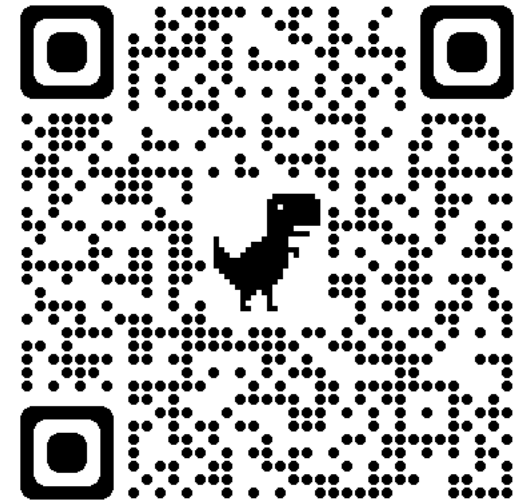


Lecture 10: 2D Transformation & Alignment

COMP 590/776: Computer Vision

Instructor: Soumyadip (Roni) Sengupta

TA: Mykhailo (Misha) Shvets



Course Website:
Scan Me!



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@jbhuang0604



The ControlNet illusion art is FUN!

In some sense, it's a *Hybrid Image* (17-year-old method). It was my first homework in the computer vision class. I remember that it takes time to properly align the two images to get good results.

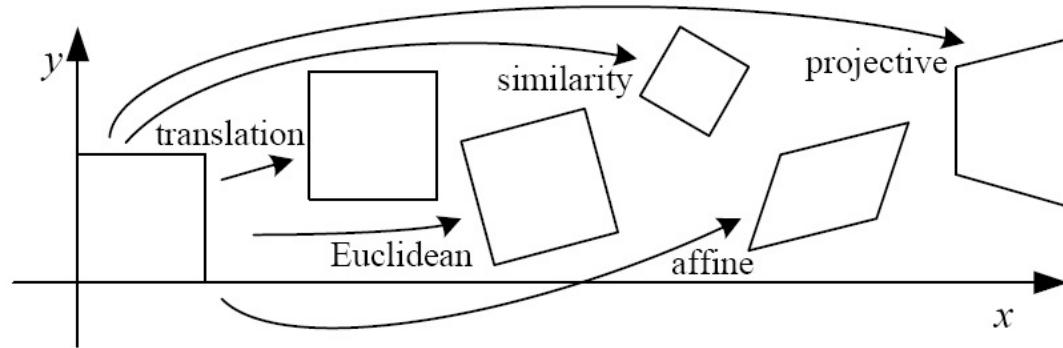
Now it's only one sentence and one click!


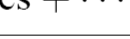
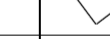




1:46 PM · Sep 27, 2023 · **821** Views

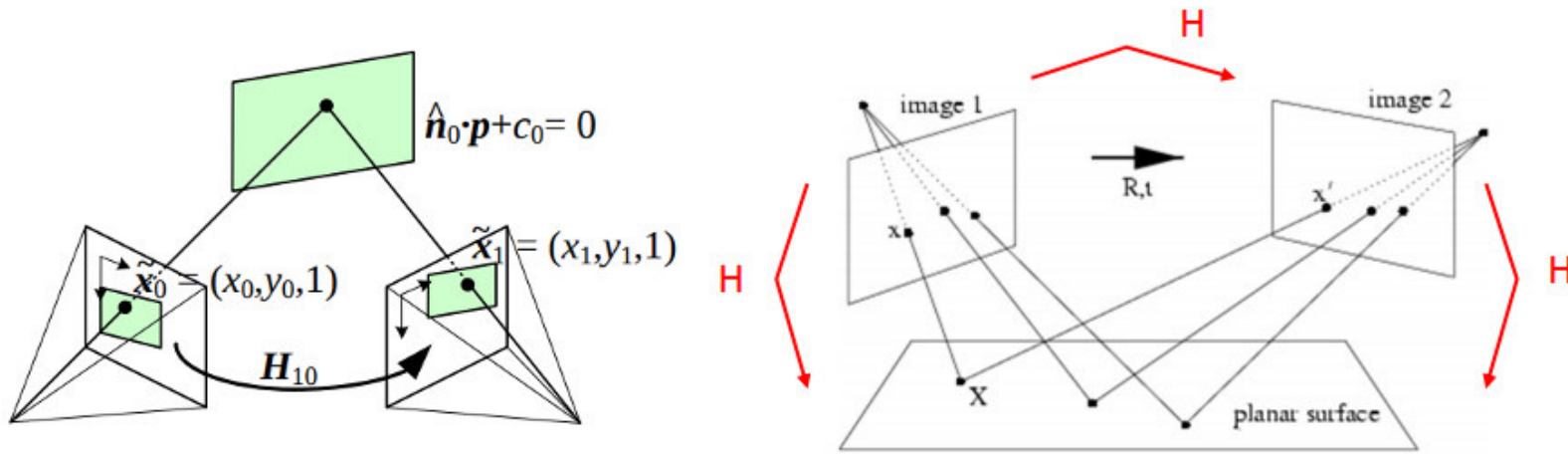
Recap

2D image transformations



Name	Matrix	# D.O.F.	Preserves:	Icon
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	

Projective Transformations *aka* Homographies *aka* Planar Perspective Maps



$$\mathbf{H} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & 1 \end{bmatrix}$$

Called a *homography*
(or *planar perspective map*)

Any two images of the same planar surface in 3D space are related by a [homography](#) (assuming a [pinhole camera model](#)).

Affine transformations

- Affine transformations are combinations of ...

- Linear transformations, and
- Translations

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

- Properties of affine transformations:
 - **Origin does not necessarily map to origin**
 - Lines map to lines
 - Parallel lines remain parallel
 - Ratios are preserved
 - Closed under composition

Homographies (Projective Transformation)

- Homographies ...
 - Affine transformations, and
 - Projective warps

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

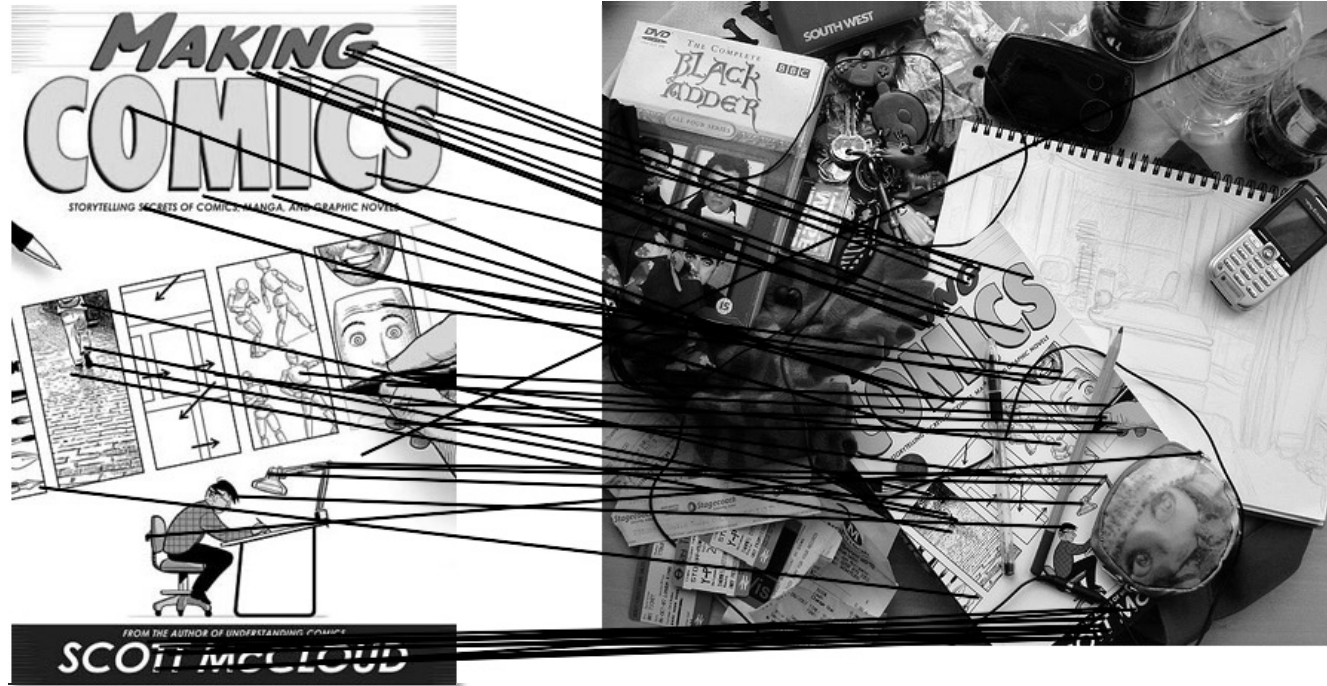
$$\begin{bmatrix} x'_i \\ y'_i \\ 1 \end{bmatrix} \cong \begin{bmatrix} h_{00} & h_{01} & h_{02} \\ h_{10} & h_{11} & h_{12} \\ h_{20} & h_{21} & h_{22} \end{bmatrix} \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix}$$

- Properties of projective transformations:
 - Origin does not necessarily map to origin
 - Lines map to lines
 - Parallel lines do not necessarily remain parallel
 - Ratios are not preserved
 - Closed under composition

where the length of the vector $[h_{00} \ h_{01} \ \dots \ h_{22}]$ is 1.

Computing transformations

- Given a set of matches between images A and B
 - How can we compute the transform T from A to B?



- Find transform T that best “agrees” with the matches

6 unknowns, at least 3 point matches required

Affine transformations

- Matrix form

$$\begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_1 & y_1 & 1 \\ x_2 & y_2 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_2 & y_2 & 1 \\ \vdots & & & & & \\ x_n & y_n & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_n & y_n & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \\ e \\ f \end{bmatrix} = \begin{bmatrix} x'_1 \\ y'_1 \\ x'_2 \\ y'_2 \\ \vdots \\ x'_n \\ y'_n \end{bmatrix}$$

A
 $2n \times 6$

t
 6×1

=

b
 $2n \times 1$

Solving for homographies

$$\begin{bmatrix}
 x_1 & y_1 & 1 & 0 & 0 & 0 & -x'_1 x_1 & -x'_1 y_1 & -x'_1 \\
 0 & 0 & 0 & x_1 & y_1 & 1 & -y'_1 x_1 & -y'_1 y_1 & -y'_1 \\
 \vdots & & & & & & & & \\
 x_n & y_n & 1 & 0 & 0 & 0 & -x'_n x_n & -x'_n y_n & -x'_n \\
 0 & 0 & 0 & x_n & y_n & 1 & -y'_n x_n & -y'_n y_n & -y'_n
 \end{bmatrix}
 \begin{bmatrix}
 h_{00} \\
 h_{01} \\
 h_{02} \\
 h_{10} \\
 h_{11} \\
 h_{12} \\
 h_{20} \\
 h_{21} \\
 h_{22}
 \end{bmatrix}
 =
 \begin{bmatrix}
 0 \\
 0 \\
 \vdots \\
 0 \\
 0
 \end{bmatrix}$$

Rank(A) = 8
 A
 $2n \times 9$

h
 9

0
 $2n$

- Smallest singular value of A also indicates how well the homography can be estimated.
- Optimal h = Singular vector corresponding to smallest singular value

