

## Chapter 5.2

# Geometric Transformations

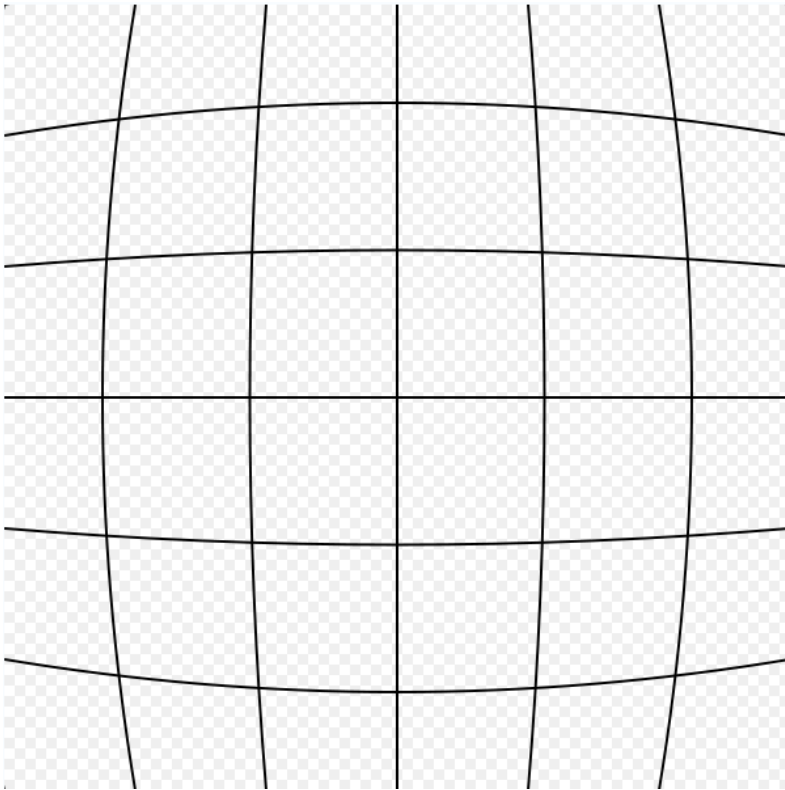
Sources:

- Sonka Textbook
- Gonzalez/Woods DIP textbook

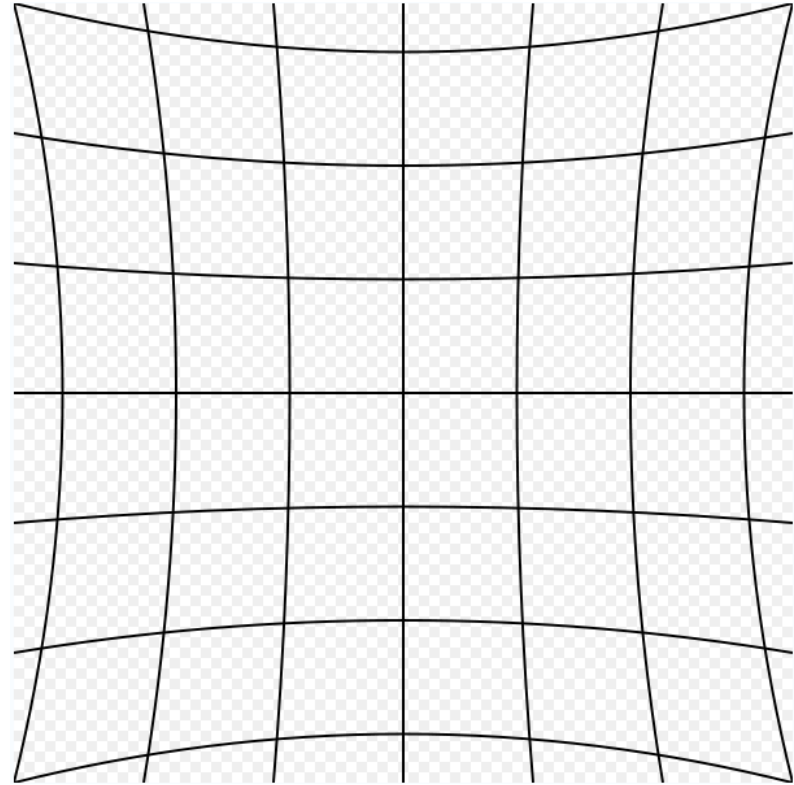
# Geometric Transformations

- Greyscale transformations -> operate on range/output (e.g. via histograms)
- Geometric transformations -> operate on image domain
  - Coordinate transformations
  - Moving image content from one place to another
- Two parts:
  - Define transformation
  - Resample greyscale image in new coordinates

# Geom Trans: Distortion From Optics



Barrel Distortion



Pincushion Distortion

# Radial Distortion

magnification/focal length different  
for different angles of inclination



pincushion  
(tele-photo)

barrel  
(wide-angle)

Can be corrected! (if parameters are know)

# Geom Trans: Distortion From Optics



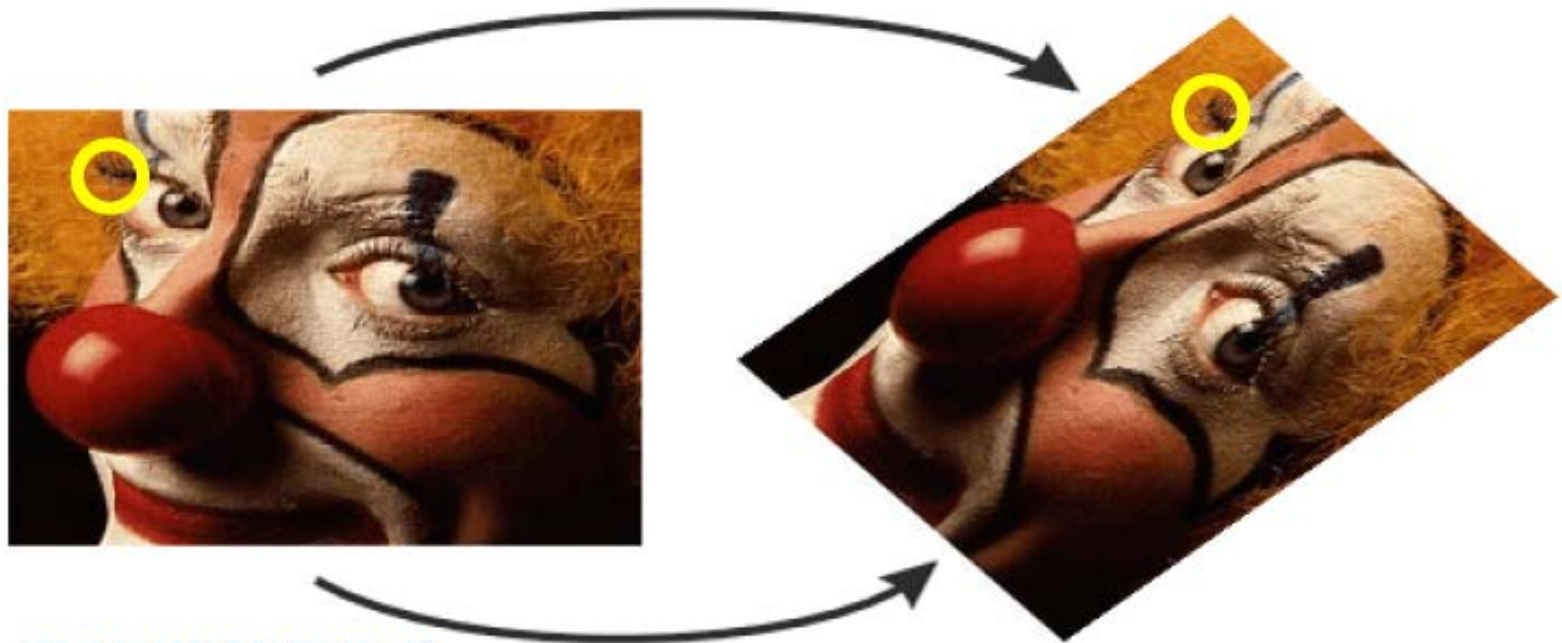


# Geom. Trans.: Mosaicing



Saint-Guérolé Church of Batz-sur-Mer Equirectangular 360° by Vincent Montibus

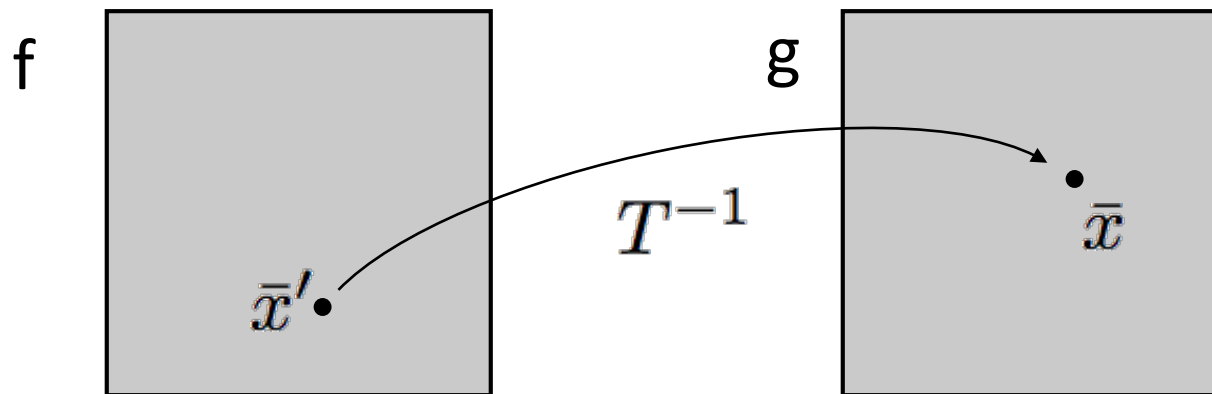
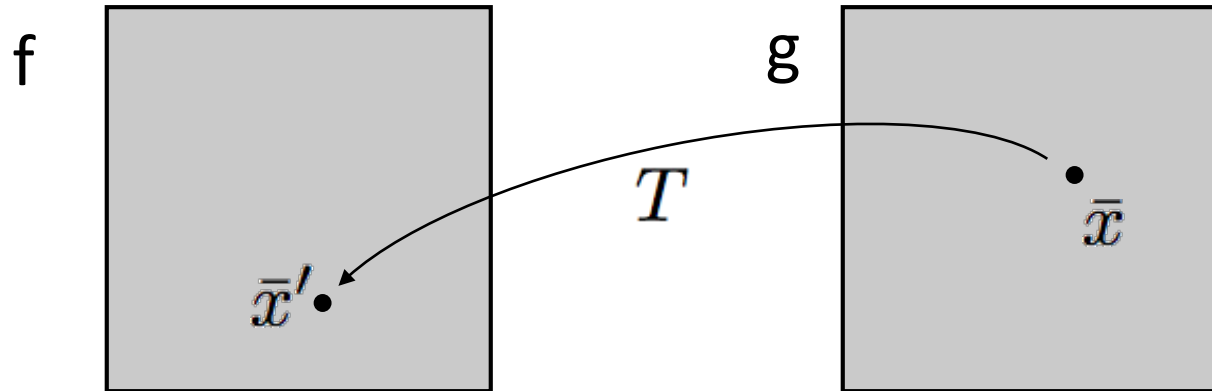
# Domain Mappings Formulation



