

Image homographies



Computer Vision
Fall 2022, Lecture 9

What are 2D Transformations?



What representation is in Python?

Homogeneous coordinates

- heterogeneous → homogeneous

$$\begin{bmatrix} x \\ y \end{bmatrix} \Rightarrow \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \stackrel{\text{def}}{=} \begin{bmatrix} ax \\ ay \\ a \end{bmatrix}$$

- Represent 2D point with a 3D vector
- 3D vectors are only defined up to scale

image point in
pixel coordinates $\mathbf{x} = \begin{bmatrix} x \\ y \end{bmatrix}$

image space



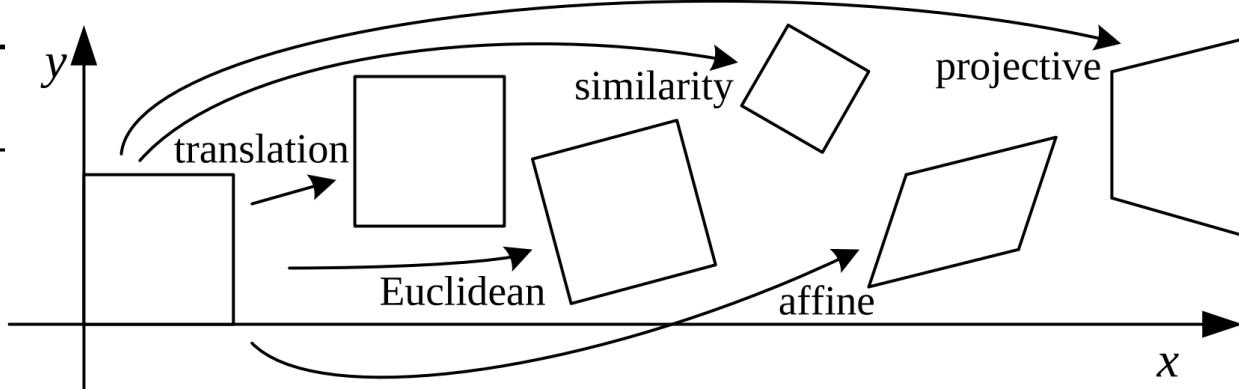
- homogeneous → heterogeneous

$$\begin{bmatrix} x \\ y \\ w \end{bmatrix} \Rightarrow \begin{bmatrix} x/w \\ y/w \end{bmatrix}$$

image point in
homogeneous
coordinates $\mathbf{X} = \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$

projective space

Transformation	Matrix	# DoF	Preserves
translation	$\begin{bmatrix} \mathbf{I} & \mathbf{t} \end{bmatrix}_{2 \times 3}$	2	orientation
rigid (Euclidean)	$\begin{bmatrix} \mathbf{R} & \mathbf{t} \end{bmatrix}_{2 \times 3}$	3	lengths
similarity	$\begin{bmatrix} s\mathbf{R} & \mathbf{t} \end{bmatrix}_{2 \times 3}$	4	angles
affine	$\begin{bmatrix} \mathbf{A} \end{bmatrix}_{2 \times 3}$	6	parallelism
projective	$\begin{bmatrix} \tilde{\mathbf{H}} \end{bmatrix}_{3 \times 3}$	8	straight lines



Euclidean (rigid):
rotation + translation

Similarity transform = translation + rotation + scale

Affine transform = translation + rotation +
scale + aspect ratio + shear

$$\begin{bmatrix} x' \\ y' \\ w' \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Projective transformation: combinations of affine transformations and projective wraps

$$\begin{aligned}x' &= ax + by + c \\y' &= dx + ey + f\end{aligned}$$

$$\begin{aligned}x' &= ax + by + c \\y' &= dx + ey + f \\w' &= gx + hy + 1\end{aligned}$$

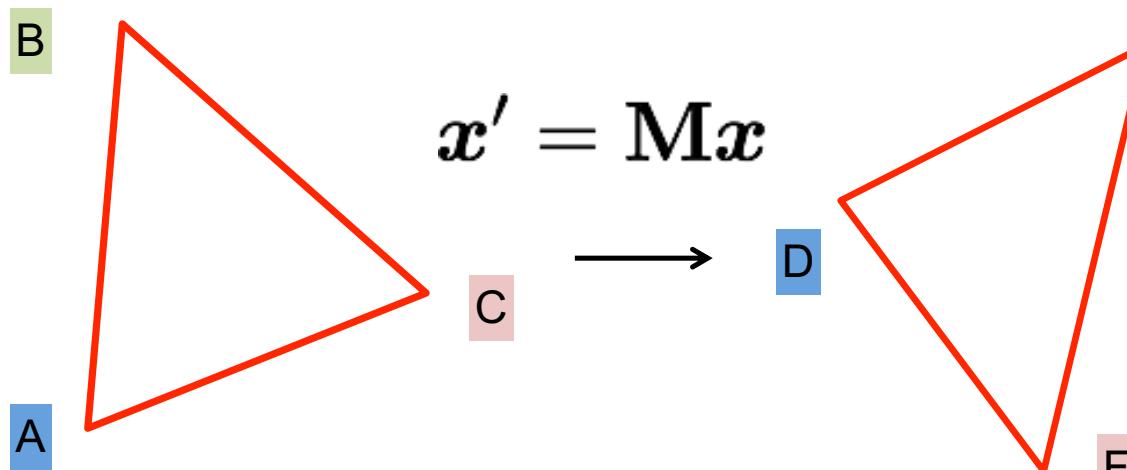


$$x'' = \frac{x'}{w'} = \frac{ax + by + c}{gx + hy + 1}$$

$$y'' = \frac{y'}{w'} = \frac{dx + ey + f}{gx + hy + 1}$$

Determining unknown transformations

Suppose we have two triangles: ABC and DEF.



$$\begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_1 & y_1 & 1 \\ x_2 & y_2 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_2 & y_2 & 1 \\ \vdots & & & & & \\ x_n & y_n & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_n & y_n & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \\ e \\ f \end{bmatrix} = \begin{bmatrix} x'_1 \\ y'_1 \\ x'_2 \\ y'_2 \\ \vdots \\ x'_n \\ y'_n \end{bmatrix}$$
$$\mathbf{A}_{2n \times 6} \quad \mathbf{t}_{6 \times 1} = \mathbf{b}_{2n \times 1}$$

Least Squares Error

- Find \mathbf{t} that minimizes

$$\|\mathbf{At} - \mathbf{b}\|^2$$

```
x = numpy.linalg.  
    solve(A, b)
```

$$\mathbf{t} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b}$$

How many points at least?

How do you create a panorama?

Panorama: an image of (near) 360° field of view.



How do you create a panorama?

Panorama: an image of (near) 360° field of view.



1. Use a very wide-angle lens.

Wide-angle lenses

Fish-eye lens: can produce (near) hemispherical field of view.



What are the pros and cons of this?

How do you create a panorama?

Panorama: an image of (near) 360° field of view.



1. Use a very wide-angle lens.
 - Pros: Everything is done optically, single capture.
 - Cons: Lens is super expensive and bulky, lots of distortion (can be dealt-with in post).

Any alternative to this?

How do you create a panorama?

Panorama: an image of (near) 360° field of view.



1. Use a very wide-angle lens.
 - Pros: Everything is done optically, single capture.
 - Cons: Lens is super expensive and bulky, lots of distortion (can be dealt-with in post).
2. Capture multiple images and combine them.

Panoramas from image stitching

1. Capture multiple images from different viewpoints.



2. Stitch them together into a virtual wide-angle image.



How do we stitch images from different viewpoints?



Will standard stitching work?

1. Translate one image relative to another.
2. (Optionally) find an optimal seam.

How do we stitch images from different viewpoints?



Will standard stitching work?

1. Translate one image relative to another.
2. (Optionally) find an optimal seam.

left on top



right on top



Translation-only stitching is not enough to mosaic these images.

How do we stitch images from different viewpoints?



What else can we try?

How do we stitch images from different viewpoints?



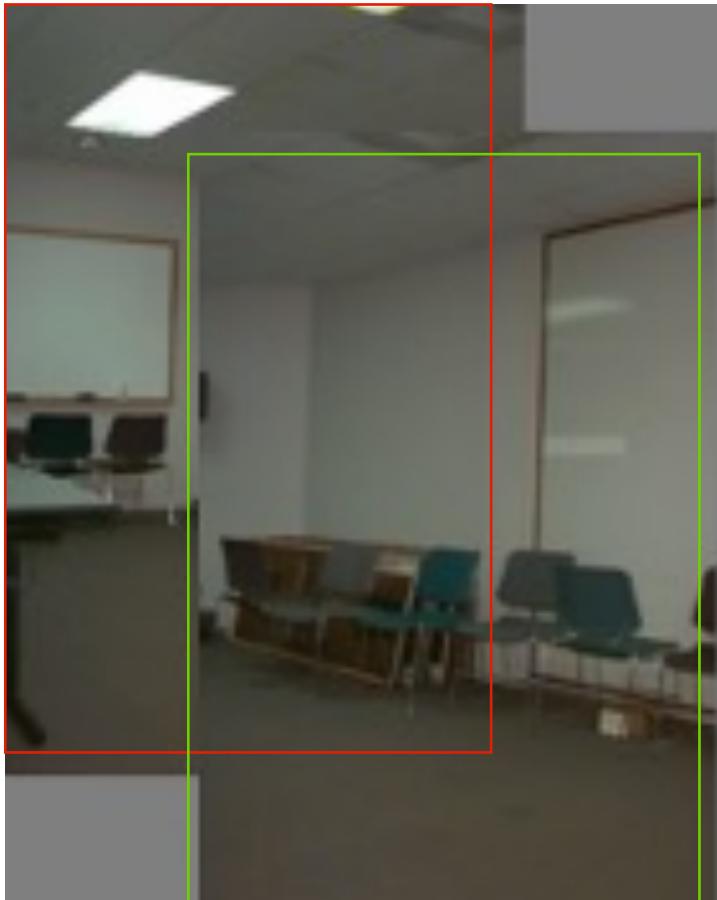
Use image homographies.



