

Lecture:

Planar Transf. & Outlier Rejection

Several slides taken from D. Lowe and M. Irani

Class Objectives

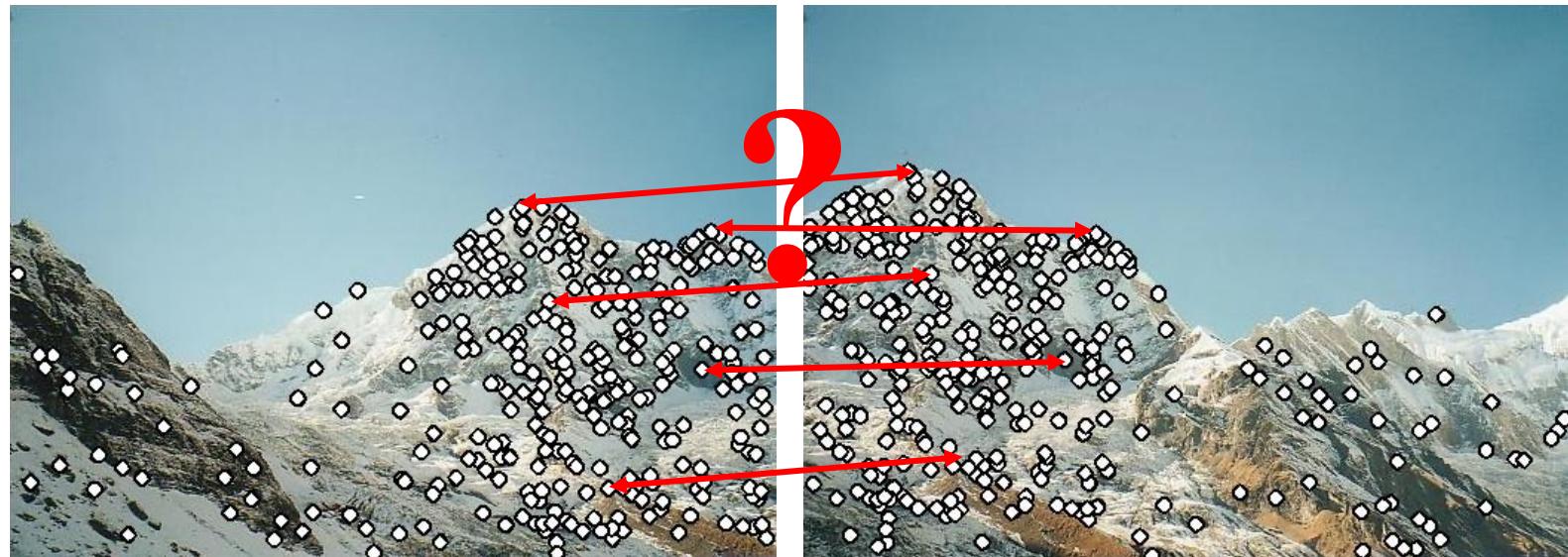
- Understand the hierarchy of different planar transformations
 - Euclidean, Similarity, Affine, Projective
- Find out how to compute an homography from a set of correspondences
- Understand the concept of Outlier
- Learn how to remove outliers with RANSAC

Outline

- A hierarchy of transformations: Euclidean, Similarity, Affine, Projective
- Homography from a projective matrix
- Computing the homography matrix
- RANSAC

Do you remember last week's problem?

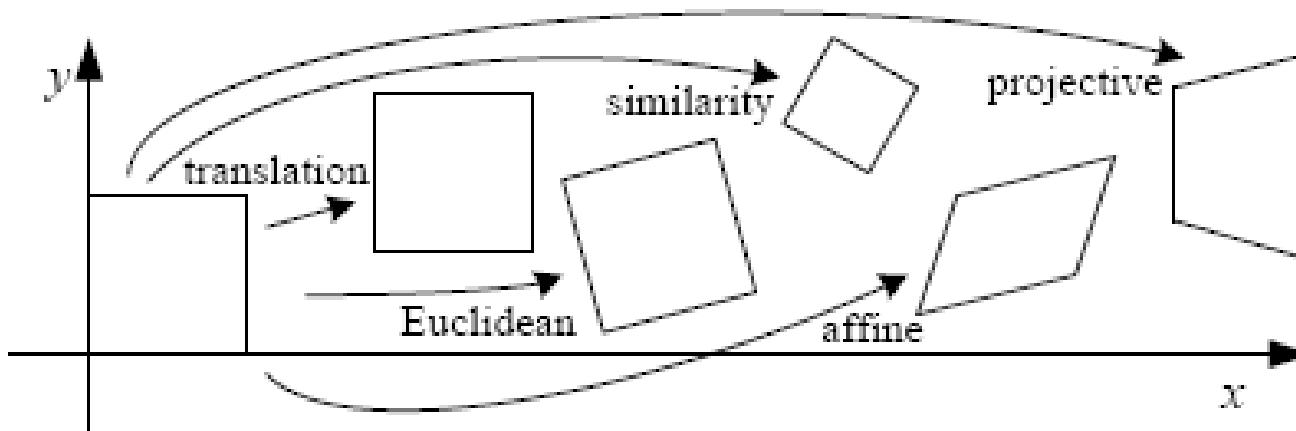
- We know how to detect points
- ... and how to match them!



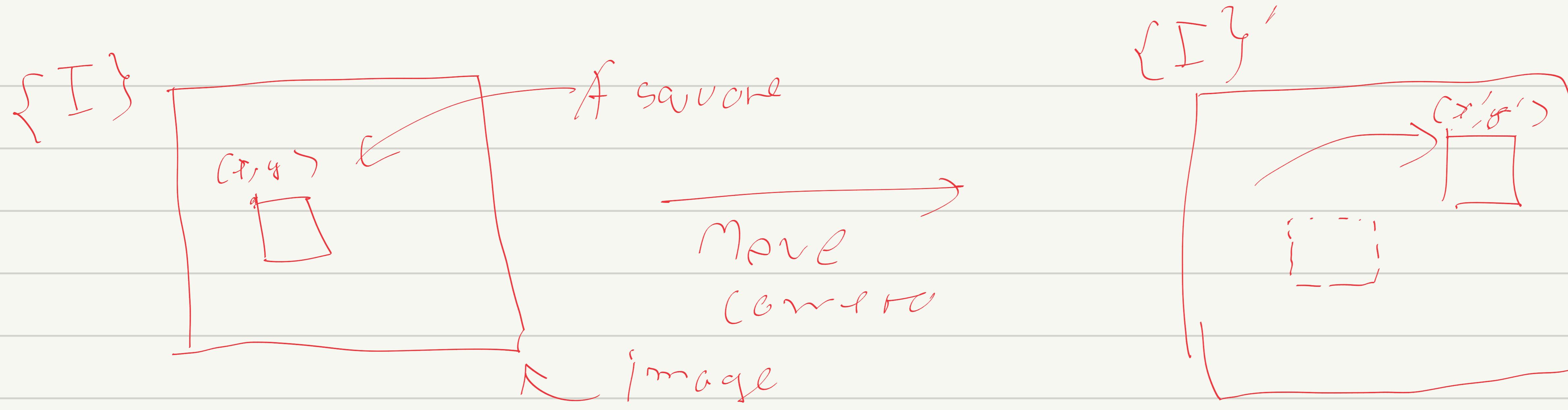
Point descriptor should be:

1. Invariant
2. Distinctive

Summary: A hierarchy of transformations



Name	Matrix	# D.O.F.	Preserves:	Icon
translation	$[I \mid t]_{2 \times 3}$	2	orientation + ...	
rigid (Euclidean)	$[R \mid t]_{2 \times 3}$	3	lengths + ...	
similarity	$[sR \mid t]_{2 \times 3}$	4	angles + ...	
affine	$[A]_{2 \times 3}$	6	parallelism + ...	
projective	$[\tilde{H}]_{3 \times 3}$	8	straight lines	



$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

→ we can make it
more complex - not
just translation.

This is Euclidean transformation.
This will not be zero if there is a rotation & so.

A diagram showing two transformations, A and B . Transformation A maps point P to $A^T_B P$. Transformation B maps point P to $B^T_A P$. The composition of transformations A and B is $A^T_B B^T_A P = P$.

$$A^T_B = \begin{bmatrix} 0 & | & A^T_B \\ \hline 0 & 0 & 0 \end{bmatrix}$$

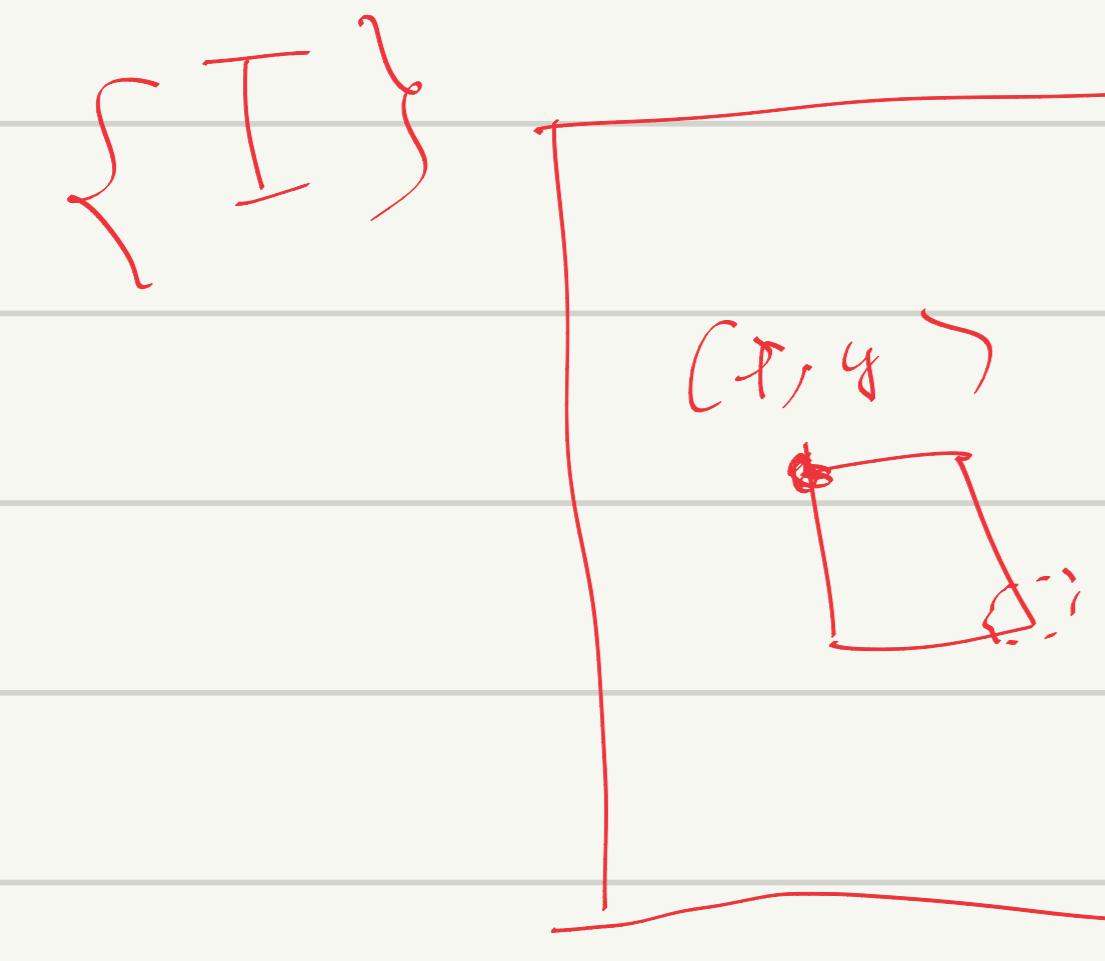
$$A^T_B B^T_A = \begin{bmatrix} 1 & | & 0 \\ \hline 0 & 0 & 0 \end{bmatrix}$$

$$f(T_B)^{-1} A^T_B = \begin{bmatrix} 1 & | & 0 \\ \hline 0 & 0 & 0 \end{bmatrix}$$

