



# Medical Images Registration

## Lecture 26-Nov

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# Outline

- Motivation
  - Image registration is an alignment problem
- Registration basics
- Rigid registration
- Non-rigid registration
- Example Applications

# Image Registration Taxonomy

- **Dimensionality**
  - 2D-2D, 3D-3D, 2D-3D
- **Nature of registration basis**
  - Image based
    - Extrinsic, Intrinsic
  - Non-image based
- **Nature of the transformation**
  - Rigid, Affine, Projective, Curved
- **Interaction**
  - Interactive, Semi-automatic, Automatic
- **Modalities involved**
  - Mono-modal, Multi-modal, Modality to model
- **Subject:**
  - Intra-subject
  - Inter-subject
  - Atlas
- **Domain of transformation**
  - Local, global
- **Optimization procedure**
  - Gradient Descent, SGD,
  - ...
- **Object**
  - Whole body, organ, ...

# Open Source Implementation

- ITK
- ANTS (advanced normalization tools) (PICSL of Upenn)
- CAVASS (MIPG of Upenn)
- Nifty Reg (UCL)
- Elastix ([www.elastix.isi.uu.nl](http://www.elastix.isi.uu.nl))
- FAIR (Modersitzki 2009), mostly matlab.
- 3D Slicer
- FSL
- ...

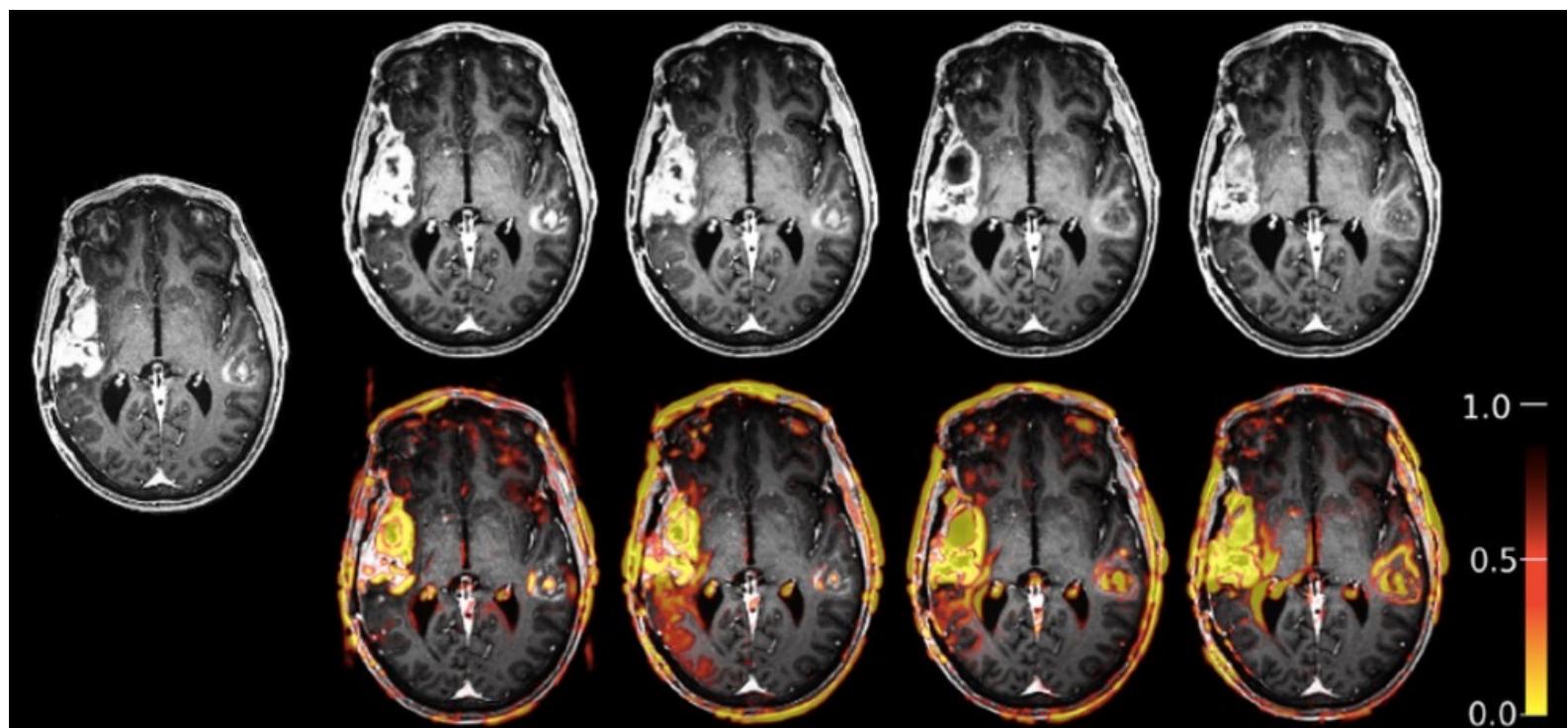
# Modalities in Medical Imaging

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# Modalities in Medical Imaging

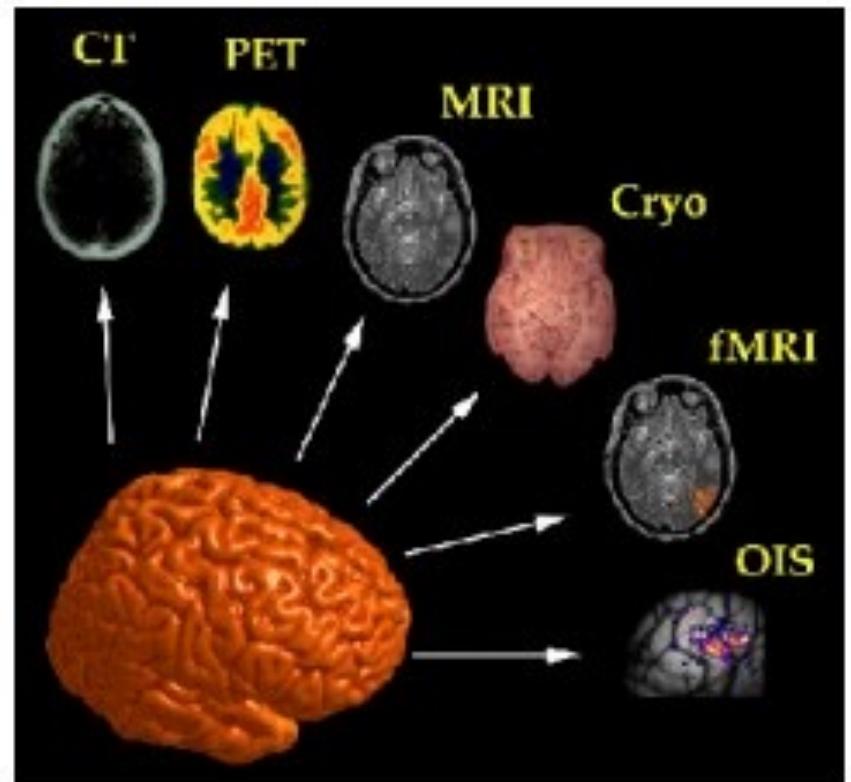
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- Multi-modality:

# Modalities in Medical Imaging

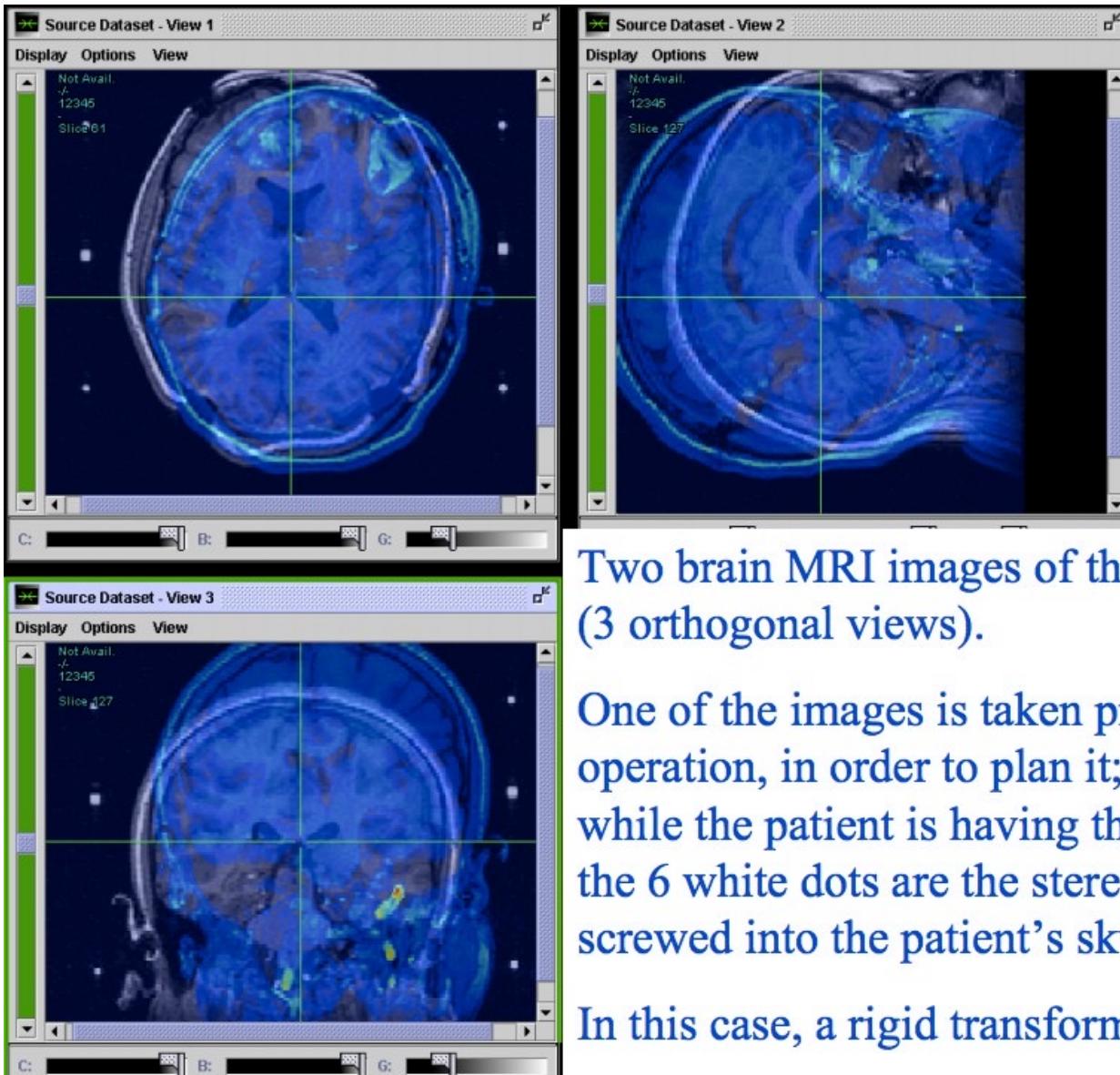
- Mono-modality:
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  - ✓ Images may be acquired weeks or months apart; taken from different viewpoints.
  - ✓ Aligning images in order to detect subtle changes in intensity or shape
- Multi-modality:
  - ✓ Complementary anatomic and functional information from multiple modalities can be obtained for the precise diagnosis and treatment.

In other words,...

- Combining modalities (**inter modality**) gives extra information.
- Repeated imaging over time same modality, e.g. MRI, (**intra modality**) equally important.
- Have to spatially register the images.