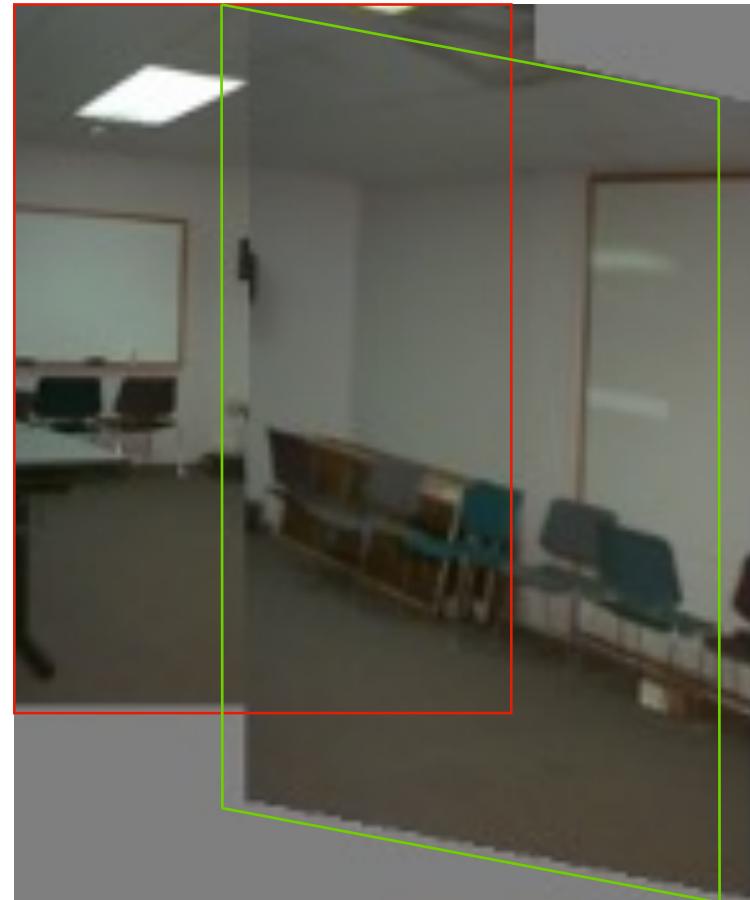
Back to warping: image homographies

Warping with different transformations

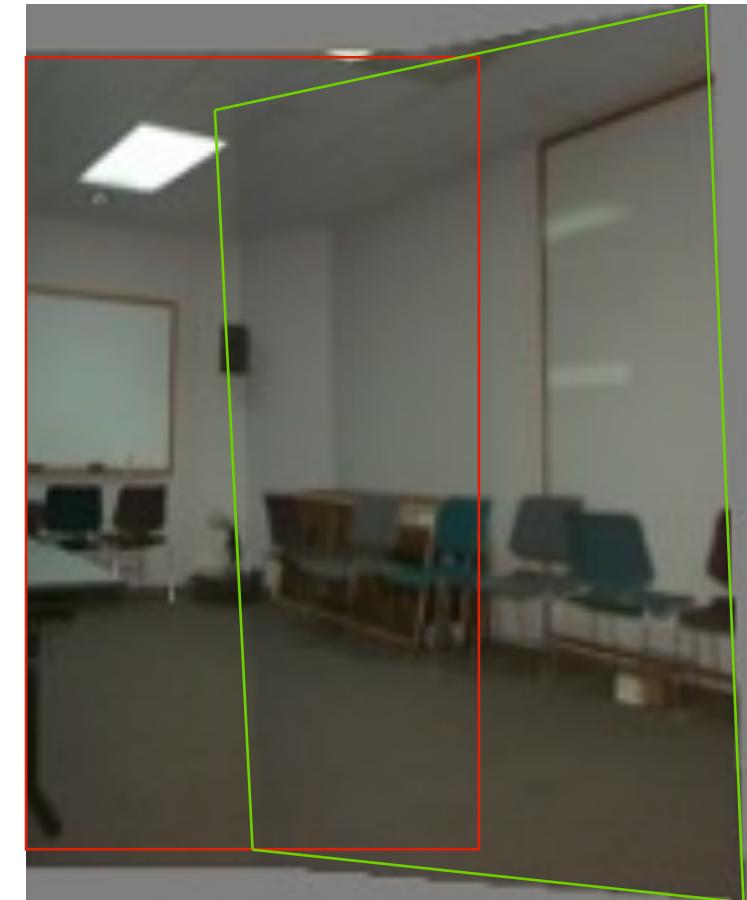
translation



affine



projective (homography)



View warping

original view



synthetic top view



synthetic side view



What are these black areas near the boundaries?

Virtual camera rotations



original view

synthetic
rotations



Street art



Understanding geometric patterns

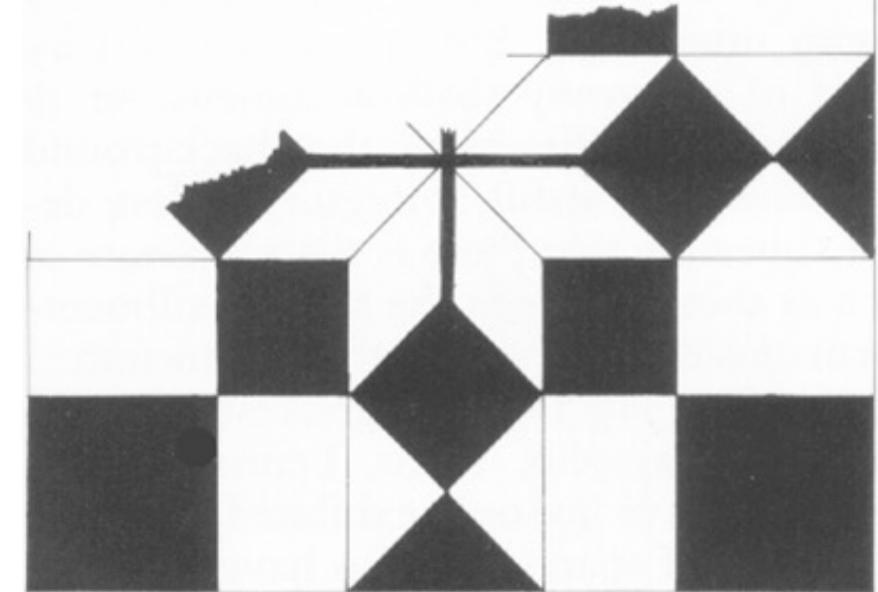
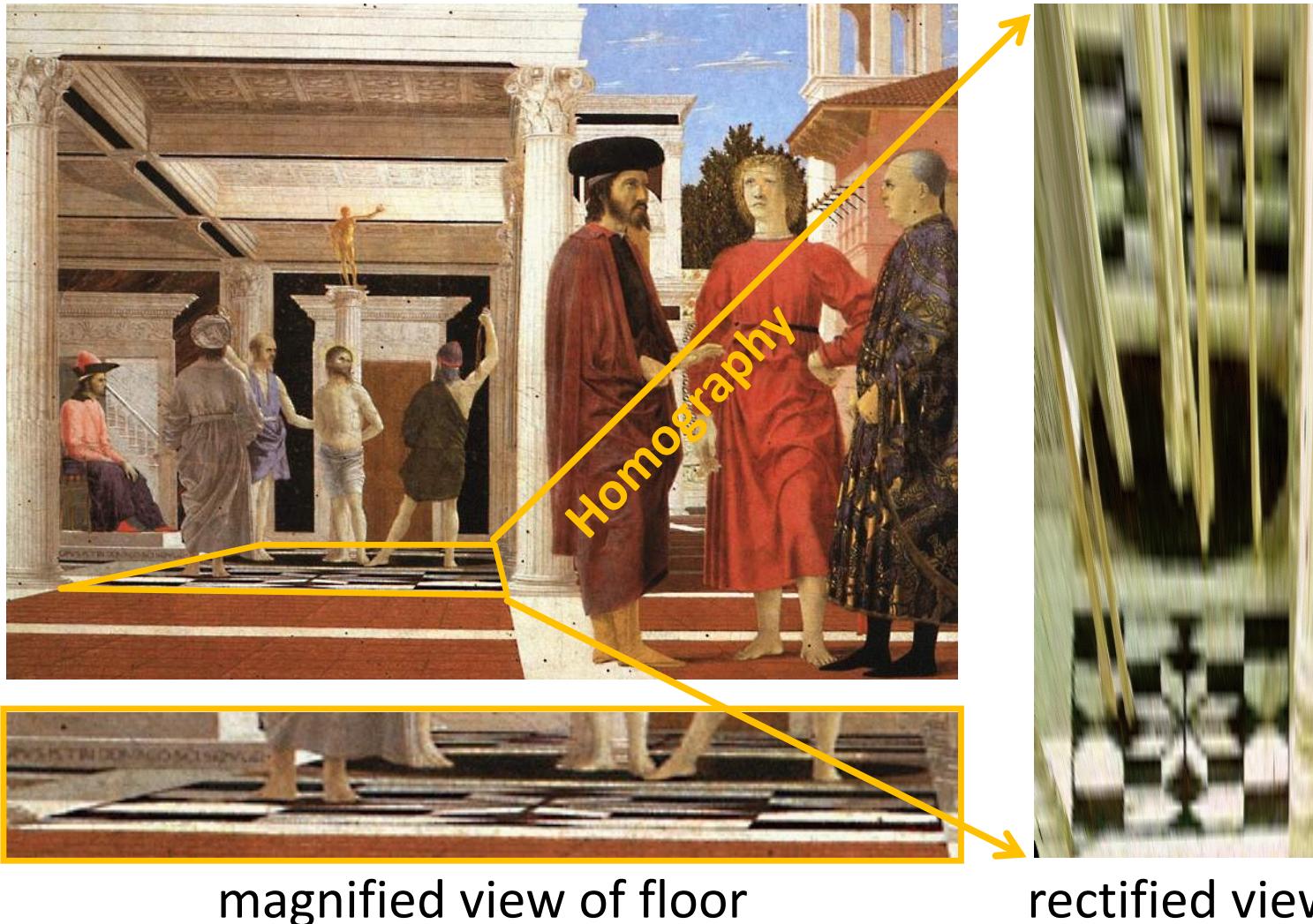
What is the pattern on the floor?



magnified view of floor

Understanding geometric patterns

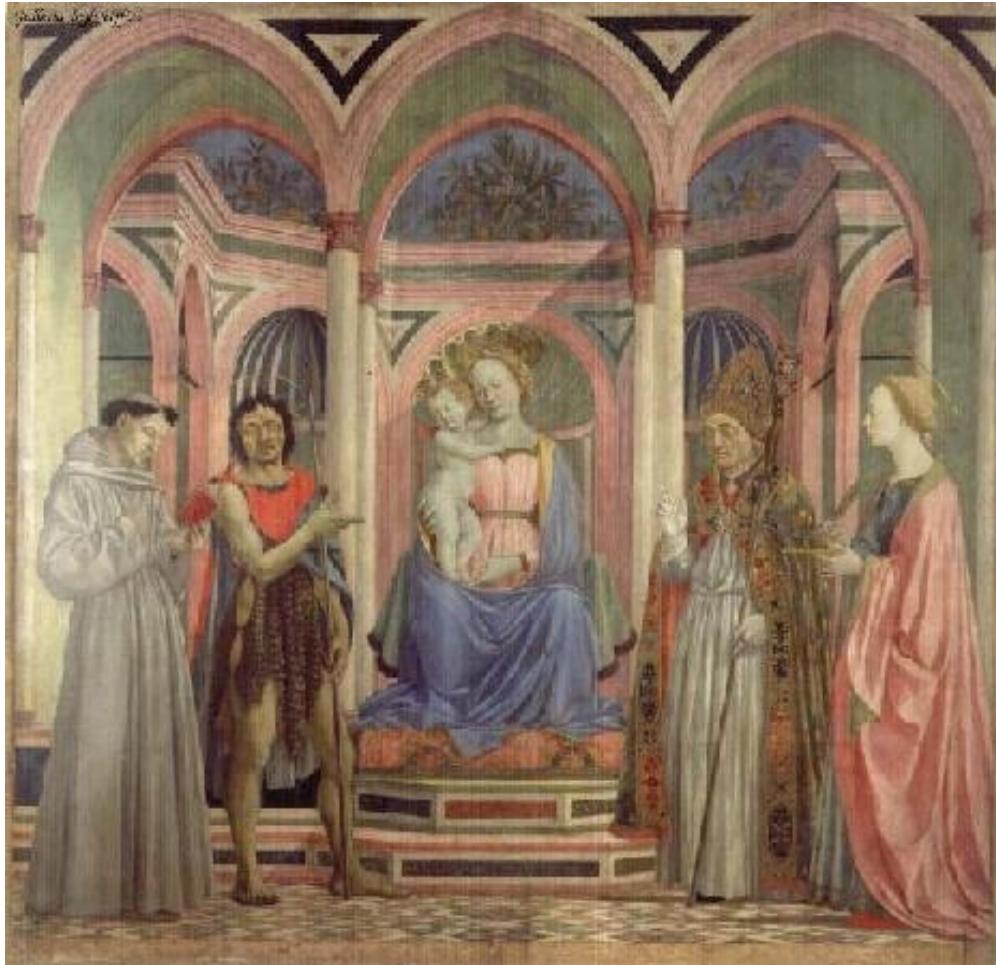
What is the pattern on the floor?