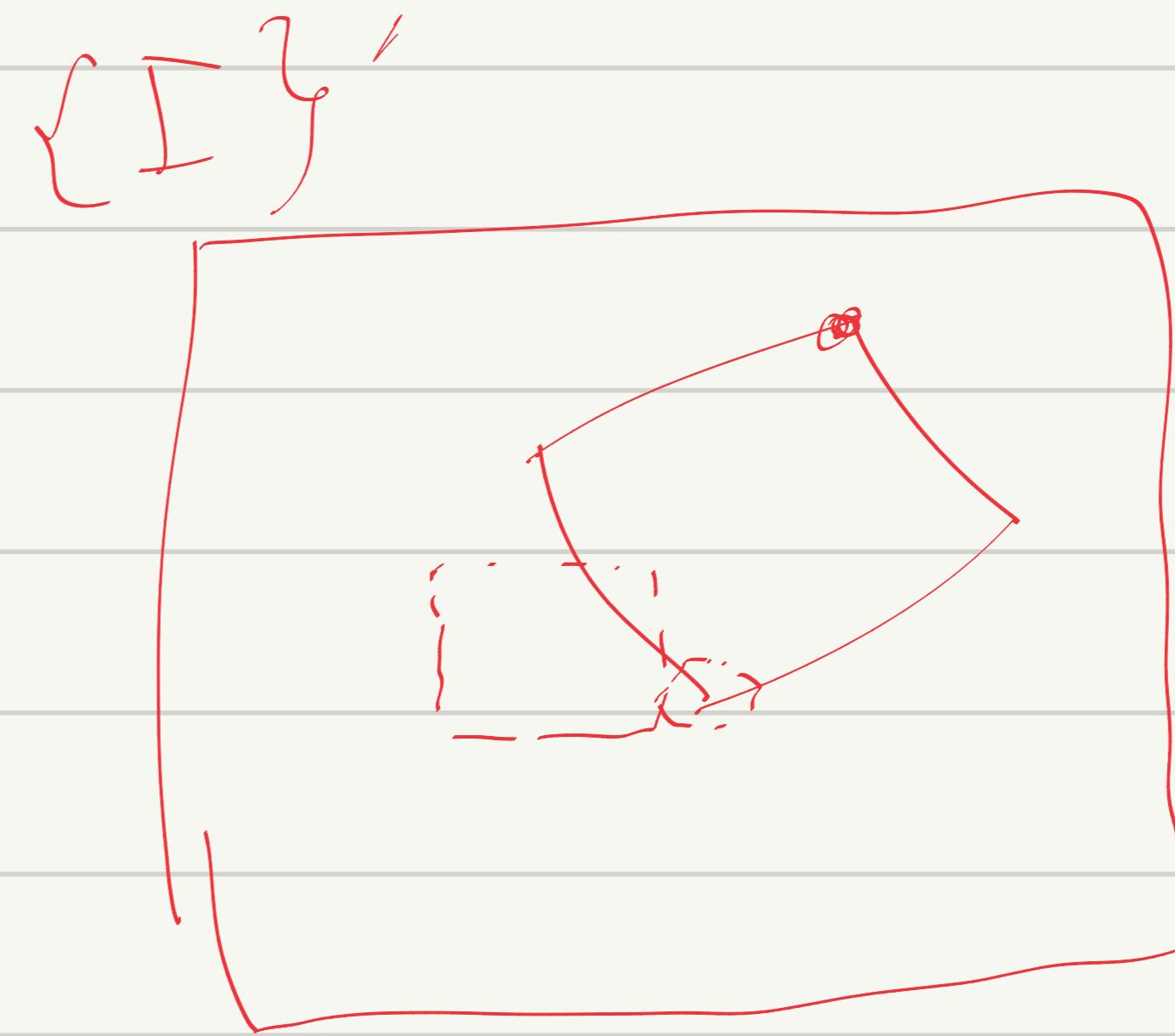
$$B^T_A = \begin{bmatrix} 1 & | & 0 \\ \hline 0 & 0 & 0 \end{bmatrix}$$

$$B^T_A = B^T_A$$

$$f(T_B)^{-1} A^T_B = f(T_B)^{-1} A^T_B$$



A source
Move
onto
the image



This is
similar
transformation

DOF \rightarrow $y \rightarrow x, y, \theta, z$ Scale /

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

$$P = (x, y, 1)^T$$

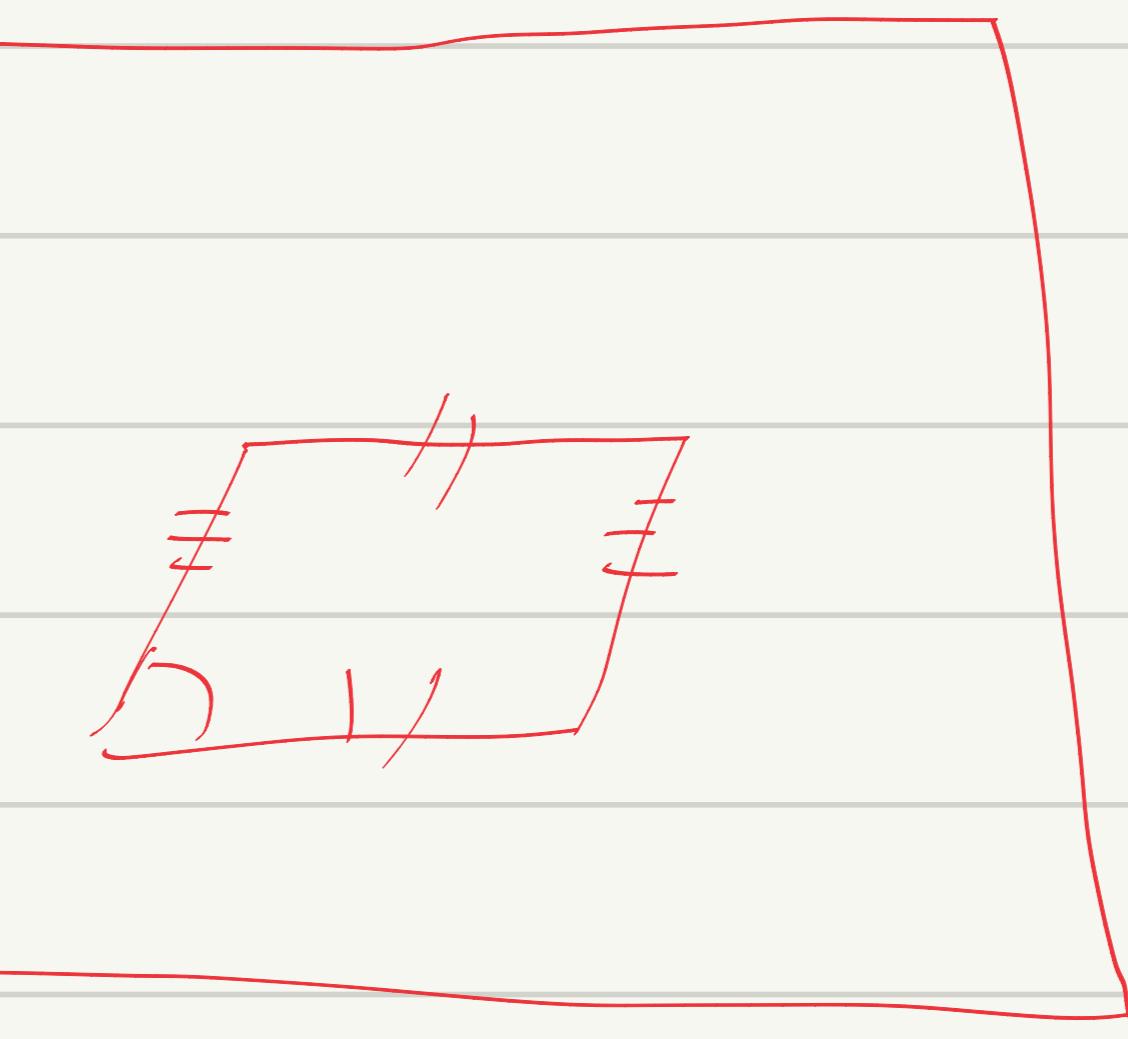
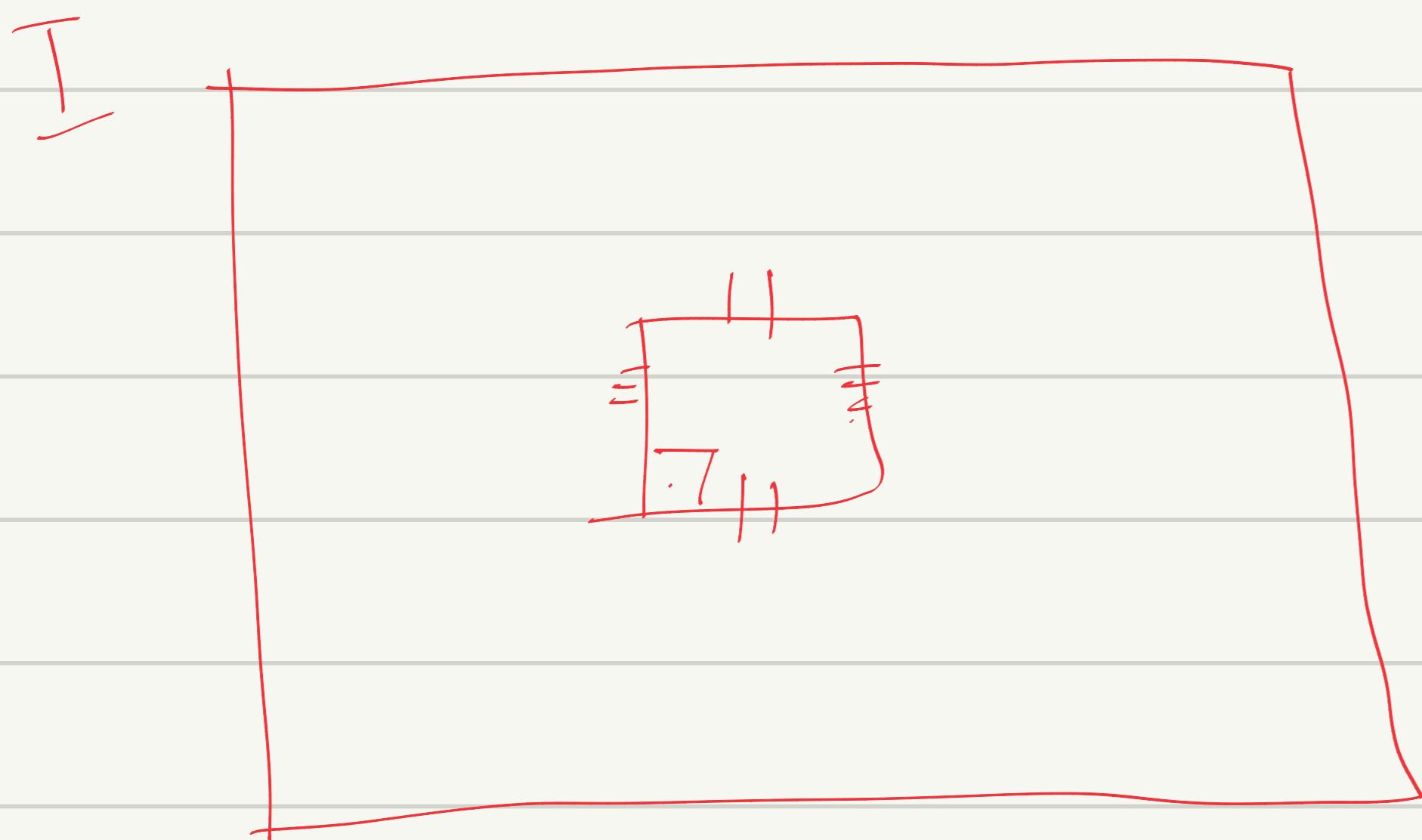
$$P' = I \cdot P$$