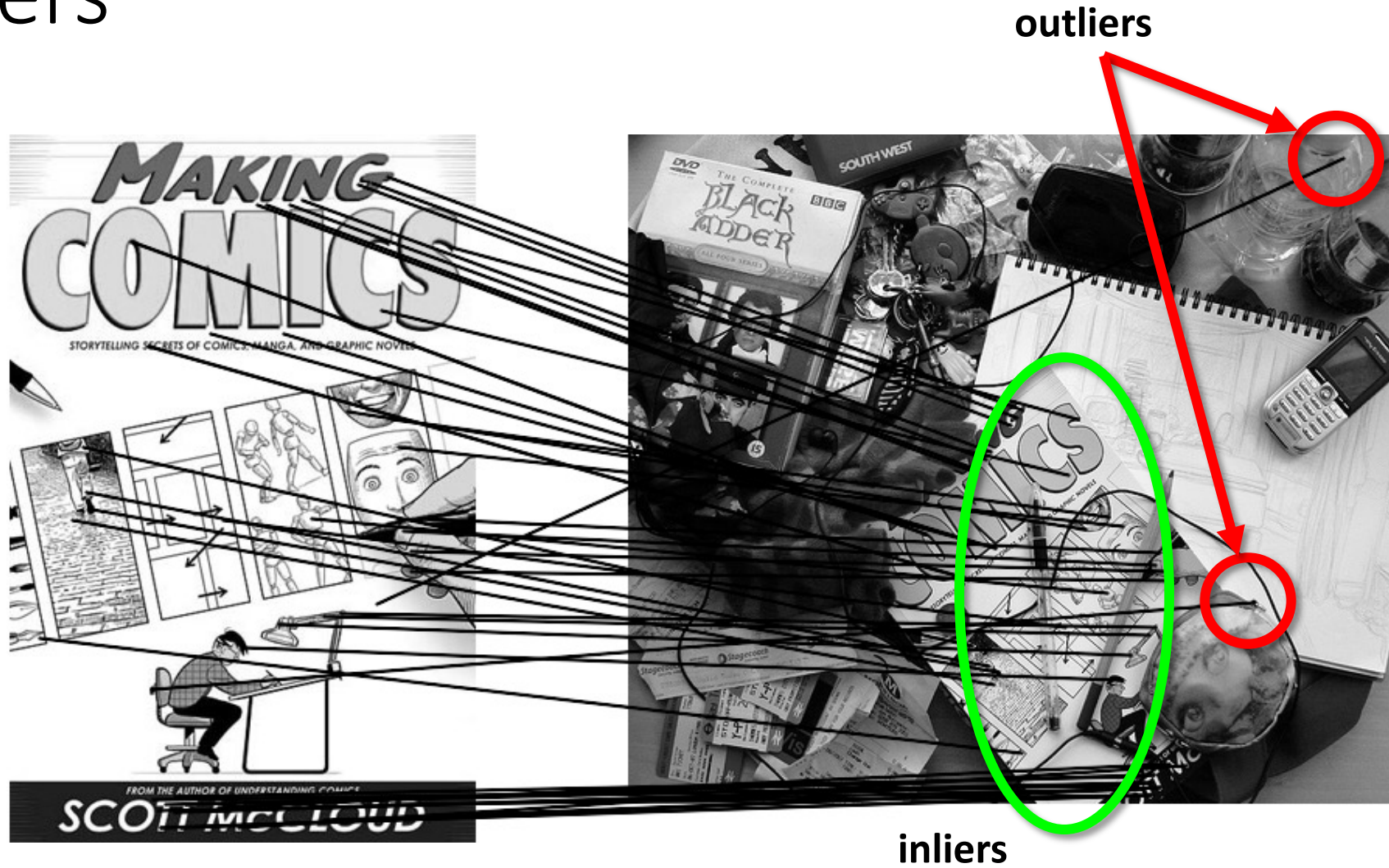
Today's class

- Fitting with outliers – RANSAC
- Warping
- Blending
- HW3 Motivation

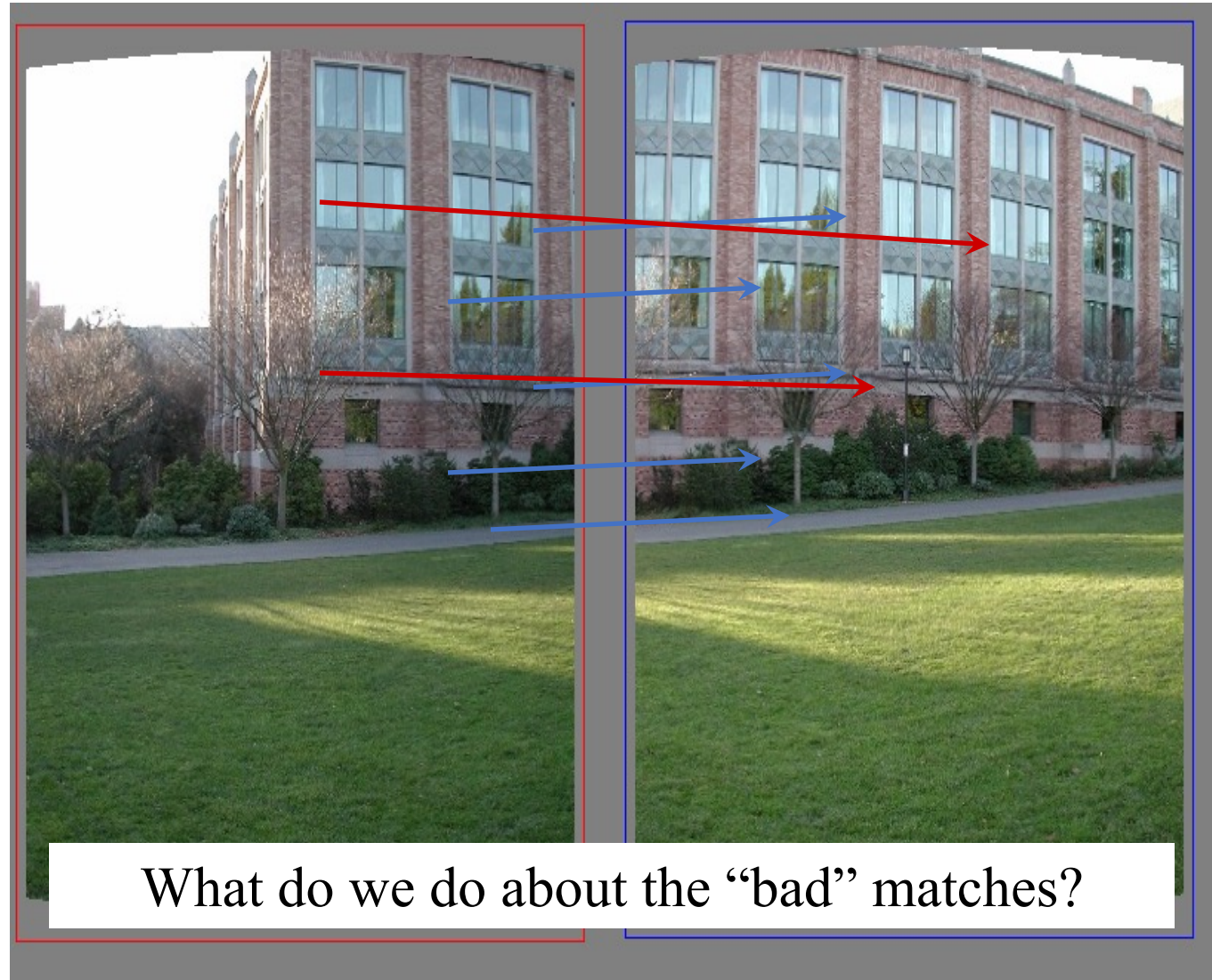
Today's class

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Outliers

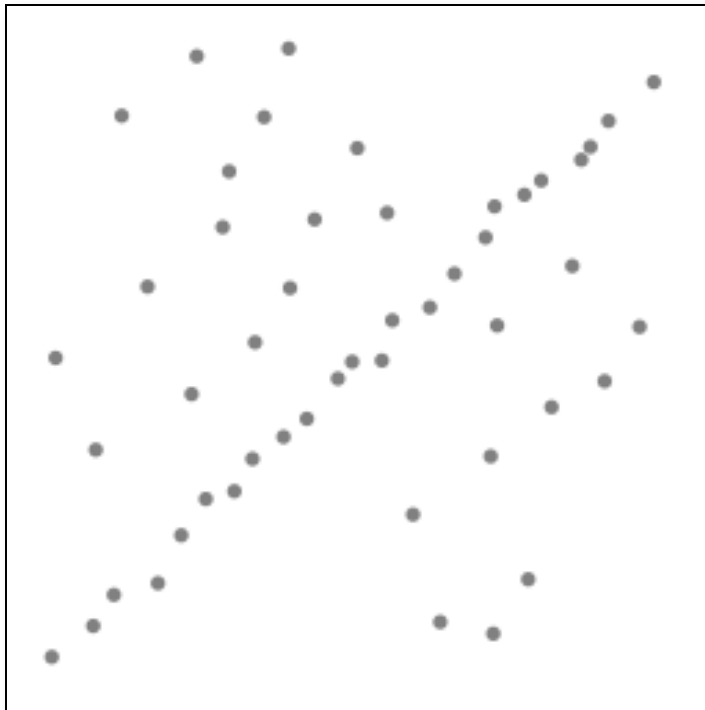


Matching features

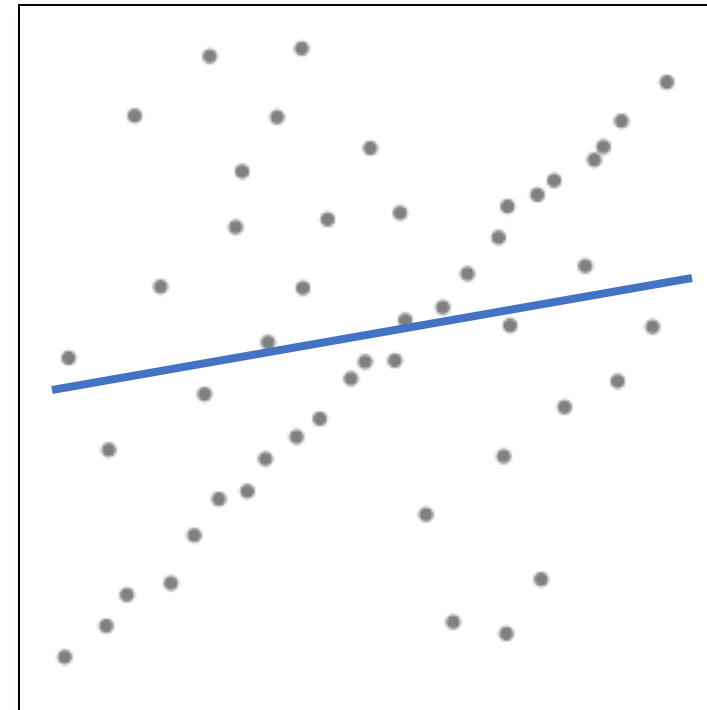
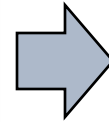


Robustness

- Let's consider the problem of linear regression



Problem: Fit a line to these datapoints



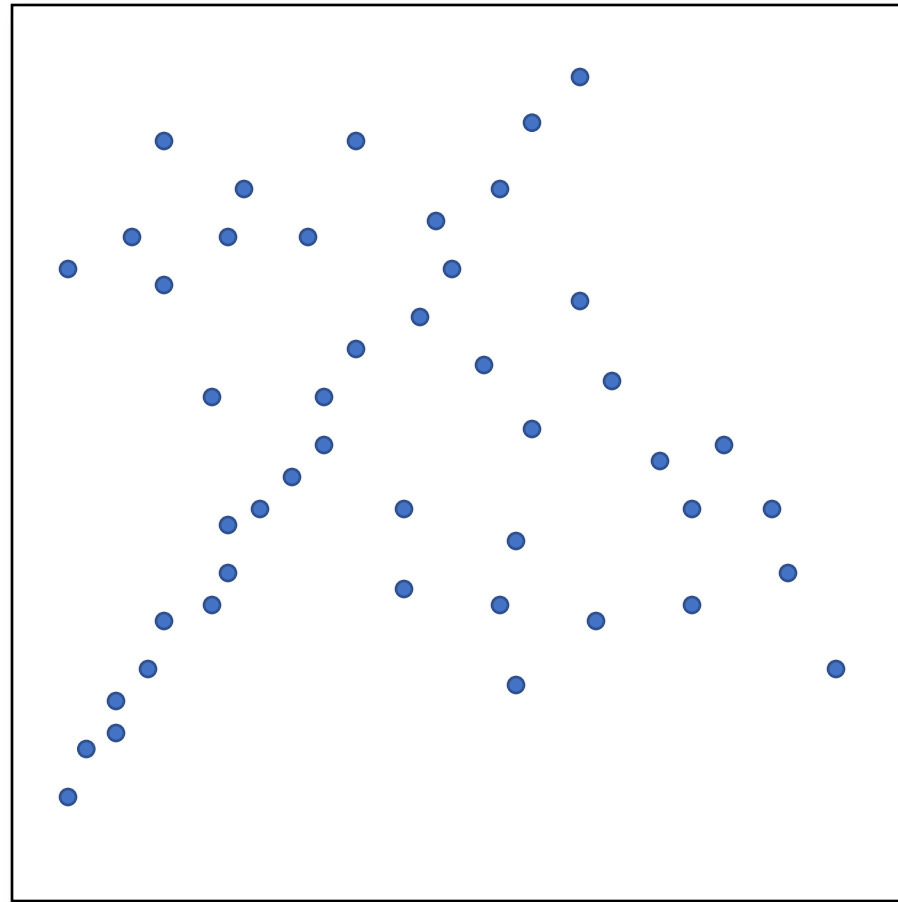
Least squares fit

- How can we fix this?