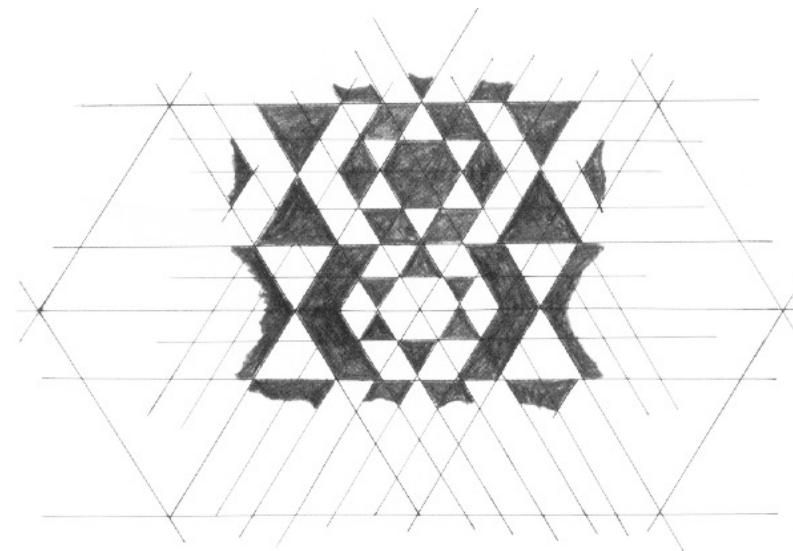
reconstruction from
rectified view

Understanding geometric patterns

Very popular in renaissance drawings (when perspective was discovered)



rectified view
of floor



reconstruction

A weird painting

Holbein, "The Ambassadors"



What's this???

A weird painting

Holbein, "The Ambassadors"



rectified view

skull under anamorphic perspective

Panoramas from image stitching

1. Capture multiple images from different viewpoints.



2. Stitch them together into a virtual wide-angle image.



When can we use homographies?

We can use homographies when...

1. ... the scene is planar; or
2. ... the scene is very far or has small (relative) depth variation
→ scene is approximately planar



We can use homographies when...

3. ... the scene is captured under camera rotation only (no translation or pose change)



Computing with homographies

Applying a homography

1. Convert to homogeneous coordinates:

$$p = \begin{bmatrix} x \\ y \end{bmatrix} \Rightarrow P = \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

What is the size of the homography matrix?



2. Multiply by the homography matrix:

$$P' = H \cdot P$$

3. Convert back to heterogeneous coordinates:

$$P' = \begin{bmatrix} x' \\ y' \\ w' \end{bmatrix} \Rightarrow p' = \begin{bmatrix} x' \\ y' \\ w' \end{bmatrix}$$

Applying a homography

1. Convert to homogeneous coordinates:

$$p = \begin{bmatrix} x \\ y \end{bmatrix} \Rightarrow P = \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

What is the size of the homography matrix?

Answer: 3 x 3

2. Multiply by the homography matrix:

$$P' = H \cdot P$$

How many degrees of freedom does the homography matrix have?

3. Convert back to heterogeneous coordinates:

$$P' = \begin{bmatrix} x' \\ y' \\ w' \end{bmatrix} \Rightarrow p' = \begin{bmatrix} x' / w' \\ y' / w' \end{bmatrix}$$

Applying a homography

1. Convert to homogeneous coordinates:

$$p = \begin{bmatrix} x \\ y \end{bmatrix} \Rightarrow P = \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

What is the size of the homography matrix?

Answer: 3 x 3

2. Multiply by the homography matrix:

$$P' = H \cdot P$$

How many degrees of freedom does the homography matrix have?

Answer: 8

3. Convert back to heterogeneous coordinates:

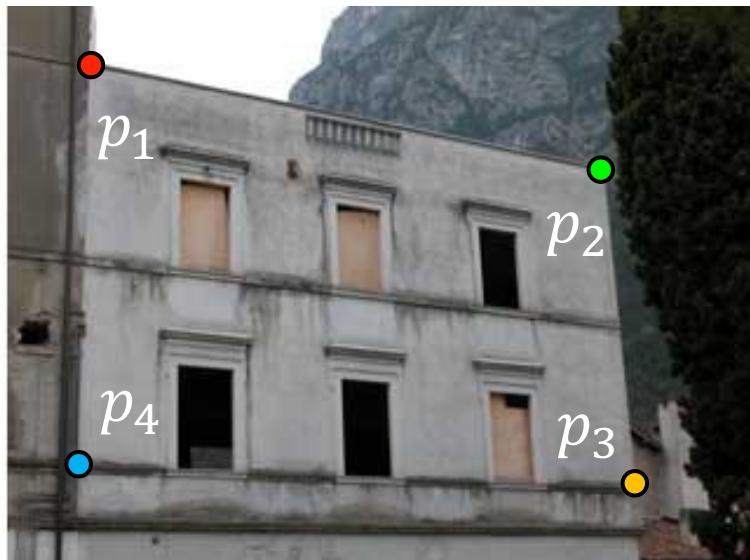
$$P' = \begin{bmatrix} x' \\ y' \\ w' \end{bmatrix} \Rightarrow p' = \begin{bmatrix} x' / w' \\ y' / w' \end{bmatrix}$$

The direct linear transform (DLT)

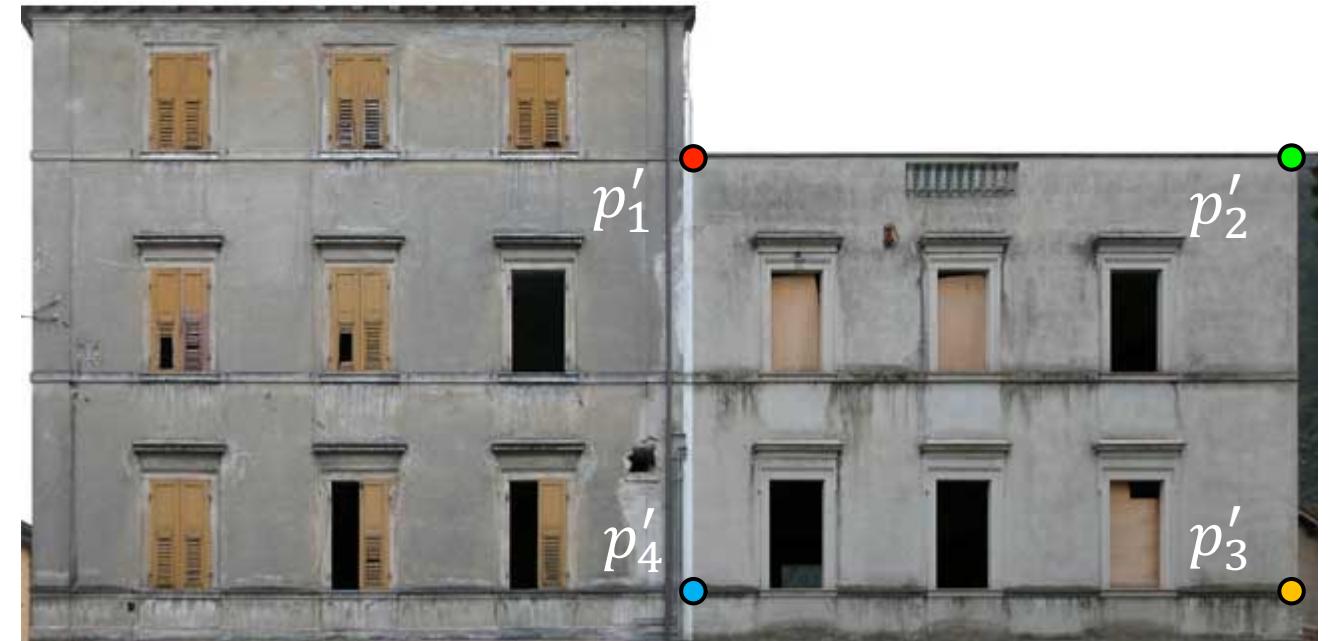
Create point correspondences

Given a set of matched feature points $\{p_i, p'_i\}$ find the best estimate of H such that

$$P' = H \cdot P$$



original image



target image

How many correspondences do we need?

Determining the homography matrix

Write out linear equation for each correspondence:

$$P' = H \cdot P \quad \text{or} \quad \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \alpha \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Determining the homography matrix

Write out linear equation for each correspondence:

$$P' = H \cdot P \quad \text{or} \quad \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \alpha \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Expand matrix multiplication:

$$x' = \alpha(h_1x + h_2y + h_3)$$

$$y' = \alpha(h_4x + h_5y + h_6)$$

$$1 = \alpha(h_7x + h_8y + h_9)$$

Determining the homography matrix

Write out linear equation for each correspondence:

$$P' = H \cdot P \quad \text{or} \quad \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \alpha \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Expand matrix multiplication:

$$x' = \alpha(h_1x + h_2y + h_3)$$

$$y' = \alpha(h_4x + h_5y + h_6)$$

$$1 = \alpha(h_7x + h_8y + h_9)$$

Divide out unknown scale factor:

$$x'(h_7x + h_8y + h_9) = (h_1x + h_2y + h_3)$$

$$y'(h_7x + h_8y + h_9) = (h_4x + h_5y + h_6)$$

*How do you
rearrange terms
to make it a
linear system?*

$$x'(h_7x + h_8y + h_9) = (h_1x + h_2y + h_3)$$

$$y'(h_7x + h_8y + h_9) = (h_4x + h_5y + h_6)$$

Just rearrange the terms



$$h_7xx' + h_8yx' + h_9x' - h_1x - h_2y - h_3 = 0$$

$$h_7xy' + h_8yy' + h_9y' - h_4x - h_5y - h_6 = 0$$

Determining the homography matrix

Re-arrange terms:

$$\begin{aligned} h_7xx' + h_8yx' + h_9x' - h_1x - h_2y - h_3 &= 0 \\ h_7xy' + h_8yy' + h_9y' - h_4x - h_5y - h_6 &= 0 \end{aligned}$$

Re-write in matrix form:

$$\mathbf{A}_i \mathbf{h} = \mathbf{0}$$

*How many equations
from one point
correspondence?*

$$\mathbf{A}_i = \begin{bmatrix} -x & -y & -1 & 0 & 0 & 0 & xx' & yx' & x' \\ 0 & 0 & 0 & -x & -y & -1 & xy' & yy' & y' \end{bmatrix}$$

$$\mathbf{h} = [h_1 \ h_2 \ h_3 \ h_4 \ h_5 \ h_6 \ h_7 \ h_8 \ h_9]^\top$$

Determining the homography matrix

Stack together constraints from multiple point correspondences:

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

$$\begin{bmatrix} -x & -y & -1 & 0 & 0 & 0 & xx' & yx' & x' \\ 0 & 0 & 0 & -x & -y & -1 & xy' & yy' & y' \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \\ h_5 \\ h_6 \\ h_7 \\ h_8 \\ h_9 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

⋮

Homogeneous linear least squares problem

General form of total least squares

(Warning: change of notation. \mathbf{x} is a vector of parameters!)