S_x

scale is affecting this matrix

$$\begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$$

Corresponding according to the transformation
 ↳ then why are we using SIFT?
 ↳ homography is computed using the correspondences



Affine Transformations \rightarrow 6 DOF

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = \begin{pmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}$$

↑
A
translation is \rightarrow t_x, t_y

never going to happen?

E-For affine.

Rotation &
something
more

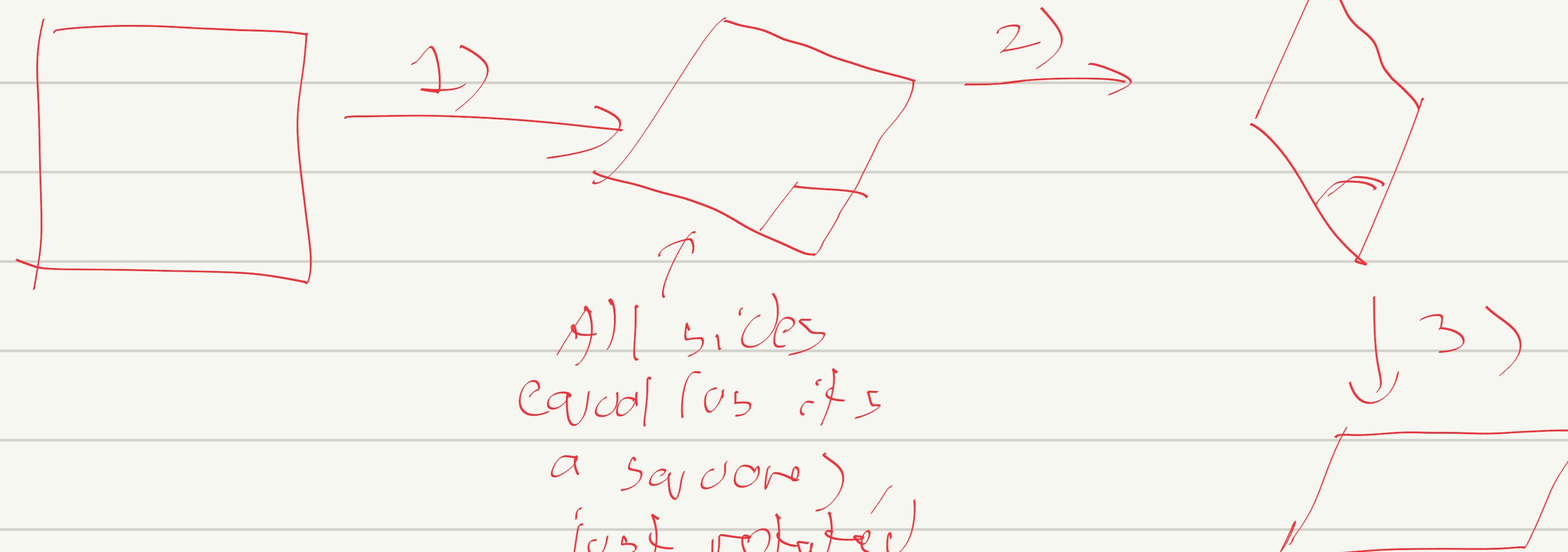
$$A = \underbrace{UDV^T}_{\text{Diagonal Matrix}} \quad \text{Rotation} \Rightarrow V^T V = I$$

matrices $V^{-1} = V^T$

3DOF \rightarrow
Different scale
in x than in y

$$\begin{pmatrix} S_x & 0 \\ 0 & S_y \end{pmatrix} \xrightarrow[3]{R(0)} R(\alpha)$$

if there is
an isotropic/
Scaling.
1DOF

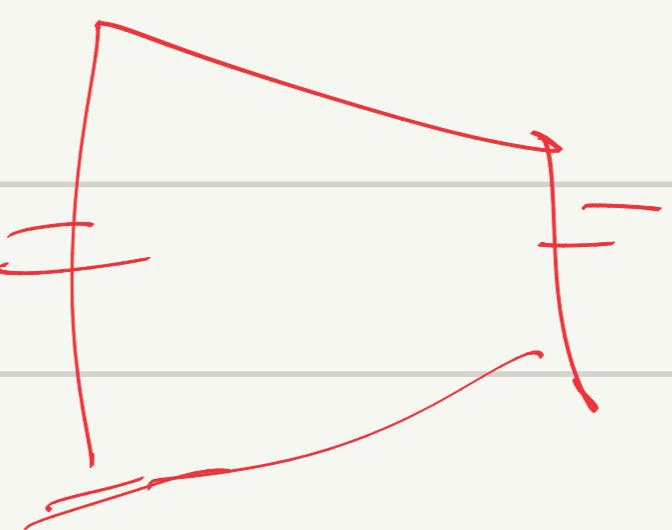


$\theta, \alpha, S_x, S_y, t_x, t_y \rightarrow 6 \text{DOF}$

2)

Now, if we can't place our camera at infinity why are we talking about it?

$$\begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = \begin{pmatrix} a & b & c \\ d & e & f \\ g & h & i \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix}$$



↳ Good transformation
to local patches

Projection

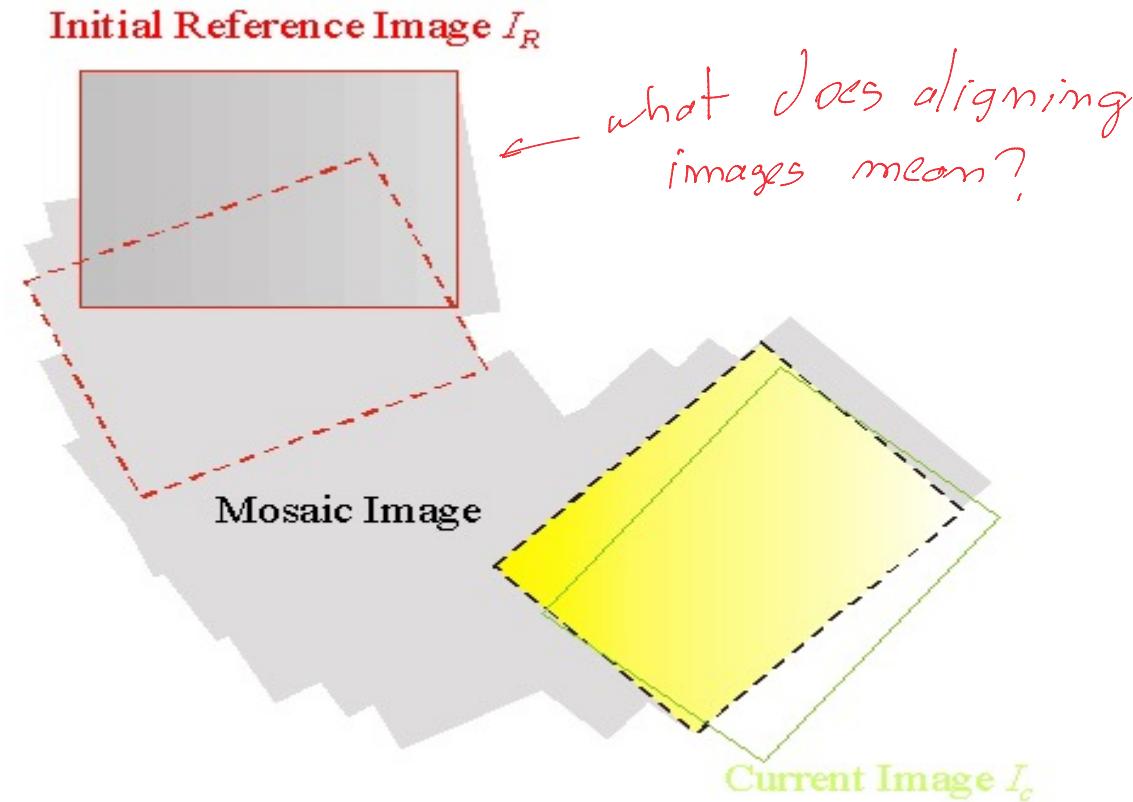
not
a little
bit clear
how does

affine transformation
helps.