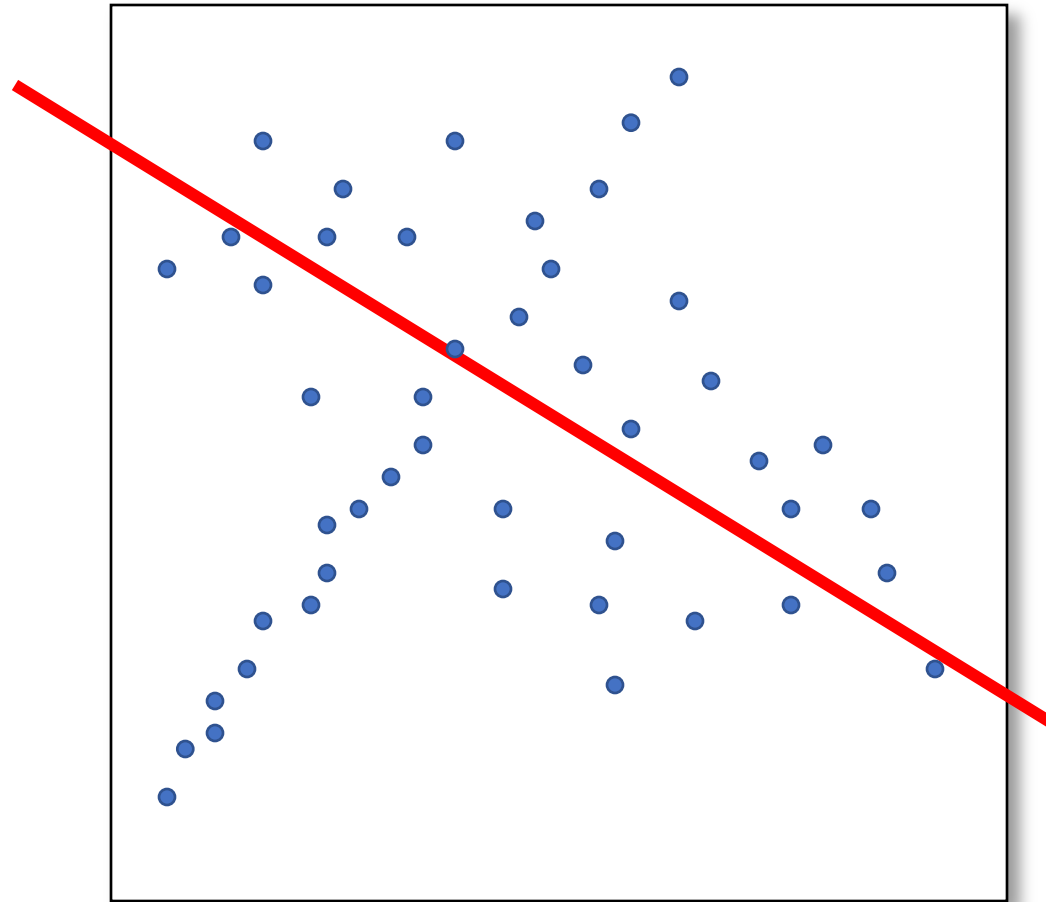
Idea

- Given a hypothesized line
- Count the number of points that “agree” with the line
 - “Agree” = within a small distance of the line
 - I.e., the **inliers** to that line
- For all possible lines, select the one with the largest number of inliers