$$\begin{aligned} E_{\text{TLS}} &= \sum_i (\mathbf{a}_i \mathbf{x})^2 \\ &= \|\mathbf{Ax}\|^2 \quad (\text{matrix form}) \end{aligned}$$

$$\|\mathbf{x}\|^2 = 1 \quad \text{constraint}$$

minimize

$$\|\mathbf{Ax}\|^2$$

subject to

$$\|\mathbf{x}\|^2 = 1$$



minimize

$$\frac{\|\mathbf{Ax}\|^2}{\|\mathbf{x}\|^2} \quad (\text{Rayleigh quotient})$$

Solution is the eigenvector
corresponding to smallest
eigenvalue of

(equivalent)

$$\mathbf{A}^\top \mathbf{A}$$

Solution is the column of \mathbf{V}
corresponding to smallest singular
value

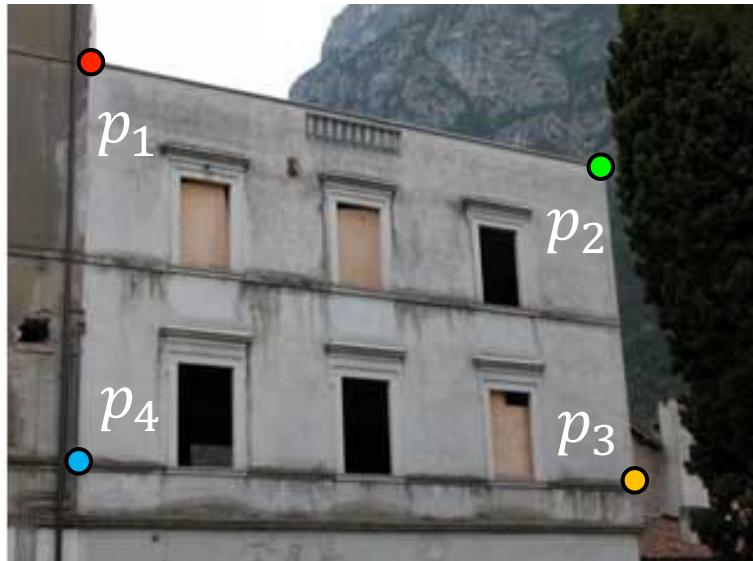
$$\mathbf{A} = \mathbf{U}\Sigma\mathbf{V}^\top$$

Solving for H using DLT

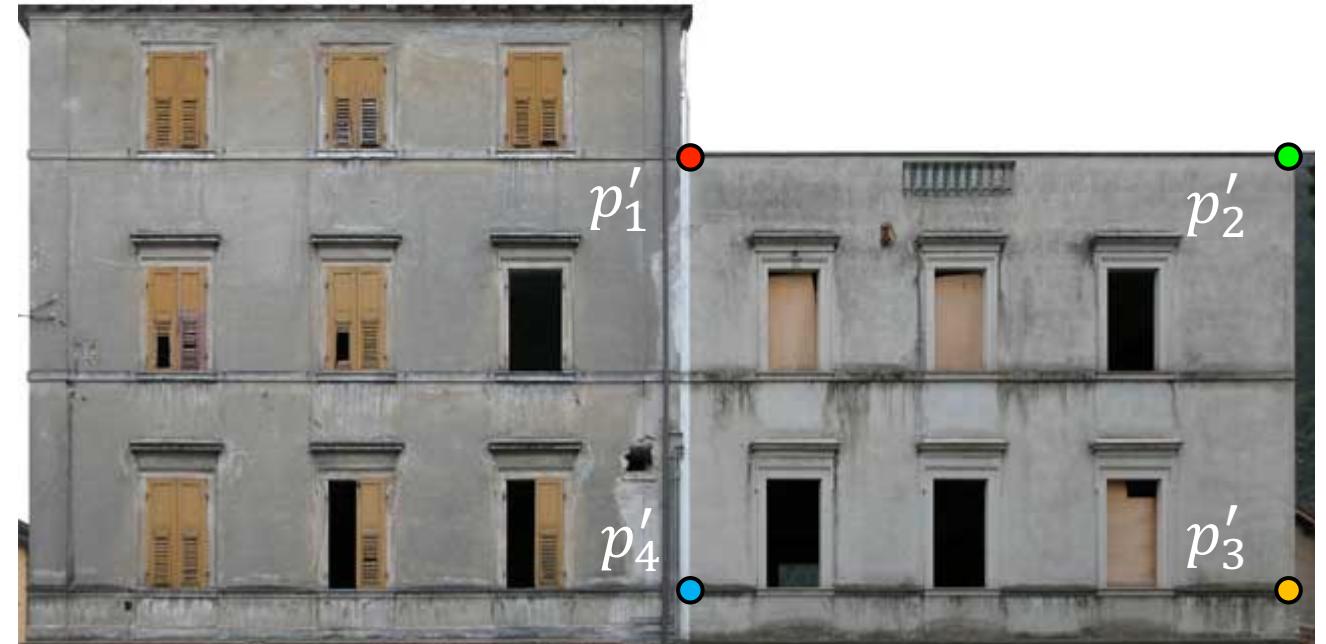
Given $\{\mathbf{x}_i, \mathbf{x}'_i\}$ solve for H such that $\mathbf{x}' = \mathbf{H}\mathbf{x}$

1. For each correspondence, create 2x9 matrix \mathbf{A}_i
2. Concatenate into single $2n \times 9$ matrix \mathbf{A}
3. Compute SVD of $\mathbf{A} = \mathbf{U}\Sigma\mathbf{V}^\top$
4. Store singular vector of the smallest singular value $\mathbf{h} = \mathbf{v}_i^\top$
5. Reshape to get \mathbf{H}

Create point correspondences



original image



target image

How do we automate this step?

The image correspondence pipeline

1. Feature point detection

- Detect corners using the Harris corner detector.

2. Feature point description

- Describe features using the Multi-scale oriented patch descriptor.

3. Feature matching

The image correspondence pipeline

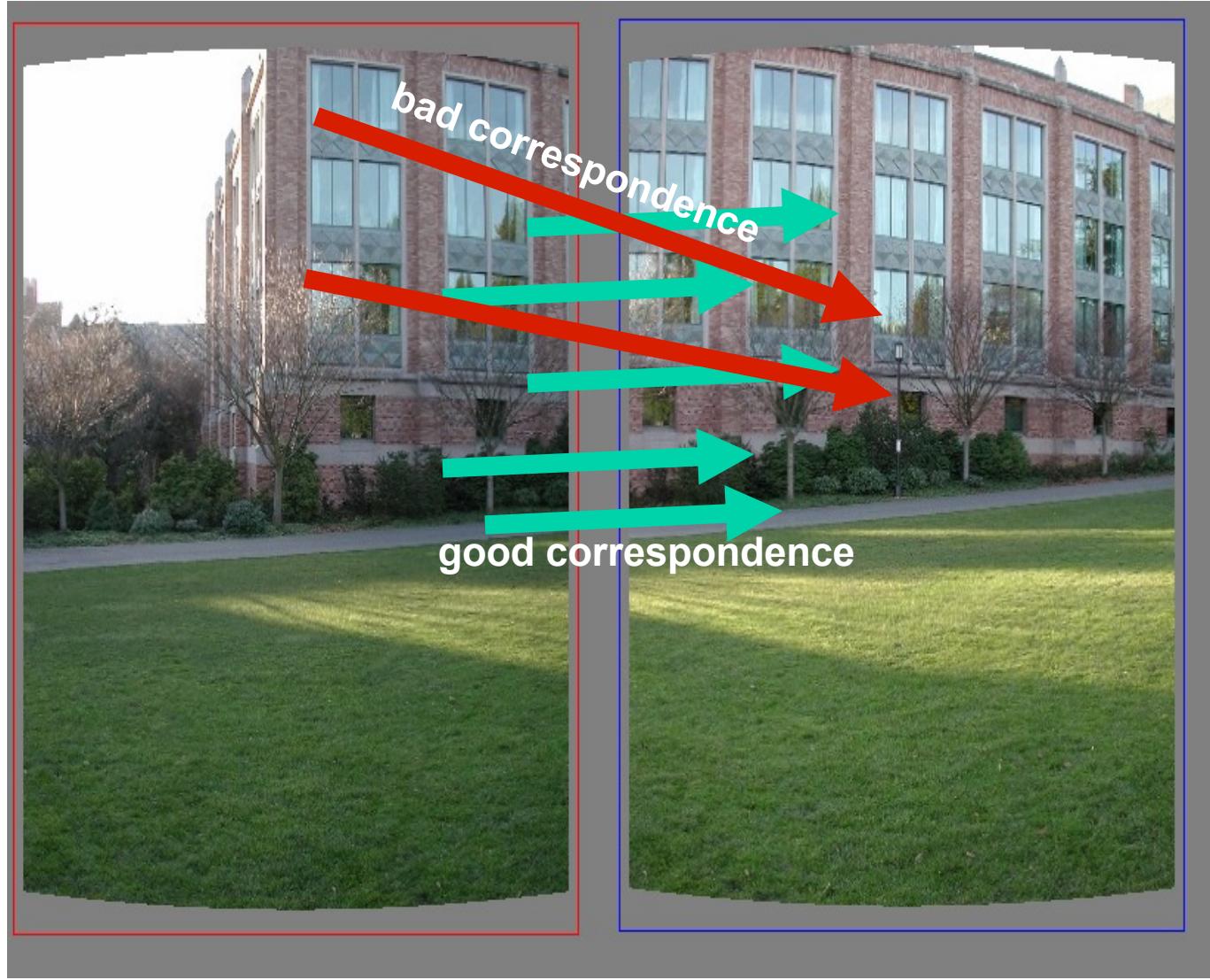
1. Feature point detection

- Detect corners using the Harris corner detector.

2. Feature point description

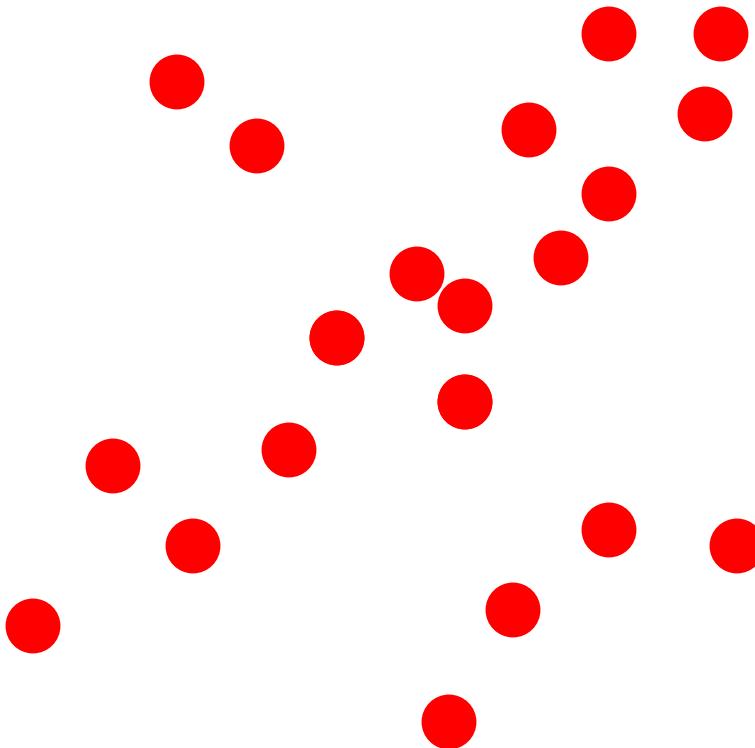
- Describe features using the Multi-scale oriented patch descriptor.