## Before Registration

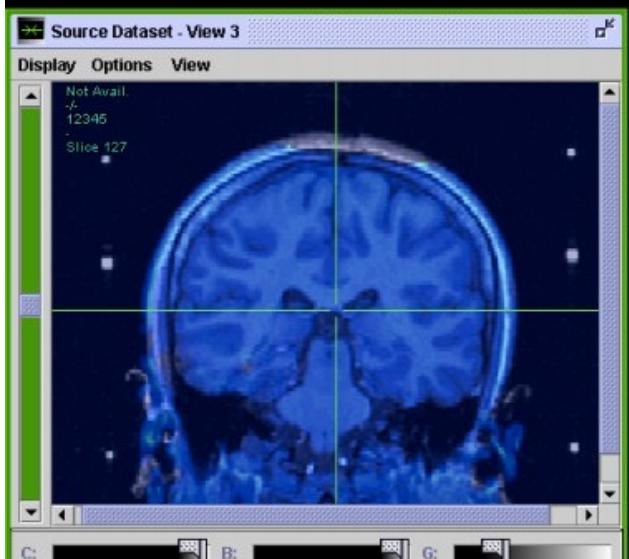
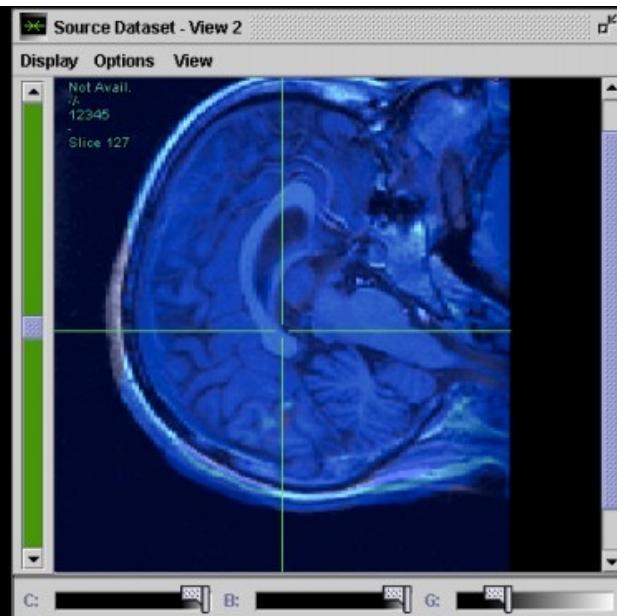
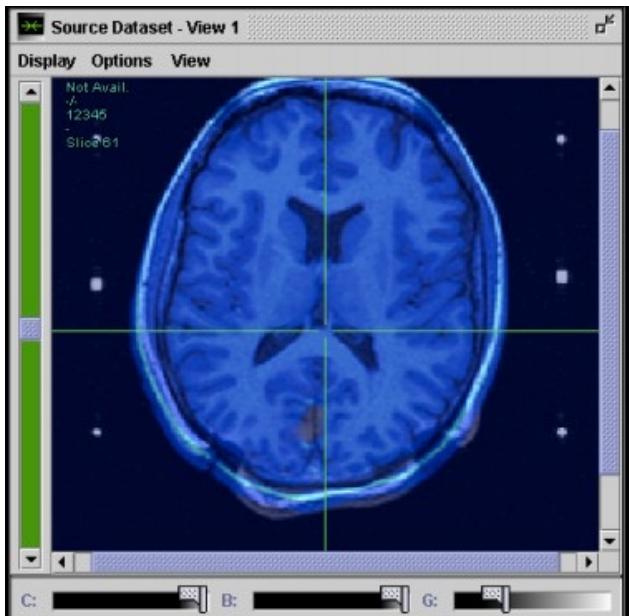


Two brain MRI images of the same patient (3 orthogonal views).

One of the images is taken prior to the operation, in order to plan it; the second while the patient is having the operation: the 6 white dots are the stereotactic frame screwed into the patient's skull.

In this case, a rigid transform suffices

## After Registration



This shows the situation after the pre-op and inter-op images have been aligned.

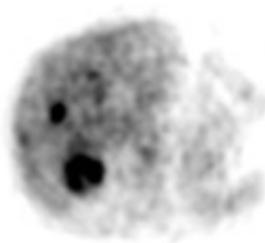
Typically, a rigid registration algorithm applied to brain images will be accurate to 1/10 of a voxel and 0.1 degrees of rotation

Fusion of information = registration plus combination  
in a single representation: PET/CT

CT



PET



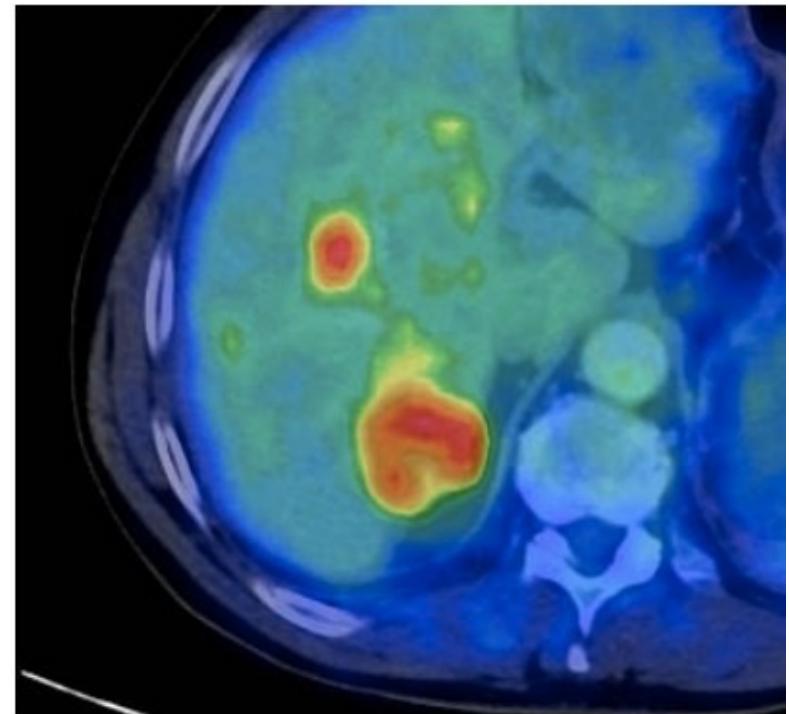
Deformable fusion- PET shows increased metabolism in lesions identified on CT, consistent with active tumour growth rather than necrosis post-radiotherapy

Fusion of information = registration plus combination in a single representation: PET/CT