Counting inliers

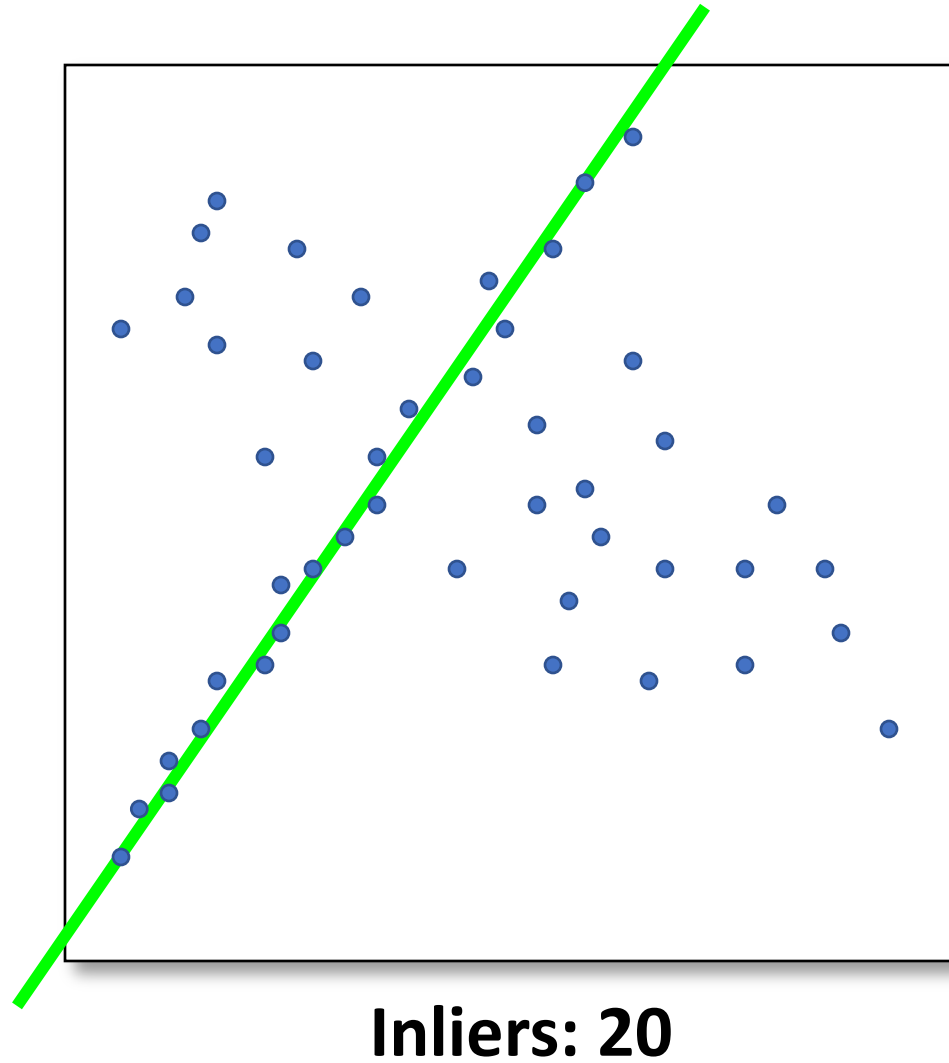


Counting inliers

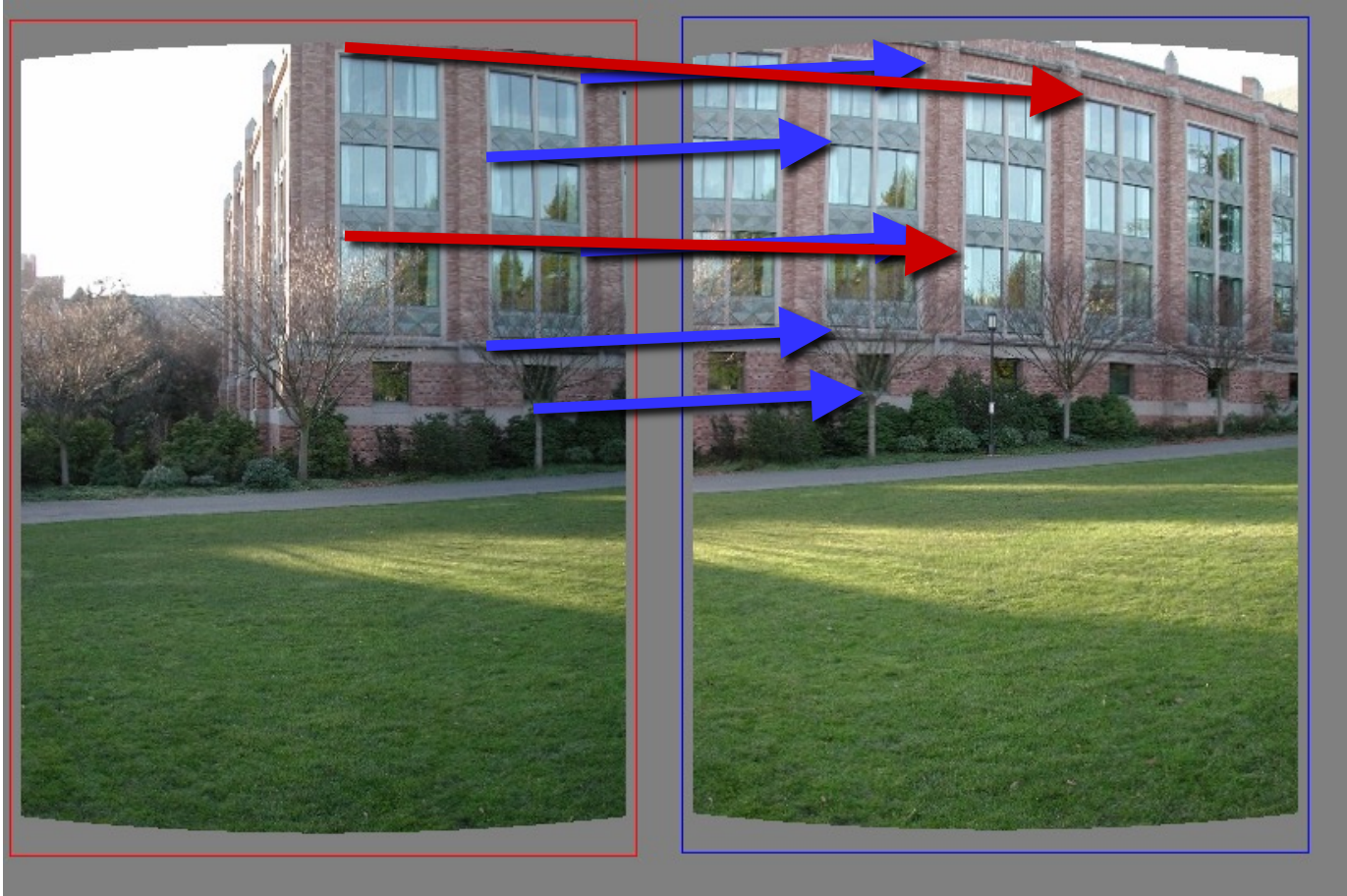


Inliers: 3

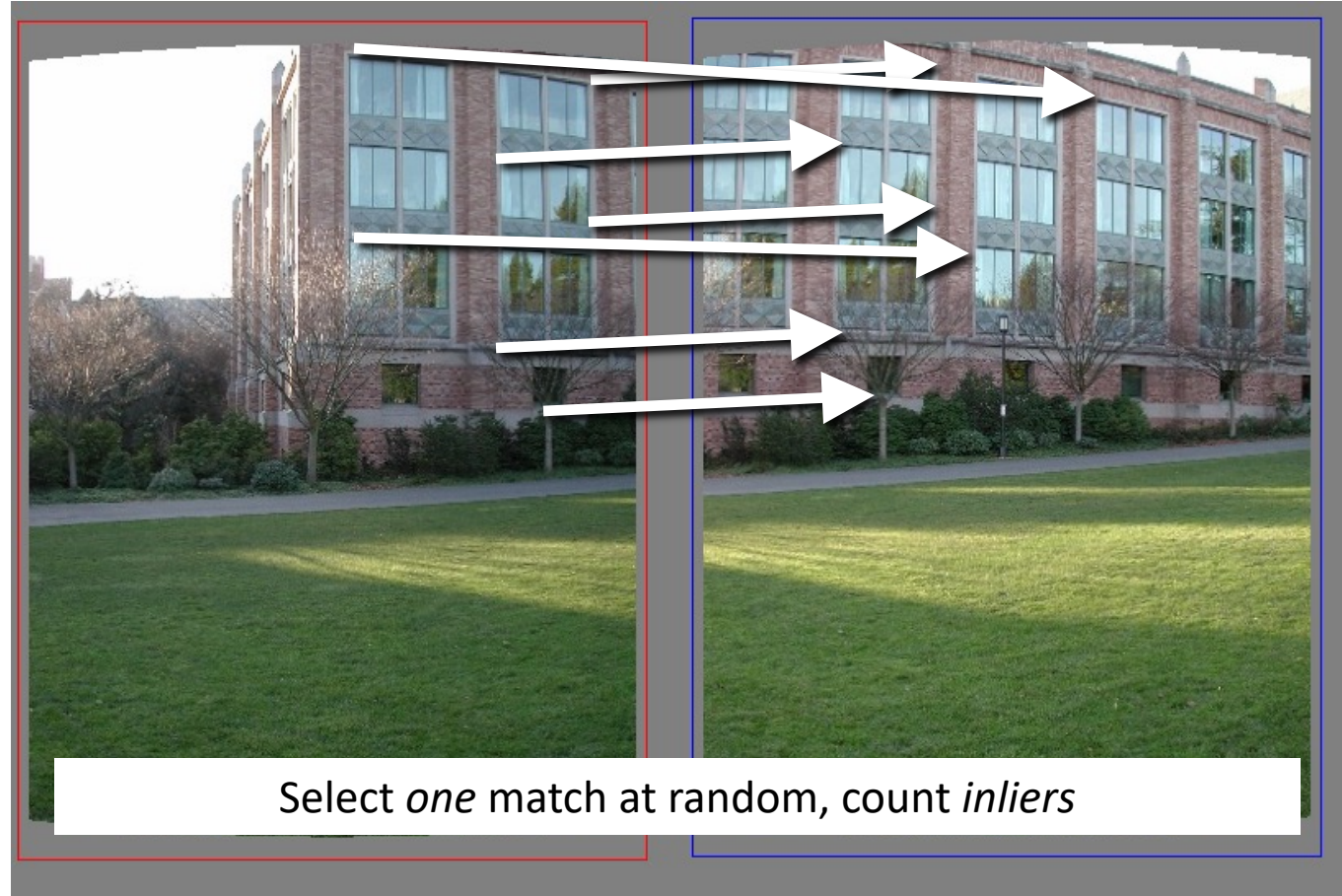
Counting inliers



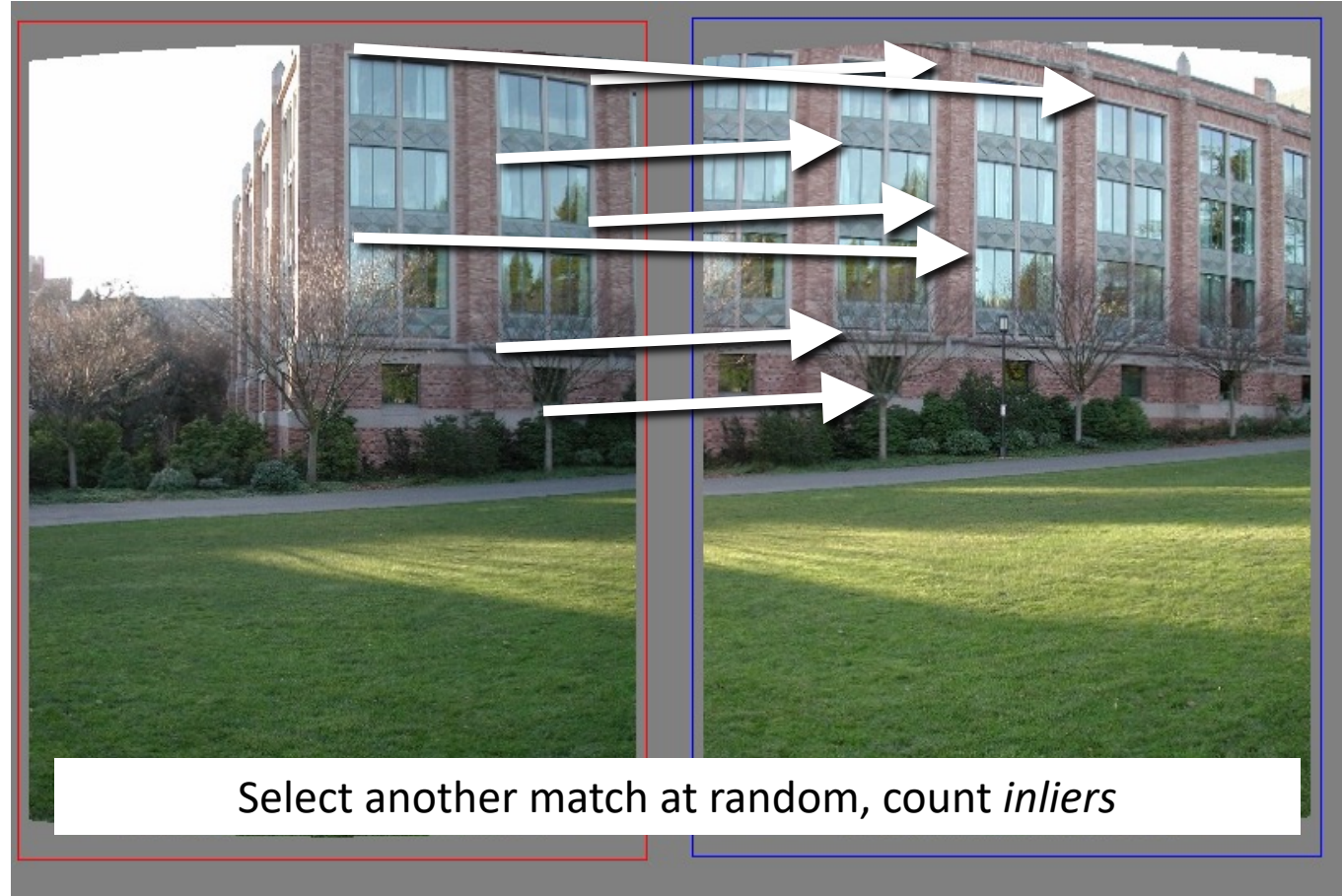
Translations



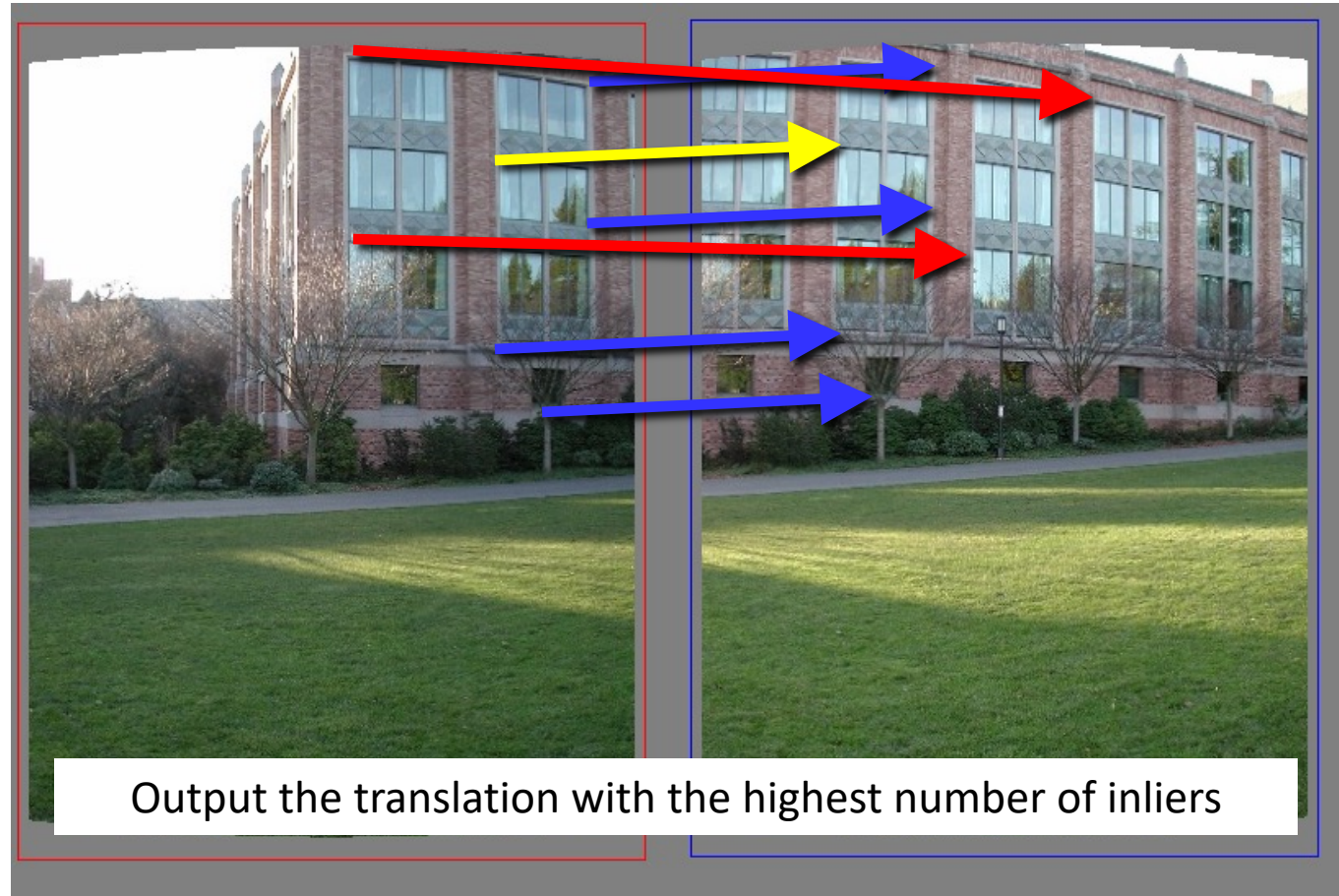
Random Sample Consensus



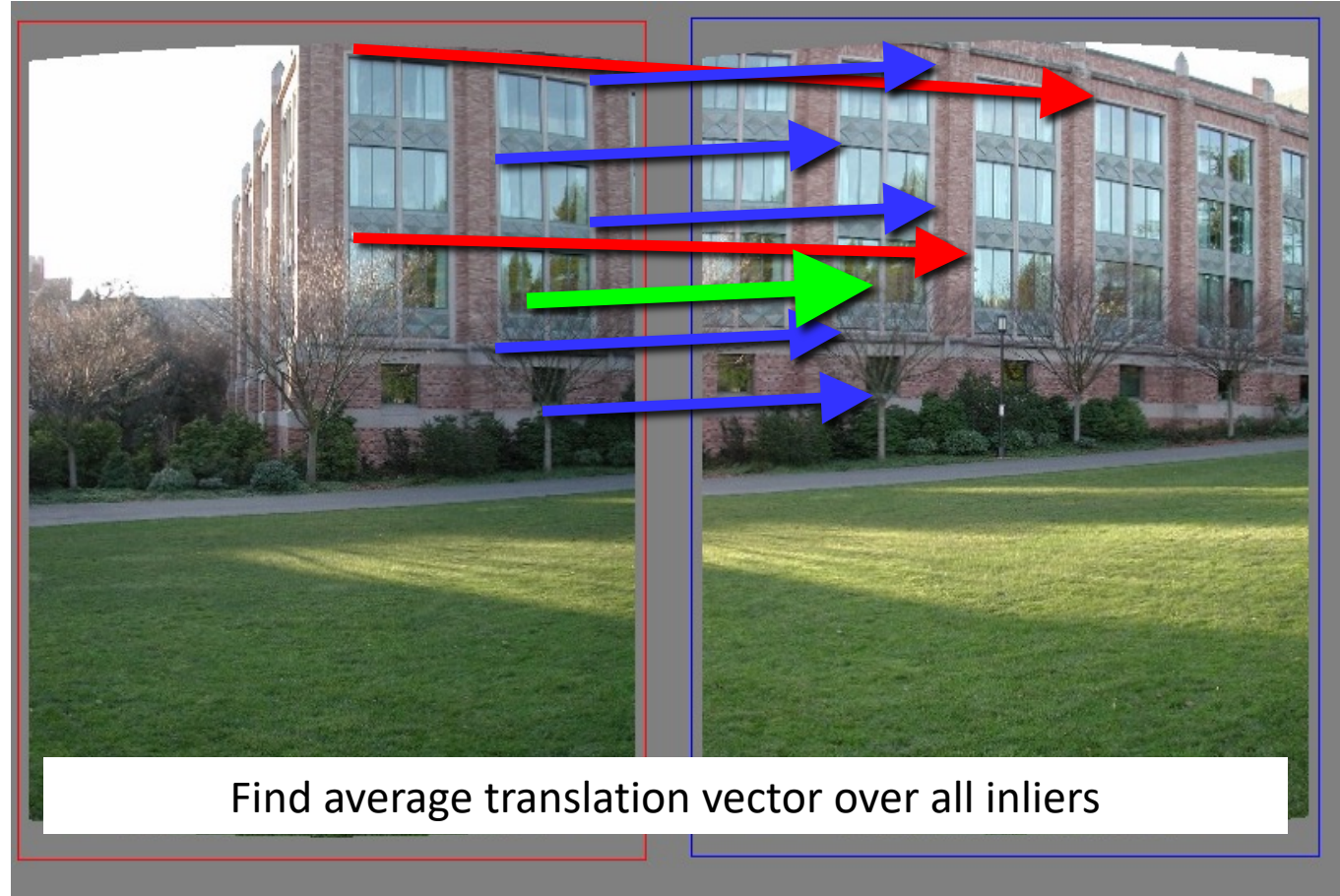
Random Sample Consensus



Random Sample Consensus



Final step: least squares fit



RANSAC

- Idea:
 - All the inliers will agree with each other on the translation vector; the (hopefully small) number of outliers will (hopefully) disagree with each other
 - RANSAC only has guarantees if there are $< 50\%$ outliers
 - “All good matches are alike; every bad match is bad in its own way.”
 - Tolstoy via Alyosha Efros

RANSAC

- General version:
 1. Randomly choose s samples
 - Typically s = minimum sample size that lets you fit a model
 2. Fit a model (e.g., line) to those samples
 3. Count the number of inliers that approximately fit the model
 4. Repeat N times
 5. Choose the model that has the largest set of inliers

RANSAC for estimating homography

- RANSAC loop:
 1. Select four feature pairs (at random)
 2. Compute homography H (exact)
 3. Compute *inliers* where $dist(p_i', \mathbf{H} p_i) < \varepsilon$
 4. Keep largest set of inliers
 5. Re-compute least-squares H estimate on all of the inliers

How many rounds?