(E. H. W. Meijering)

$g$  is the same (intensity) image as  $f$ , but sampled on these new coordinates

# Domain Mappings





# Domain Mappings Formulation

$$f \longrightarrow g$$

New image from old one

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = T(x, y) = \begin{pmatrix} T_1(x, y) \\ T_2(x, y) \end{pmatrix}$$

Coordinate transformation  
Two parts – vector valued

$$g(x, y) = f(x', y')$$

$$g(x, y) = f(x', y') = \tilde{f}(x, y)$$

$g$  is the same image as  $f$ , but  
sampled on these new  
coordinates

# Domain Mappings Formulation

$$\bar{x}' = T(\bar{x})$$

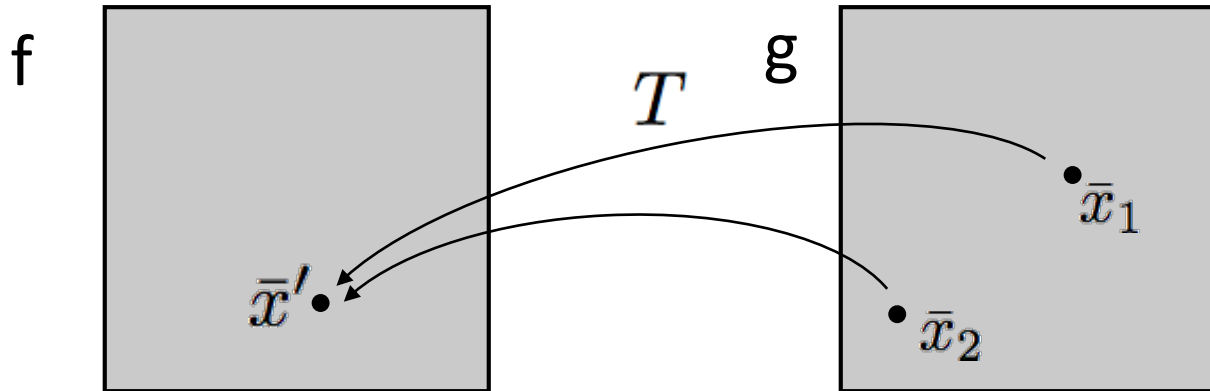
Vector notation is convenient.  
Bar used some times, depends on context.

$$g(\bar{x}) = \tilde{f}(\bar{x}) = f(\bar{x}') = f(T(\bar{x}))$$

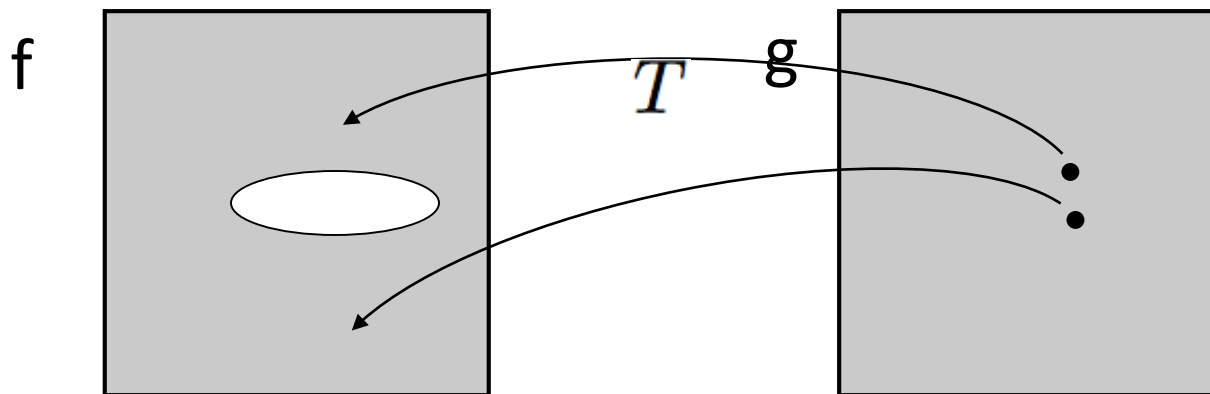
$$\bar{x} = T^{-1}(\bar{x}')$$

T may or may not have an inverse. If not, it means that information was lost.

# No Inverse?

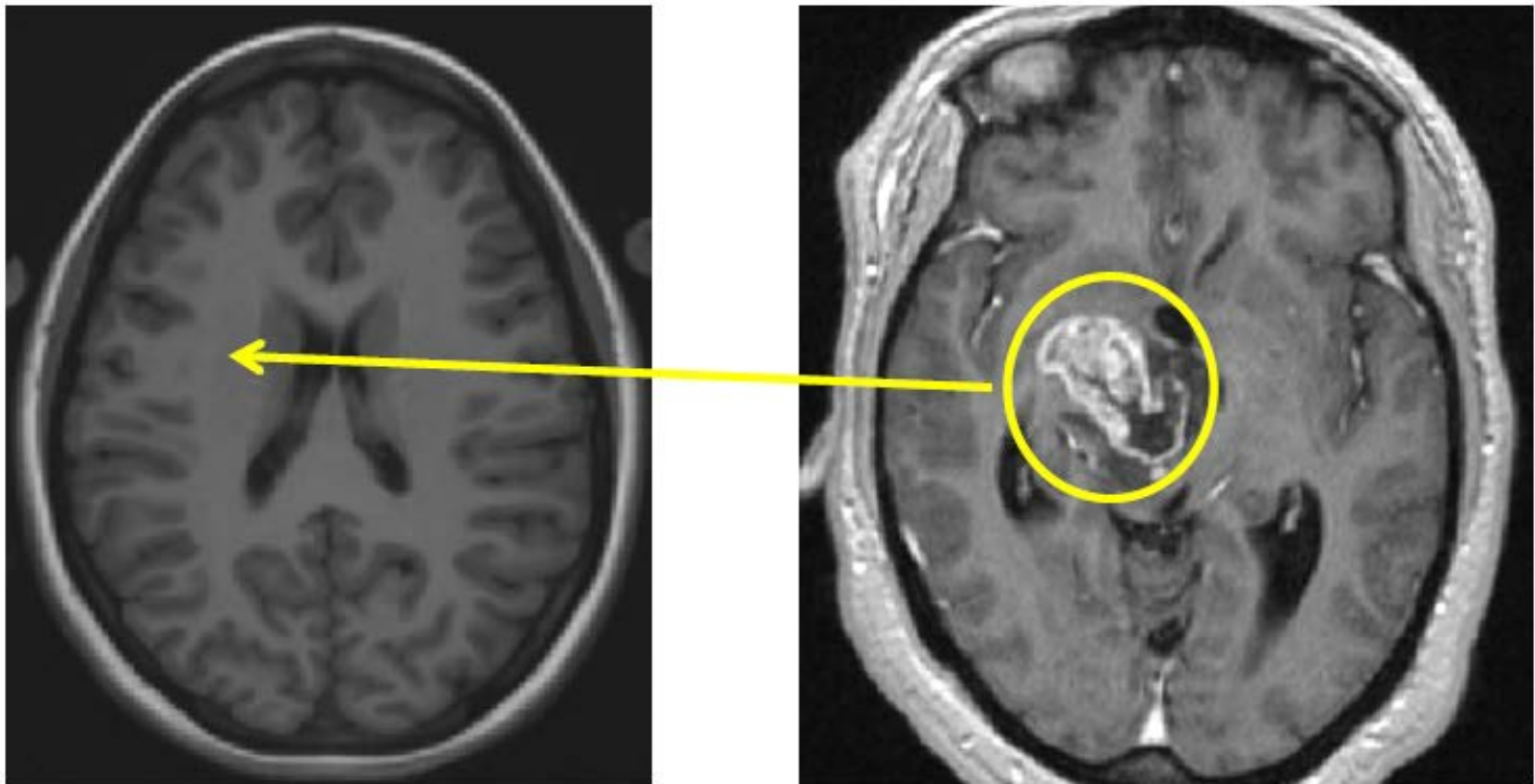


Not “one to one”



Not “onto” -  
doesn’t cover  
 $f$

# Example





# Transformation Examples

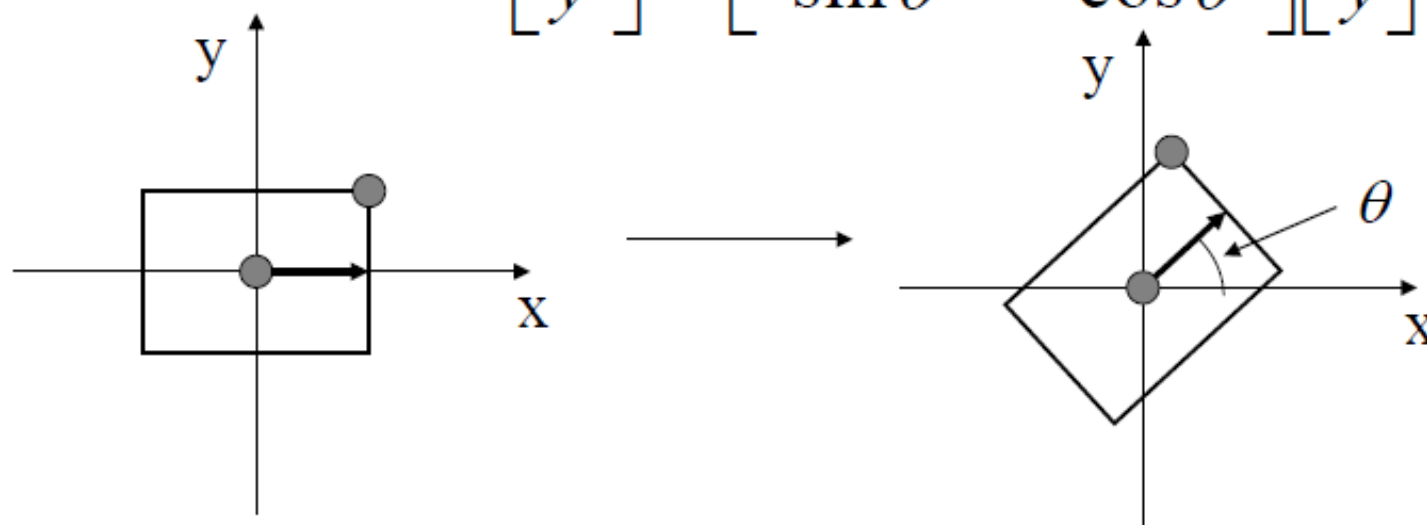
- **Linear**  $\bar{x}' = A\bar{x} + \bar{x}_0$   $A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$   
 $x' = ax + by + x_0$   
 $y' = cx + dy + y_0$



