are dealing with)
  - Needs to know the outlier ratio to estimate the number of samples
  - Requires a threshold for determining whether points are inliers
- Various improvements to standard approaches [Torr'99, Murray'02, Nister'04, Matas'05, Sutter'05 and many others

Adaptive RANSAC

- s = infinity, sample_count = 0;
- While s > sample_count repeat
  - choose a sample and count the number of inliers
  - set $\epsilon = 1 -$ (number_of_inliers/total_number_of_points)
  - set s from ϵ and $\rho = 0.99$
  - increment sample_count by 1
- terminate

Robust technique



(a) correspondences. (b) identified inliers. (c) identified outliers.

More correspondences and Robust matching

- Select set of putative correspondences $\mathbf{x}_1^j, \mathbf{x}_2^j$

$$\mathbf{x}_2^T F \mathbf{x}_1 = 0$$

- Repeat

  1. Select at random a set of 8 successful matches

  2. Compute fundamental matrix

  3. Determine the subset of inliers, compute distance to epipolar line

$$d^{2}_{j} \doteq \frac{(\mathbf{x}_2^{jT} F_k \mathbf{x}_1^j)^2}{\|\widehat{e}_3 F \mathbf{x}_1^j\|^2 + \|\mathbf{x}_2^{jT} F \widehat{e}_3\|^2} \qquad d_j \leq \tau_d$$

  4. Count the number of points in the consensus set

RANSAC in action

$$d_j \leq \tau_d$$

Inliers

$$d_j > \tau_d$$

Outliers

Epipolar Geometry

- Epipolar geometry in two views
- Refined epipolar geometry using nonlinear estimation of F
- The techniques mentioned so far simple linear least-squares estimation methods. The obtained estimates are used as initialization for non-linear optimization methods

Special Motions – Pure Rotation

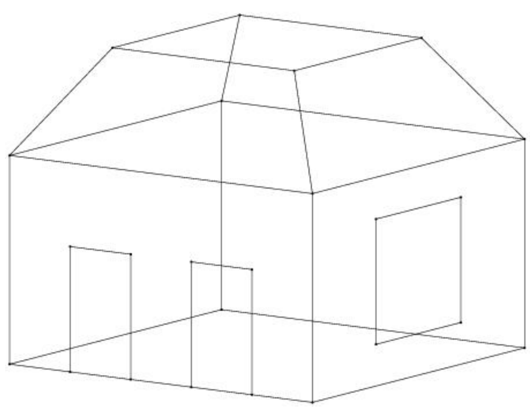
- Calibrated Two views related by rotation only $\widehat{\mathbf{x}_2} R \mathbf{x}_1 = 0$
  $\lambda_2 \mathbf{x}_2 = R \lambda_1 \mathbf{x}_1$
- Uncalibrated Case $\mathbf{x}' = K\mathbf{x}$ $\mathbf{x} = K^{-1}\mathbf{x}'$
  $$\hat{\mathbf{x}}_2' H \mathbf{x}_1' = \hat{\mathbf{x}}_2' K R K^{-1} \mathbf{x}_1' = 0$$
- Mapping to a reference view – H can be estimated

- Mapping to a cylindrical surface - applications – image mosaics

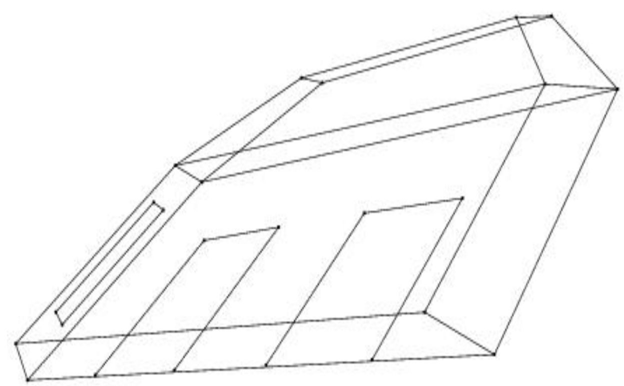
Projective Reconstruction

- Euclidean Motion Cannot be obtained in uncalibrated setting (F cannot be uniquely decomposed into R,T and K matrix)
- Can we still say something about 3D ?
- Notion of the projective 3D structure

  (study of projective geometry)



Euclidean reconstruction



Projective reconstruction

Euclidean vs Projective reconstruction

- Euclidean reconstruction – true metric properties of objects lenghts (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