- If we have to choose s samples each time
 - with an outlier ratio e
 - and we want the right answer with probability p

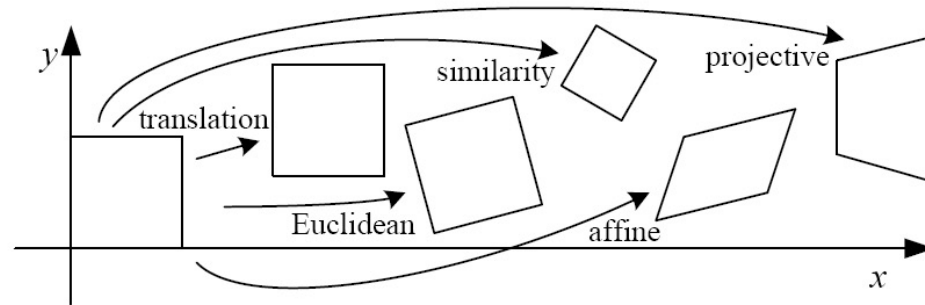
$$N \geq \frac{\log(1 - p)}{\log(1 - (1 - e)^s)}$$






proportion of outliers e							
s	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

$p = 0.99$

How big is s ?

- For alignment, depends on the motion model
 - Here, each sample is a correspondence (pair of matching points)



Name	Matrix	# D.O.F.	Preserves:	Icon
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	

RANSAC pros and cons

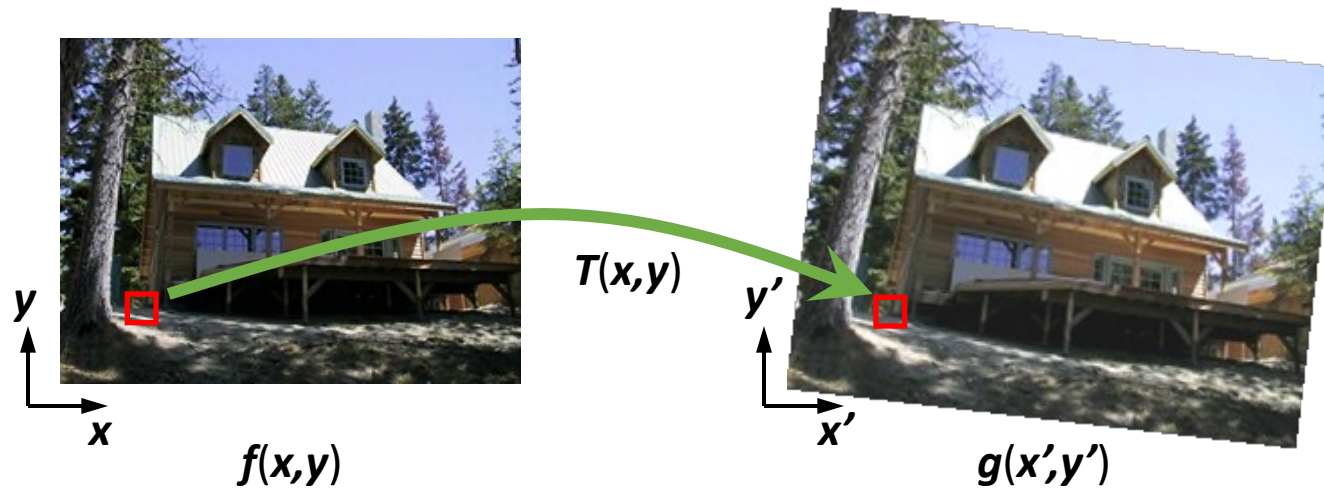
- Pros
 - Simple and general
 - Applicable to many different problems
 - Often works well in practice
- Cons
 - Parameters to tune
 - Sometimes too many iterations are required
 - Can fail for extremely low inlier ratios
 - We can often do better than brute-force sampling

Today's class

- Fitting with outliers – RANSAC
- **Warping**
- Blending
- HW3 Motivation

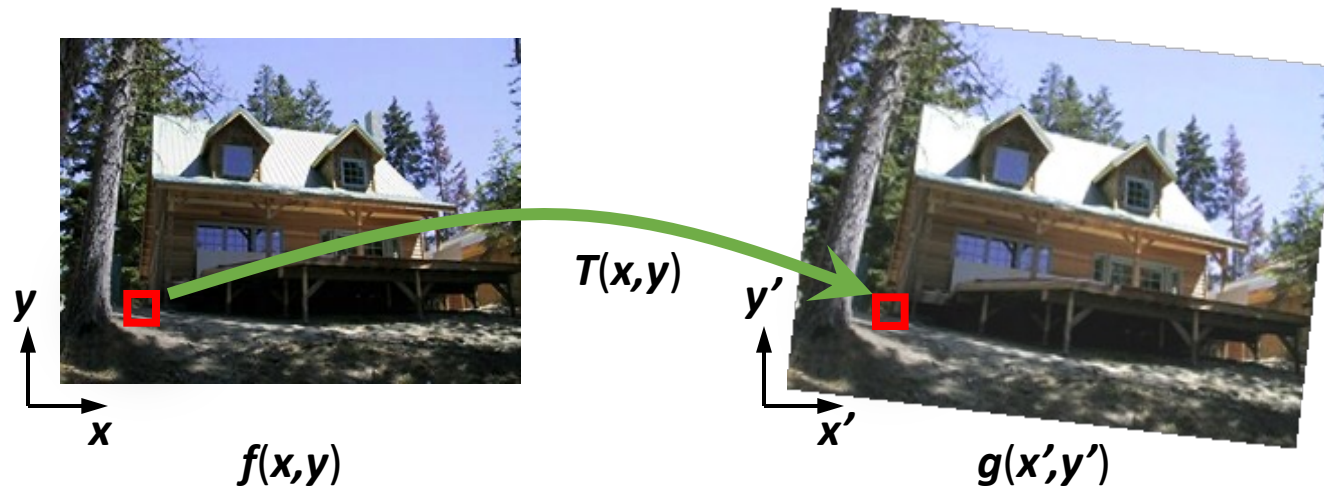
Implementing image warping

- Given a coordinate xform $(x',y') = T(x,y)$ and a source image $f(x,y)$, how do we compute a transformed image $g(x',y') = f(T(x,y))$?



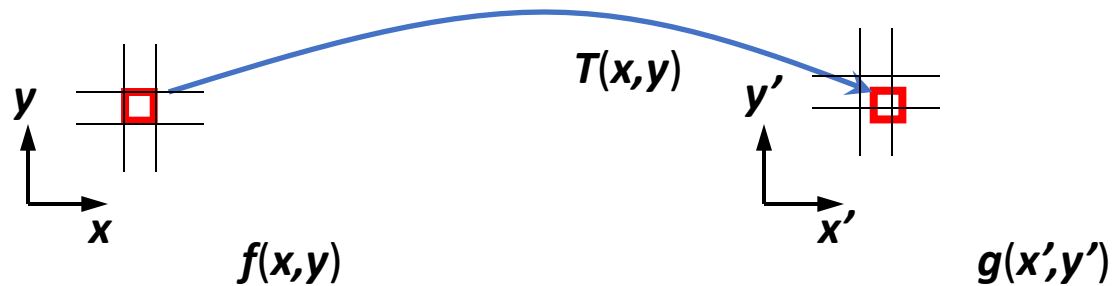
Forward Warping

- Send each pixel (x, y) to its corresponding location $(x', y') = T(x, y)$ in $g(x', y')$
 - What if pixel lands “between” two pixels?



Forward Warping

- Send each pixel (x, y) to its corresponding location $(x', y') = T(x, y)$ in $g(x', y')$
 - What if pixel lands “between” two pixels?
 - Answer: add “contribution” to several pixels, normalize later (*splatting*)
 - Can still result in holes



Today's class

- Fitting with outliers – RANSAC
- Warping
- **Blending**
- HW3 Motivation

Blending

- We've aligned the images – now what?

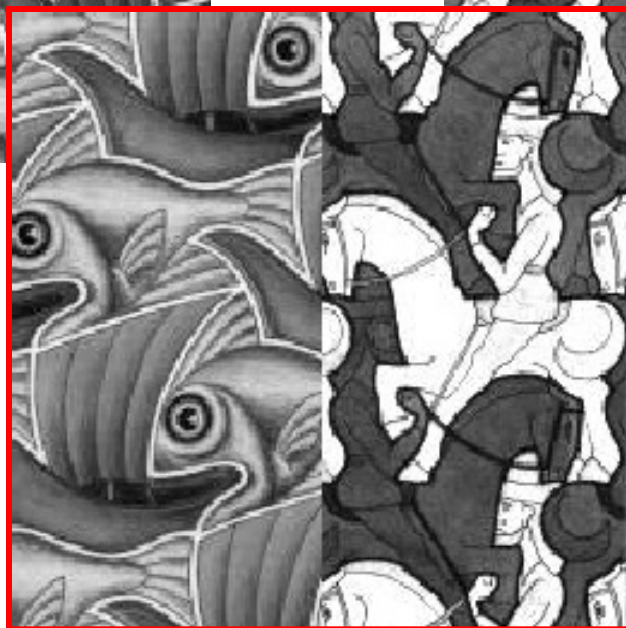
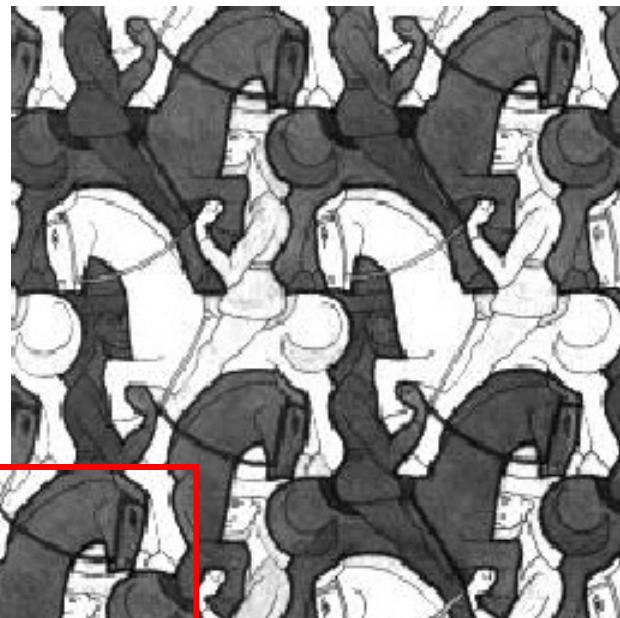
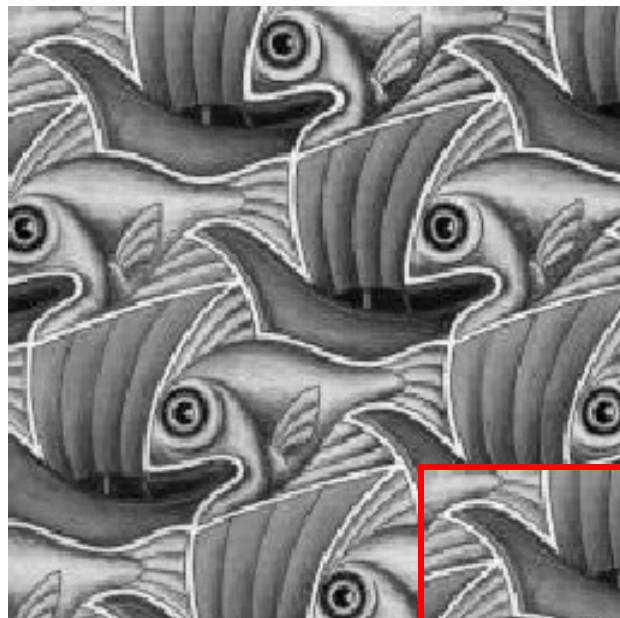


