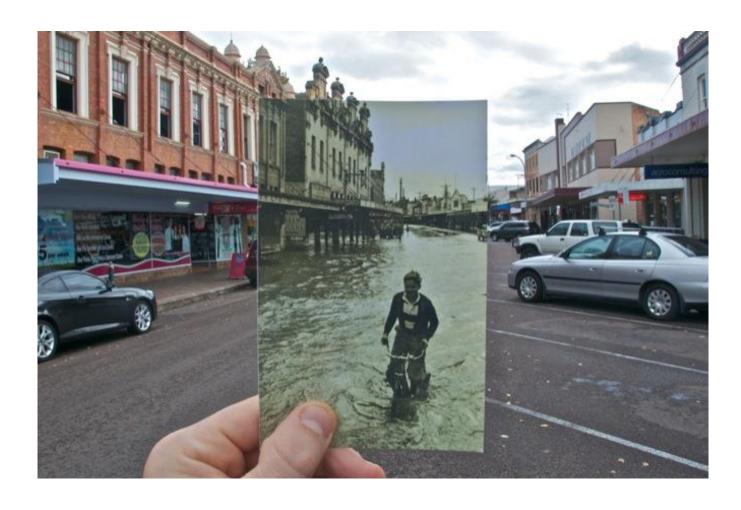
# Image homographies



16-385 Computer Vision Fall 2019, Lecture 8

Motivation for image alignment: panoramas.

# 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.

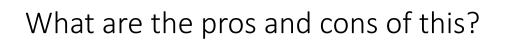


1. Use a very wide-angle lens.

# Wide-angle lenses

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







# 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

Capture multiple images from different viewpoints.



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















Will standard stitching work?

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













Will standard stitching work?

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







right on top

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













What else can we try?









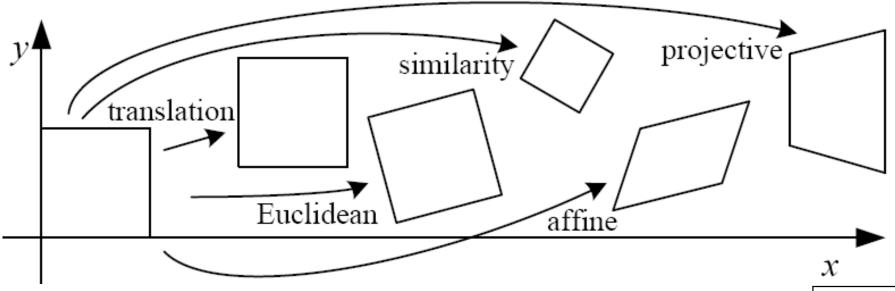




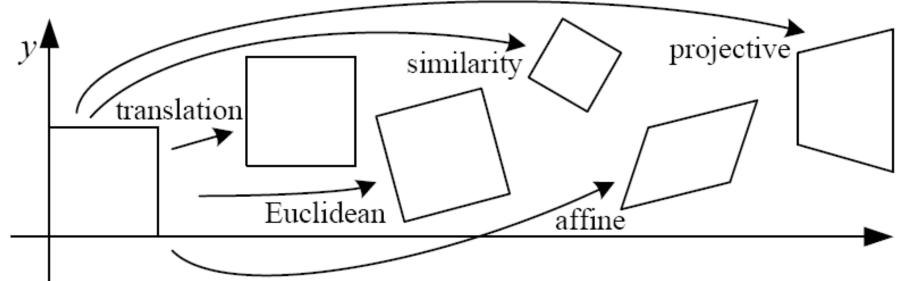
Use image homographies.



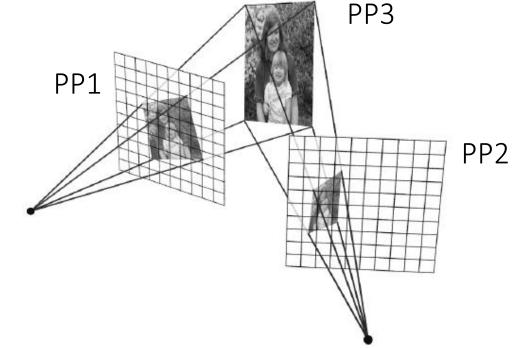
Back to warping: image homographies

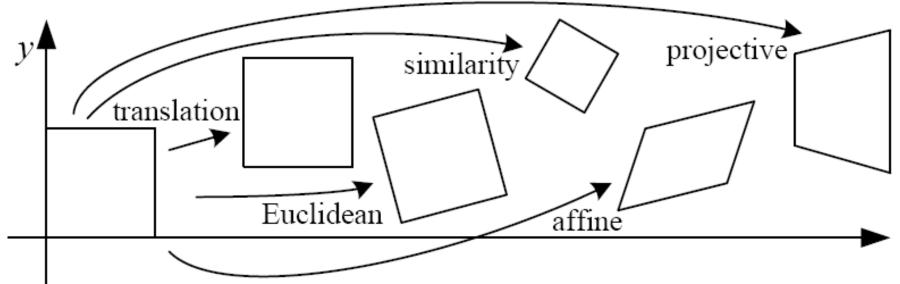


Name	Matrix	# D.O.F.
translation	$egin{bmatrix} ig[ egin{array}{c c} I & t \end{bmatrix}_{2 imes 3} \end{array}$	2
rigid (Euclidean)	$igg[egin{array}{c c} igg[oldsymbol{R} ig oldsymbol{t}igg]_{2 imes 3} \end{array}$	3
similarity	$\left[\begin{array}{c c} sR & t\end{array}\right]_{2 imes 3}$	4
affine	$\left[egin{array}{c} oldsymbol{A} \end{array} ight]_{2 imes 3}$	6
projective	$\left[egin{array}{c}  ilde{m{H}} \end{array} ight]_{3 imes 3}$	8



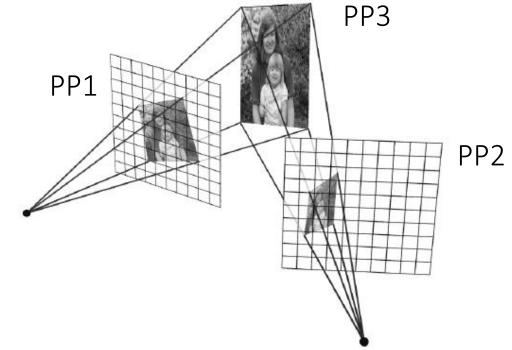
Which kind transformation is needed to warp projective plane 1 into projective plane 2?





Which kind transformation is needed to warp projective plane 1 into projective plane 2?

A projective transformation (a.k.a. a homography).