# 2D Rotation

- Rotate counter-clockwise about the origin by an angle  $\theta$

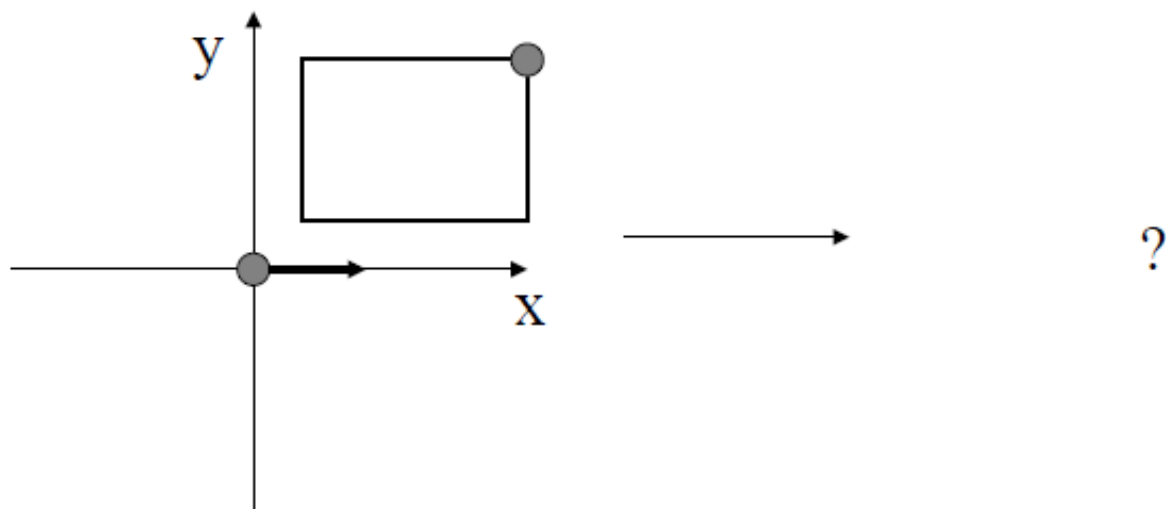
$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$





# Rotating About An Arbitrary Point

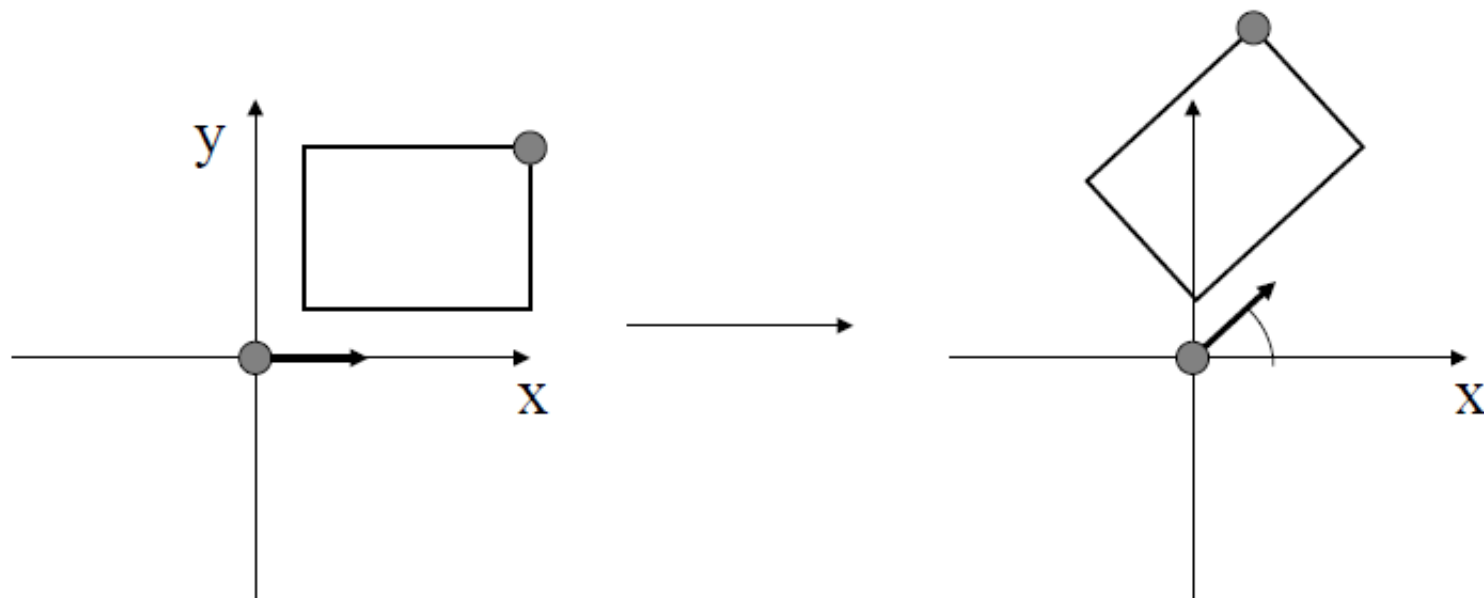
- What happens when you apply a rotation transformation to an object that is not at the origin?





# Rotating About An Arbitrary Point

- What happens when you apply a rotation transformation to an object that is not at the origin?
  - It translates as well

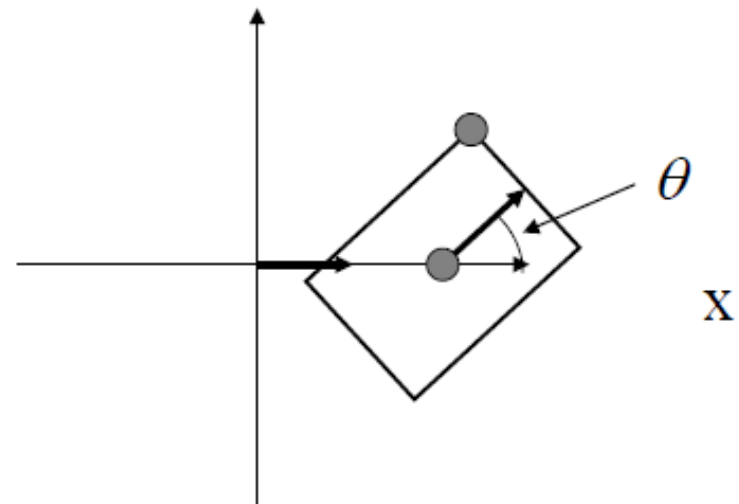
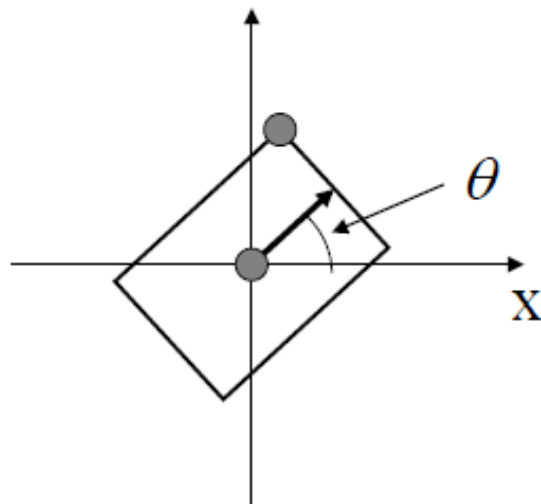






# Now: First Rotate, then Translate

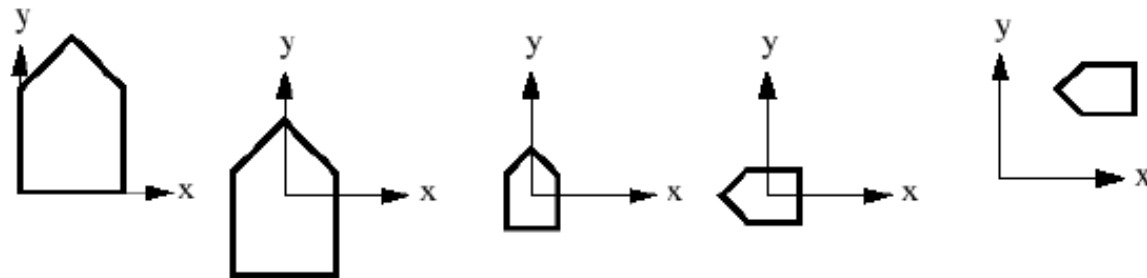
- Rotation followed by translation is **not the same** as translation followed by rotation:
- $T(R(\text{object})) \neq R(T(\text{object}))$



# Series of Transformations

---

2D Object: Translate, scale, rotate, translate again



$$\vec{P'} = T2 + (R \cdot S \cdot (T1 + \vec{P}))$$

➡ Problem: Rotation, scaling, shearing are multiplicative transforms, but translation is additive.