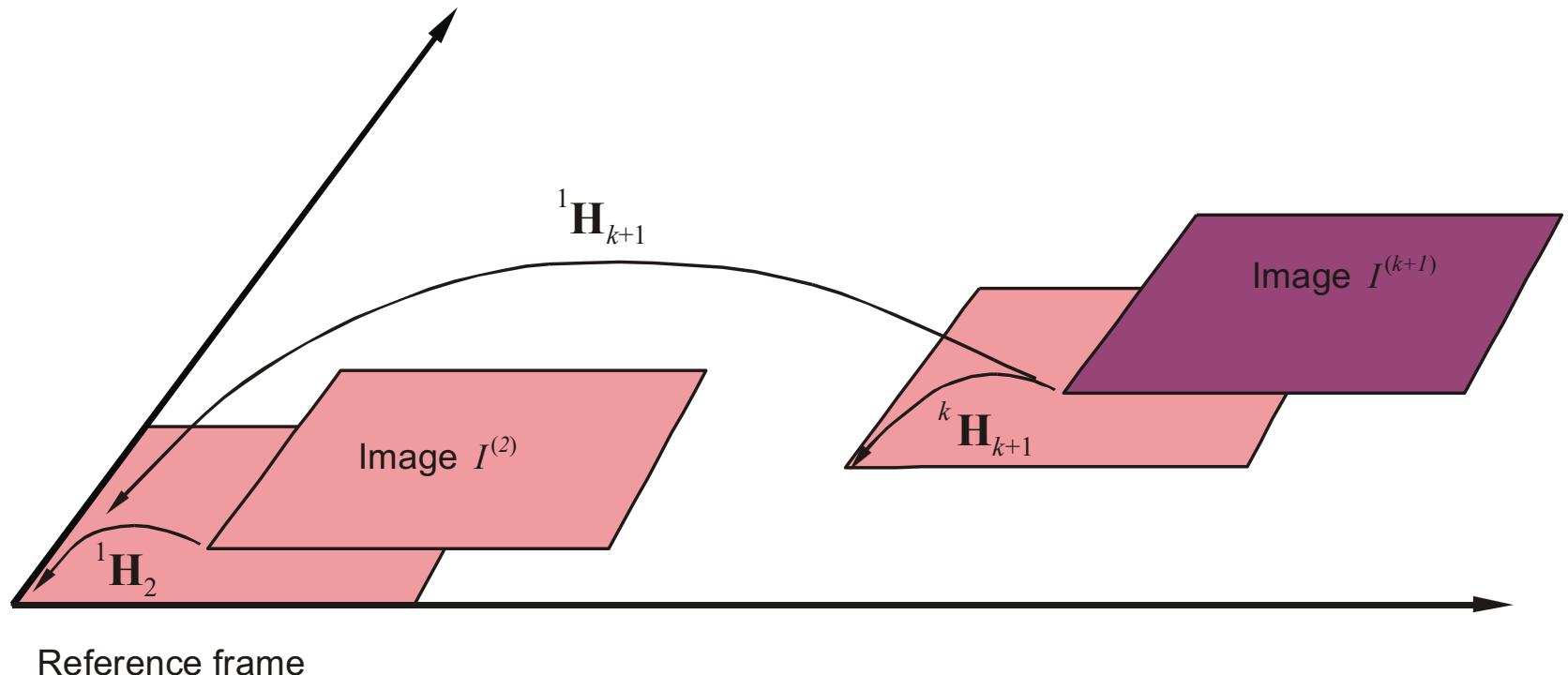
Application: mosaicing

- Cascade of homographies



Mosaicing

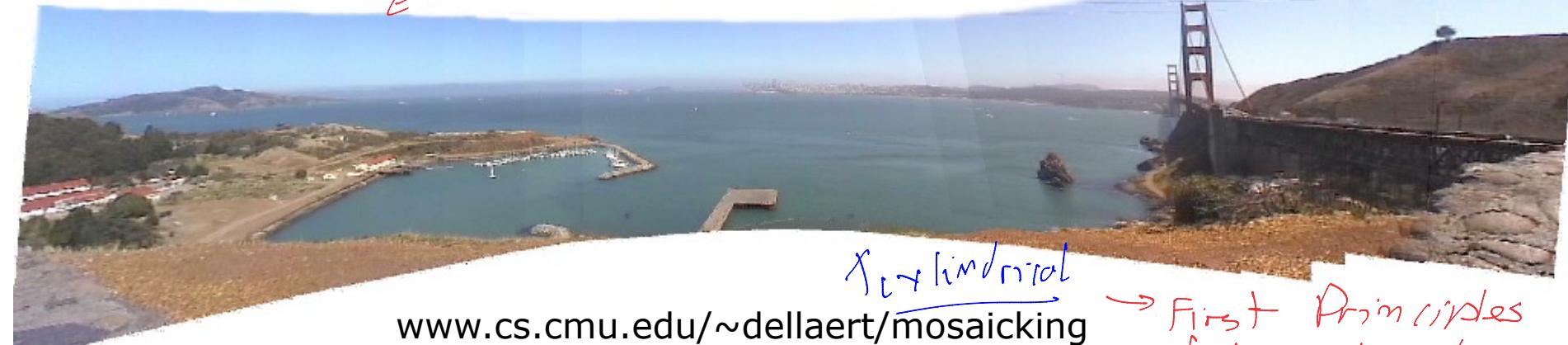
- Chain the incremental Homographies ${}^1\mathbf{H}_{k+1} = \prod_{i=1..k} {}^i\mathbf{H}_{i+1}$



Mosaicking: Homography



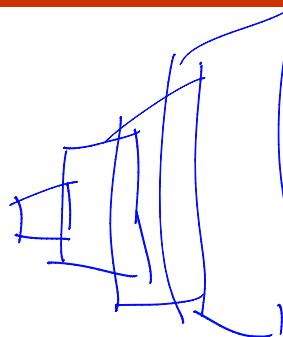
How did we build this? ✓ Projective Transformation.



$\xrightarrow{\text{Homographic}}$
www.cs.cmu.edu/~dellaert/mosaicking

→ First Principles
of Computer Vision

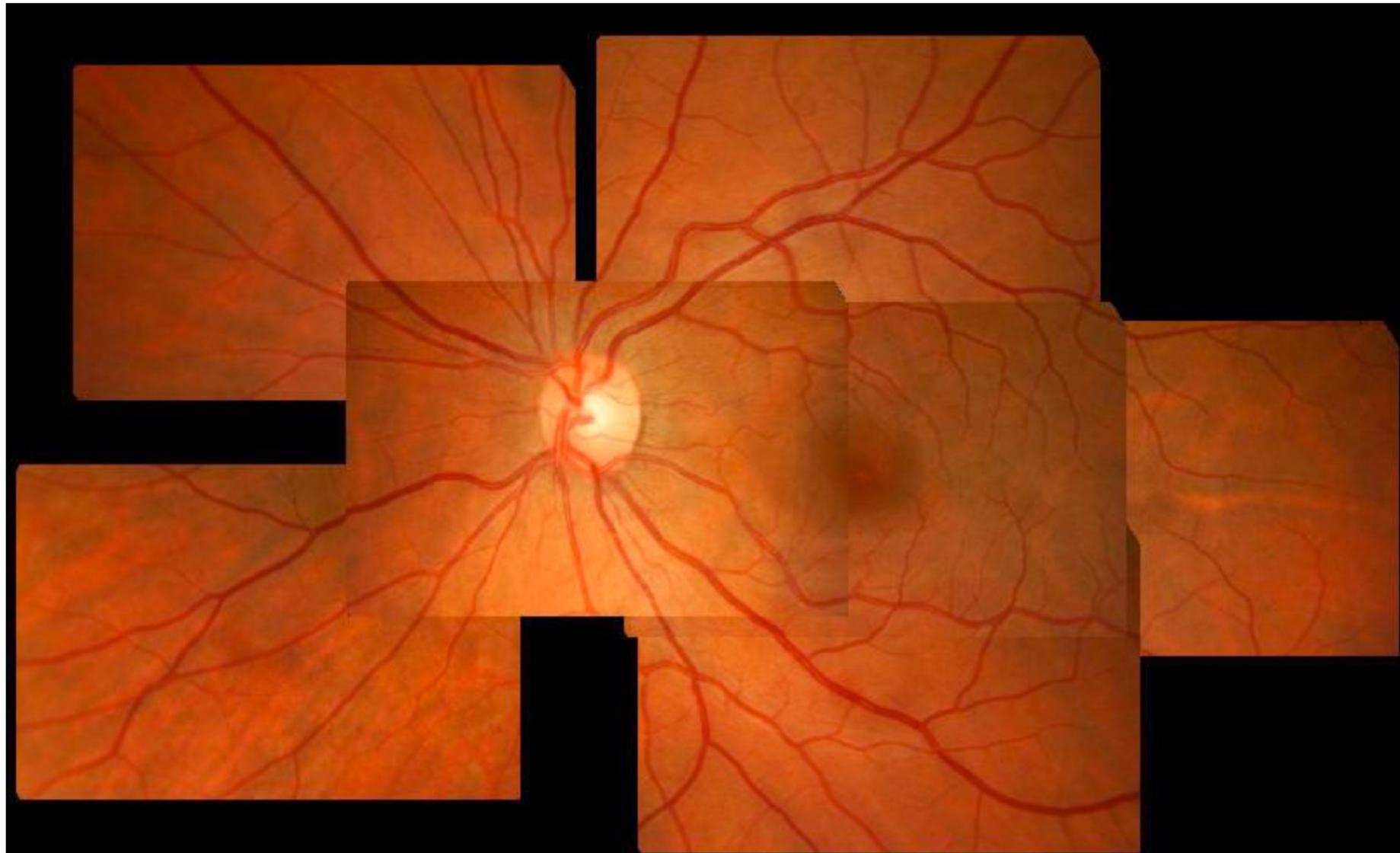
Lecture
Image Stitching



Building a mosaic

- At each time, the current mosaic is represented by a graph, with images being the nodes
- An edge between two images indicates, that these have been stitched successfully. The result of the pairwise stitching (a homography) is assigned to the edge.

Mosaicing \rightarrow planar scene
 \rightarrow 3D scene, but camera
is just rubble..