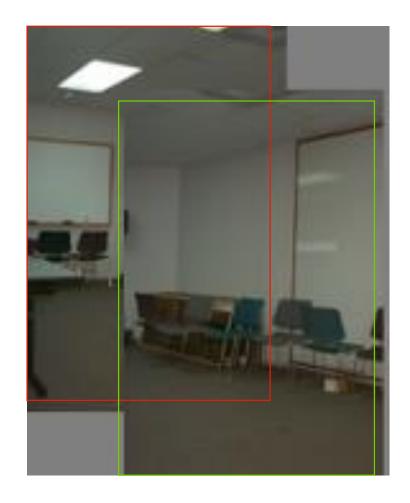


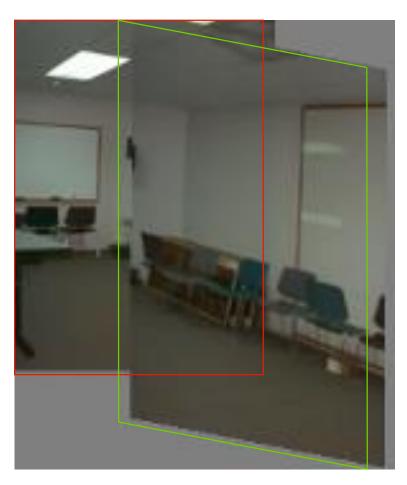
# Warping with different transformations

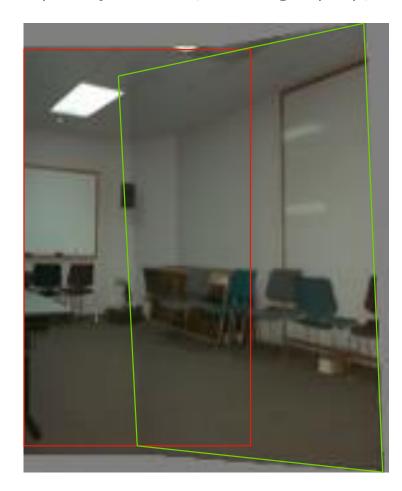
translation

affine

pProjective (homography)







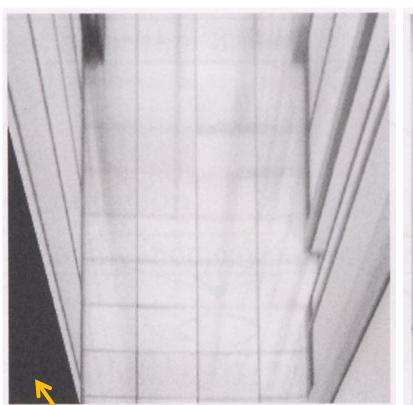
# View warping

original view

synthetic top view

synthetic side view





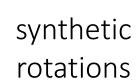


What are these black areas near the boundaries?

### Virtual camera rotations



original view





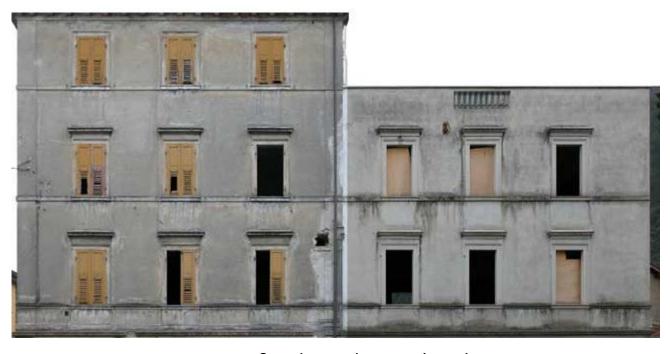


# Image rectification



two original images





rectified and stitched

### Street art



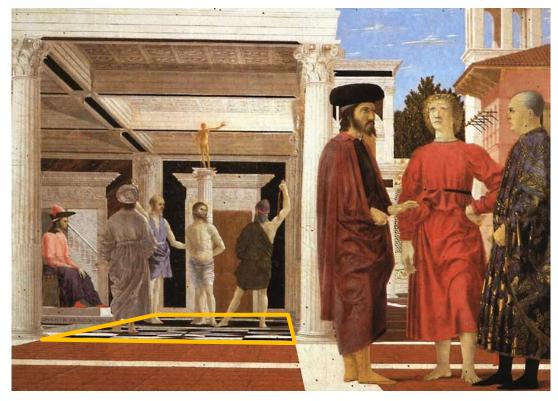






# Understanding geometric patterns

What is the pattern on the floor?

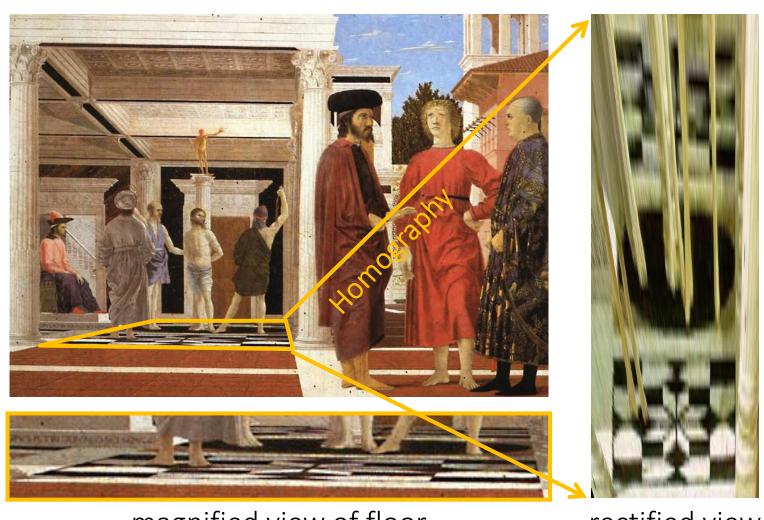




magnified view of floor

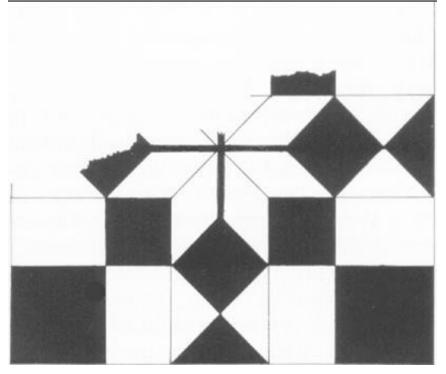
### Understanding geometric patterns

What is the pattern on the floor?



magnified view of floor

rectified view



reconstruction from rectified view

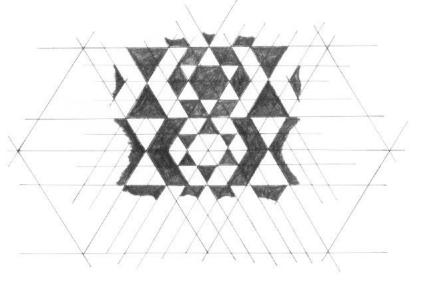
### Understanding geometric patterns

Very popular in renaissance drawings (when perspective was discovered)





rectified view of floor



reconstruction

Holbein, "The Ambassadors"



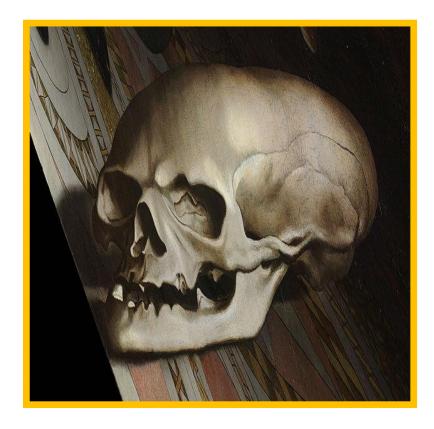
Holbein, "The Ambassadors"



What's this???