# Transformation Examples

- **Linear**  $\bar{x}' = A\bar{x} + \bar{x}_0$   $A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$   
 $x' = ax + by + x_0$   
 $y' = cx + dy + y_0$

# Transformation Examples

- **Linear**  $\bar{x}' = A\bar{x} + \bar{x}_0$   $A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$   
 $x' = ax + by + x_0$   
 $y' = cx + dy + y_0$

- **Trick: Add one dimension**

$$\bar{x} = \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \quad A = \begin{pmatrix} 1 & 0 & x_0 \\ 0 & 1 & y_0 \\ 0 & 0 & 1 \end{pmatrix} \quad \text{Example: Translation}$$

$$\bar{x}' = A\bar{x} \quad \begin{aligned} x' &= x + x_0 \\ y' &= y + y_0 \\ 1 &= 1 \end{aligned}$$



# Transformation Examples

- **Linear**  $\bar{x}' = A\bar{x} + \bar{x}_0$   $A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$   
 $x' = ax + by + x_0$   
 $y' = cx + dy + y_0$

- **Homogeneous coordinates**

$$\bar{x} = \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \quad A = \begin{pmatrix} a & b & x_0 \\ c & d & y_0 \\ 0 & 0 & 1 \end{pmatrix}$$

$$\bar{x}' = A\bar{x}$$



# Homogeneous Coordinates

- Use three numbers to represent a point
- $(x,y)=(wx,wy,w)$  for any constant  $w \neq 0$ 
  - Typically,  $(x,y)$  becomes  $(x,y,1)$
  - To go backwards, divide by  $w$
- Translation can now be done with matrix multiplication!

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a_{xx} & a_{xy} & b_x \\ a_{yx} & a_{yy} & b_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$



# Basic Transformations

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- Translation:  $\begin{bmatrix} 1 & 0 & b_x \\ 0 & 1 & b_y \\ 0 & 0 & 1 \end{bmatrix}$       Rotation:  $\begin{bmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$
- Scaling:  $\begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{bmatrix}$

# Special Cases of Linear

- Translation

$$A = \begin{pmatrix} 0 & 0 & x_0 \\ 0 & 0 & y_0 \\ 0 & 0 & 1 \end{pmatrix}$$

- Rotation

$$A = \begin{pmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

- Rigid = rotation + translation

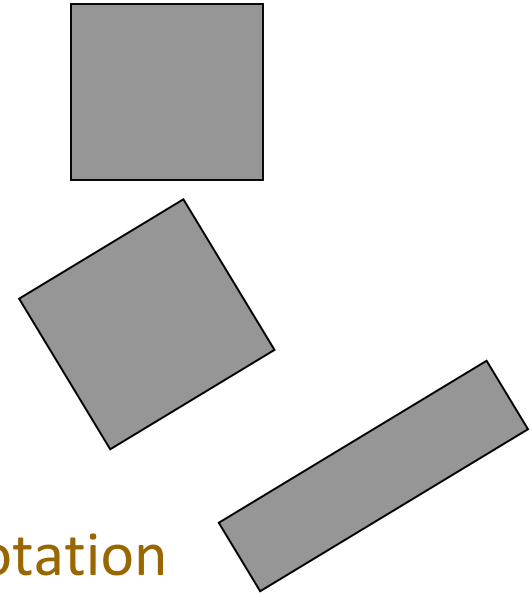
– Include forward and backward rotation for arbitrary axis

- Scaling  $A = \begin{pmatrix} p & 0 & 0 \\ 0 & q & 0 \\ 0 & 0 & 1 \end{pmatrix}$   $p, q < 1$  : expand

- Skew









- Reflection





# Linear Transformations

Transformation Name	Affine Matrix, $T$	Coordinate Equations	Example
Identity	$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$	$x = v$ $y = w$	
Scaling	$\begin{bmatrix} c_x & 0 & 0 \\ 0 & c_y & 0 \\ 0 & 0 & 1 \end{bmatrix}$	$x = c_x v$ $y = c_y w$	
Rotation	$\begin{bmatrix} \cos \theta & \sin \theta & 0 \\ -\sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$	$x = v \cos \theta - w \sin \theta$ $y = v \sin \theta + w \cos \theta$	
Translation	$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ t_x & t_y & 1 \end{bmatrix}$	$x = v + t_x$ $y = w + t_y$	
Shear (vertical)	$\begin{bmatrix} 1 & 0 & 0 \\ s_v & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$	$x = v + s_v w$ $y = w$	
Shear (horizontal)	$\begin{bmatrix} 1 & s_h & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$	$x = v + s_h w$ $y = w$	

$$\begin{bmatrix} x & y & 1 \end{bmatrix} = \begin{bmatrix} v & w & 1 \end{bmatrix} \mathbf{T} = \begin{bmatrix} v & w & 1 \end{bmatrix} \begin{bmatrix} t_{11} & t_{12} & 0 \\ t_{21} & t_{22} & 0 \\ t_{31} & t_{32} & 1 \end{bmatrix}$$

# Resulting Transformations

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$$S = \begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad R = \begin{bmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad T = \begin{bmatrix} 1 & 0 & d_x \\ 0 & 1 & d_y \\ 0 & 0 & 1 \end{bmatrix}$$

new:

$$\vec{P'} = T2 \cdot R \cdot S \cdot T1 \cdot \vec{P}$$

before:  $\vec{P'} = T2 + (R \cdot S \cdot (T1 + \vec{P}))$

# Cascading of Transformations

Excellent Introduction Materials (MIT):

<http://groups.csail.mit.edu/graphics/classes/6.837/F01/Lecture07/>

Demo:

<http://groups.csail.mit.edu/graphics/classes/6.837/F01/Lecture07/Slide09.html>



# Excellent Materials for self study

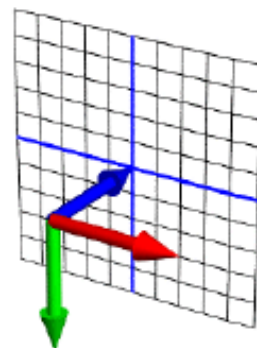
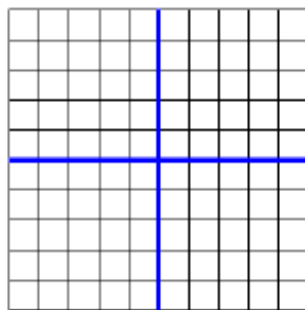
<http://groups.csail.mit.edu/graphics/classes/6.837/F01/Lecture07/Slide01.html>

## Problems with this Form

- Must consider Translation and Rotation separately
- Computing the inverse transform involves multiple steps
- Order matters between the R and T parts

$$R(T(\bar{x})) \neq T(R(\bar{x}))$$

*These problem can be remedied by considering our 2 dimensional image plane as a 2D subspace within 3D.*



Link: <http://groups.csail.mit.edu/graphics/classes/6.837/F01/Lecture07/Slide01.html>

# Linear Transformations

- Also called “affine”
  - 6 parameters
- Rigid -> 3 parameters
- Invertibility  $T^{-1}(\bar{x}) = A^{-1}\bar{x}$ 
  - Invert matrix
- What does it mean if A is not invertible?

# Implementation

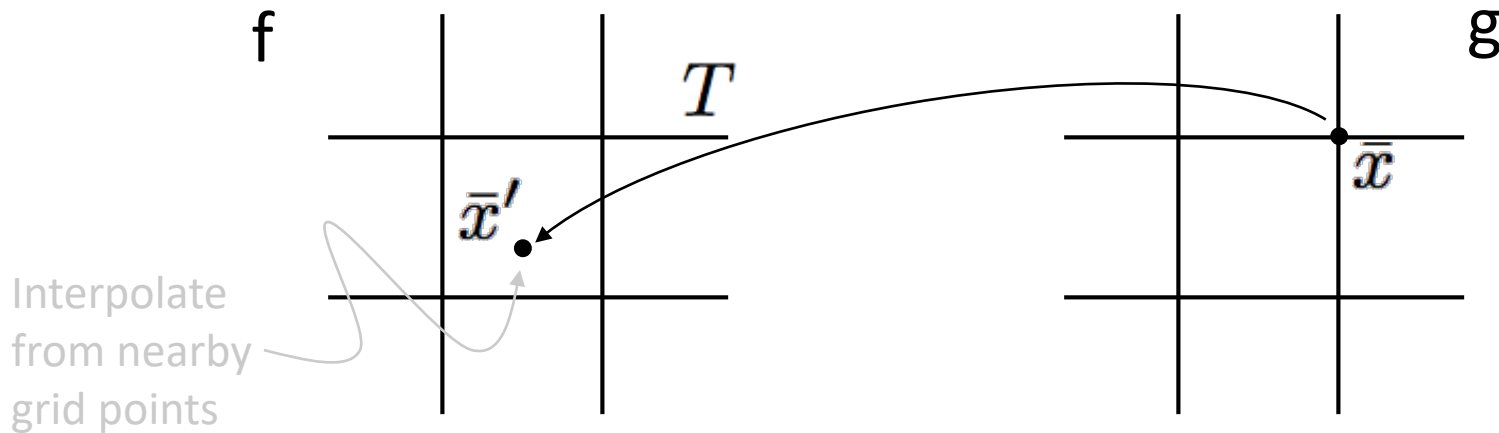
Two major procedures:

1. Definition or estimation of transformation type and parameters
2. Application of transformation: Actual transformation of image

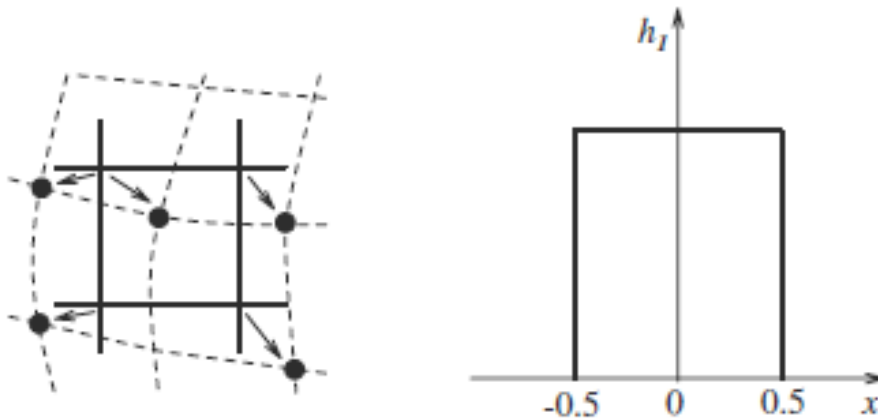
# Implementation – Two Approaches

## 1. Pixel filling – backward mapping

- $T()$  takes you from coords in  $g()$  to coords in  $f()$
- Need random access to pixels in  $f()$
- Sample grid for  $g()$ , interpolate  $f()$  as needed



- Nearest-neighborhood interpolation
  - Assigned to point  $(x,y)$  brightness value of nearest point  $g$  in discrete raster

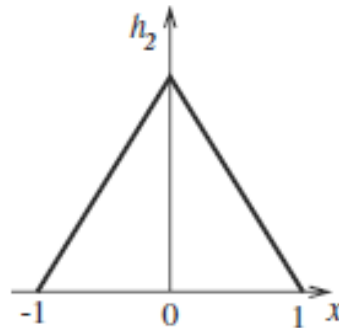
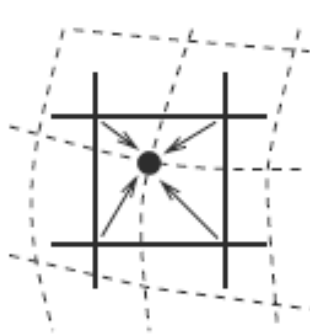


**Figure 5.6:** Nearest-neighborhood interpolation. The discrete raster of the original image is depicted by the solid line. © Cengage Learning 2015.