CT



PET

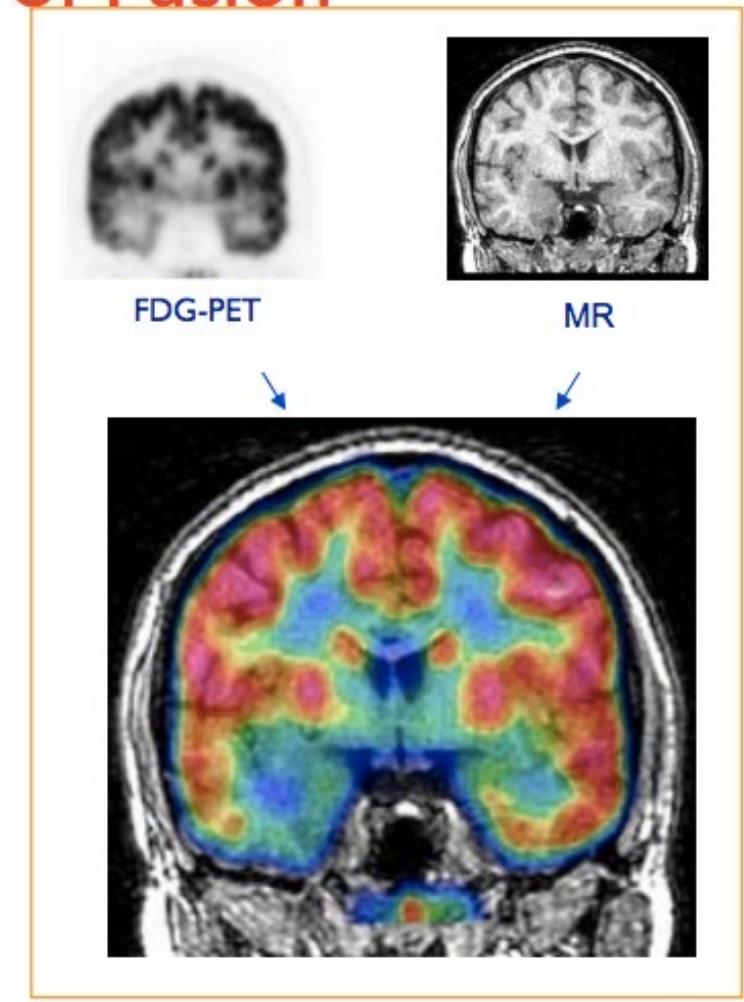


Deformable fusion- PET shows increased metabolism in lesions identified on CT, consistent with active tumour growth rather than necrosis post-radiotherapy

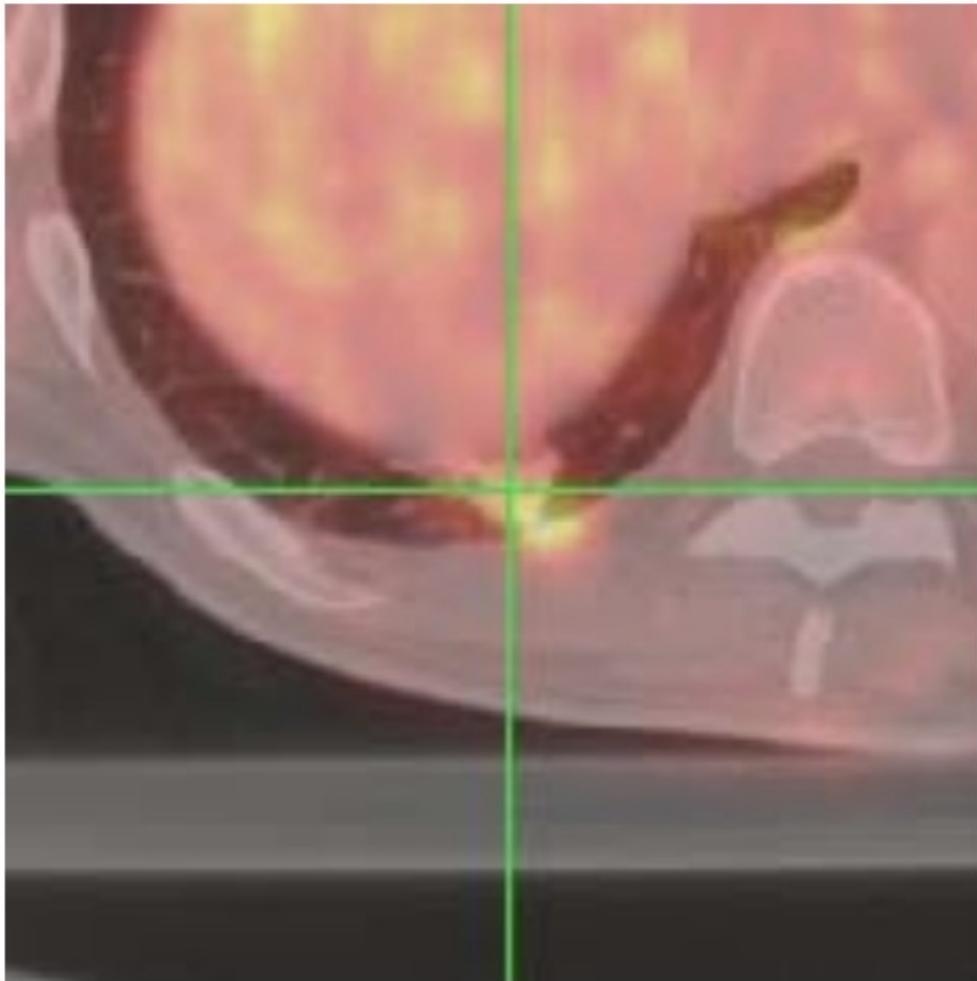
# Many Clinical Applications of Fusion

- Cancer staging
- Biopsy planning
- Radiotherapy treatment planning
- Quantitative assessment of treatment response
- Pre-surgical assessment of other conditions e.g. epilepsy
- As an effective communication tool when reporting to clinical meetings, referring physicians or to patients
- Whenever multiple data sources may be better assessed together

*PET data identifies a region of hypometabolism due to epilepsy. Fusion with MR localises the damage to the anterior and medial areas of the right temporal gyrus*