Holbein, "The Ambassadors"



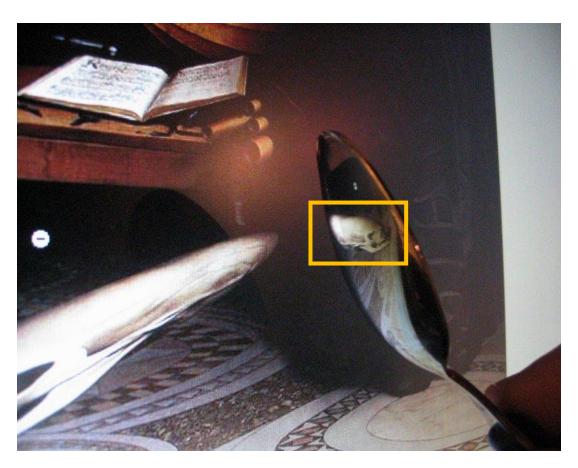


rectified view

skull under anamorphic perspective

Holbein, "The Ambassadors"





DIY: use a polished spoon to see the skull

# Panoramas from image stitching

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)







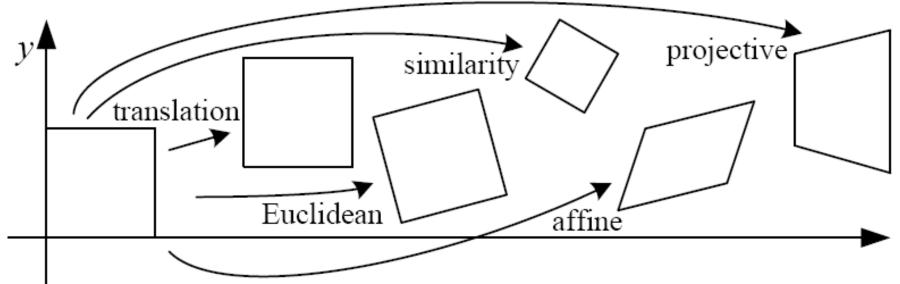






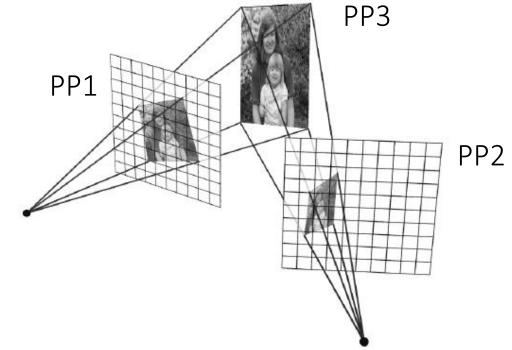
More on why this is the case in a later lecture.

# Computing with homographies



Which kind transformation is needed to warp projective plane 1 into projective plane 2?

A projective transformation (a.k.a. a homography).



# Applying a homography

1. Convert to homogeneous coordinates:

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

What is the size of the homography matrix?

2. Multiply by the homography matrix:

$$P' = H \cdot P$$

3. Convert back to heterogeneous coordinates:

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

# Applying a homography

1. Convert to homogeneous coordinates:

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

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

Convert to homogeneous coordinates:

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

What is the size of the homography matrix? \

Answer: 3 x 3

Multiply by the homography matrix:

$$P' = H \cdot P$$

How many degrees of freedom does the homography matrix have? Answer: 8

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

What is the size of the homography matrix?  $\sqrt{\phantom{a}}$ 

$$P' = H \cdot P$$

How many degrees of freedom does the homography matrix have? Answer: 8

Answer: 3 x 3

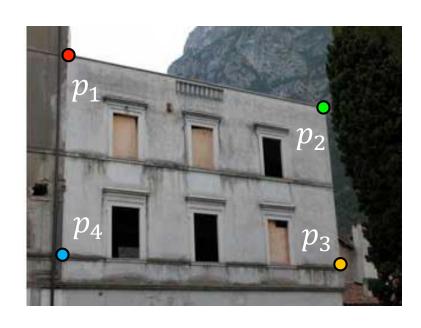
How do we compute the homography matrix?

The direct linear transform (DLT)

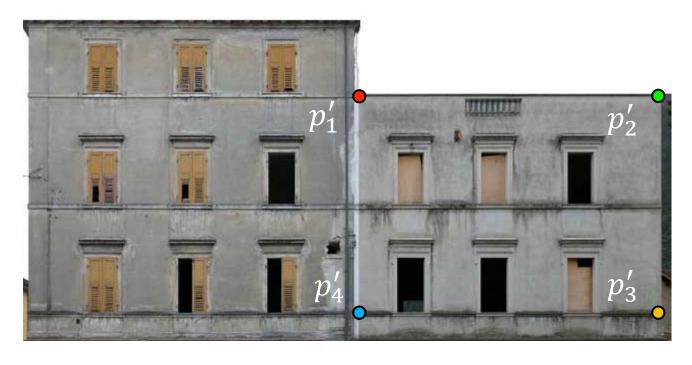
#### Create point correspondences

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

$$P' = H \cdot P$$







target image

How many correspondences do we need?

Write out linear equation for each correspondence:

$$P'=H\cdot P$$
 or  $\left[egin{array}{c} x' \ y' \ 1 \end{array}
ight]=lpha \left[egin{array}{cccc} h_1 & h_2 & h_3 \ h_4 & h_5 & h_6 \ h_7 & h_8 & h_9 \end{array}
ight] \left[egin{array}{c} x \ y \ 1 \end{array}
ight]$ 

Write out linear equation for each correspondence:

$$P'=H\cdot P$$
 or  $\left|egin{array}{c|c} x' \ y' \ 1 \end{array}
ight|=lpha\left|egin{array}{c|c} h_1 & h_2 & h_3 \ h_4 & h_5 & h_6 \ h_7 & h_8 & h_9 \end{array}
ight|\left|egin{array}{c|c} x \ y \ 1 \end{array}
ight|$ 

Expand matrix multiplication:

$$x' = \alpha(h_1x + h_2y + h_3)$$
$$y' = \alpha(h_4x + h_5y + h_6)$$
$$1 = \alpha(h_7x + h_8y + h_9)$$

Write out linear equation for each correspondence:

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

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

$$h_7xx' + h_8yx' + h_9x' - h_1x - h_2y - h_3 = 0$$
  
$$h_7xy' + h_8yy' + h_9y' - h_4x - h_5y - h_6 = 0$$

Re-arrange terms:

$$h_7xx' + h_8yx' + h_9x' - h_1x - h_2y - h_3 = 0$$
  
$$h_7xy' + h_8yy' + h_9y' - h_4x - h_5y - h_6 = 0$$

Re-write in matrix form:

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

How many equations from one point correspondence?