Global optimization

- *In the global optimisation step, we try to find parameters for each image, such that the difference between the pairwise homography and the pairwise homography induced by the global parameters is minimal.*
- *The main steps of the algorithm:*
 - Feature extraction for each image
 - Matching two images
 - Global optimization

Global optimization

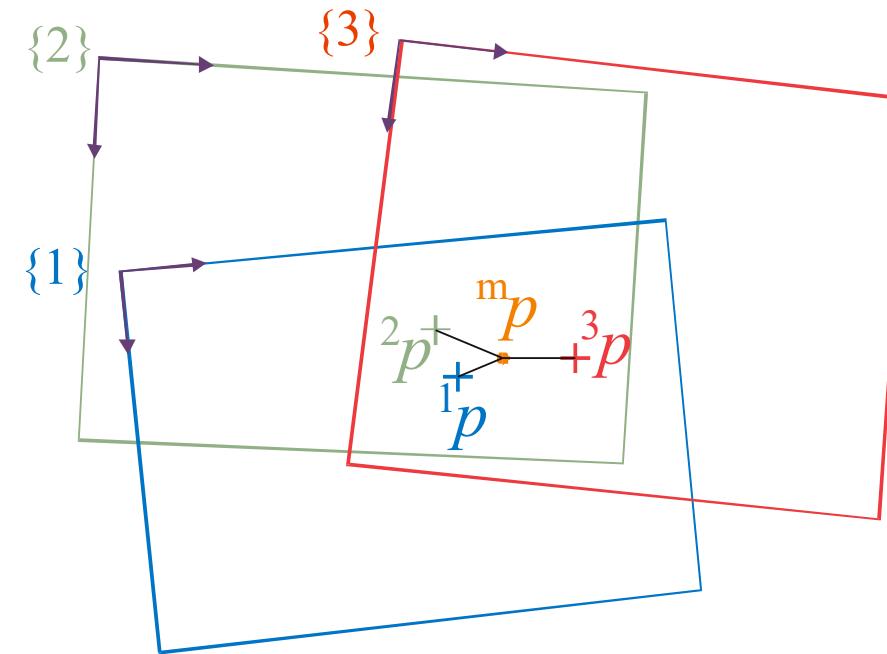
Bundle adjustment

{m}

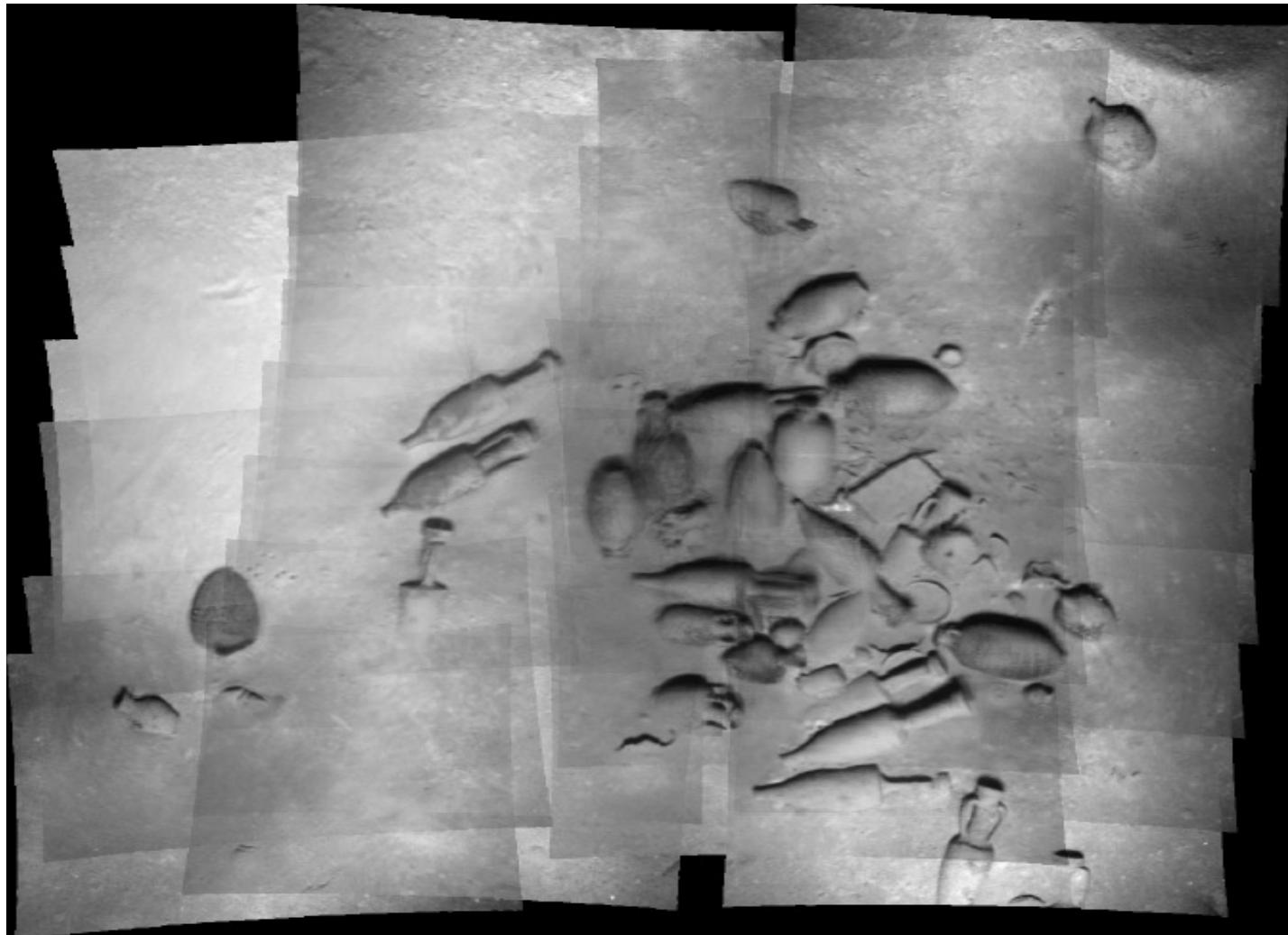
?
what's this?

$(^1 p, ^2 p, ^3 p) \in \Delta$

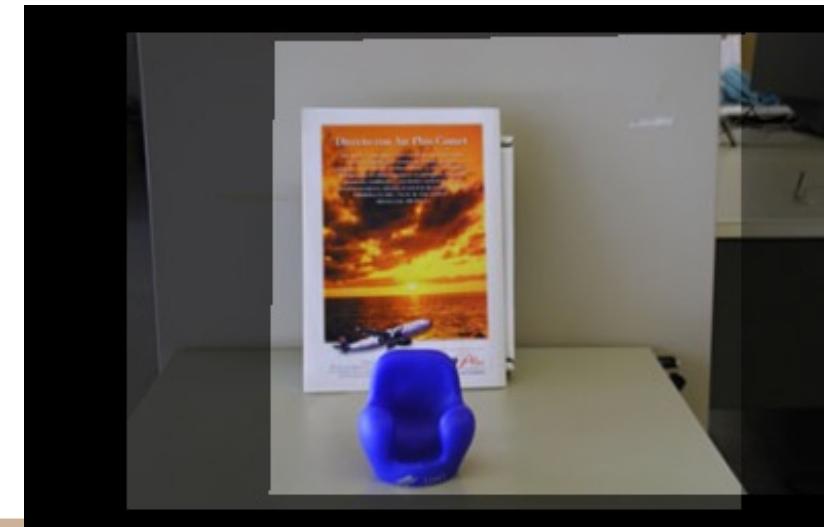
$$c = \min_{^n \mathbf{H}_m, ^m p_i} \left[\sum_{j=1}^N \sum_{^n p_i \in \Delta_j} d^2 (^n p_i, ^n \mathbf{H}_m ^m p_i) \right]$$



Global optimization



3D scene and a rotating camera



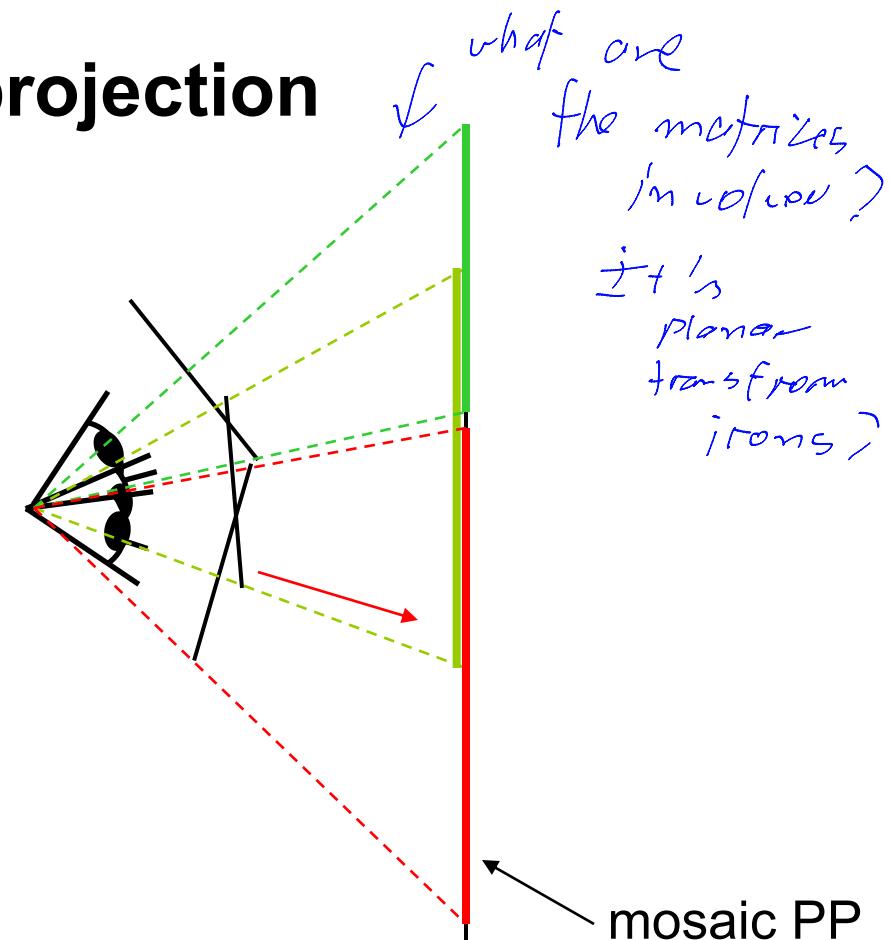
→
m°
Parall/oy

Parallax in a translating camera



Image reprojection

- The mosaic has a natural interpretation in 3D
 - The images are reprojected onto a common plane
 - The mosaic is formed on this plane
- Only valid in **absence** of translation



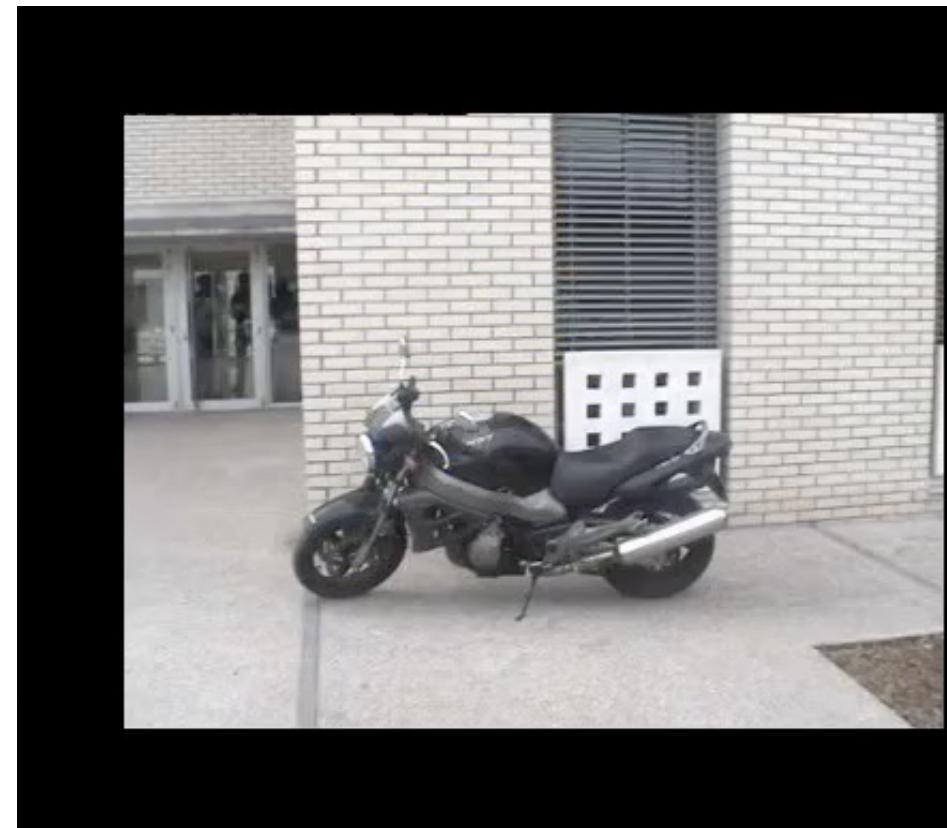
Application: video stabilization

w^t
w^t
what do we
do with
the points?
A

original so
that original
points don't move
Find correspondences to put them
back on