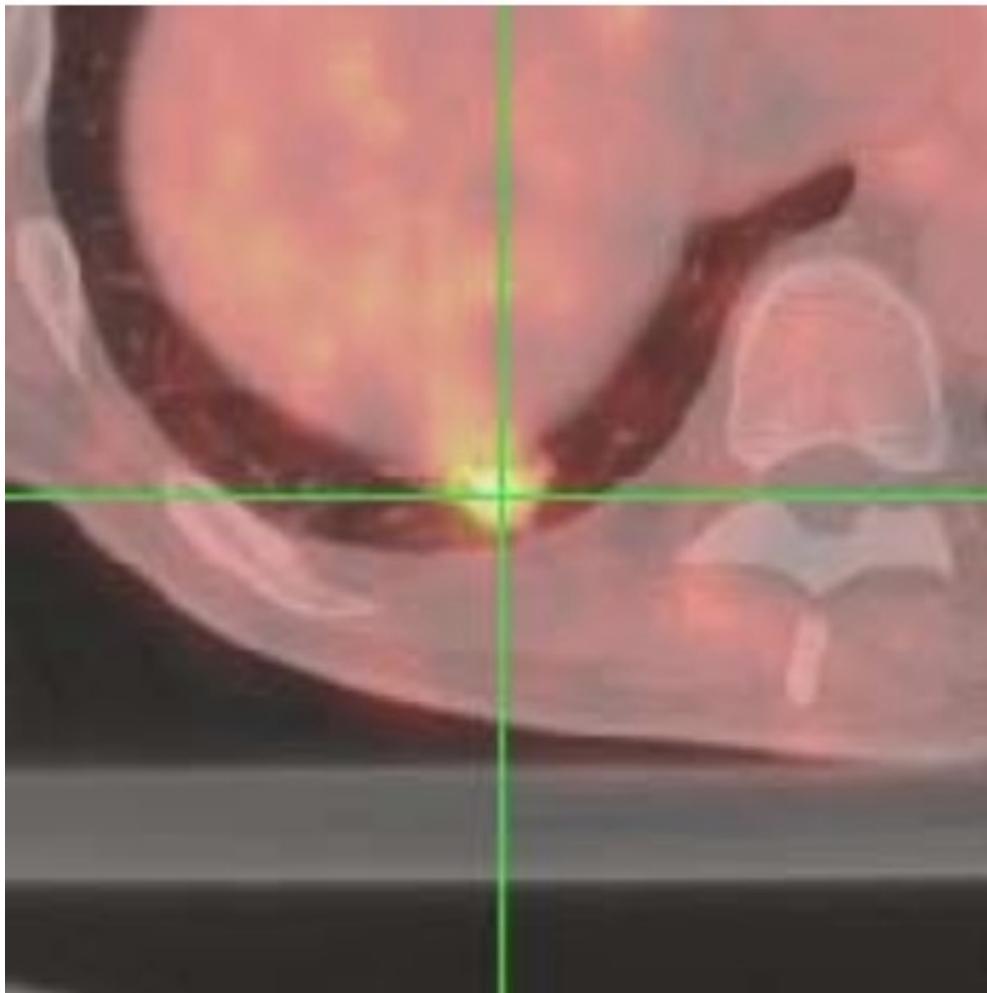


# Rigid registration poor



Is the tumour in  
the lungs or the  
stomach?

# Non-rigid registration



Looks plausible;  
but how could you  
be sure?

Are you prepared  
to risk your  
software against  
getting sued?

# Summary of Mostly Used Applications

- **Diagnosis**
  - Combining information from multiple imaging modalities
- **Studying disease progression**
  - Monitoring changes in size, shape, position or image intensity over time
- **Image guided surgery or radiotherapy**
  - Relating pre-operative images and surgical plans to the physical reality of the patient
- **Patient comparison or atlas construction**
  - Relating one individual's anatomy to a standardized atlas
    - This atlas provides a **standardized set of coordinates to determine specific sites within the region of interest.**

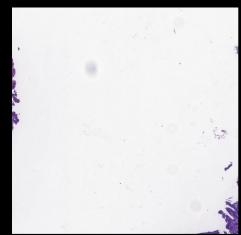


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Stitched Image



Current Image

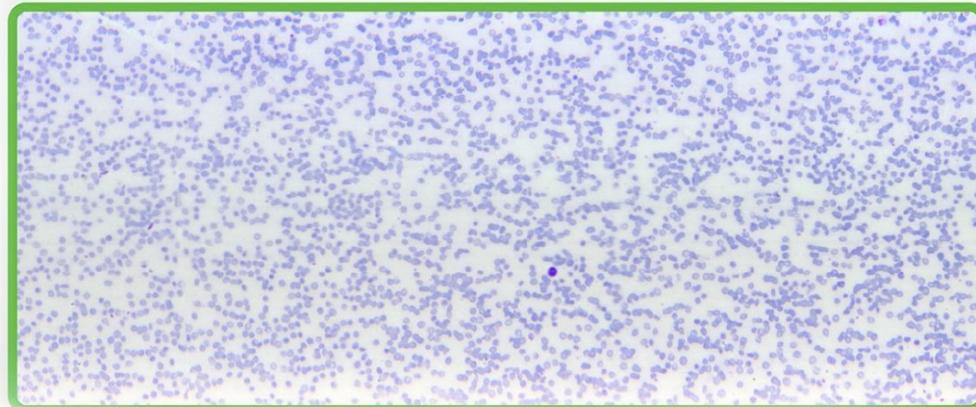
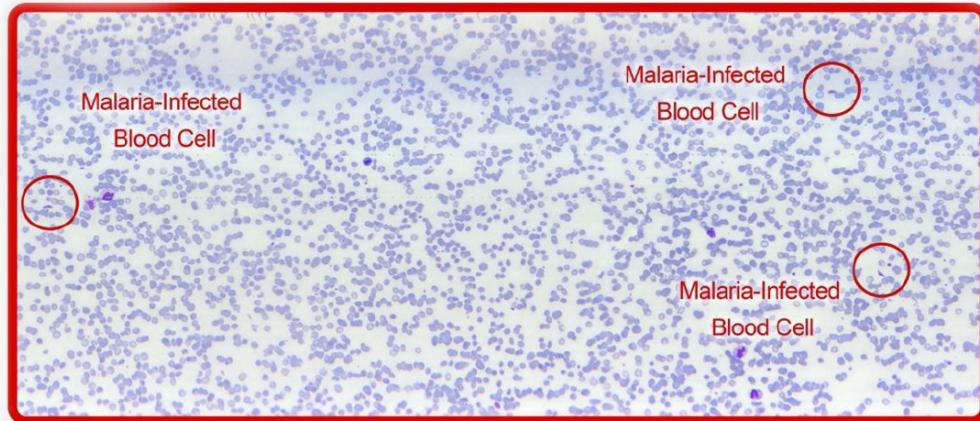