Stack together constraints from multiple point correspondences:

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

$$\left[ egin{array}{c} h_1 \ h_2 \ h_3 \ h_4 \ h_5 \ h_6 \ h_7 \ h_8 \ h_9 \ \end{array} 
ight] = \left[ egin{array}{c} 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ \end{array} 
ight]$$

Homogeneous linear least squares problem

### Reminder: Determining unknown transformations

Affine transformation:

$$\left[ egin{array}{c} x' \ y' \end{array} 
ight] = \left[ egin{array}{ccc} p_1 & p_2 & p_3 \ p_4 & p_5 & p_6 \end{array} 
ight] \left[ egin{array}{c} x \ y \ 1 \end{array} 
ight] \qquad \qquad \hbox{Why can we drop the last line?}$$

Vectorize transformation parameters:

Stack equations from point correspondences:

$$\begin{bmatrix} x' \\ y' \\ x' \\ y' \end{bmatrix} = \begin{bmatrix} x & y & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x & y & 1 \\ x & y & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x & y & 1 \end{bmatrix} \begin{bmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \\ p_5 \\ p_6 \end{bmatrix}$$

$$\vdots \qquad \vdots \qquad \begin{bmatrix} x & y & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x & y & 1 \end{bmatrix}$$

Notation in system form:

### Reminder: Determining unknown transformations

Convert the system to a linear least-squares problem:

$$E_{\mathrm{LLS}} = \|\mathbf{A}\boldsymbol{x} - \boldsymbol{b}\|^2$$

Expand the error:

$$E_{\text{LLS}} = \boldsymbol{x}^{\top} (\mathbf{A}^{\top} \mathbf{A}) \boldsymbol{x} - 2 \boldsymbol{x}^{\top} (\mathbf{A}^{\top} \boldsymbol{b}) + \|\boldsymbol{b}\|^{2}$$

Minimize the error:

Set derivative to 0 
$$(\mathbf{A}^{ op}\mathbf{A})oldsymbol{x} = \mathbf{A}^{ op}oldsymbol{b}$$

Solve for x 
$$oldsymbol{x} = (\mathbf{A}^{ op} \mathbf{A})^{-1} \mathbf{A}^{ op} oldsymbol{\longleftarrow}$$

In Matlab:

$$x = A \setminus b$$

Note: You almost <u>never</u> want to compute the inverse of a matrix.

Stack together constraints from multiple point correspondences:

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

$$egin{bmatrix} egin{bmatrix} -x & -y & -1 & 0 & 0 & 0 & xx' & yx' & x' \ 0 & 0 & 0 & -x & -y & -1 & xy' & yy' & y' \ 0 & 0 & 0 & -x & -y & -1 & xy' & yy' & y' \ \end{bmatrix} egin{bmatrix} h_1 \ h_2 \ h_3 \ h_4 \ h_5 \ \end{bmatrix} \ = egin{bmatrix} 0 \ 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{b$$

$$\left[ egin{array}{c} h_1 \ h_2 \ h_3 \ h_4 \ h_5 \ h_6 \ h_7 \ h_8 \ h_9 \ \end{array} 
ight] = \left[ egin{array}{c} 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ \end{array} 
ight]$$

Homogeneous linear least squares problem

How do we solve this?

Stack together constraints from multiple point correspondences:

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

$$egin{bmatrix} egin{bmatrix} -x & -y & -1 & 0 & 0 & 0 & xx' & yx' & x' \ 0 & 0 & 0 & -x & -y & -1 & xy' & yy' & y' \ 0 & 0 & 0 & -x & -y & -1 & xy' & yy' & y' \ \end{bmatrix} egin{bmatrix} h_1 \ h_2 \ h_3 \ h_4 \ h_5 \ \end{bmatrix} \ = egin{bmatrix} 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \ 0 \ 0 \ 0 \ \end{bmatrix} \ egin{bmatrix} 0 \$$

$$\left[ egin{array}{c} h_1 \ h_2 \ h_3 \ h_4 \ h_5 \ h_6 \ h_7 \ h_8 \ h_9 \ \end{array} 
ight] = \left[ egin{array}{c} 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ \end{array} 
ight]$$

Homogeneous linear least squares problem

Solve with SVD

#### Singular Value Decomposition

$$\mathbf{A} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^{ op}$$
 unit norm constraint  $\mathbf{A} = \mathbf{V} \mathbf{\Sigma} \mathbf{V}^{ op}$  unit norm constraint  $\mathbf{A} = \mathbf{V} \mathbf{\Sigma} \mathbf{V}^{ op}$  unit norm constraint  $\mathbf{A} = \mathbf{V} \mathbf{V}^{ op}$  unit norm constraint  $\mathbf{A} = \mathbf{V} \mathbf{V}^{ op}$   $\mathbf{A} \mathbf{V}^$ 

Each column of V represents a solution for

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

where the singular value represents the reprojection error

# Solving for H using DLT

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

- 1. For each correspondence, create 2x9 matrix  ${f A}_i$
- 2. Concatenate into single 2n x 9 matrix  $\mathbf{A}$
- 3. Compute SVD of  $\mathbf{A} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^{\mathsf{T}}$
- 4. Store singular vector of the smallest singular value  $h=v_{\hat{i}}$
- 5. Reshape to get

#### General form of total least squares

(**Warning:** change of notation. x is a vector of parameters!)

$$E_{ ext{TLS}} = \sum_i (oldsymbol{a}_i oldsymbol{x})^2 \ = \|oldsymbol{A} oldsymbol{x}\|^2 \qquad ext{ iny (matrix form)}$$