3. Feature matching



Random Sample Consensus (RANSAC)

Fitting lines
(with outliers)

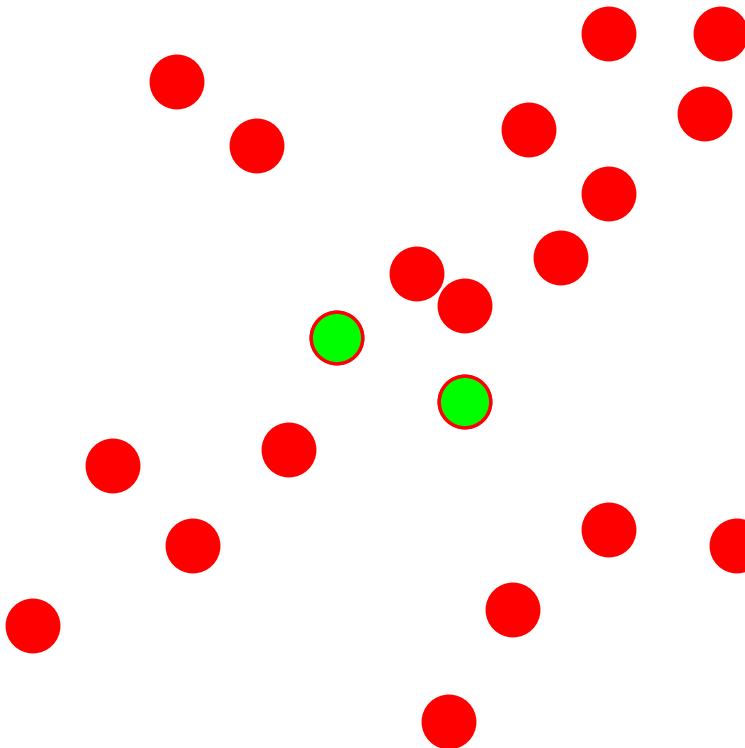


Algorithm:

1. Sample (randomly) the number of points required to fit the model
2. Solve for model parameters using samples
3. Score by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found with high confidence

Fitting lines
(with outliers)

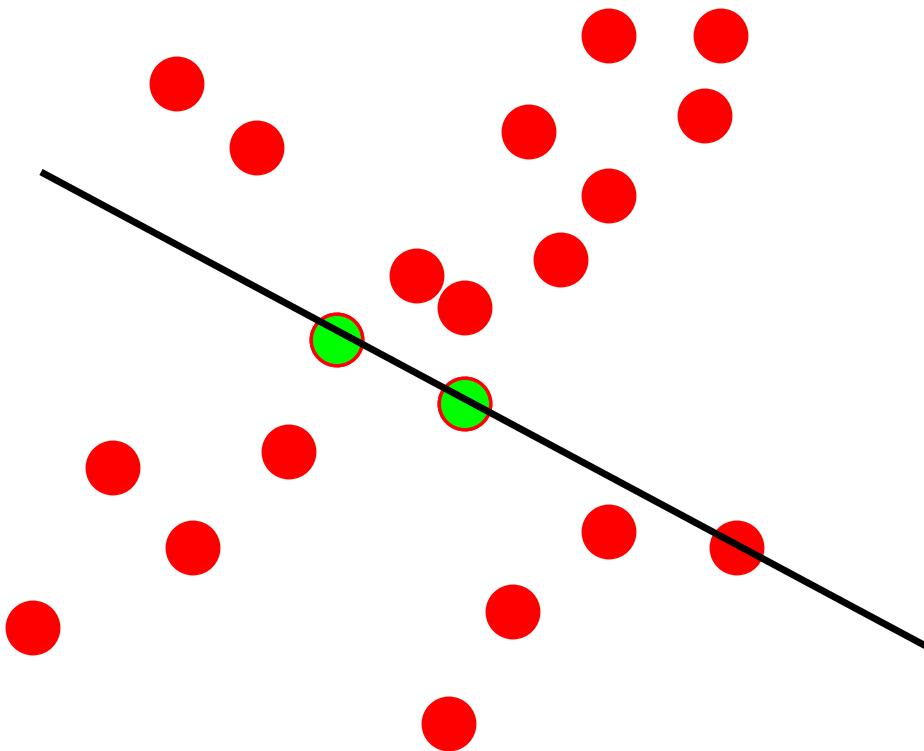


Algorithm:

1. **Sample (randomly) the number of points required to fit the model**
2. Solve for model parameters using samples
3. Score by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found with high confidence

Fitting lines
(with outliers)



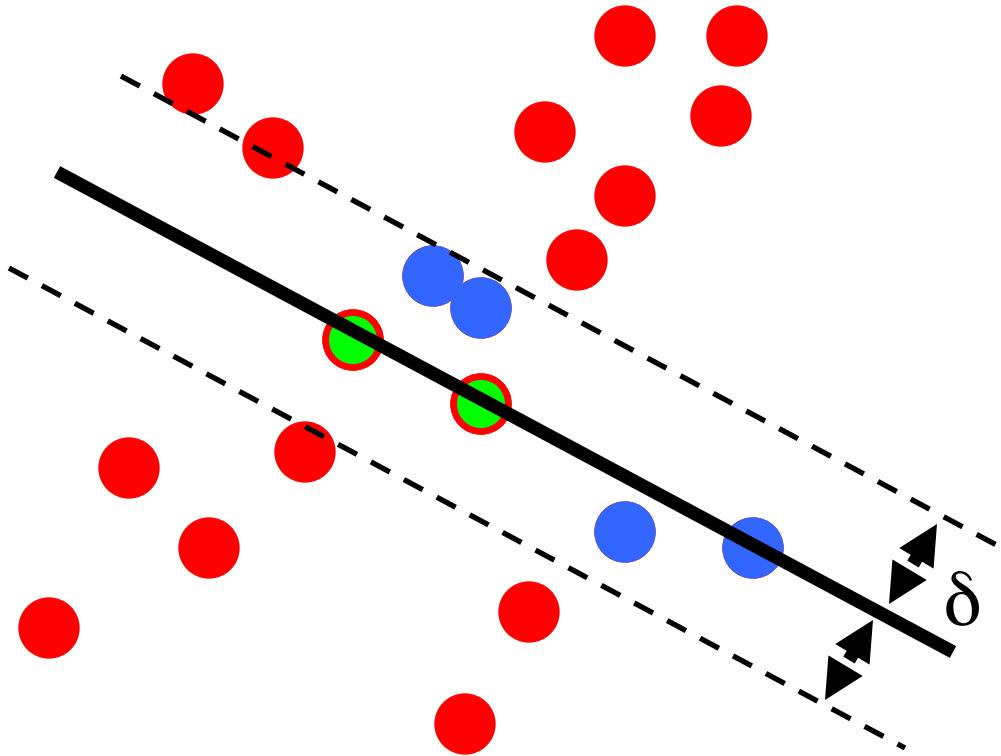
Algorithm:

1. Sample (randomly) the number of points required to fit the model
2. **Solve for model parameters using samples**
3. Score by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found with high confidence

Fitting lines
(with outliers)

$$N_I = 6$$

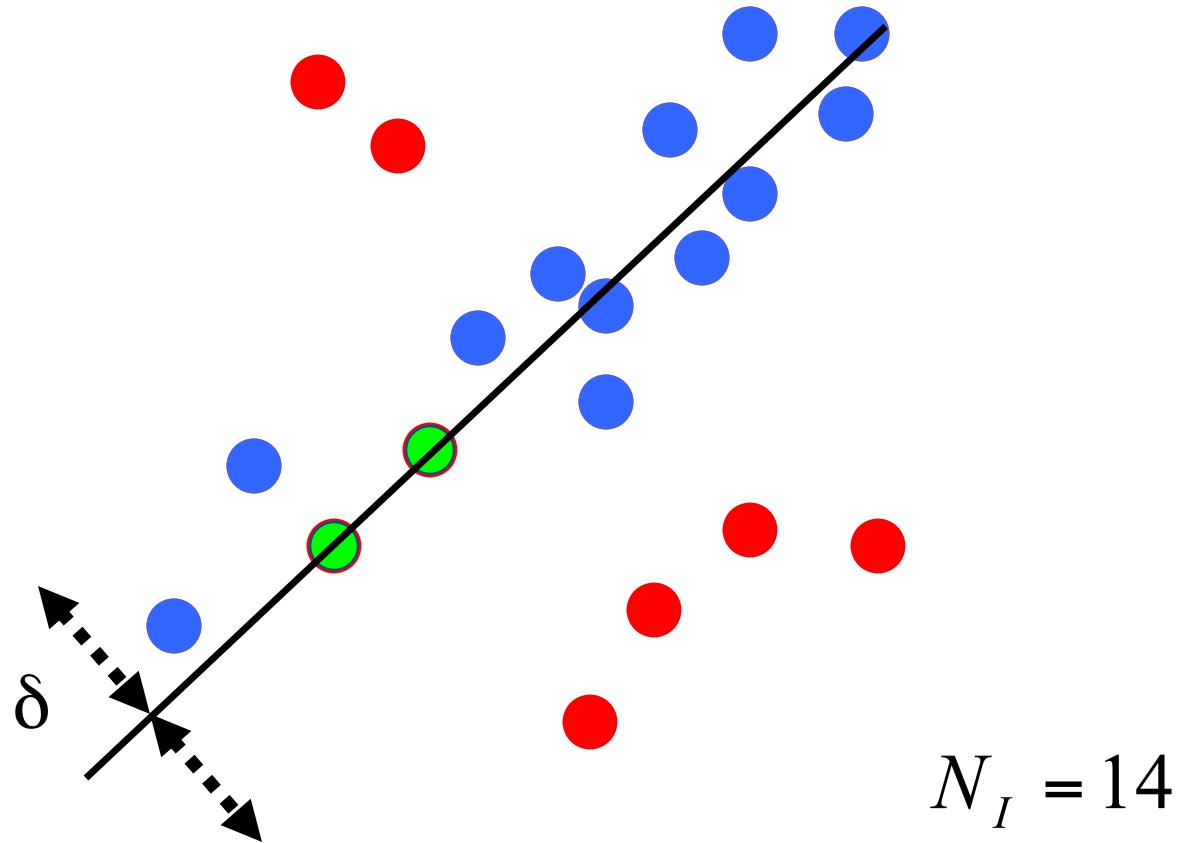


Algorithm:

1. Sample (randomly) the number of points required to fit the model
2. Solve for model parameters using samples
3. **Score by the fraction of inliers within a preset threshold of the model**

Repeat 1-3 until the best model is found with high confidence

Fitting lines
(with outliers)



Algorithm:

1. Sample (randomly) the number of points required to fit the model
2. Solve for model parameters using samples
3. Score by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found with high confidence

Given two images...



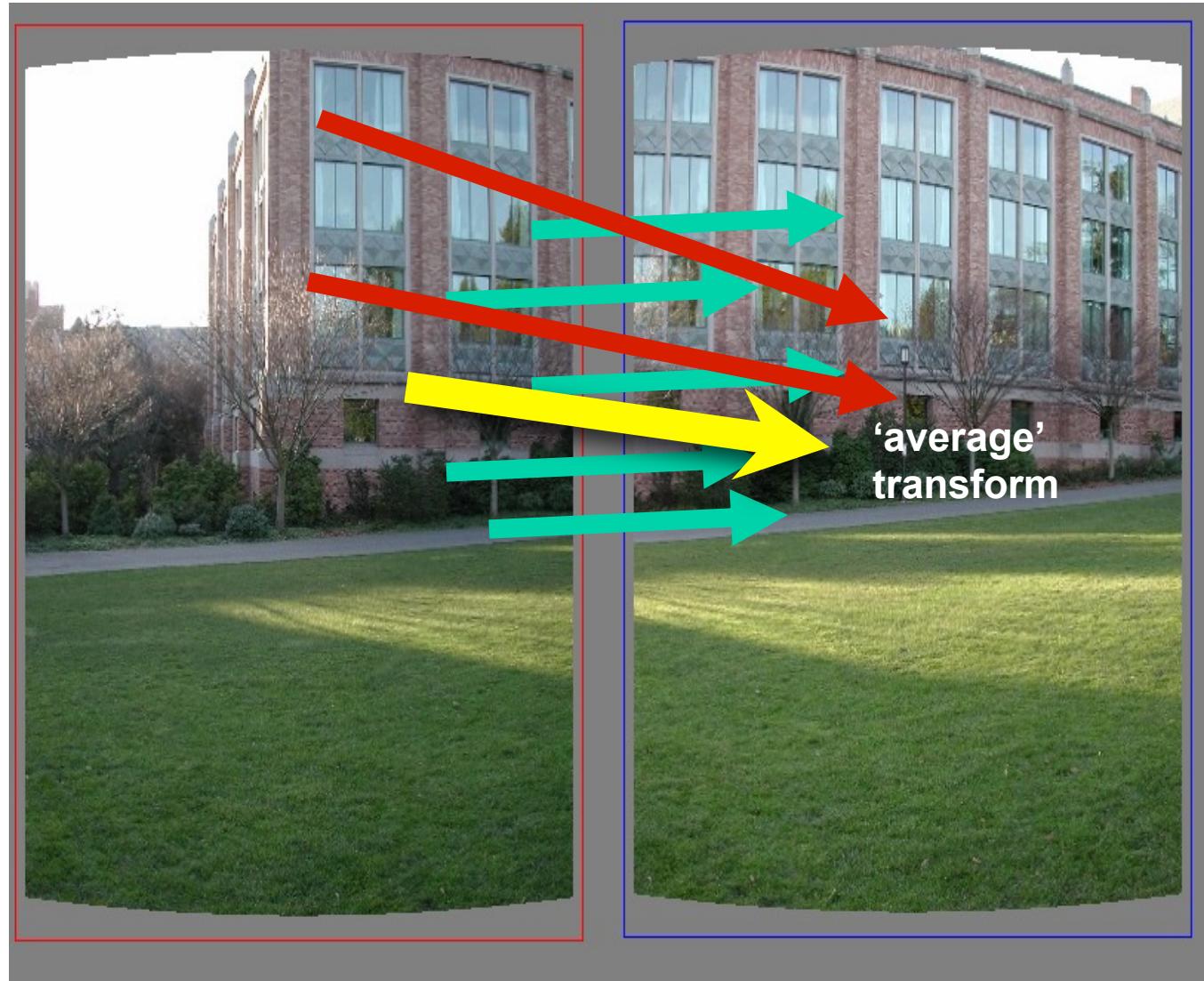
find matching features (e.g., SIFT) and a translation transform