Blending

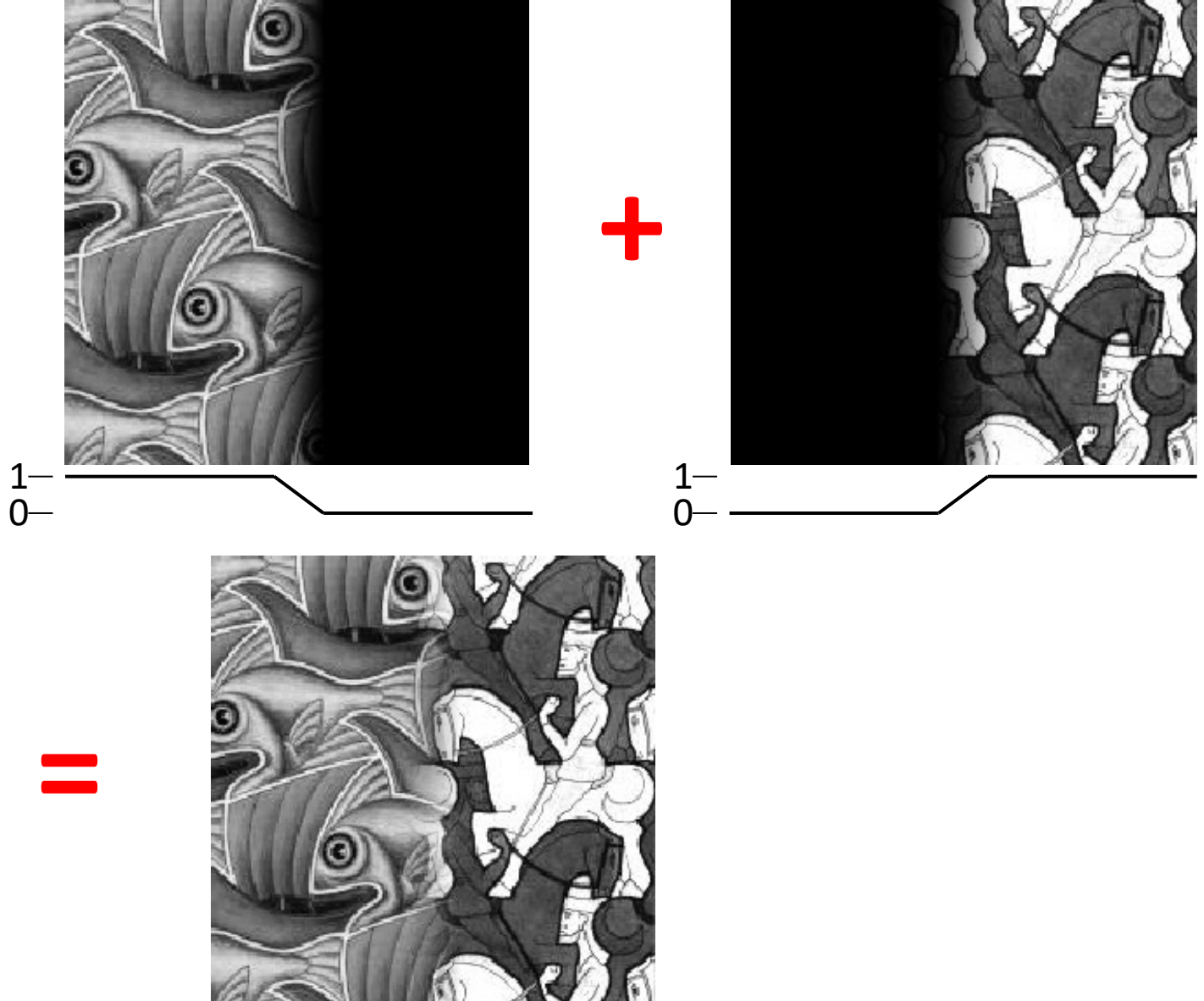
- Want to seamlessly blend them together



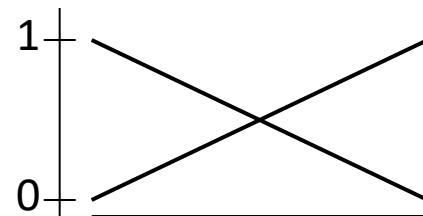
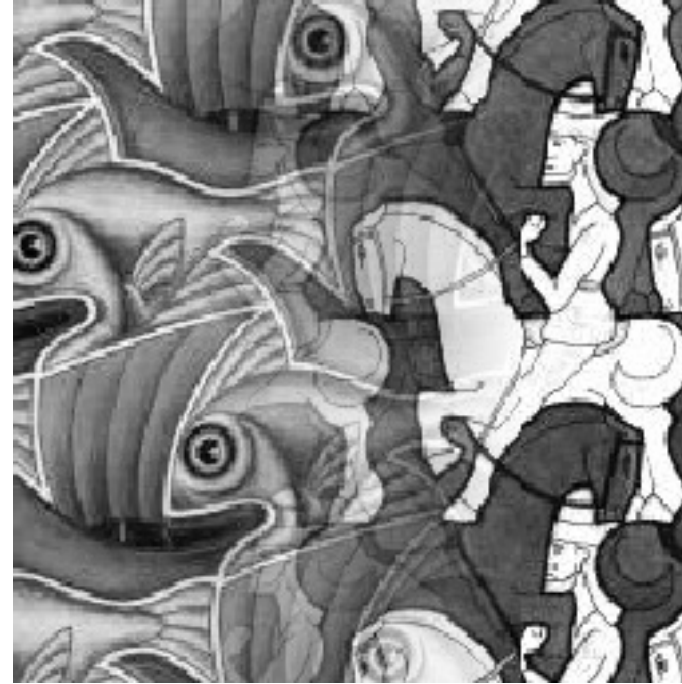
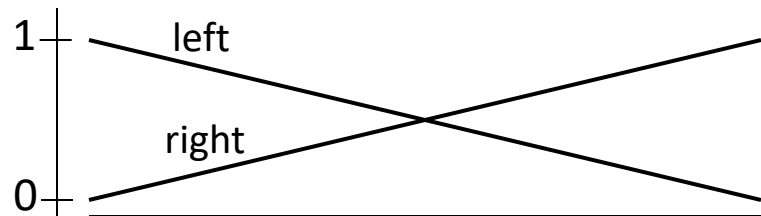
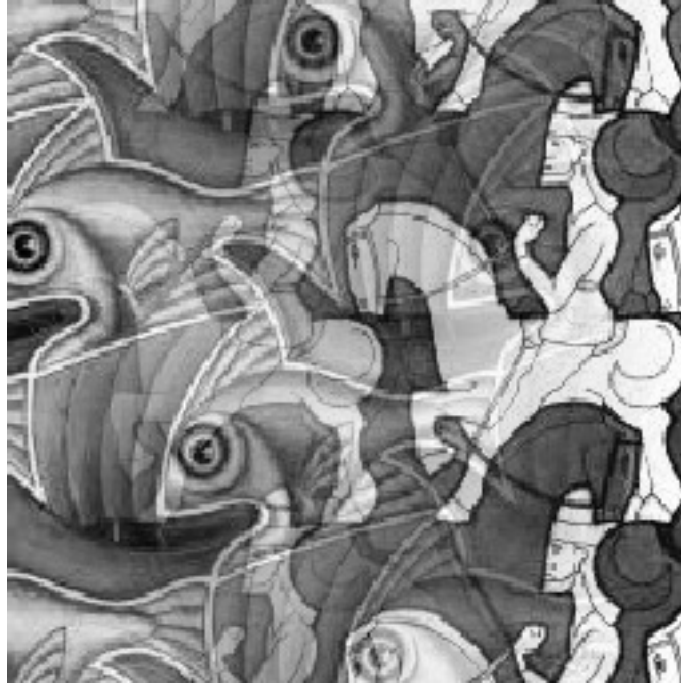
Image Blending



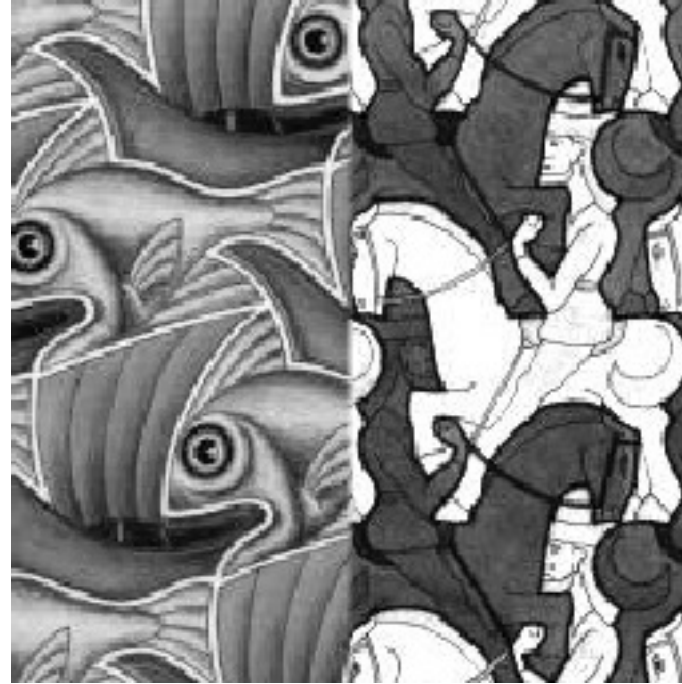
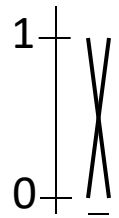
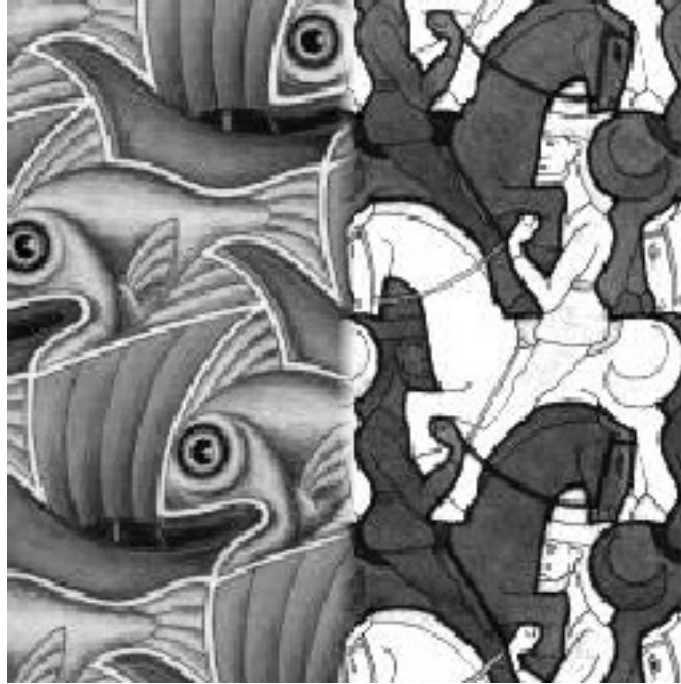
Feathering