Reference
image world
be changing
at new world



Application: video stabilization



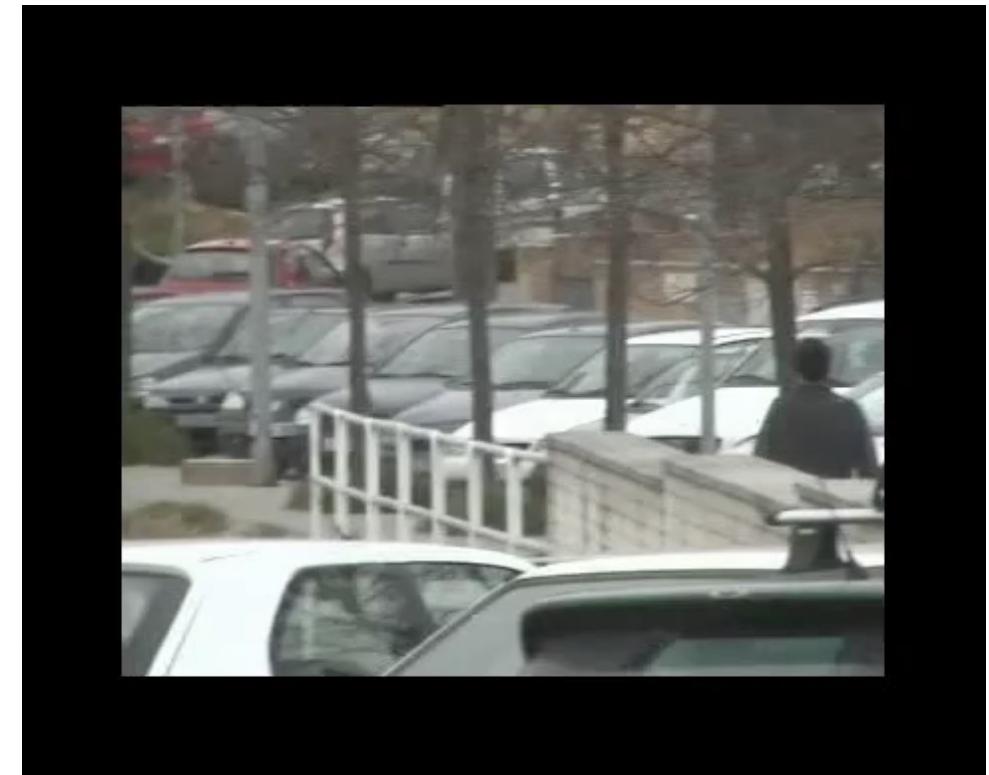
Application: video stabilization



Application: video stabilization

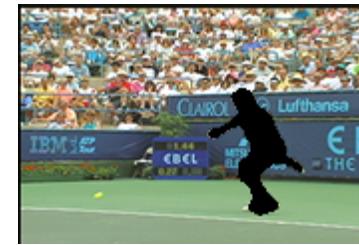


Application: video stabilization



Mosaics for Video Coding

- Convert masked images into a background sprite for content-based coding



=



→ what
do we
do here?

Computing the homography matrix

$$\begin{bmatrix} {}^r x_i \\ {}^r y_i \\ 1 \end{bmatrix} = \begin{bmatrix} s \cos \theta & -s \sin \theta & t_x \\ s \sin \theta & s \cos \theta & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} {}^c x_i \\ {}^c y_i \\ 1 \end{bmatrix}$$

Similarity transformation

$$\begin{bmatrix} {}^r x_i \\ {}^r y_i \\ 1 \end{bmatrix} = \begin{bmatrix} a & -b & c \\ b & a & d \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} {}^c x_i \\ {}^c y_i \\ 1 \end{bmatrix}$$



Lecture Activity: solve for a, b, c and d

8 DOF (Projective) Case

$$\begin{bmatrix} kx_i \\ ky_i \\ k \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & 1 \end{bmatrix} \begin{bmatrix} x'_i \\ y'_i \\ 1 \end{bmatrix}$$

$$x_i = \frac{h_{11}x'_i + h_{12}y'_i + h_{13}}{h_{31}x'_i + h_{32}y'_i + 1}$$

$$y_i = \frac{h_{21}x'_i + h_{22}y'_i + h_{23}}{h_{31}x'_i + h_{32}y'_i + 1}$$

8 DOF (Projective) Case

$$x_i = \frac{h_{11}x'_i + h_{12}y'_i + h_{13}}{h_{31}x'_i + h_{32}y'_i + 1}$$

$$y_i = \frac{h_{21}x'_i + h_{22}y'_i + h_{23}}{h_{31}x'_i + h_{32}y'_i + 1}$$

$$\left. \begin{array}{l} (h_{31}x'_i + h_{32}y'_i + 1)x_i = h_{11}x'_i + h_{12}y'_i + h_{13} \\ (h_{31}x'_i + h_{32}y'_i + 1)y_i = h_{21}x'_i + h_{22}y'_i + h_{23} \end{array} \right\}$$

$$\left. \begin{array}{l} x_i = h_{11}x'_i + h_{12}y'_i + h_{13} - h_{31}x_i x'_i - h_{32}x_i y'_i \\ y_i = h_{21}x'_i + h_{22}y'_i + h_{23} - h_{31}y_i x'_i - h_{32}y_i y'_i \end{array} \right\}$$

8 DOF (Projective) Case

$$\left. \begin{array}{l} x_i = h_{11}x'_i + h_{12}y'_i + h_{13} - h_{31}x_i x'_i - h_{32}x_i y'_i \\ y_i = h_{21}x'_i + h_{22}y'_i + h_{23} - h_{31}y_i x'_i - h_{32}y_i y'_i \end{array} \right\}$$

$$\begin{bmatrix} x'_1 & y'_1 & 1 & 0 & 0 & 0 & -x_1 \cdot x'_1 & -x_1 \cdot y'_1 \\ 0 & 0 & 0 & x'_1 & y'_1 & 1 & -y_1 \cdot x'_1 & -y_1 \cdot y'_1 \\ \vdots & \vdots \\ x'_n & y'_n & 1 & 0 & 0 & 0 & -x_n \cdot x'_n & -x_n \cdot y'_n \\ 0 & 0 & 1 & x'_n & y'_n & 1 & -y_n \cdot x'_n & -y_n \cdot y'_n \end{bmatrix} \cdot \begin{bmatrix} h_{11} \\ h_{12} \\ h_{13} \\ h_{21} \\ h_{22} \\ h_{23} \\ h_{31} \\ h_{32} \end{bmatrix} = \begin{bmatrix} x_1 \\ y_1 \\ \vdots \\ x_n \\ y_n \end{bmatrix}$$

And if some correspondences are wrong?: RANSAC Algorithm

- Stands for “Random Sampling Consensus”
- Used for fitting a model to data with outliers
- Algorithm:
 - Many sets random samples are chosen from data and a model is calculated
 - ‘Fitness’ of the model is calculated using the entire data
 - The ‘best’ model and the corresponding samples are removed from the data and algorithm is run again
 - Algorithm continues until not enough samples fit any model

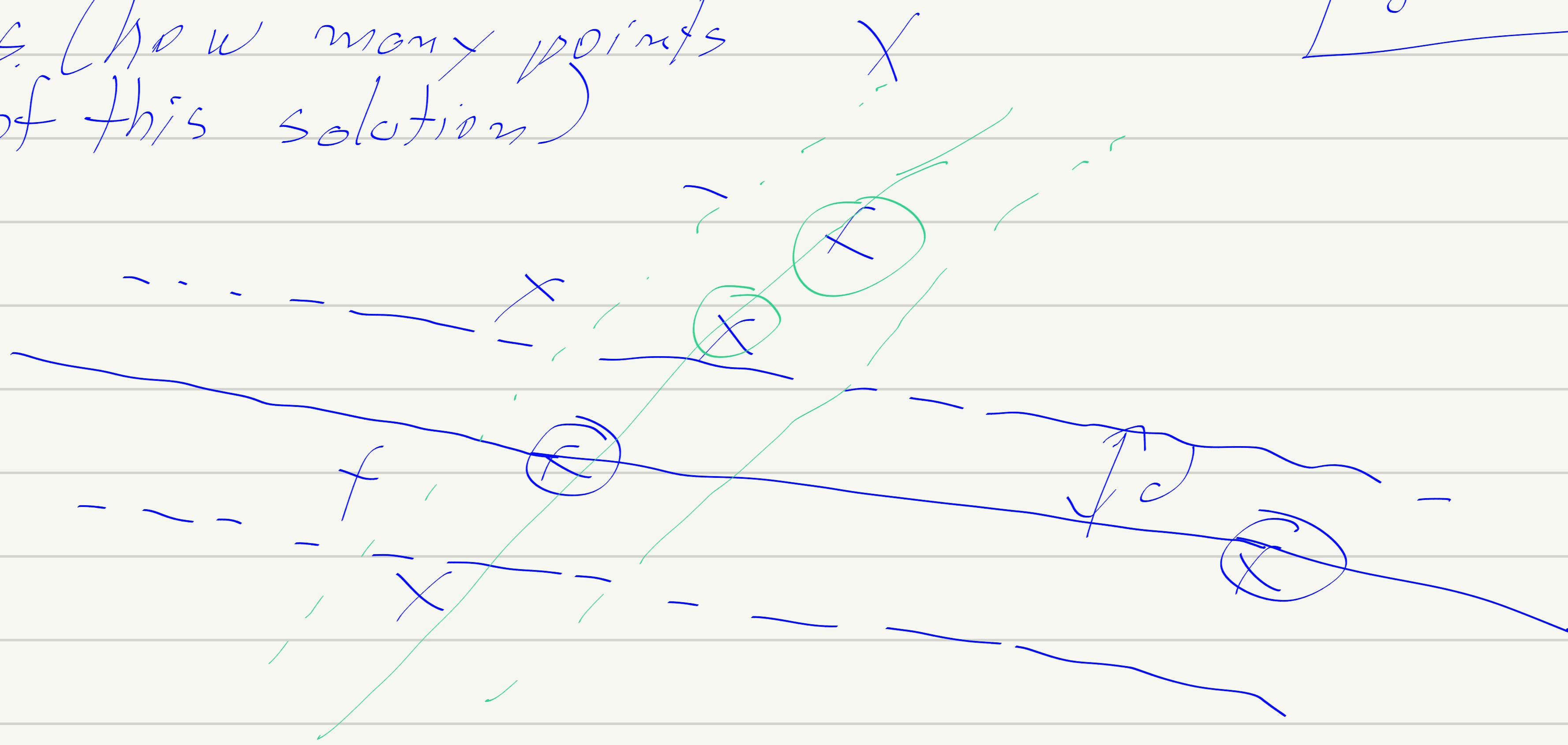
1) Randomly select two points for a line.
2) Within a given bound about your solution (c),
count the consensus (how many points X
are within the bounds of this solution)

model..