subject to

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



minimize

$$\frac{\|\mathbf{A} \boldsymbol{x}\|^2}{\|\boldsymbol{x}\|^2}$$

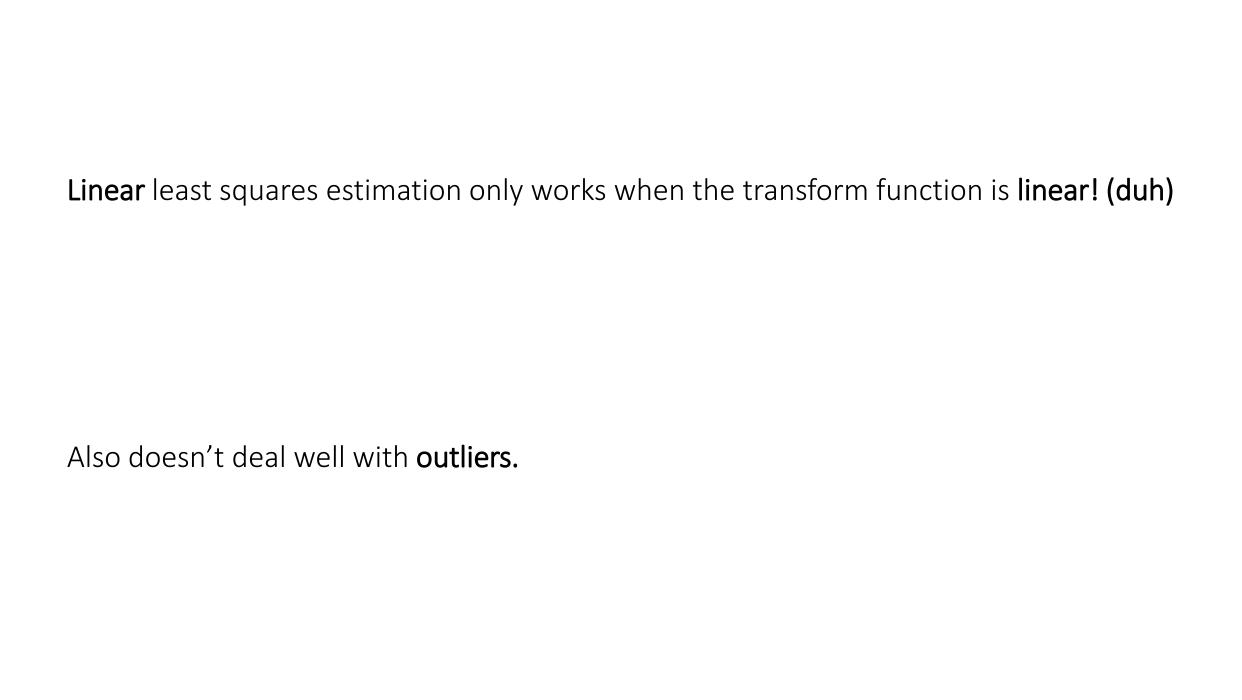
Solution is the eigenvector corresponding to smallest eigenvalue of

$$\mathbf{A}^{ op}\mathbf{A}$$

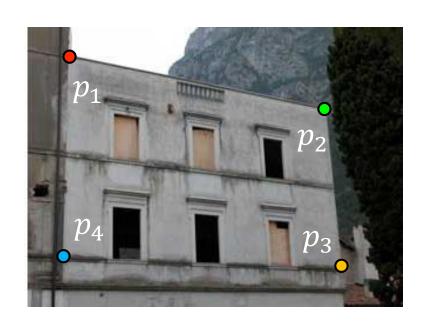
(equivalent)

Solution is the column of **V** corresponding to smallest singular value

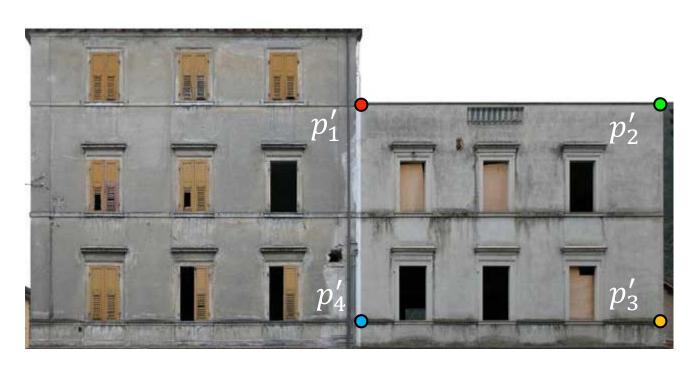
$$\mathbf{A} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^{\top}$$



### 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.

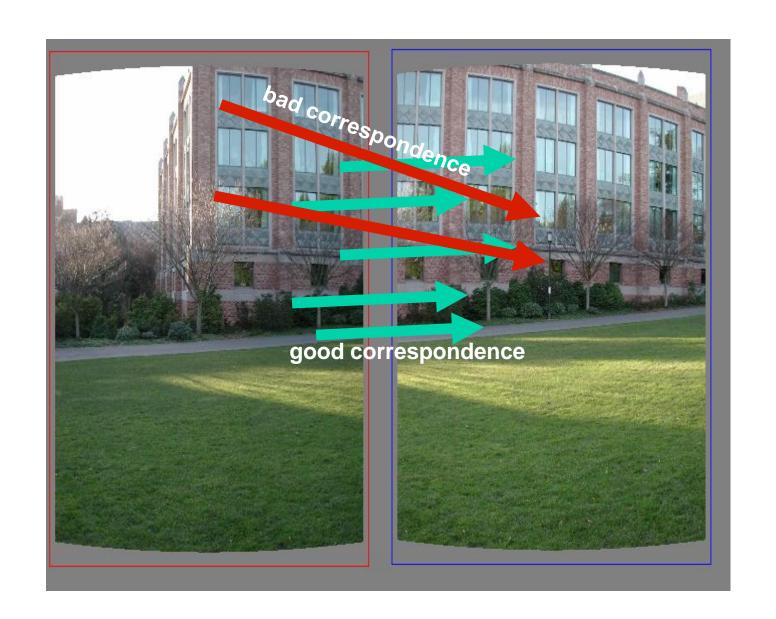
3. Feature matching

### The image correspondence pipeline

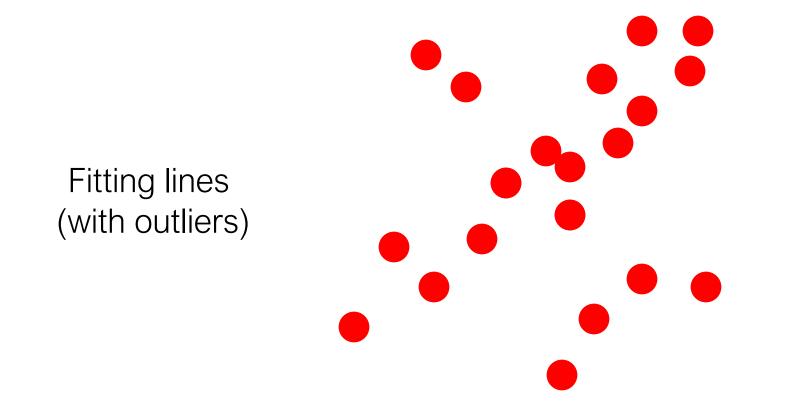
- 1. Feature point detection
  - Detect corners using the Harris corner detector.

- 2. Feature point description
  - Describe features using the Multi-scale oriented patch descriptor.