- Linear interpolation

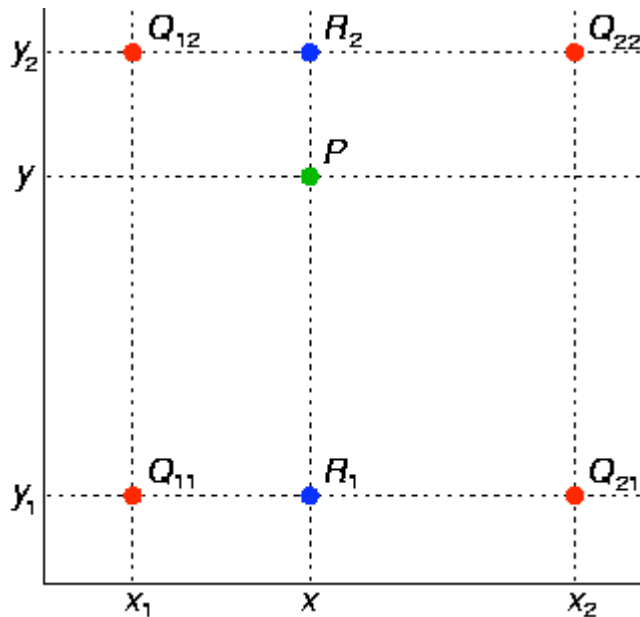
- Explores four points neighboring the point  $(x,y)$  and assumes that the brightness function is linear in this neighborhood



**Figure 5.7:** Linear interpolation. The discrete raster of the original image is depicted by the solid line. © Cengage Learning 2015.

# Interpolation: Bilinear

- Successive application of linear interpolation along each axis



$$f(R_1) \approx \frac{x_2 - x}{x_2 - x_1} f(Q_{11}) + \frac{x - x_1}{x_2 - x_1} f(Q_{21})$$

$$f(R_2) \approx \frac{x_2 - x}{x_2 - x_1} f(Q_{12}) + \frac{x - x_1}{x_2 - x_1} f(Q_{22})$$

$$f(P) \approx \frac{y_2 - y}{y_2 - y_1} f(R_1) + \frac{y - y_1}{y_2 - y_1} f(R_2).$$

Source: Wikipedia

# Binlinear Interpolation

- *Not* linear in  $x, y$

$$\begin{aligned} f(x, y) \approx & \frac{f(Q_{11})}{(x_2 - x_1)(y_2 - y_1)}(x_2 - x)(y_2 - y) \\ & + \frac{f(Q_{21})}{(x_2 - x_1)(y_2 - y_1)}(x - x_1)(y_2 - y) \\ & + \frac{f(Q_{12})}{(x_2 - x_1)(y_2 - y_1)}(x_2 - x)(y - y_1) \\ & + \frac{f(Q_{22})}{(x_2 - x_1)(y_2 - y_1)}(x - x_1)(y - y_1). \end{aligned}$$

$$b_1 + b_2x + b_3y + b_4xy$$

---

$$b_1 = f(0, 0)$$

$$b_2 = f(1, 0) - f(0, 0)$$

$$b_3 = f(0, 1) - f(0, 0)$$

$$b_4 = f(0, 0) - f(1, 0) - f(0, 1) + f(1, 1).$$

# Binlinear Interpolation

- Convenient form
  - Normalize to unit grid  $[0,1] \times [0,1]$

$$f(x, y) \approx f(0, 0) (1 - x)(1 - y) + f(1, 0) x(1 - y) + f(0, 1) (1 - x)y + f(1, 1)xy.$$

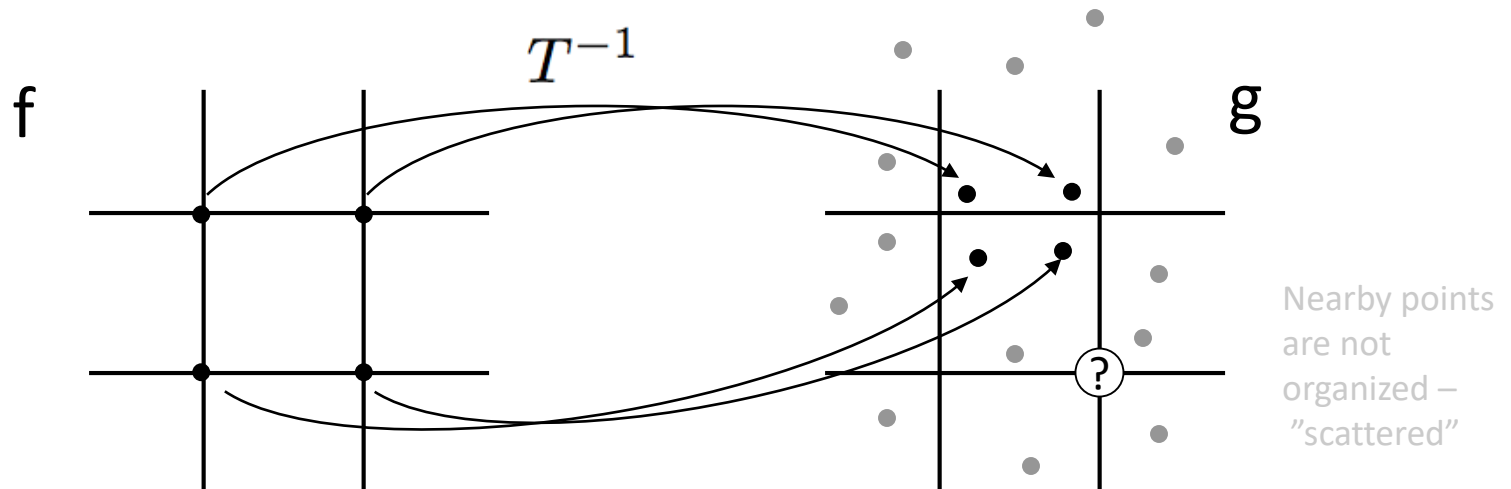
$$f(x, y) \approx \begin{bmatrix} 1 - x & x \end{bmatrix} \begin{bmatrix} f(0, 0) & f(0, 1) \\ f(1, 0) & f(1, 1) \end{bmatrix} \begin{bmatrix} 1 - y \\ y \end{bmatrix}.$$

- Bilinear is **NONLINEAR** in  $x$  and  $y$  !

# Implementation – Two Approaches

## 2. Splatting – forward mapping

- $T^{-1}()$  takes you from coords in  $f()$  to coords in  $g()$
- You have  $f()$  on grid, but you need  $g()$  on grid
- Push grid samples onto  $g()$  grid and do interpolation from unorganized data (kernel)



# Scattered Data Interpolation With Kernels

## Shepard's method

- Define kernel
  - Falls off with distance, radially symmetric

$$K(\bar{x}_1, \bar{x}_2) = K(|\bar{x}_1 - \bar{x}_2|)$$

$$g(x) = \frac{1}{\sum_{j=1}^N w_j} \sum_{i=1}^N w_i f(x'_i)$$

$$w_j = K(|\bar{x} - T^{-1}(\bar{x}'_j)|)$$

Required  
grid  
coordinates  
in g

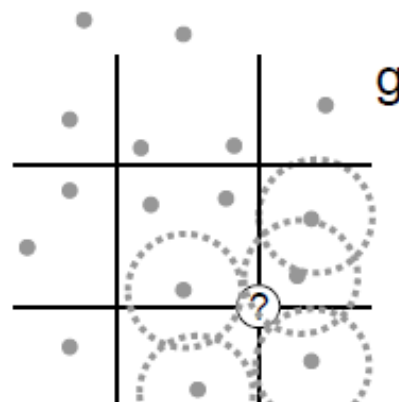
Transformed  
coord. from f

Grid coordinates in f

Kernel examples

$$K(\bar{x}_1, \bar{x}_2) = \frac{1}{2\pi\sigma^2} e^{-\frac{|\bar{x}_1 - \bar{x}_2|^2}{2\sigma^2}}$$

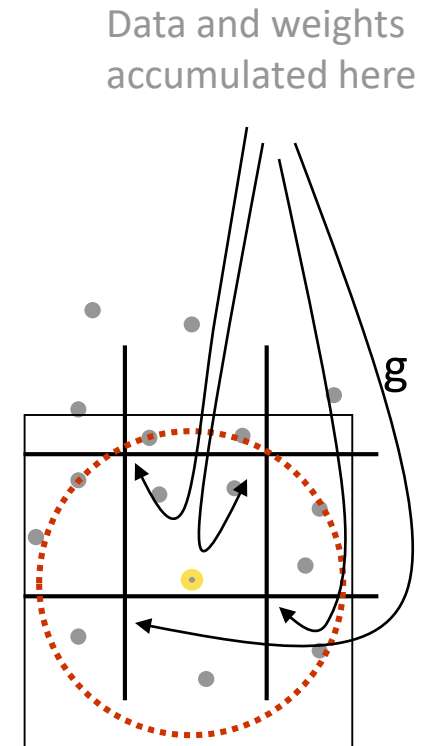
$$K(\bar{x}_1, \bar{x}_2) = \frac{1}{|\bar{x}_1 - \bar{x}_2|^p}$$