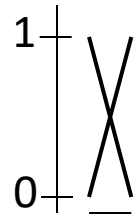
Effect of window size



Effect of window size



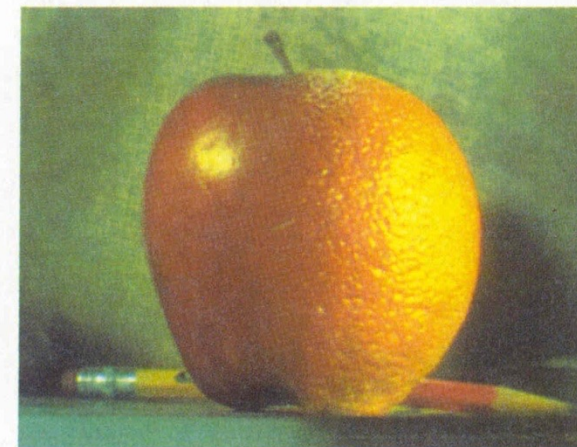
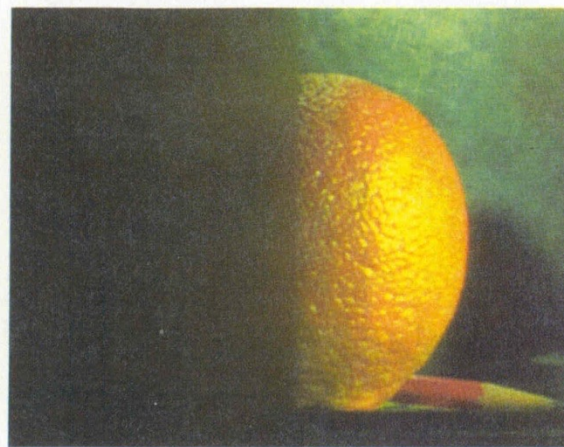
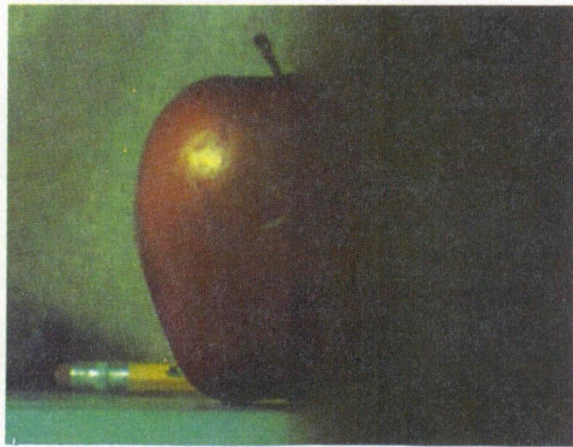
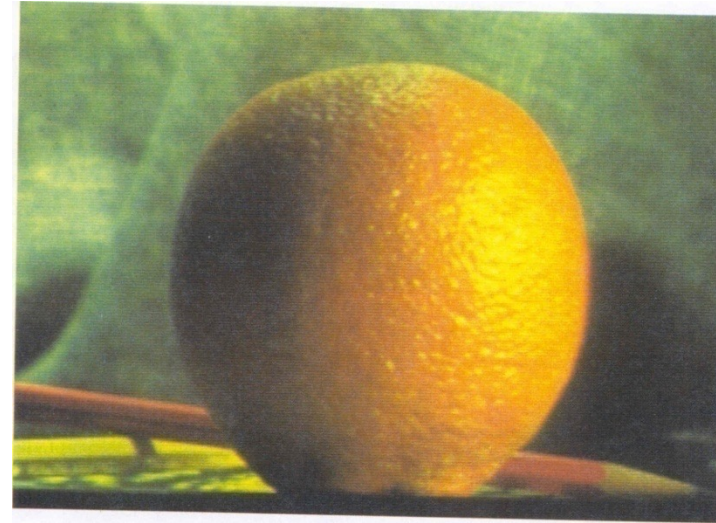
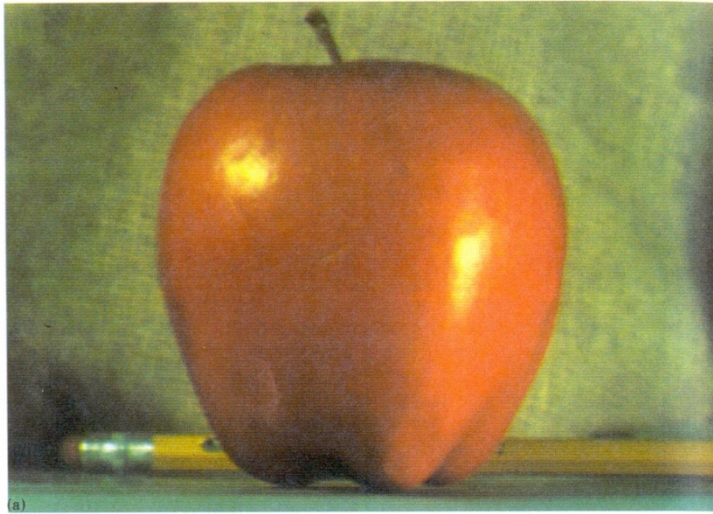
Good window size



“Optimal” window: smooth but not ghosted

- Doesn't always work...

Pyramid blending

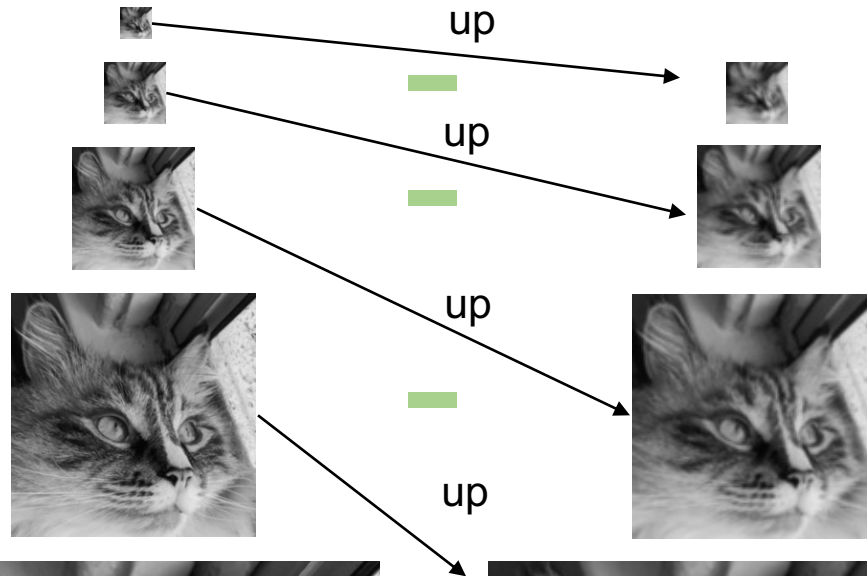


Create a Laplacian pyramid, blend each level

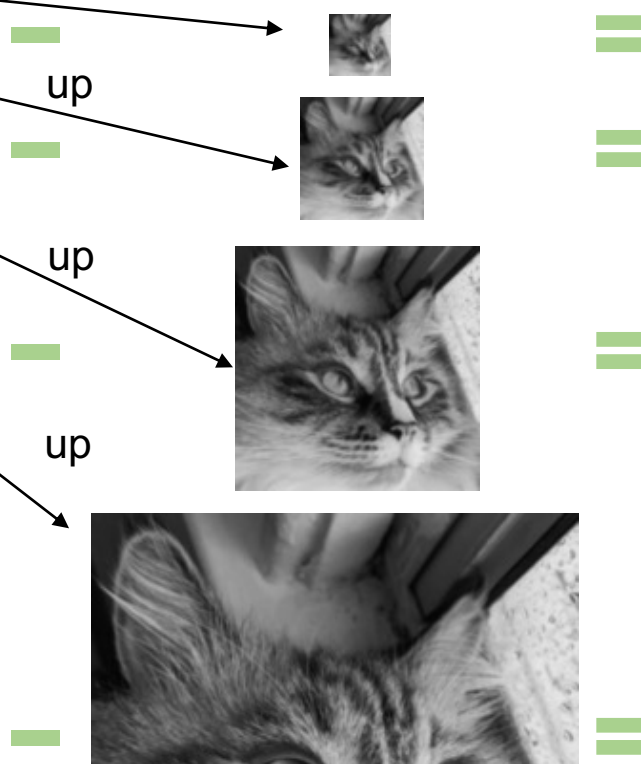
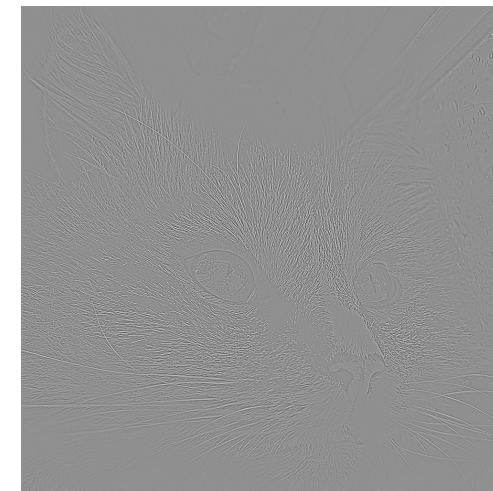
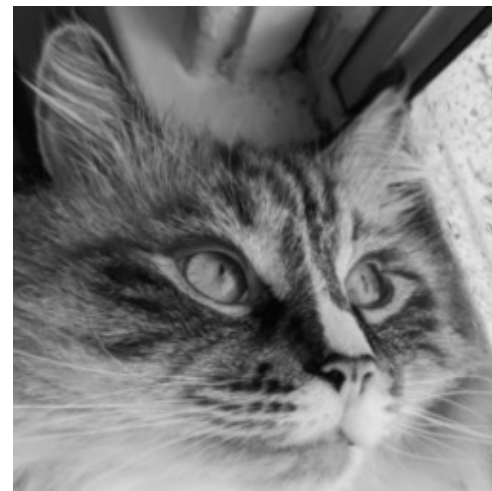
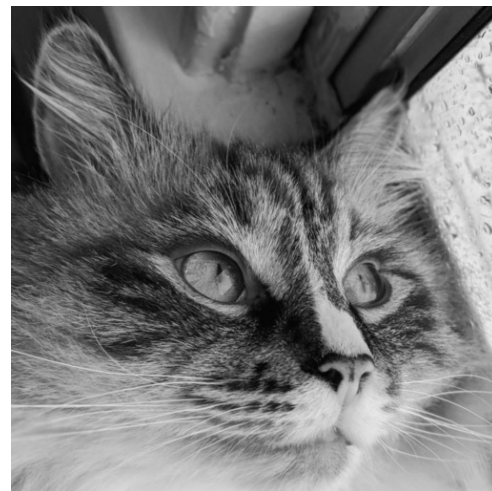
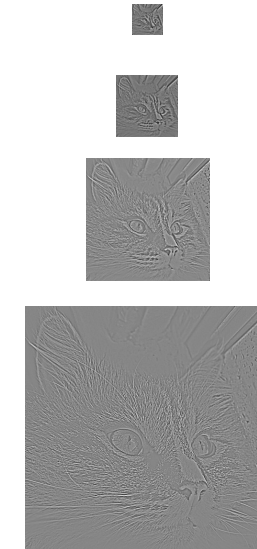
- Burt, P. J. and Adelson, E. H., [A multiresolution spline with applications to image mosaics](#), ACM Transactions on Graphics, 42(4), October 1983, 217-236.

Band-pass filtering in spatial domain

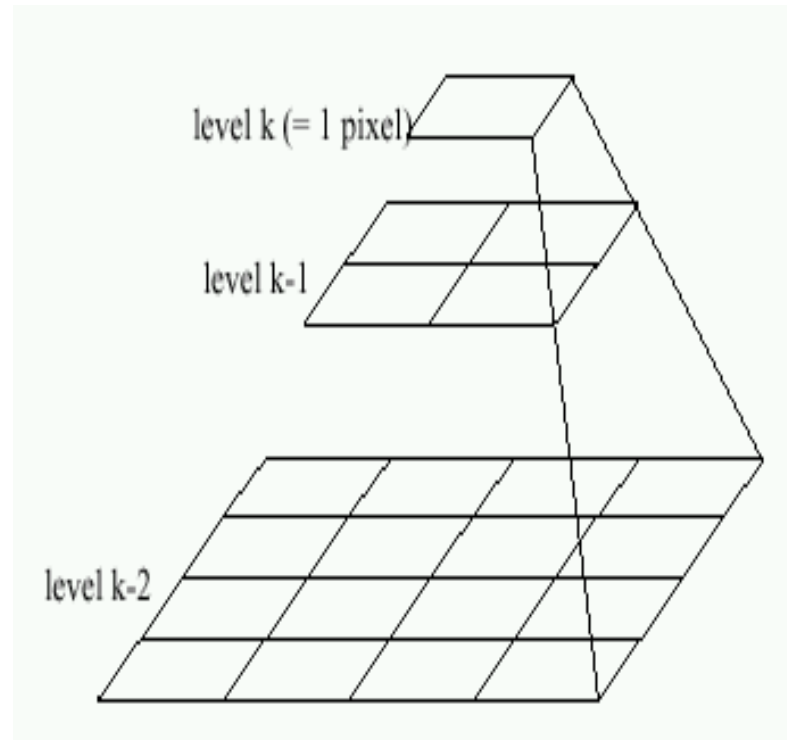
Gaussian Pyramid
(low-pass images) :



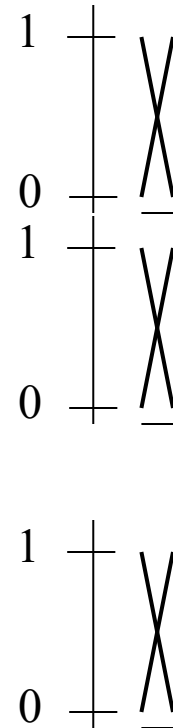
Laplacian Pyramid
(sub-band images)