Matched points will usually contain bad correspondences



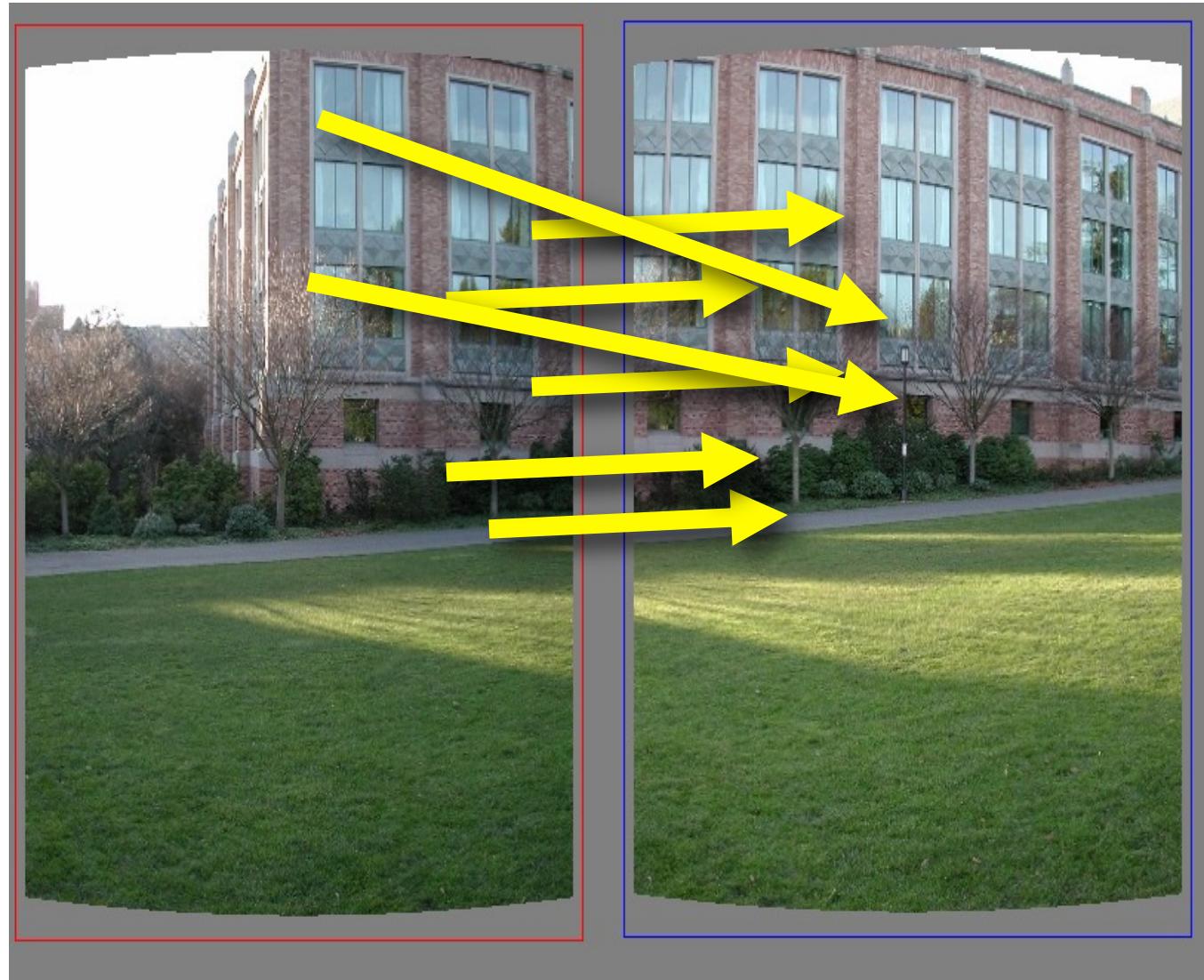
how should we estimate the transform?

LLS will find the "average" transform

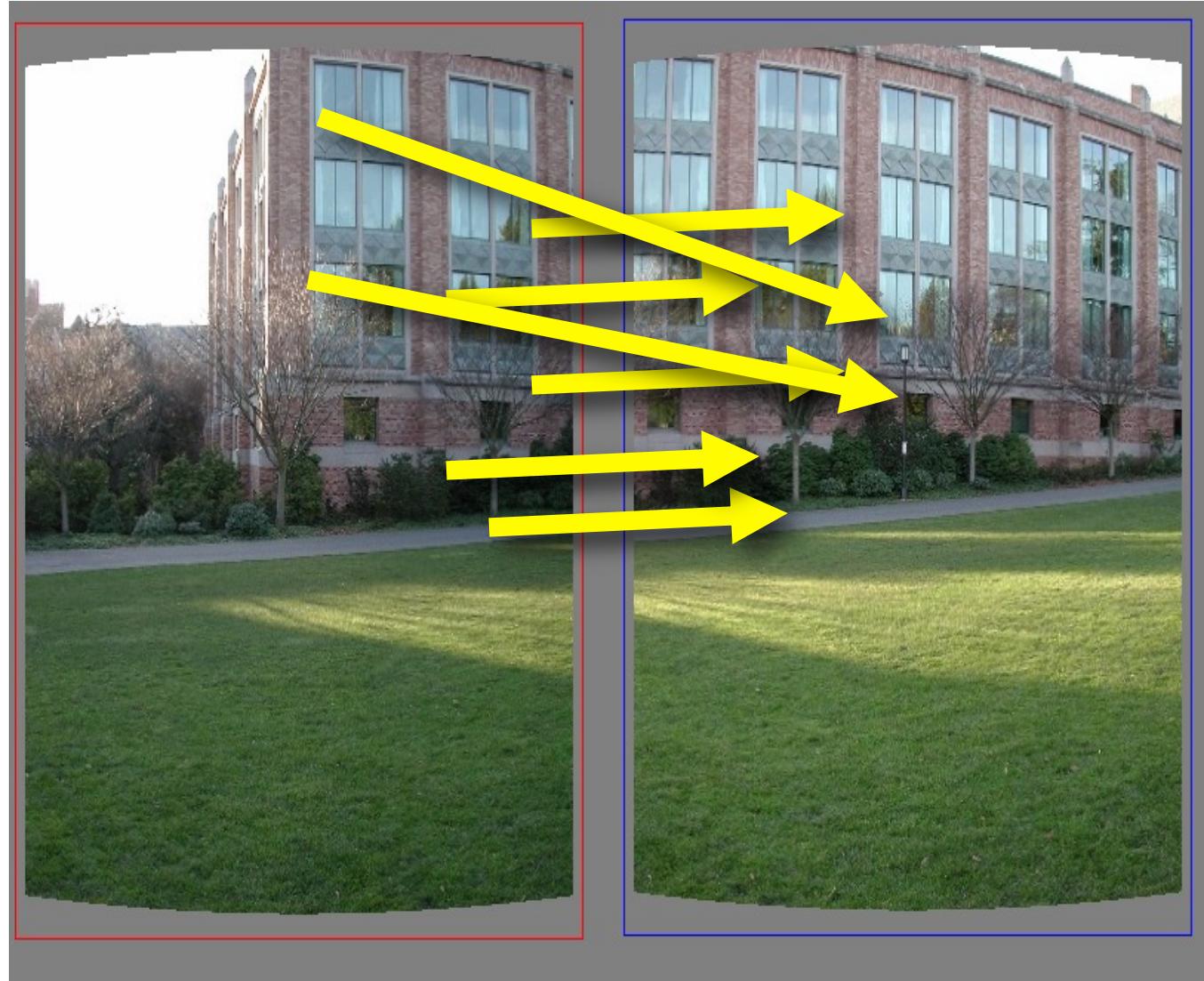


solution is corrupted by bad correspondences

Use RANSAC

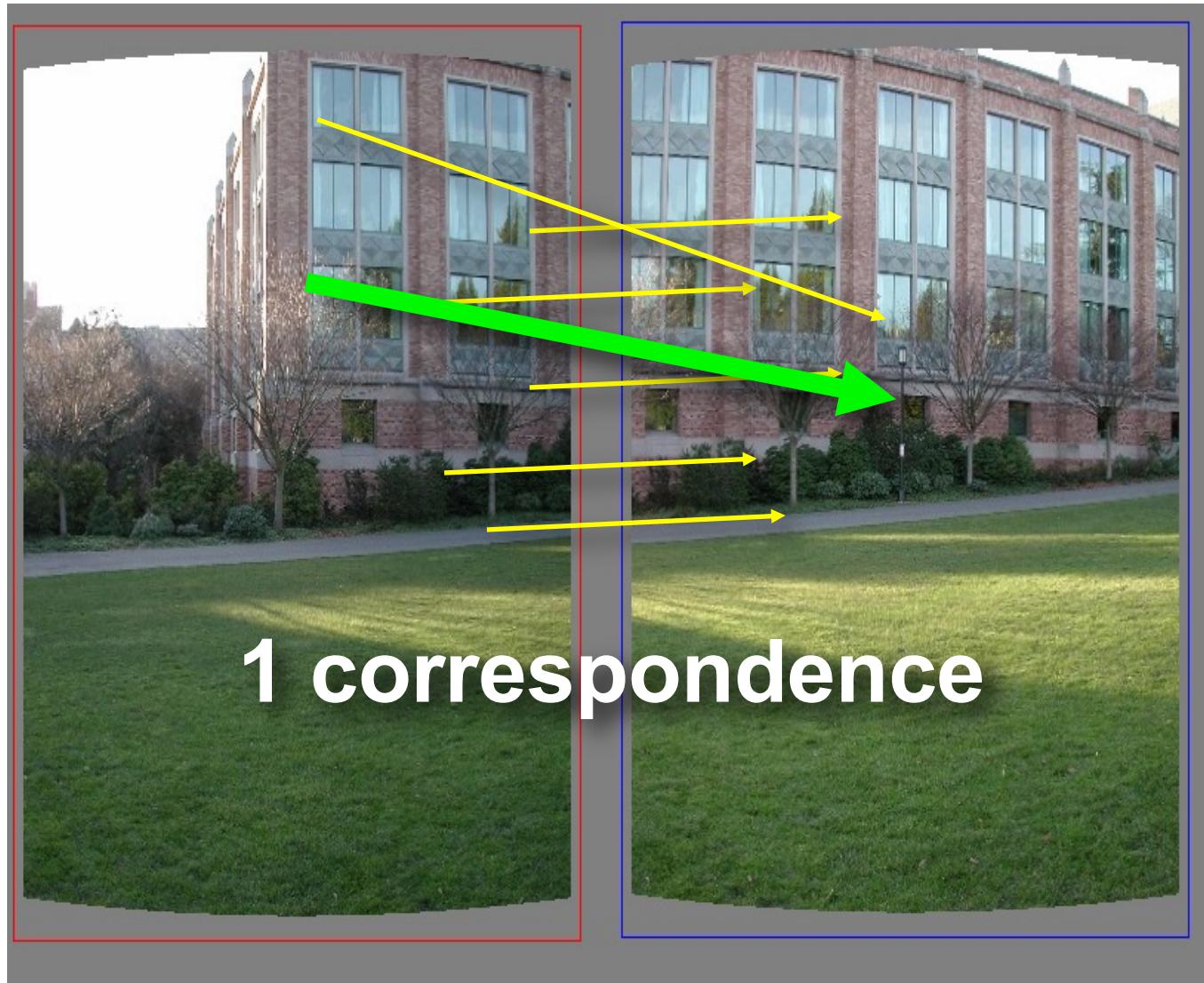


How many correspondences to compute translation transform?