Current Image

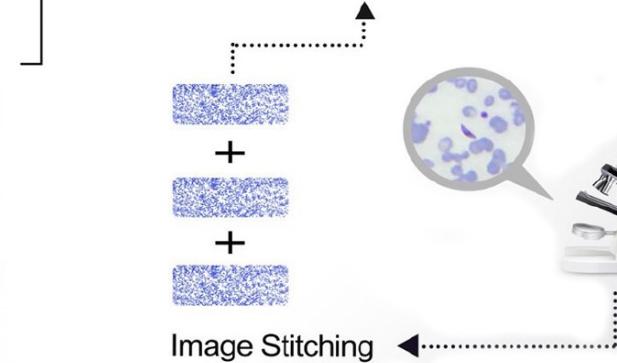
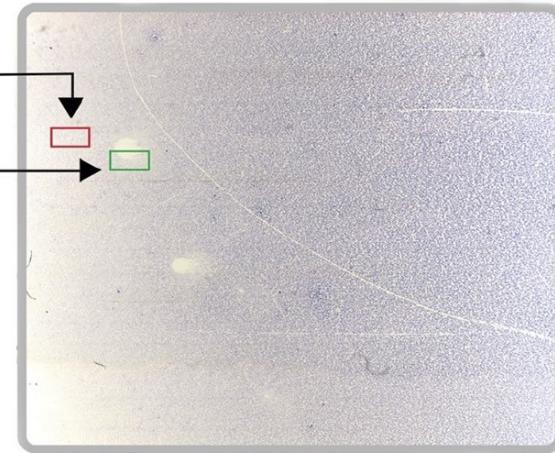
Stitched Image