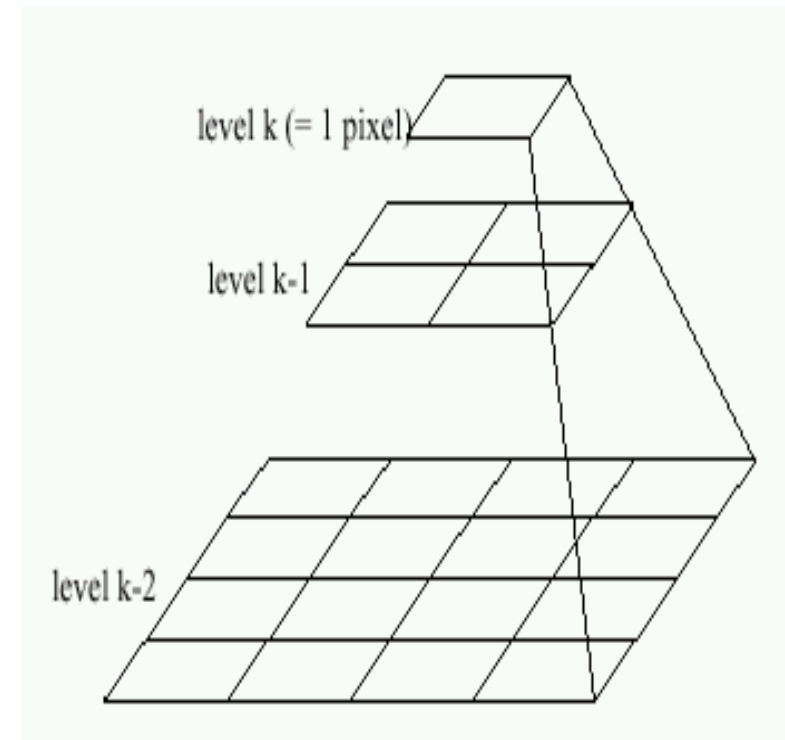
Pyramid Blending



Left pyramid

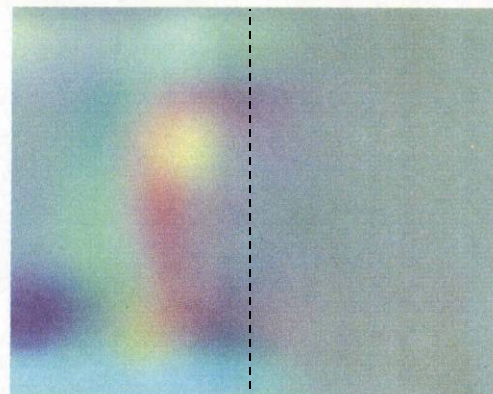


blend

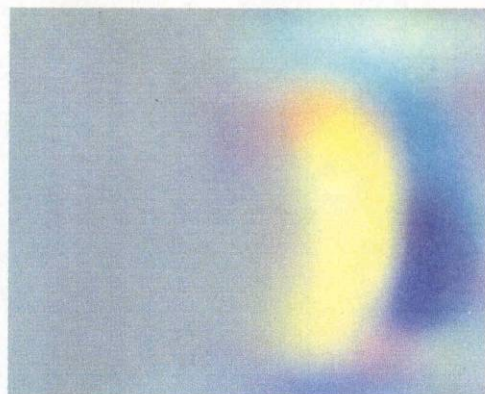


Right pyramid

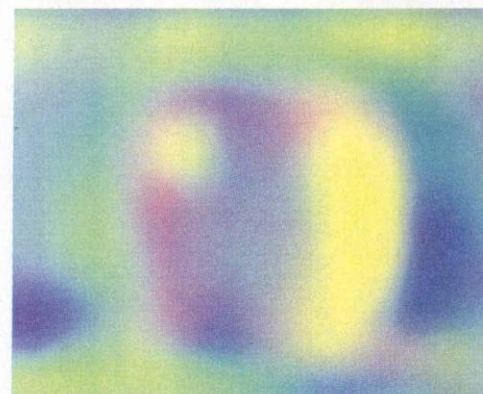
laplacian
level
4



(c)

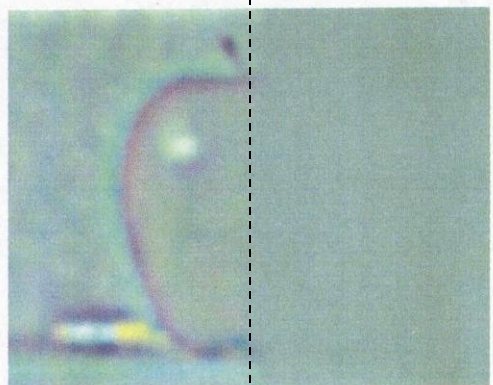


(g)

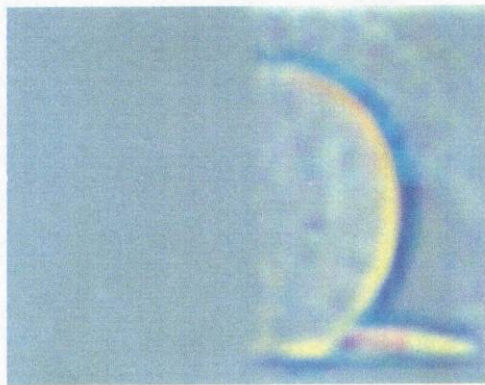


(k)

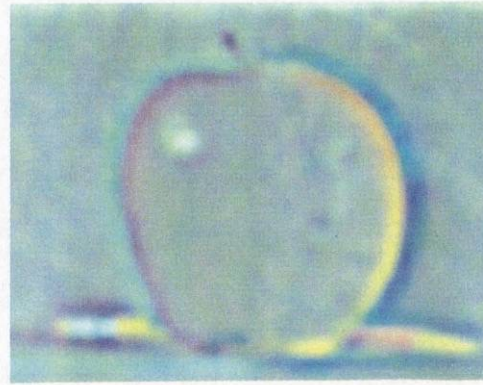
laplacian
level
2



(b)

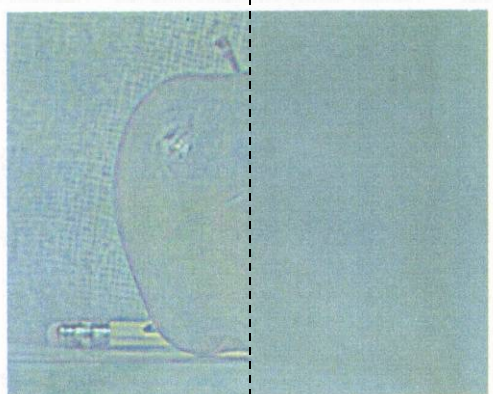


(f)

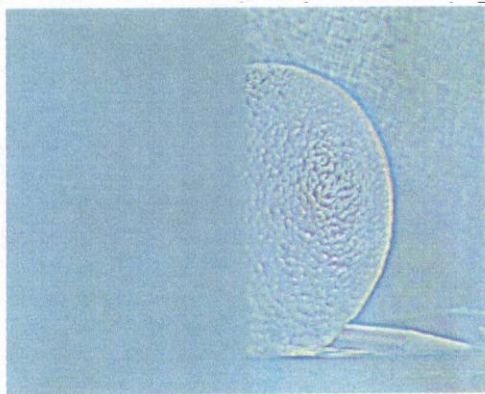


(j)

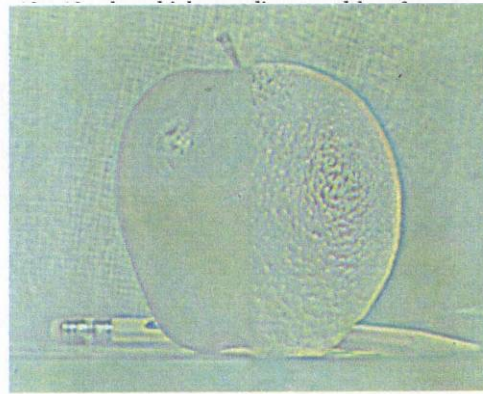
laplacian
level
0



(a)



(e)



(i)

left pyramid

right pyramid

blended pyramid

Laplacian Pyramid: Blending

- General Approach:
 1. Build Laplacian pyramids LA and LB from images A and B
 2. Build a Gaussian pyramid GR from selected region R
 3. Form a combined pyramid LS from LA and LB using nodes of GR as weights:
 - $LS(i,j) = GR(i,j)*LA(i,j) + (1-GR(i,j))*LB(i,j)$
 4. Collapse the LS pyramid to get the final blended image

Poisson Image Editing



For more info: [Perez et al, SIGGRAPH 2003](#)

Today's class

- Fitting with outliers – RANSAC
- Warping
- Blending
- **HW3 Motivation**

Fun with homographies

Original image



St.Petersburg
photo by A. Tikhonov

Virtual camera rotations



Analysing patterns and shapes

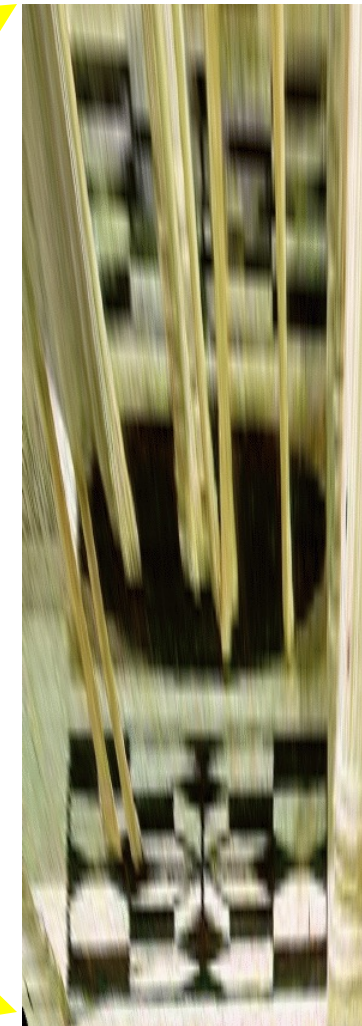
What is the shape of the b/w floor pattern?



Homography



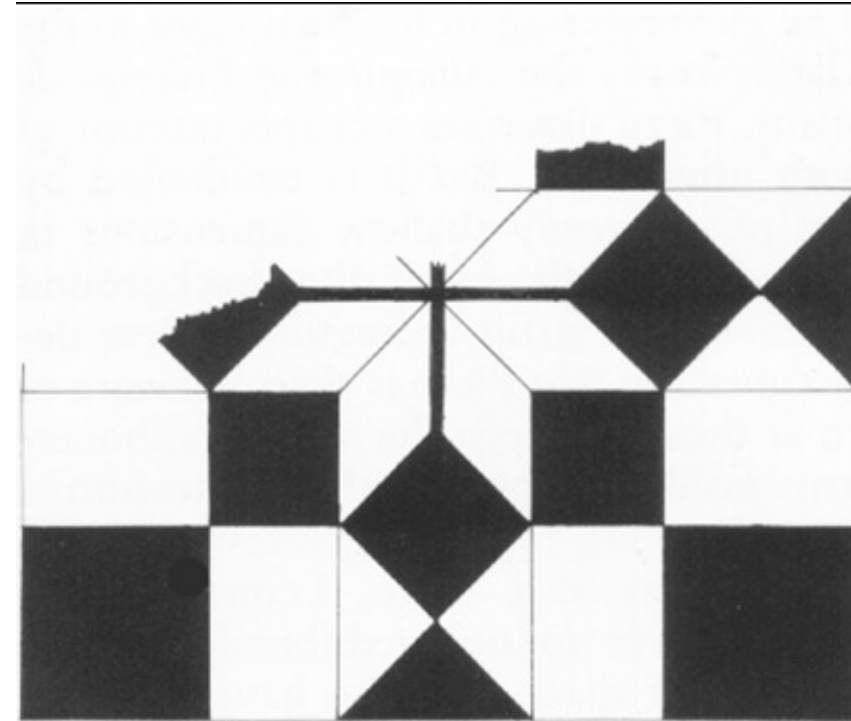
The floor (enlarged)



Automatically rectified floor

Analysing patterns and shapes

Automatic rectification



From Martin Kemp *The Science of Art*
(*manual reconstruction*)

2 patterns have been discovered !

Analysing patterns and shapes



What is the (complicated) shape of the floor pattern?



Automatically rectified floor

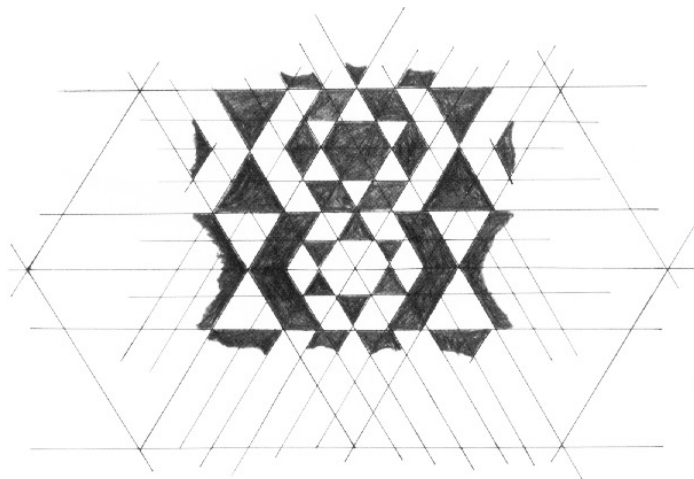
St. Lucy Altarpiece, D. Veneziano

Slide from Criminisi

Analysing patterns and shapes



**Automatic
rectification**



**From Martin Kemp, *The Science of Art*
(*manual reconstruction*)**



virtual wide-angle camera

Some panorama examples



“Before SIGGRAPH Deadline” Photo credit: Doug Zongker

Some panorama examples

- Every image on Google Streetview



Slide Credits

- [CS5670, Introduction to Computer Vision](#), **Cornell Tech**, by **Noah Snavely**.
- [CS 194-26/294-26: Intro to Computer Vision and Computational Photography](#), **UC Berkeley**, by **Alyosha Efros**.