# Shepard's Method Implementation

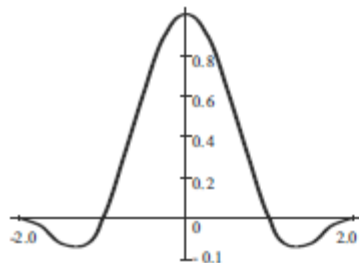
- If points are dense enough
  - Truncate kernel
  - For each point in  $f()$ 
    - Form a small box around it in  $g()$  – beyond which truncate
    - Put weights and data onto grid in  $g()$
  - Accumulate contributions at grid  $g()$
  - Divide total data by total weights:  $B/A$

$$A = \sum_{j=1}^N w_j \quad B = \sum_{i=1}^N w_i f(T^{-1}(x'_i))$$



- **Bi-cubic interpolation**

- Improves the model of the brightness function by approximating it locally by a bi-cubic polynomial surface
- 16 neighboring points are used for interpolation
- Does not suffer from step-like boundary problem of nearest-neighborhood interpolation
- Often used in raster displays that enable zooming with respect to an arbitrary point



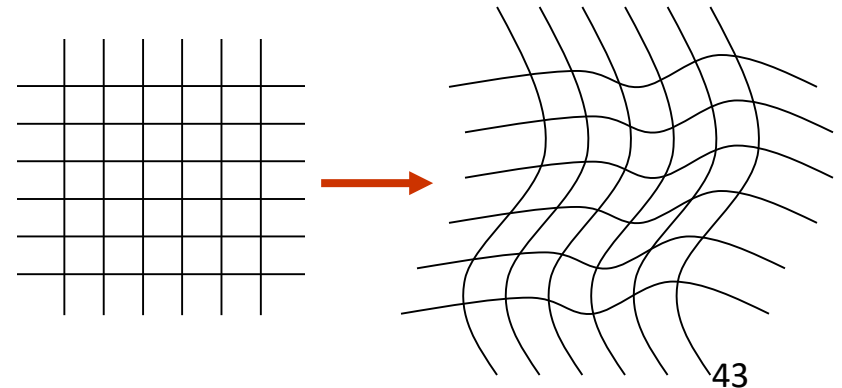
**Figure 5.8:** Bi-cubic interpolation kernel.  
© Cengage Learning 2015.



# ESTIMATION OF TRANSFORMATIONS

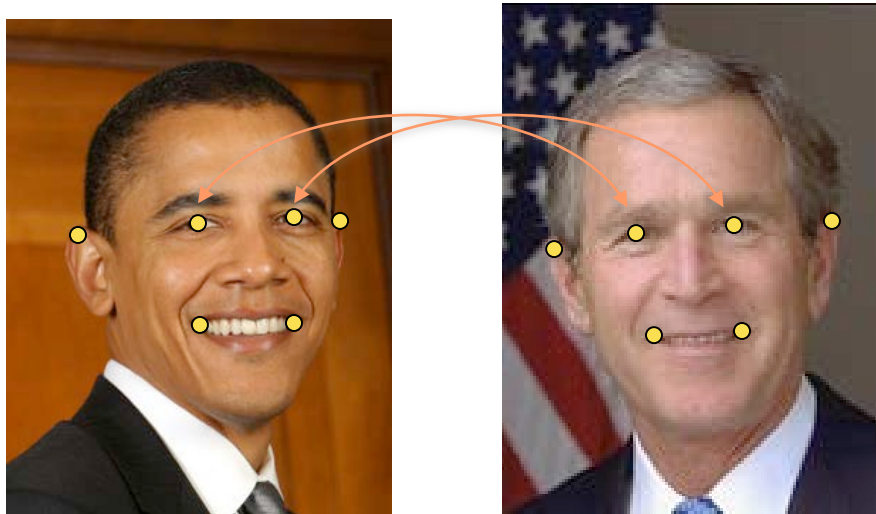
# Determine Transformations

- All polynomials of  $(x,y)$
- Any vector valued function with 2 inputs
- How to construct transformations?
  - Define form or class of a transformation
  - Choose parameters within that class
    - Rigid - 3 parameters  $(T,R)$
    - Affine - 6 parameters



# Correspondences

- Also called “landmarks” or “fiducials”



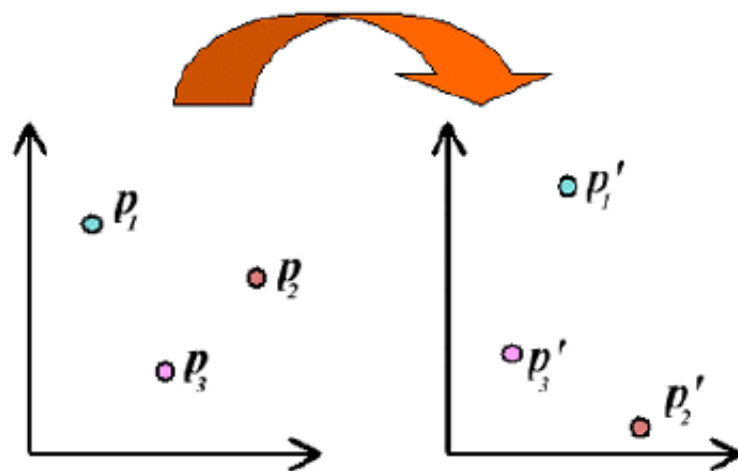
$\bar{c}_1, \bar{c}'_1$   
 $\bar{c}_2, \bar{c}'_2$   
 $\bar{c}_3, \bar{c}'_3$   
 $\bar{c}_4, \bar{c}'_4$   
 $\bar{c}_5, \bar{c}'_5$   
 $\bar{c}_6, \bar{c}'_6$

Question: How many  
landmarks for affine T?

# Question: How many landmarks for affine T?

- Estimation of 6 parameters  $\rightarrow$  3 corresponding point pairs with (x,y) coordinates

The coordinates of three corresponding points uniquely determine an Affine Transform



If we know where we would like at least three points to map to, we can solve for an Affine transform that will give this mapping.

# Transformations/Control Points Strategy

1. Define a functional representation for  $T$  with  $k$  parameters ( $B$ )  
 $T(\beta, \bar{x})$   
 $\beta = (\beta_1, \beta_2, \dots, \beta_K)$
2. Define (pick)  $N$  correspondences

3. Find  $B$  so that

$$\bar{c}'_i = T(\beta, \bar{c}_i) \quad i = 1, \dots, N$$

4. If overconstrained ( $K < 2N$ ) then solve

$$\arg \min_{\beta} \left[ \sum_{i=1}^N (\bar{c}'_i - T(\beta, \bar{c}_i))^2 \right]$$

# Example Affine Transformation: 3 Corresponding Landmarks

## Solution Method

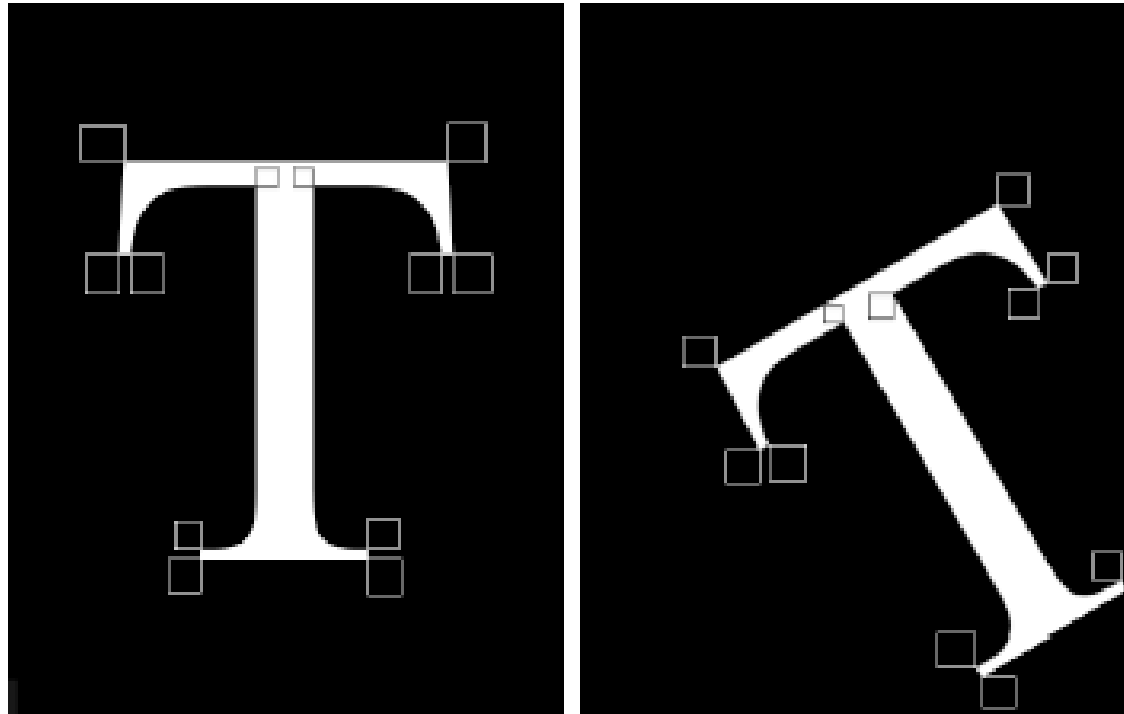
We've used this technique several times now. We set up 6 linear equations in terms of our 6 unknown values. In this case, we know the coordinates before and after the mapping, and we wish to solve for the entries in our Affine transform matrix.