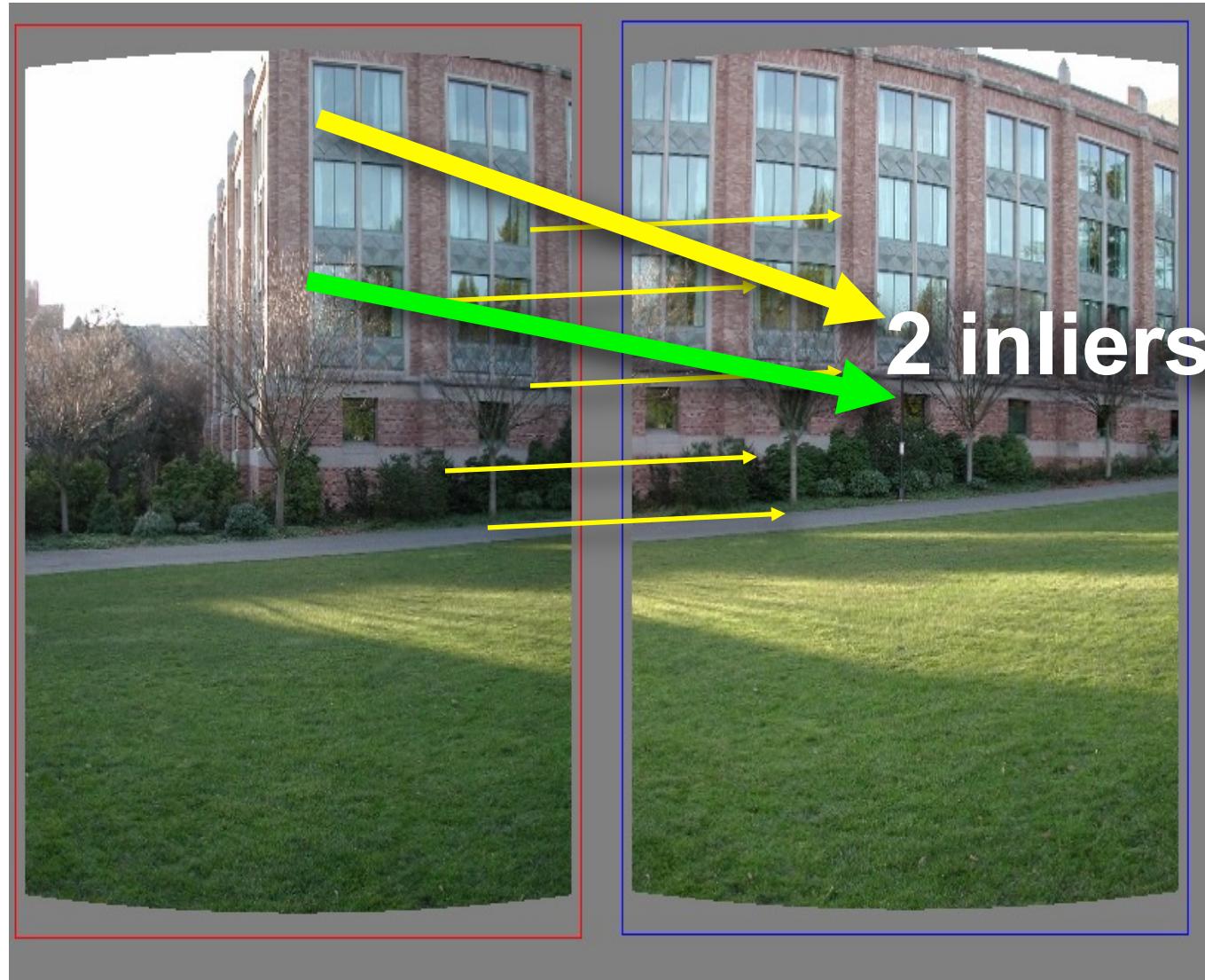


Need only **one correspondence**, to find translation model

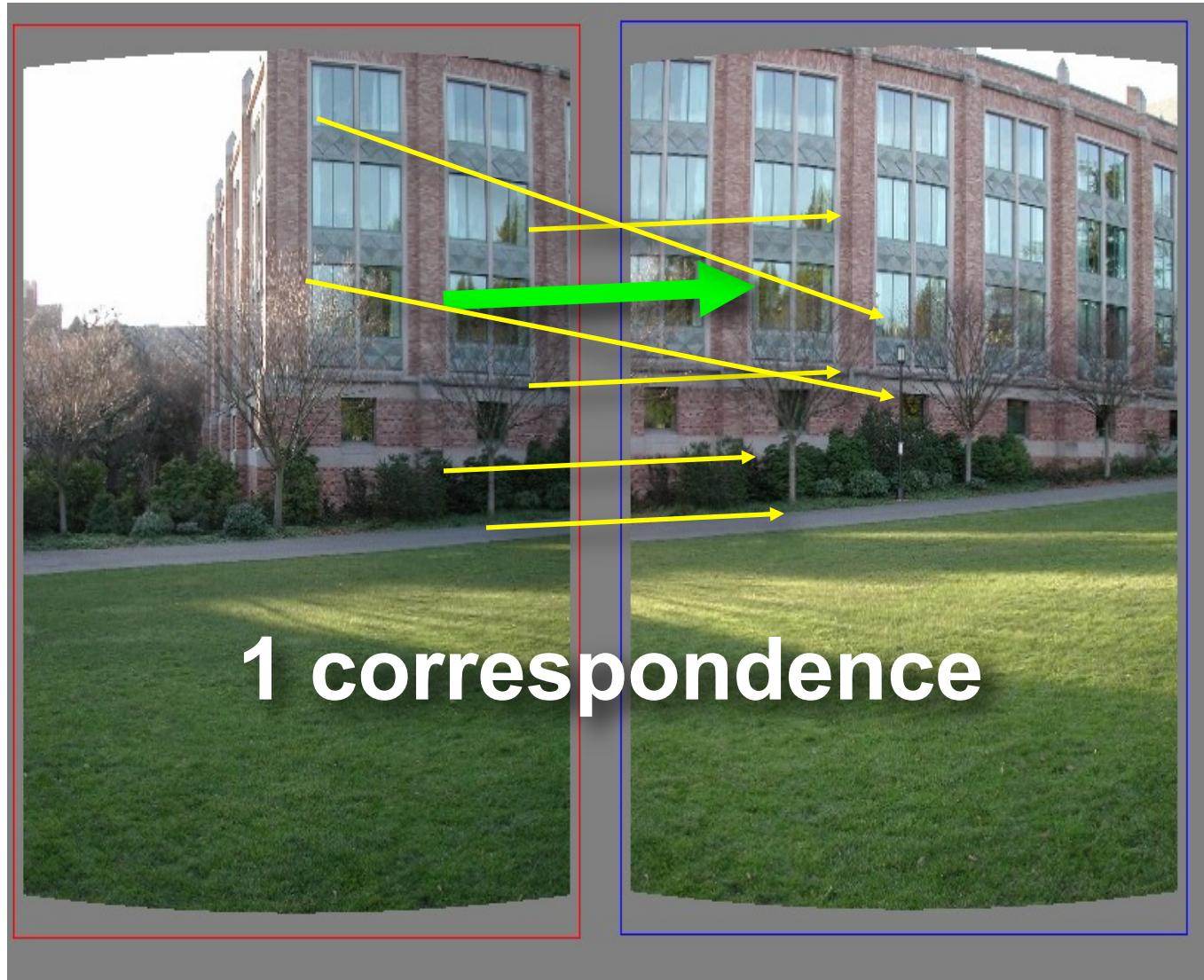
Pick one correspondence, count inliers



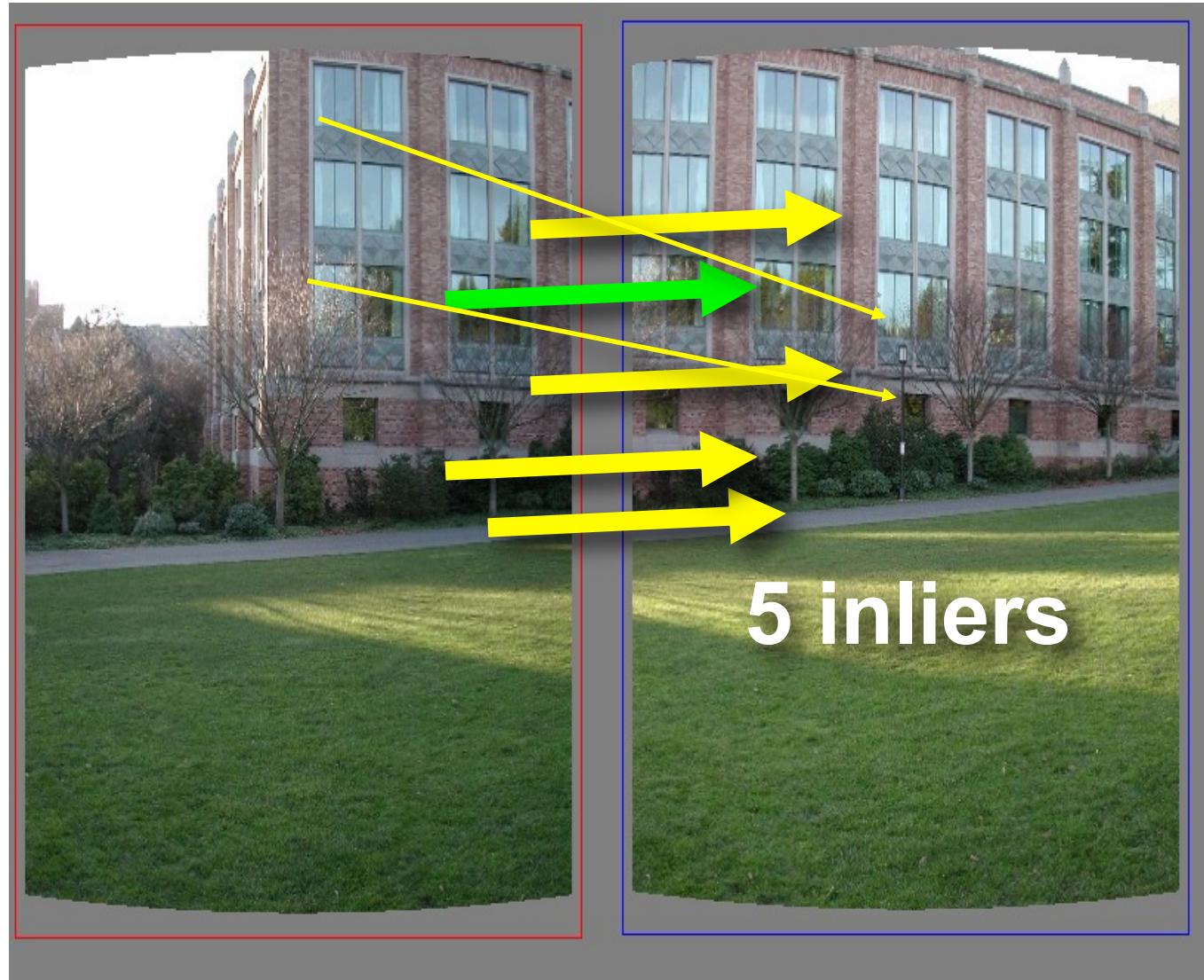
Pick one correspondence, count inliers



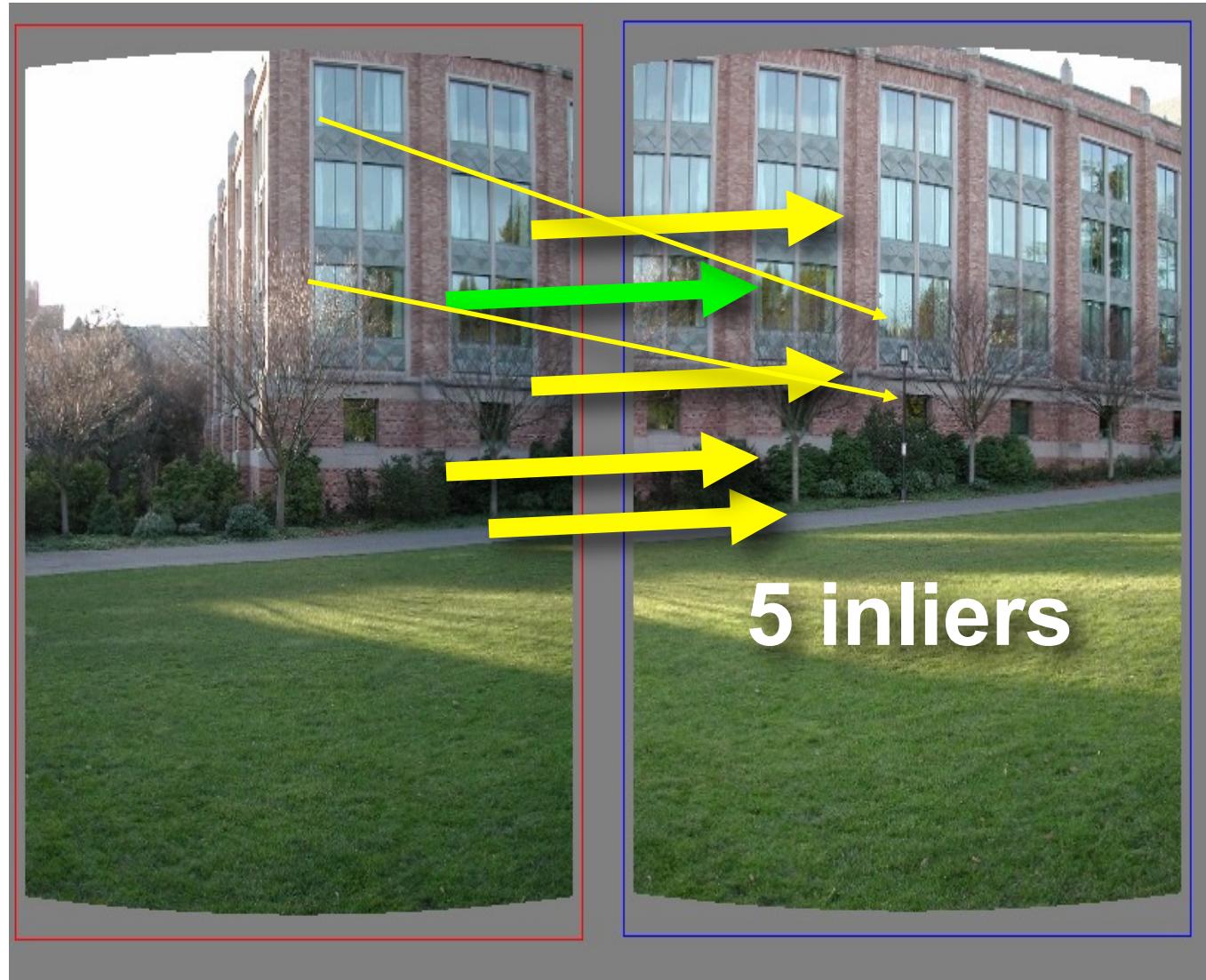
Pick one correspondence, count inliers



Pick one correspondence, count inliers



Pick one correspondence, count inliers



Pick the model with the highest number of inliers!

Estimating homography using RANSAC

- RANSAC loop
 1. Get  point correspondences (randomly)

Estimating homography using RANSAC

- RANSAC loop
 1. Get four point correspondences (randomly)
 2. Compute H using 

Estimating homography using RANSAC

- RANSAC loop
 1. Get four point correspondences (randomly)