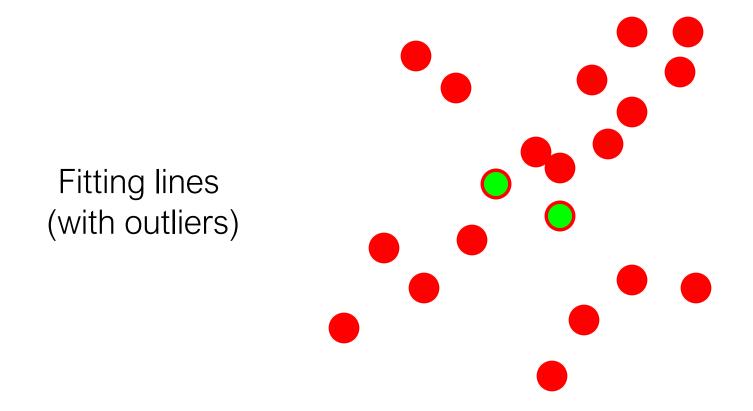
3. Feature matching



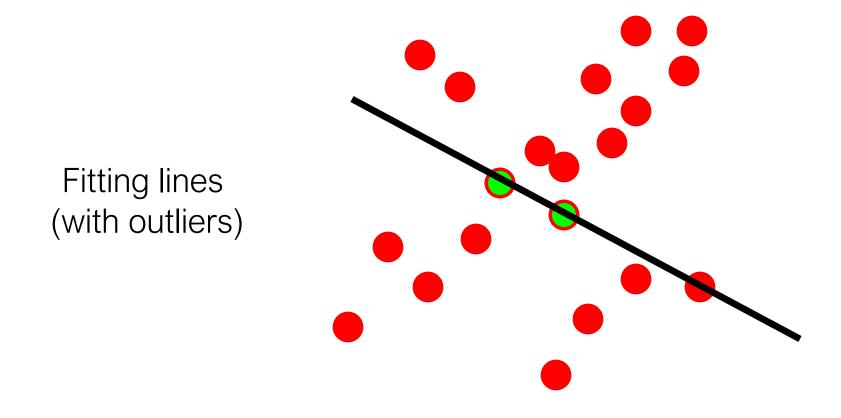
### Random Sample Consensus (RANSAC)



- 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



- 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

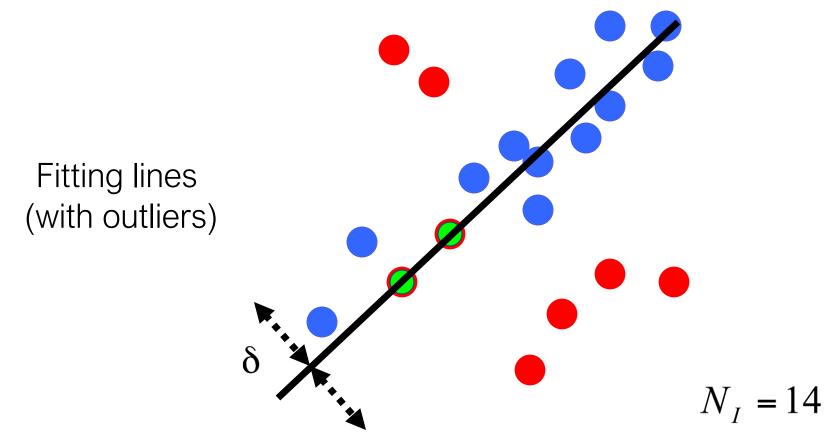


- 1. Sample (randomly) the number of points required to fit the model
- 2. Solve for model parameters using samples
- 3. Score by the fraction of inliers within a preset threshold of the model

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



- 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

### How to choose parameters?

- Number of samples N
  - Choose N so that, with probability p, at least one random sample is free from outliers (e.g. p=0.99) (outlier ratio: e)
- Number of sampled points s
  - -Minimum number needed to fit the model
- Distance threshold δ
  - Choose  $\delta$  so that a good point with noise is likely (e.g., prob=0.95) within threshold
  - Zero-mean Gaussian noise with std. dev.  $\sigma$ :  $t^2=3.84\sigma^2$

$$N = \frac{\log(1-p)}{\log\left(1 - (1-e)^s\right)}$$

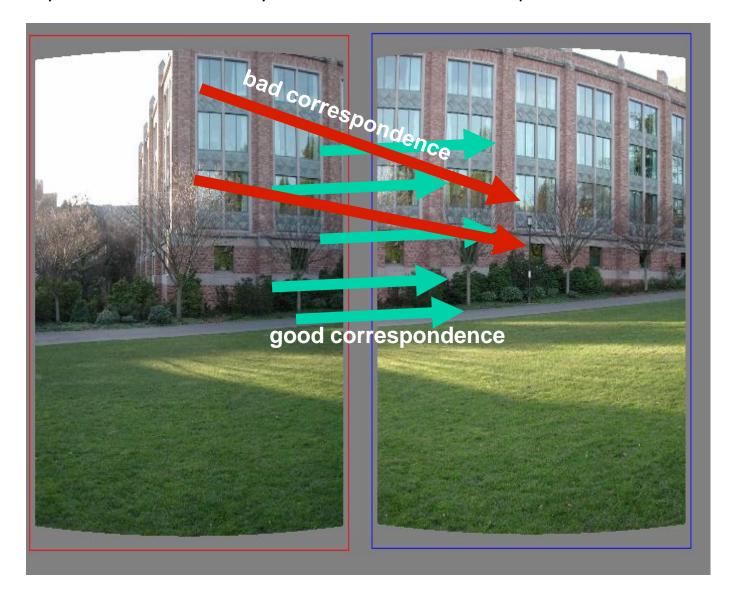
s	proportion of outliers <i>e</i>						
	5%	10%	20%	25%	30%	40%	50%
2	2	3	5	6	7	11	17
3	3	4	7	9	11	19	35
4	3	5	9	13	17	34	72
5	4	6	12	17	26	57	146
6	4	7	16	24	37	97	293
7	4	8	20	33	54	163	588
8	5	9	26	44	78	272	1177

#### Given two images...



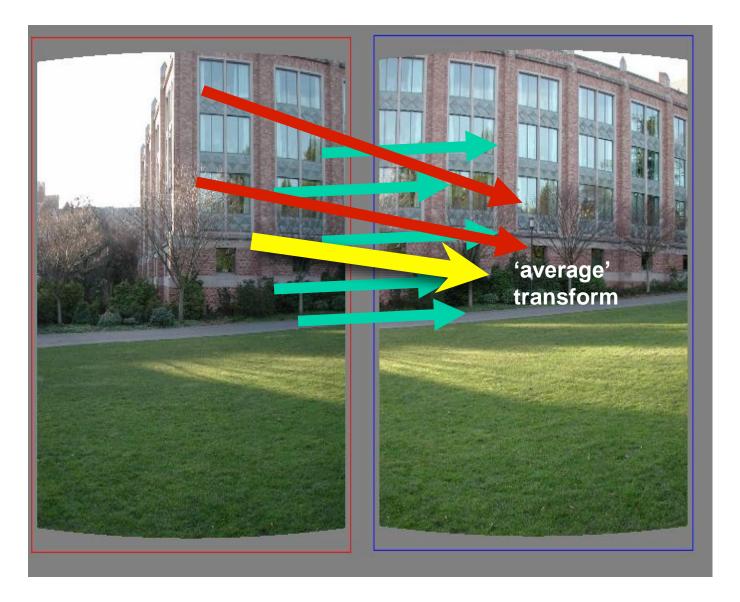
find matching features (e.g., SIFT) and a translation transform