$$y = cx + b \leftarrow c, b?$$

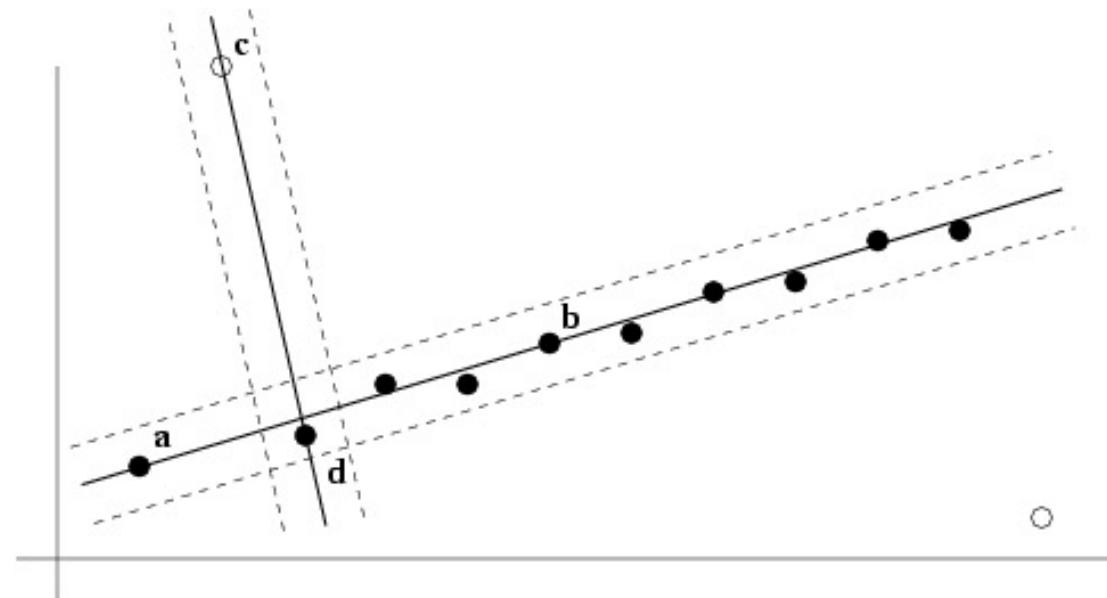
Sol 1) Consensus
 $c = 3$

Sol 2) $c = 4$



Robust estimation

- What if set of matches contains gross outliers?
(to keep things simple let's consider line fitting first)



For Euclidean homography

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{pmatrix} a & -b & c \\ b & a & d \\ 0 & 0 & 1 \end{pmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

→ each correspondences gives 2 pair of equations
↳ . 4 unknowns

↳ 2 points required

Objective

Robust fit of model to data set S which contains outliers

Algorithm ↳ what is the consensus for homography?

- (i) Randomly select a sample of s data points from S and instantiate the model from this subset.
- (ii) Determine the set of data points S_i which are within a distance threshold t of the model. The set S_i is the consensus set of samples and defines the inliers of S.
- (iii) If the subset of S_i is greater than some threshold T , re-estimate the model using all the points in S_i and terminate
- (iv) If the size of S_i is less than T , select a new subset and repeat the above.
- (v) After N trials the largest consensus set S_i is selected, and the model is re-estimated using all the points in the subset S_i

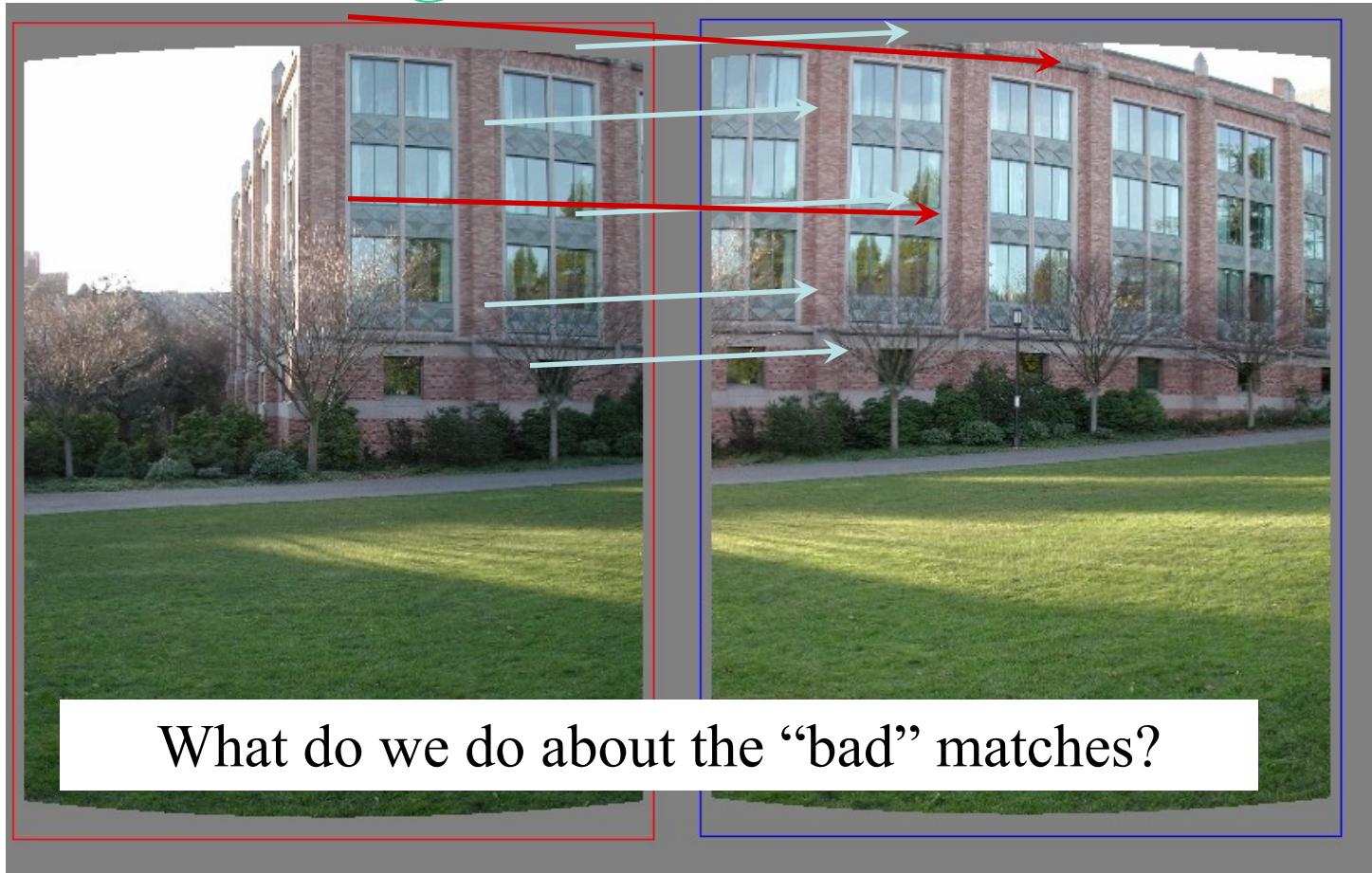
Matching features

physical
meaning?

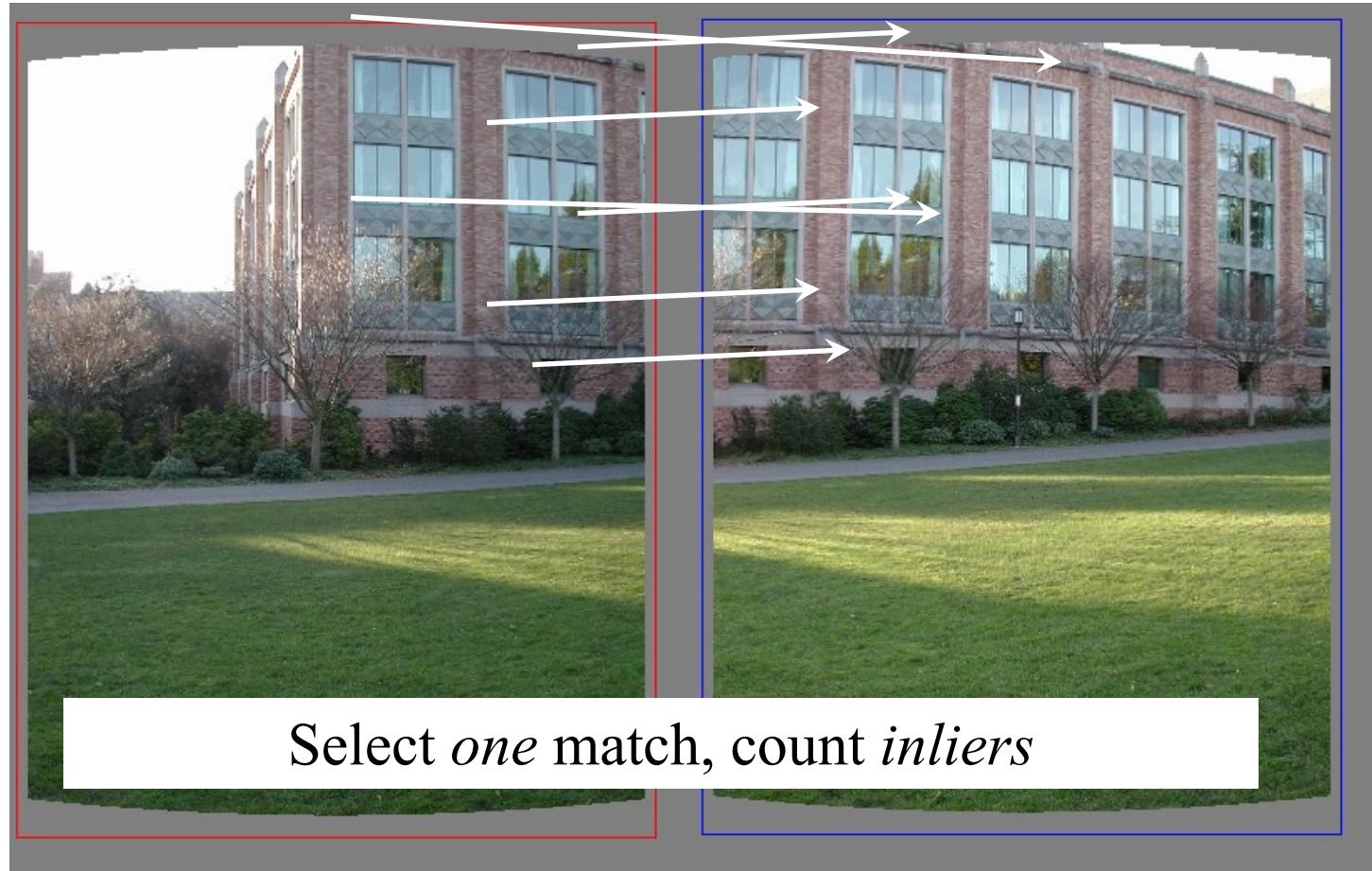
↗ for all SIFT

correspondences?