 2. Compute H using DLT
 3. Count 

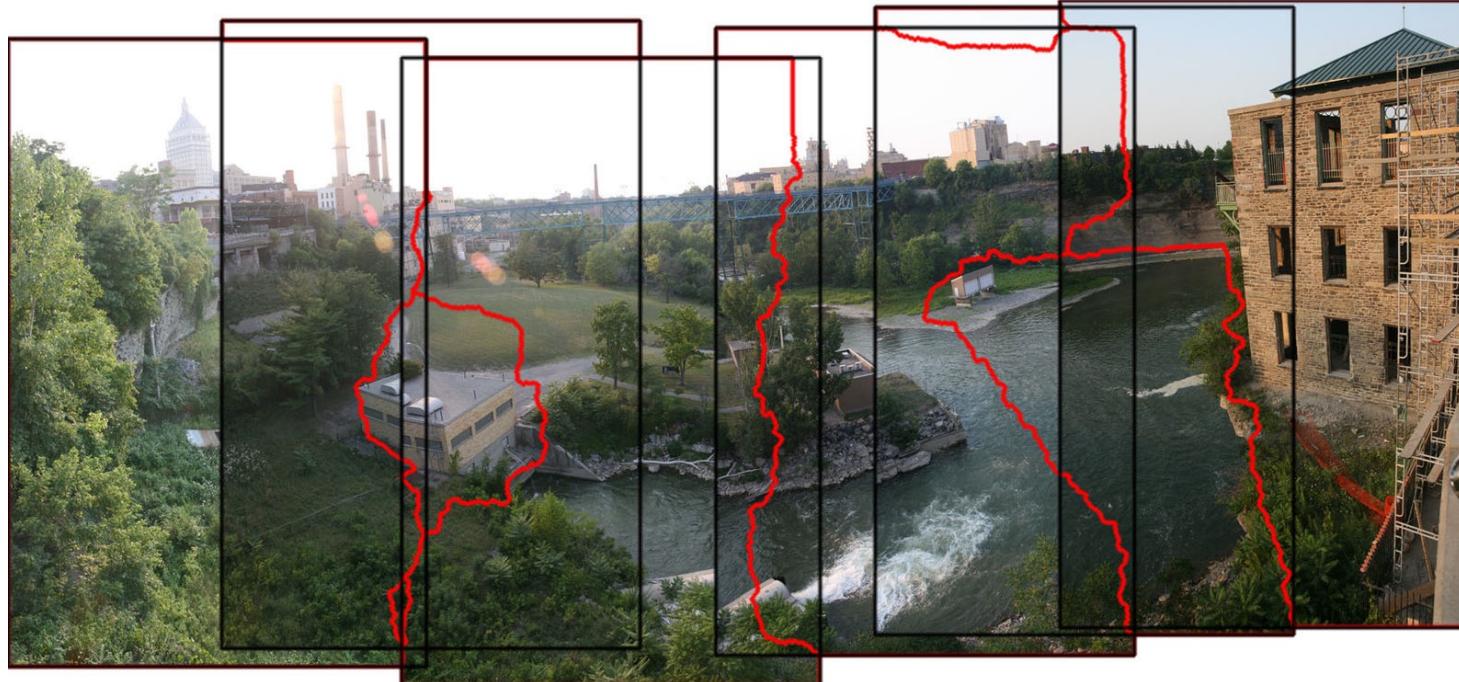
Estimating homography using RANSAC

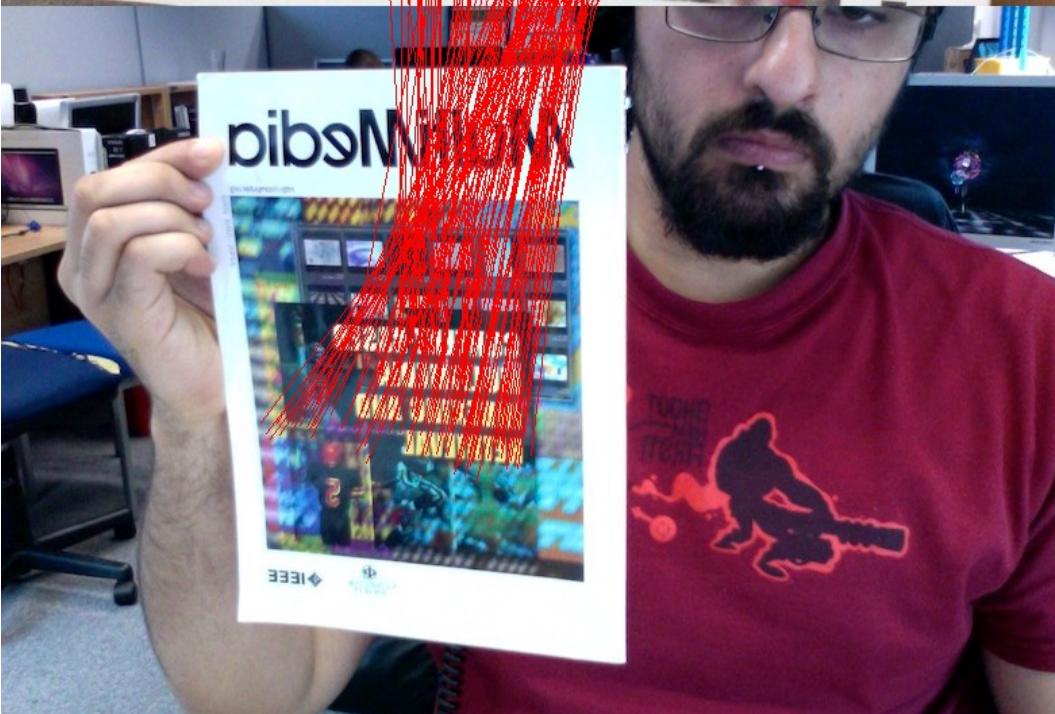
- RANSAC loop
 1. Get four point correspondences (randomly)
 2. Compute H using DLT
 3. Count inliers
 4. Keep H if 

Estimating homography using RANSAC

- RANSAC loop
 - 1. Get four point correspondences (randomly)
 - 2. Compute H using DLT
 - 3. Count inliers
 - 4. Keep H if largest number of inliers
- Recompute H using all inliers

Useful for...





The image correspondence pipeline

1. Feature point detection

- Detect corners using the Harris corner detector.

2. Feature point description

- Describe features using the Multi-scale oriented patch descriptor.

3. Feature matching *and* homography estimation

- Do both simultaneously using RANSAC.