This gives the following solution:

$$\mathbf{X}^{-1}\mathbf{x}' = \mathbf{a}$$

$$\underbrace{\begin{bmatrix} x'_1 \\ y'_1 \\ x'_2 \\ y'_2 \\ x'_3 \\ y'_3 \end{bmatrix}}_{\mathbf{x}'} = \underbrace{\begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_1 & y_1 & 1 \\ x_2 & y_2 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_2 & y_2 & 1 \\ x_3 & y_3 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_3 & y_3 & 1 \end{bmatrix}}_{\mathbf{X}} \underbrace{\begin{bmatrix} a_{11} \\ a_{12} \\ a_{13} \\ a_{21} \\ a_{22} \\ a_{23} \end{bmatrix}}_{\mathbf{a}}$$

# Example



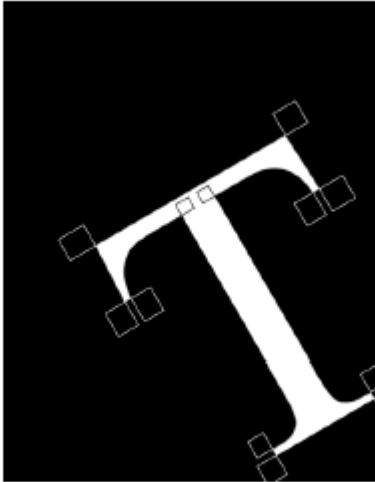
Left: source\_letter\_T.tif

Right: target\_letter\_T.tif

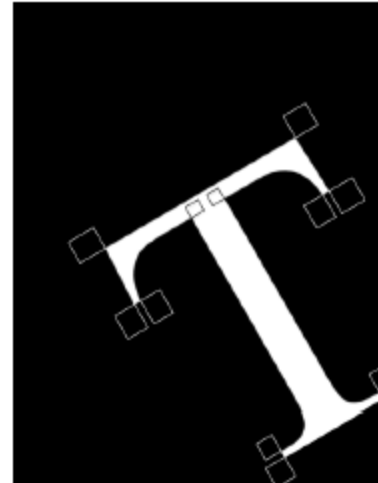


# Example ctd.

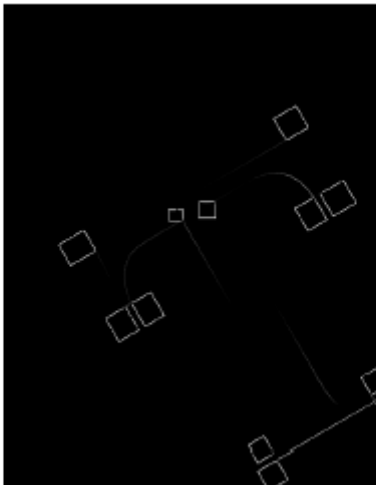
When choose all the marked points of the letter T image, I get the result:



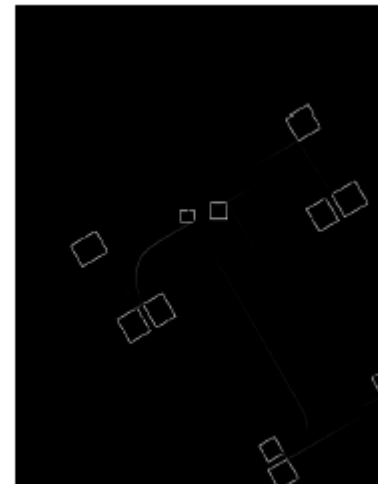
after\_landmarks\_affine\_transform\_3\_points\_source\_letter\_T.tif



after\_landmarks\_affine\_transform\_12\_points\_source\_letter\_T.tif



difference\_between\_source\_and\_target\_3\_points\_source\_letter\_T.tif



difference\_between\_source\_and\_target\_12\_points\_source\_letter\_T.tif

# Example: Quadratic

Transformation

$$T_x = \beta_x^{00} + \beta_x^{10}x + \beta_x^{01}y + \beta_x^{11}xy + \beta_x^{20}x^2 + \beta_x^{02}y^2$$

$$T_y = \beta_y^{00} + \beta_y^{10}x + \beta_y^{01}y + \beta_y^{11}xy + \beta_y^{20}x^2 + \beta_y^{02}y^2$$

Denote  $\bar{c}_i = (c_{x,i}, c_{y,i})$

Correspondences must match

$$c'_{y,i} = \beta_y^{00} + \beta_y^{10}c_{x,i} + \beta_y^{01}c_{y,i} + \beta_y^{11}c_{x,i}c_{y,i} + \beta_y^{20}c_{x,i}^2 + \beta_y^{02}c_{y,i}^2$$

$$c'_{x,i} = \beta_x^{00} + \beta_x^{10}c_{x,i} + \beta_x^{01}c_{y,i} + \beta_x^{11}c_{x,i}c_{y,i} + \beta_x^{20}c_{x,i}^2 + \beta_x^{02}c_{y,i}^2$$

Note: these equations are linear in the unknowns

# Write As Linear System

$$\begin{pmatrix} 1 & c_{x,1} & c_{y,1} & c_{x,1}c_{y,1} & c_{x,1}^2 & c_{y,1}^2 \\ 1 & c_{x,2} & c_{y,2} & c_{x,2}c_{y,2} & c_{x,2}^2 & c_{y,2}^2 \\ & & & \vdots & & \\ & & & & 0 & \\ 1 & c_{x,N} & c_{y,N} & c_{x,N}c_{y,N} & c_{x,N}^2 & c_{y,N}^2 \\ & & & & 1 & c_{x,1} & c_{y,1} & c_{x,1}c_{y,1} & c_{x,1}^2 & c_{y,1}^2 \\ & & & & 1 & c_{x,2} & c_{y,2} & c_{x,2}c_{y,2} & c_{x,2}^2 & c_{y,2}^2 \\ & & & & & & & \vdots & & \\ & & & & & & & 1 & c_{x,N} & c_{y,N} & c_{x,N}c_{y,N} & c_{x,N}^2 & c_{y,N}^2 \end{pmatrix} \begin{pmatrix} \beta_x^{00} \\ \beta_x^{10} \\ \beta_x^{01} \\ \beta_x^{11} \\ \beta_x^{20} \\ \beta_x^{02} \\ \beta_y^{00} \\ \beta_y^{10} \\ \beta_y^{01} \\ \beta_y^{11} \\ \beta_y^{20} \\ \beta_y^{02} \end{pmatrix} = \begin{pmatrix} c'_{x,1} \\ c'_{x,2} \\ \vdots \\ c'_{x,N} \\ c'_{y,1} \\ c'_{y,2} \\ \vdots \\ c'_{y,N} \end{pmatrix}$$

$$Ax = b$$

A – matrix that depends on the (unprimed) correspondences and the transformation

x – unknown parameters of the transformation

b – the primed correspondences

# Linear Algebra Background

$$Ax = b$$

$$\begin{array}{rcl} a_{11}x_1 + \dots + a_{1N}x_N & = & b_1 \\ a_{21}x_1 + \dots + a_{2N}x_N & = & b_2 \\ & \dots & \dots \\ a_{M1}x_1 + \dots + a_{MN}x_N & = & b_M \end{array}$$

Simple case: A is square ( $M=N$ ) and invertible ( $\det[A]$  not zero)

$$A^{-1}Ax = Ix = x = A^{-1}b$$

Numerics: Don't find A inverse. Use Gaussian elimination or some kind of decomposition of A

# Solving Least Squares Systems

- Psuedoinverse (normal equations)

$$A^T A x = A^T b$$
$$x = (A^T A)^{-1} A^T b$$

– Issue: often not well conditioned (nearly singular)

- Alternative: *singular value decomposition*  
*SVD*

# Singular Value Decomposition

$$\begin{pmatrix} A \end{pmatrix} = UWV^T = \begin{pmatrix} U \end{pmatrix} \begin{pmatrix} w_1 & & & 0 \\ & w_2 & & \\ & & \dots & \\ 0 & & \dots & w_N \end{pmatrix} \begin{pmatrix} V^T \end{pmatrix}$$

$$I = U^T U = U U^T = V^T V = V V^T$$

Invert matrix A with SVD

$$A^{-1} = V W^{-1} U^T \quad W^{-1} = \begin{pmatrix} \frac{1}{w_1} & & & 0 \\ & \frac{1}{w_2} & & \\ & & \dots & \\ & & \dots & \\ 0 & & & \frac{1}{w_N} \end{pmatrix}$$

# SVD for Singular Systems

- If a system is singular, some of the  $w$ 's will be zero

$$x = VW^*U^Tb$$

$$w_j^* = \begin{cases} 1/w_j & |w_j| > \epsilon \\ 0 & \text{otherwise} \end{cases}$$

- Properties:
  - Underconstrained: solution with shortest overall length
  - Overconstrained: least squares solution

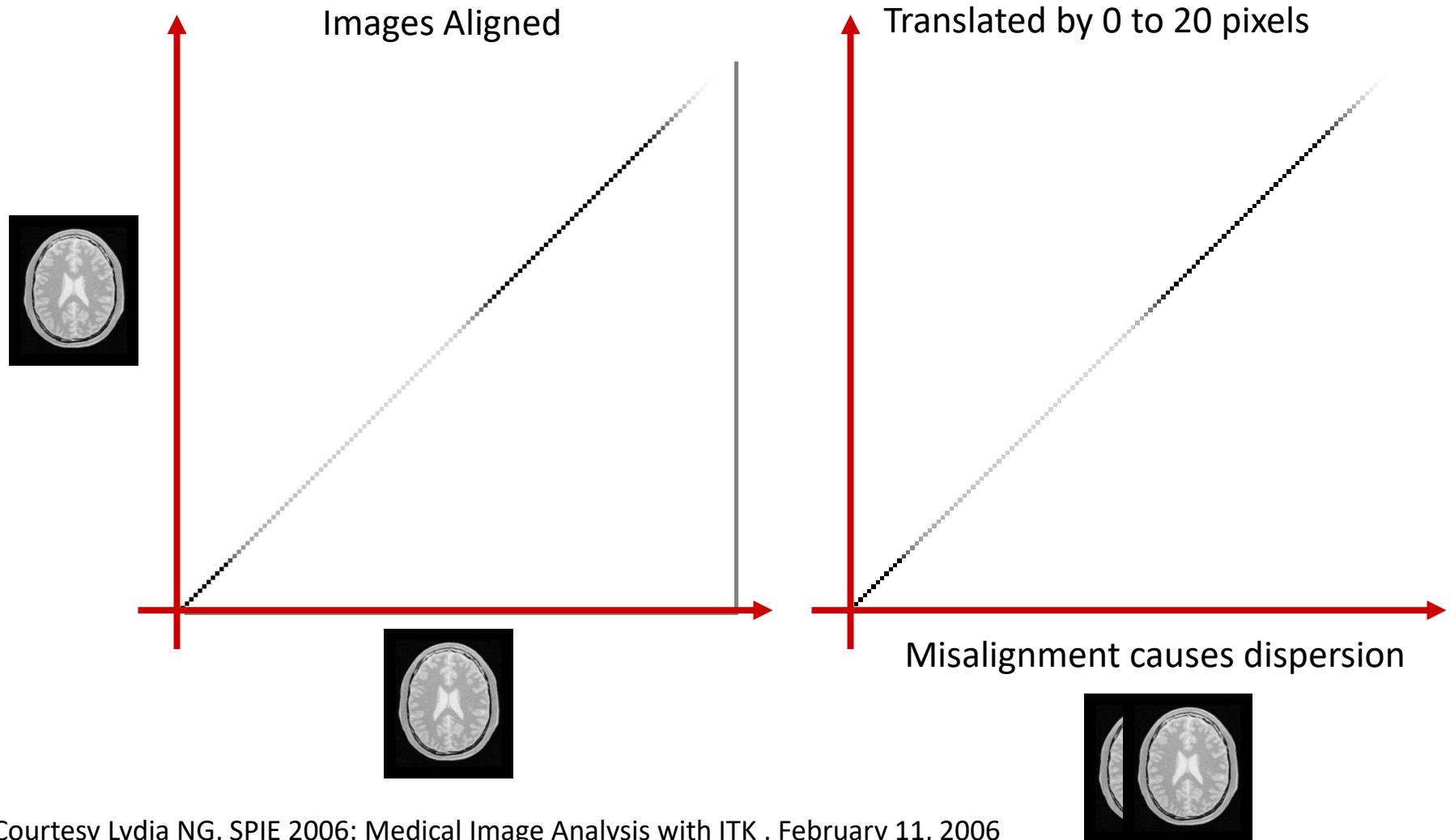
# Landmark-free Image Registration

- Use “image match” function between source and transformed target image to calculate transformation parameters.
- Common: SSD between target and transformed source images:

$$\underset{\beta}{\operatorname{argmin}} \left[ \sum_{i=1}^{\text{pixels}} (I'(x_i) - T(\beta, I(x_i)))^2 \right]$$