#### Matched points will usually contain bad correspondences



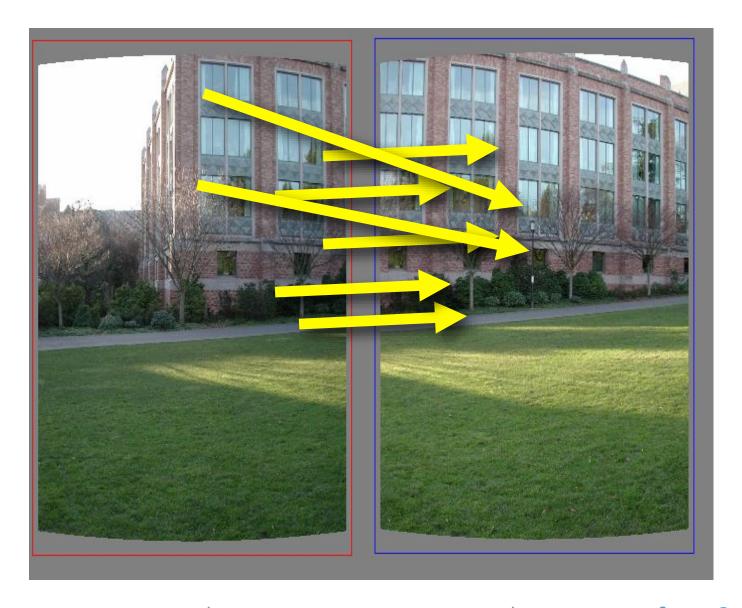
how should we estimate the transform?

LLS will find the 'average' transform

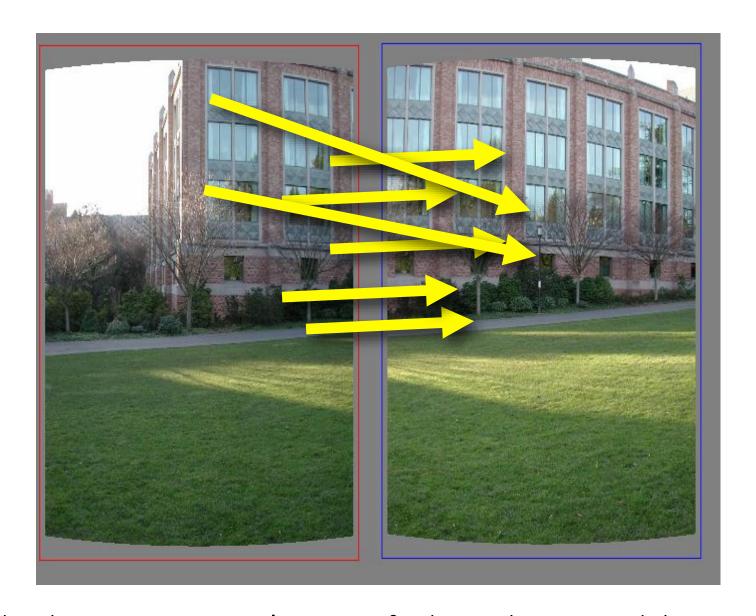


solution is corrupted by bad correspondences

#### Use RANSAC

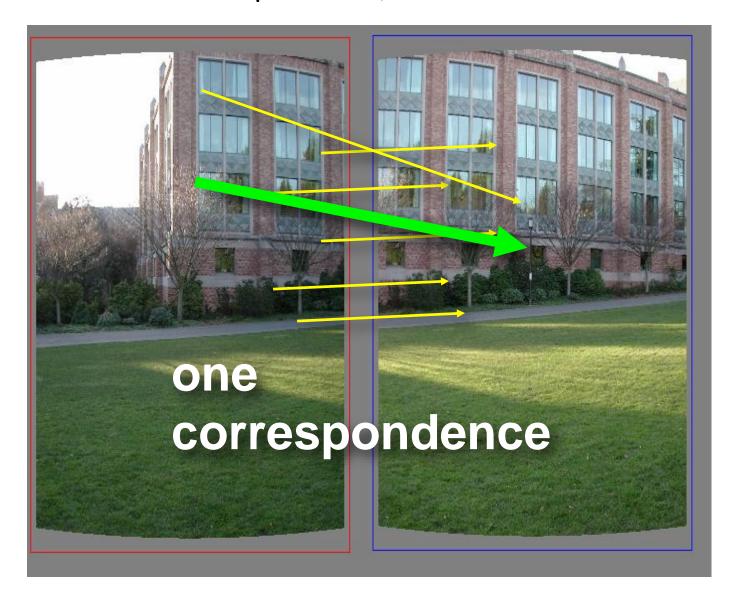


How many correspondences to compute translation transform?

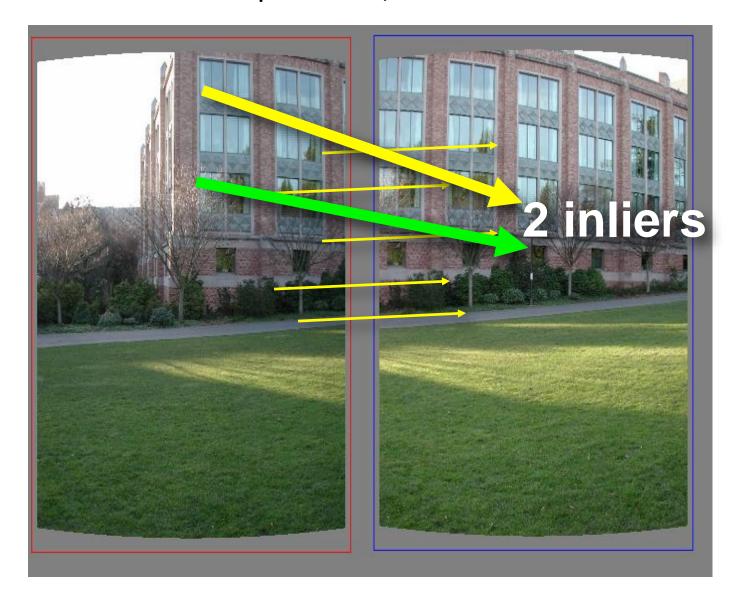


Need only **one correspondence**, to find translation model

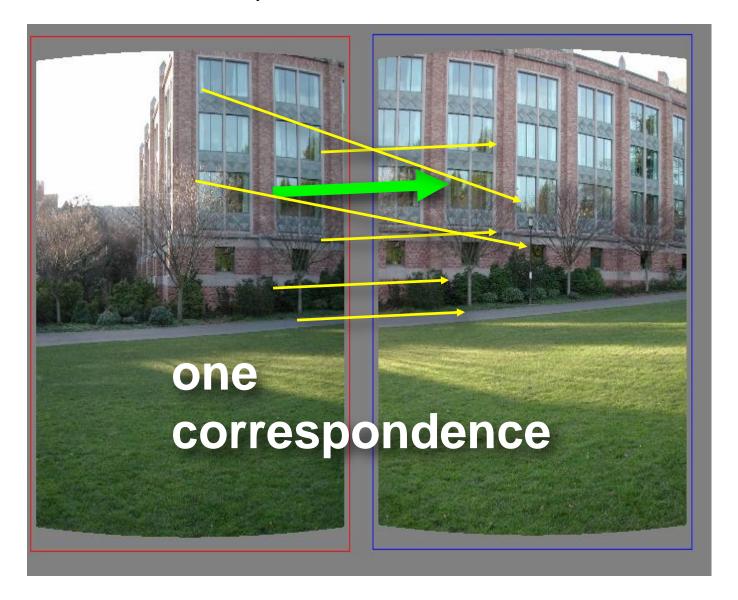
#### Pick one correspondence, count inliers