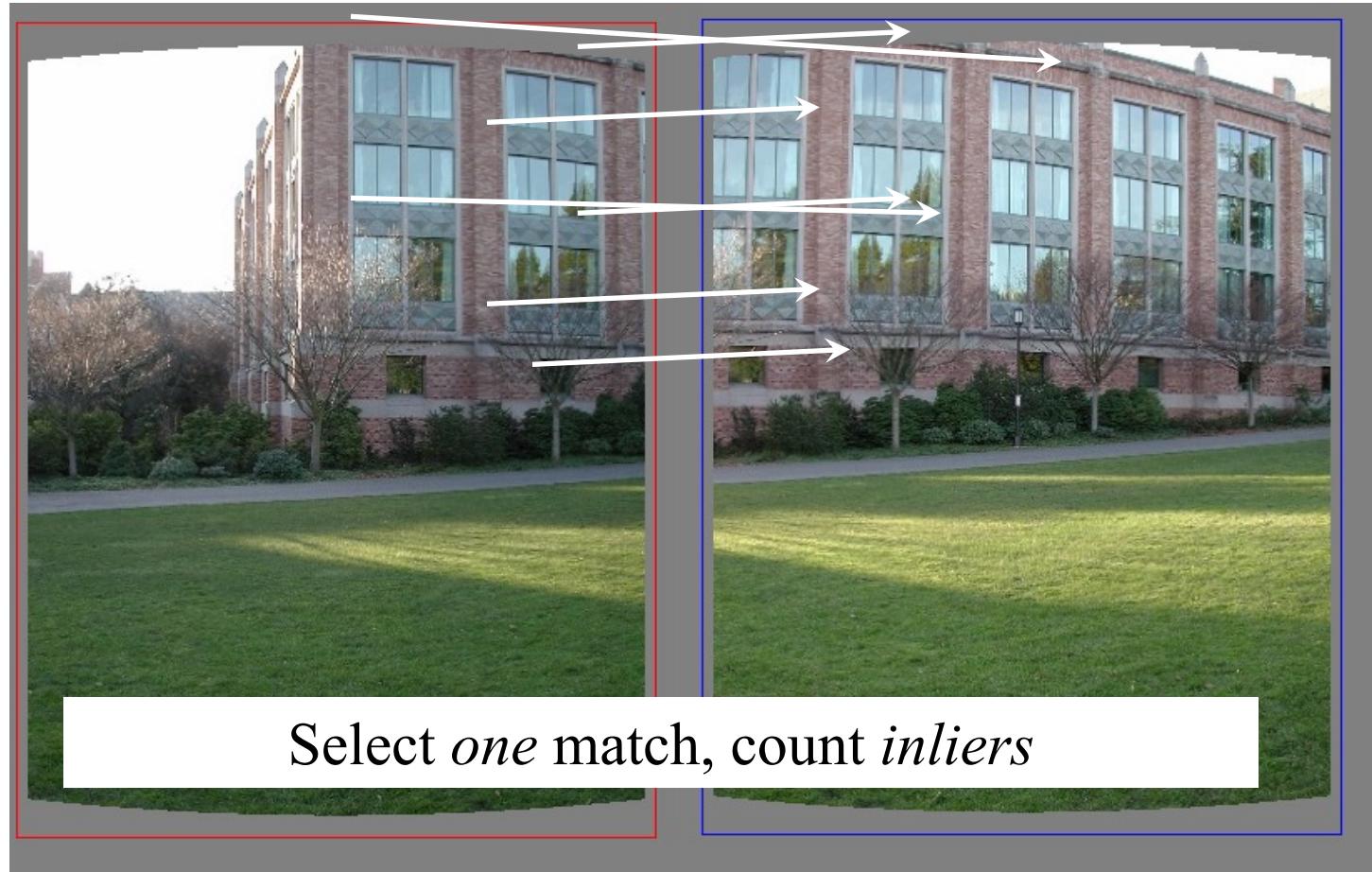
What is the meaning of threshold?



RAndom SAmple Consensus

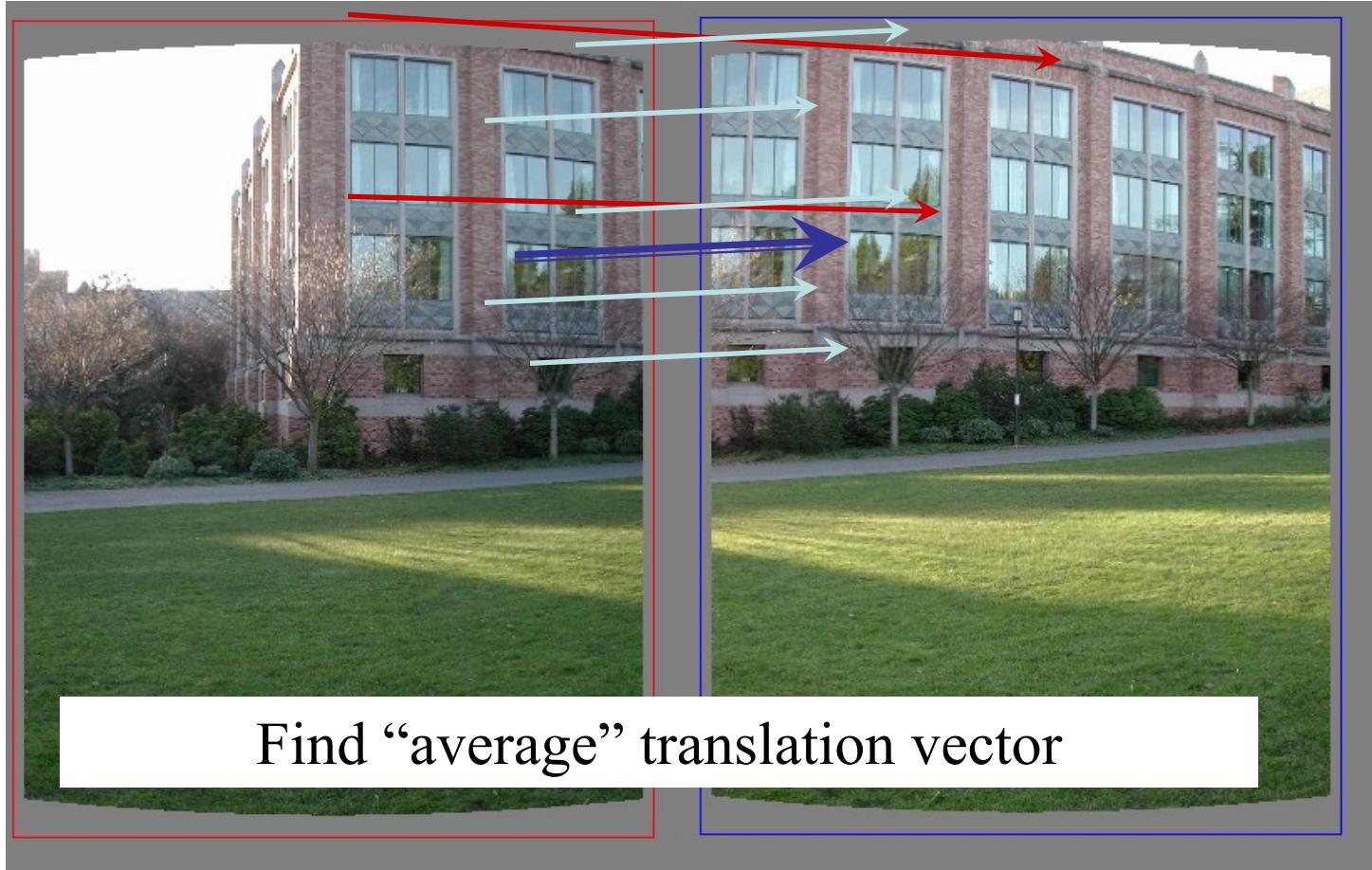


RAndom SAmple Consensus



what is SIFT
what is RANSAC
what is used for

Least squares fit



Distance threshold

Choose t so probability for inlier is α (e.g. 0.95)

- Often empirically
- Zero-mean Gaussian noise σ then d_{\perp}^2 follows a χ_m^2 distribution with m DOFs (m = codimension of model)
(dimension+codimension=dimension space)

Codimension	Model	t^2
1	line,F	$3.84\sigma^2$
2	H,P	$5.99\sigma^2$
3	T	$7.81\sigma^2$

How many samples?

- Choose N so that, with probability p , at least one random sample is free from outliers. e.g. $p=0.99$

Each point is
a correspondence -
do we know
how many correspondences
that corresponds
is an outlier?

amount
of data
+ instantiation
homography

$$\left(1 - \left(1 - e\right)^s\right)^N = 1 - p \quad \text{Probability to be an outlier}$$
$$N = \log(1 - p) / \log\left(1 - \left(1 - e\right)^s\right)$$

s	proportion of outliers e						
	5%	10% <i>(10% outliers)</i>	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

Acceptable consensus set?

- Typically, terminate when inlier ratio reaches expected ratio of inliers

$$T = (1 - e) n$$

Adaptively determining the number of samples

e is often unknown a priori, so pick worst case, i.e. 0, and adapt if more inliers are found, e.g. 80% would yield $e=0.2$

- $N=\infty$, $\text{sample_count} = 0$
- While $N > \text{sample_count}$ repeat
 - Choose a sample and count the number of inliers
 - Set $e = 1 - (\text{number of inliers}) / (\text{total number of points})$
 - Recompute N from e ($N = \log(1 - p) / \log(1 - (1 - e)^s)$)
 - Increment the sample_count by 1
- Terminate

Summary RANSAC – the RANdom SAmple Consensus

- Randomly pick up enough data points (sample) for estimation.
- Count the number of the supporting points for each estimation
- Get the best estimation which have the most supports
- Use all the supporting points to get the best estimation

Summary

We have seen today:

- a hierarchy of transformations: Euclidean, Similarity, Affine, Projective
- What is a Homography
- How to compute a homography matrix using the adequate (motion) model
- Applications of planar transformations
- How to detect outliers

References

- RANSAC:
 - M. Fischler and R. Bolles. Random sampling consensus: a paradigm for model fitting with application to image analysis and automated cartography. *Communications of ACM*, vol. 24, no.6, pp. 381–395, 1981.