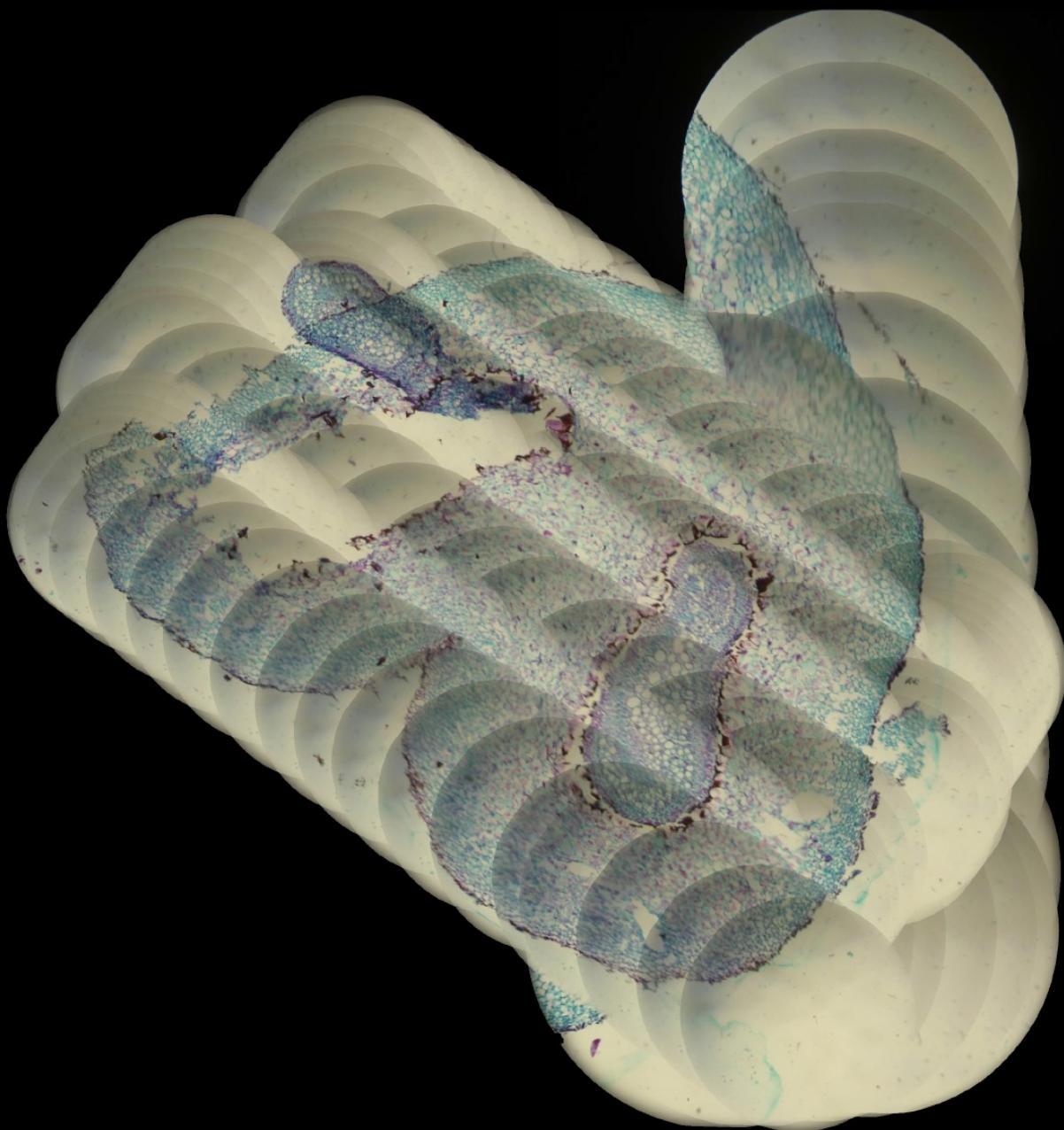
Compound Microscope

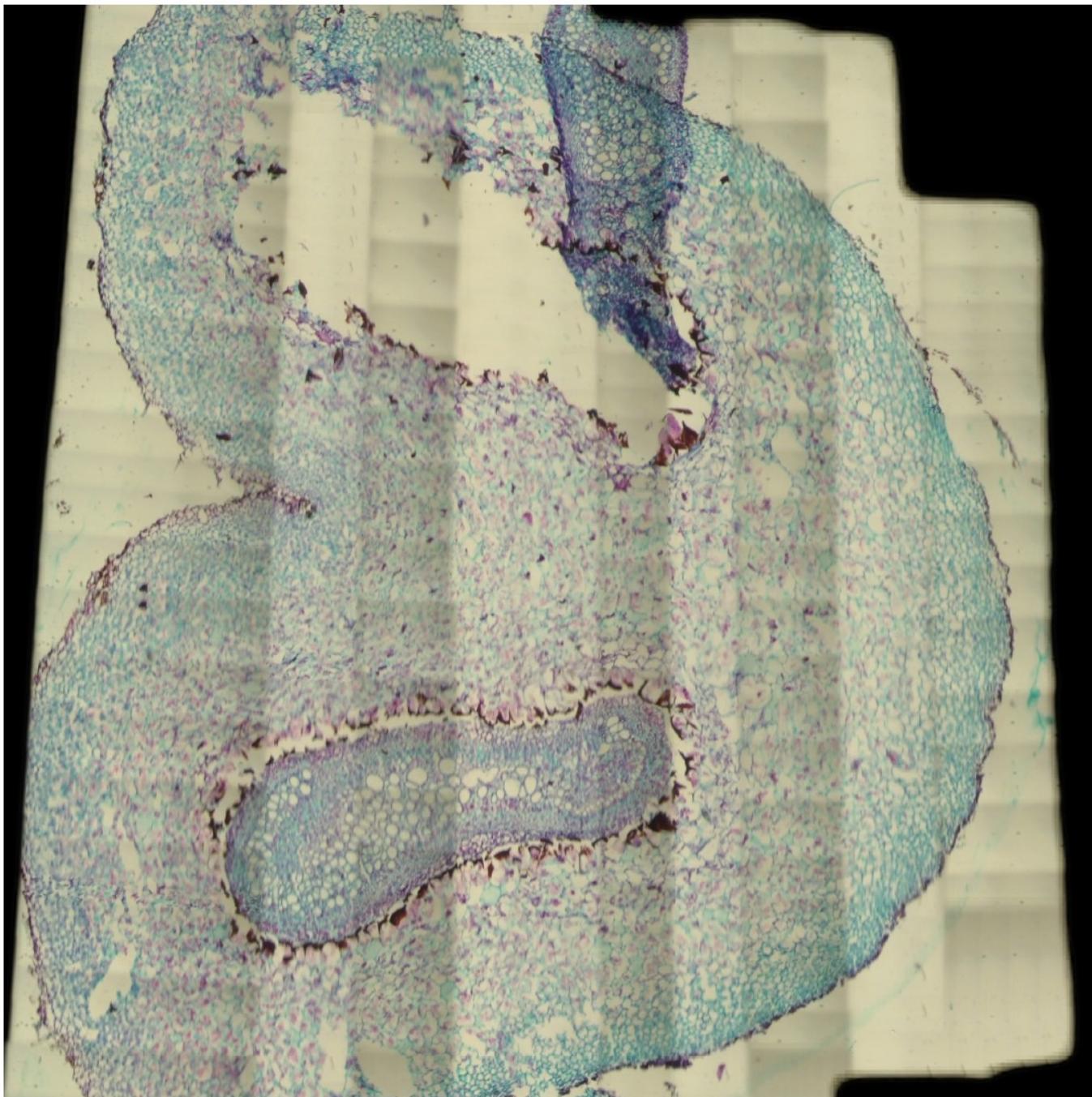




High Resolution Slide View

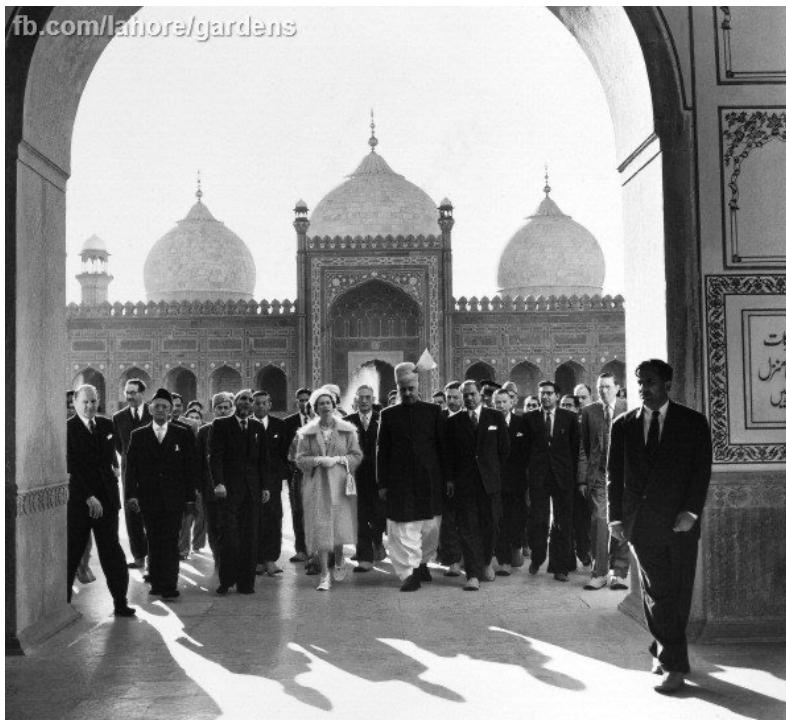








# Old and New

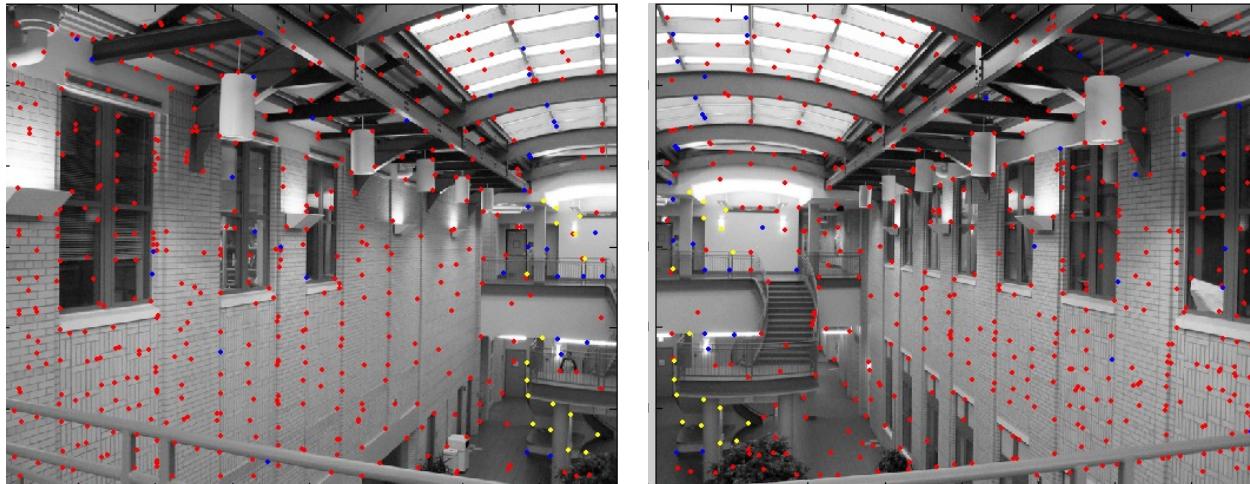


Src: Dr. Mohsen Ali



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# Example: Stitching

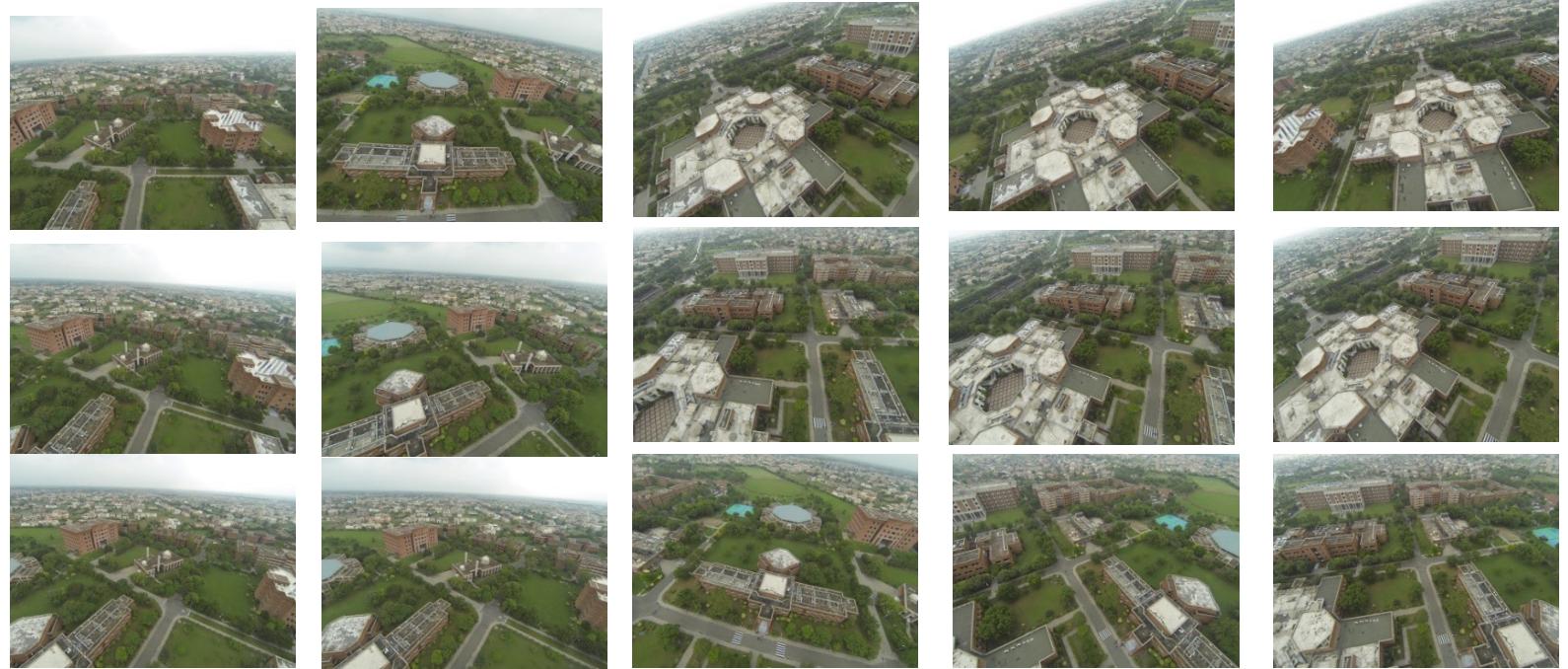


Slide Credit:  
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u/courses/15-  
463/2010\\_spring/..  
. ./feature-  