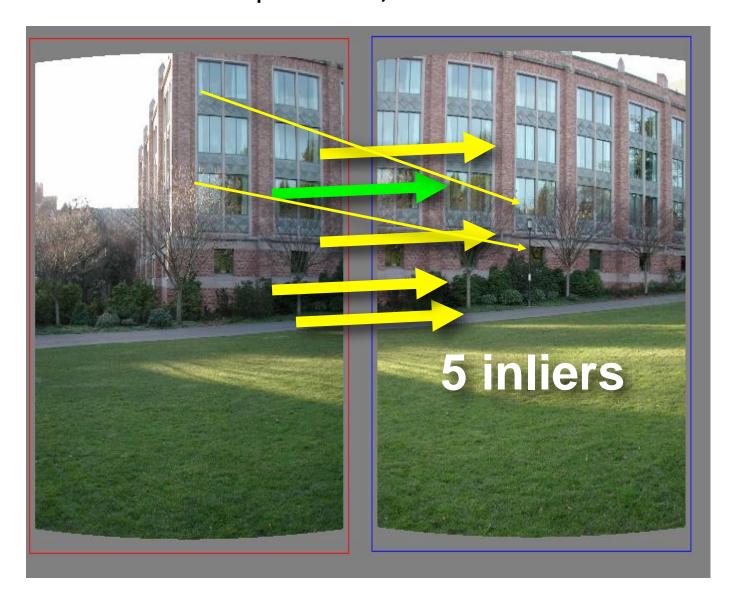
#### Pick one correspondence, count inliers



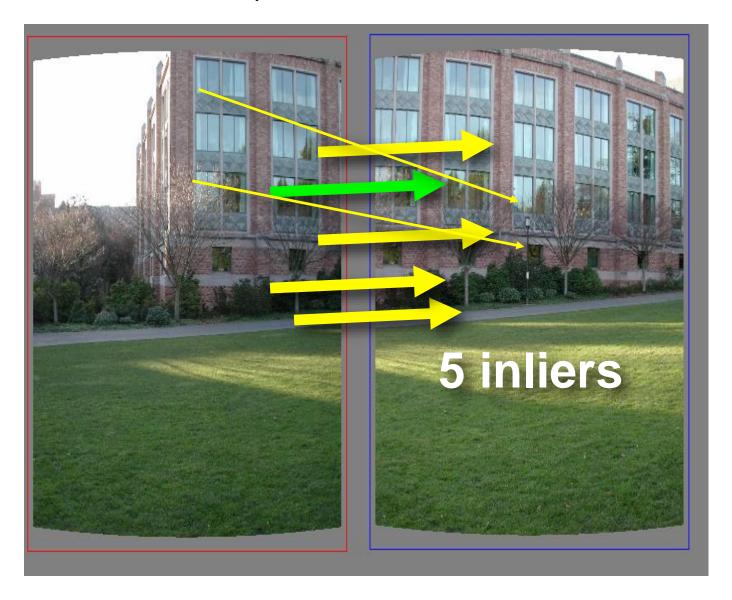
### Pick one correspondence, count inliers



### Pick one correspondence, count inliers



#### Pick one correspondence, count inliers



Pick the model with the highest number of inliers!

- RANSAC loop
  - 1. Get point correspondences (randomly)

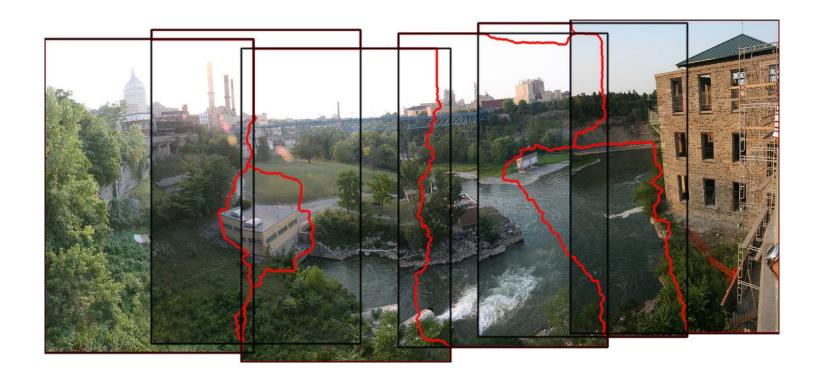
- RANSAC loop
  - 1. Get four point correspondences (randomly)
  - 2. Compute H using

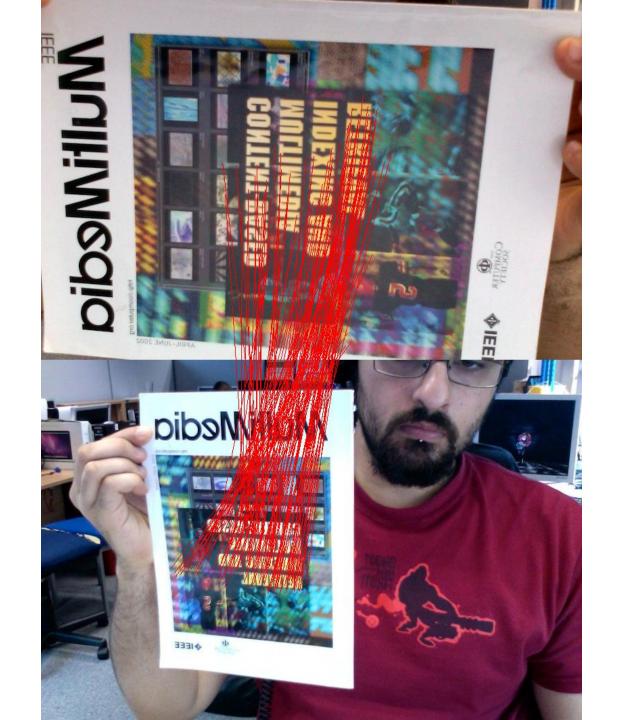
- RANSAC loop
  - 1. Get four point correspondences (randomly)
  - 2. Compute H using DLT
  - 3. Count

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

- 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.

### References

#### Basic reading:

• Szeliski textbook, Sections 6.1.

#### Additional reading:

Hartley and Zisserman, "Multiple View Geometry," Cambridge University Press 2003.
 as usual when it comes to geometry and vision, this book is the best reference; Sections 2 and 4 in particular discuss everything about homography estimation