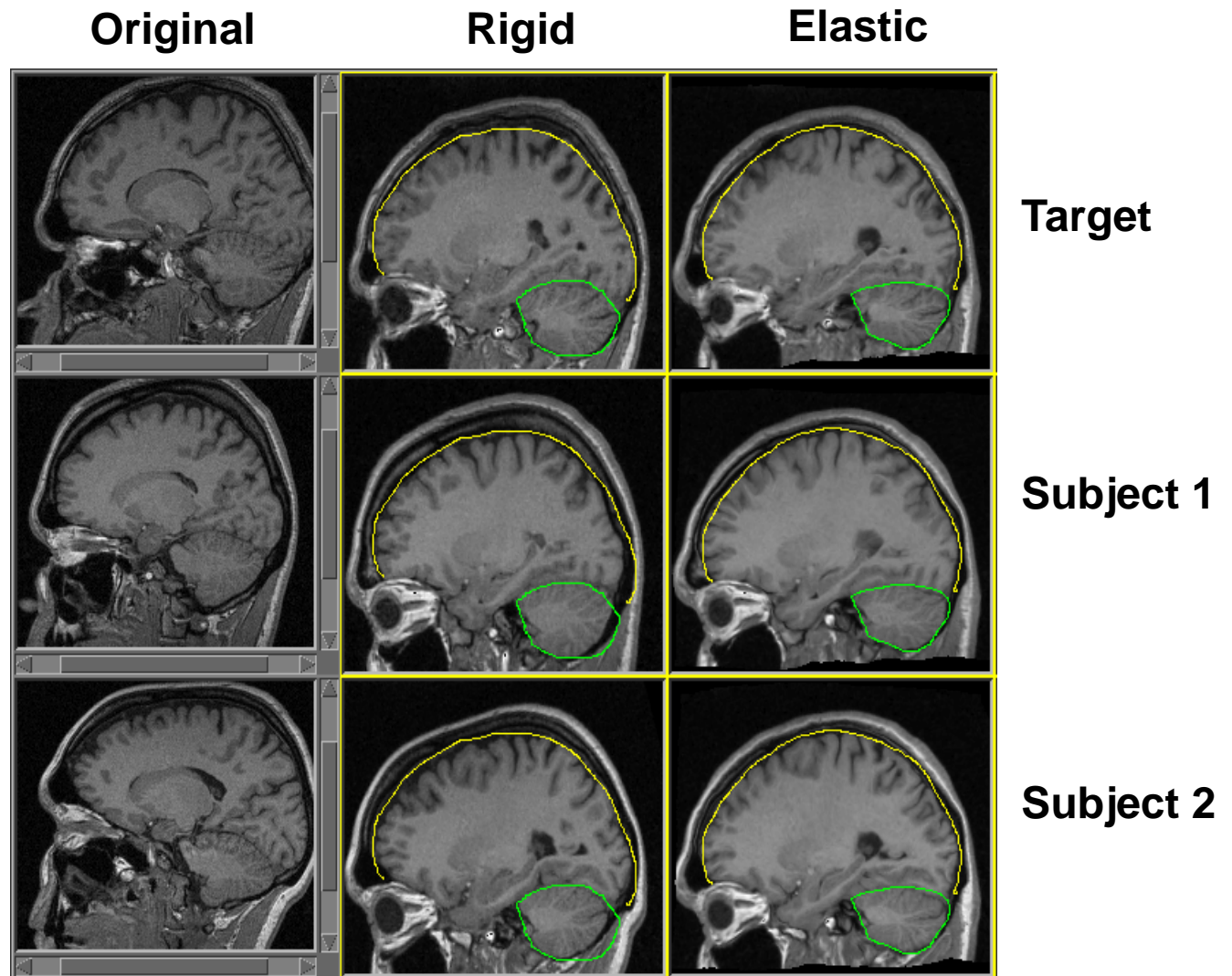
# Concept via Joint Histograms: Intensity similarity btw transformed images



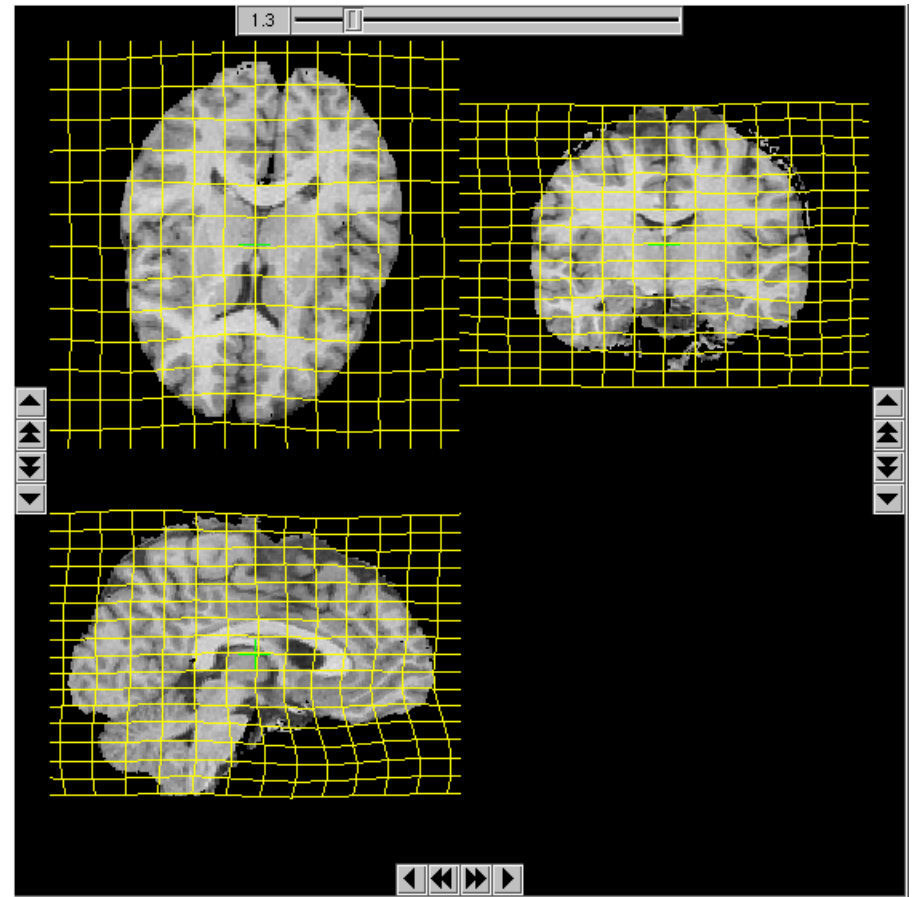
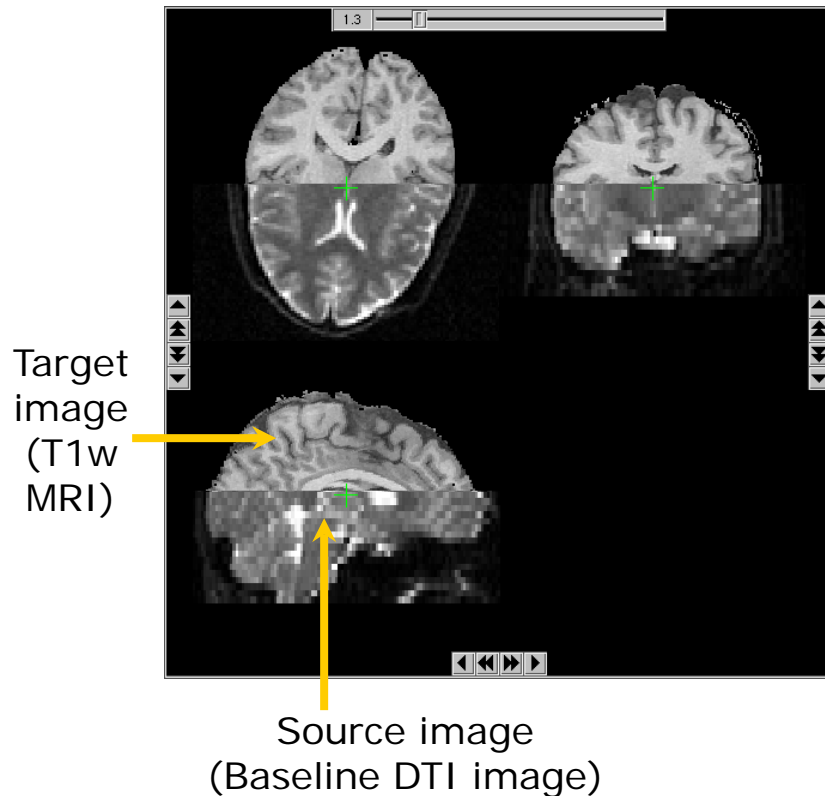
# Choices: Linear/Nonlinear

rigid: 'Mirit'  
(F.Maes)

elastic: 'Demons'  
(J.P. Thirion)



# Example Nonlinear B-Spline warping



IRTK Software (Image Registration Toolkit, Daniel Rueckert, Imperial College:

<http://www.doc.ic.ac.uk/~dr/software/>