alignment.ppt](http://graphics.cs.cmu.edu/u/courses/15-463/2010_spring/.. ./feature-alignment.ppt)



# Panoramas

## Multiple Images Stitched Together



# Panoramas

## Multiple Images Stitched Together

Applications of 2D  
Image Registration



© Sergey Semenov

Image by Sergey Semenov (<http://www.sergesemenov.com/>) - Winner of Epson International Photographic Pano Award 2013  
<http://www.dailymail.co.uk/sciencetech/article-2260276/New-York-youve-seen-Incredible-interactive-panorama-lets-zoom.html>

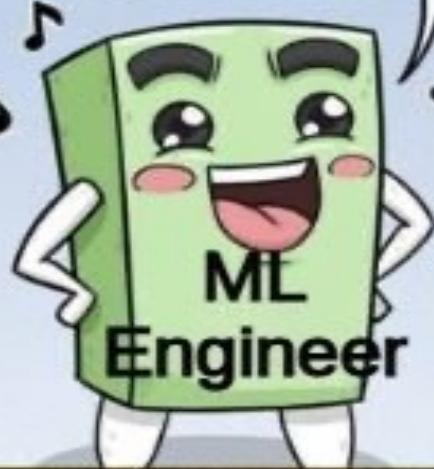
# Video Stabilization



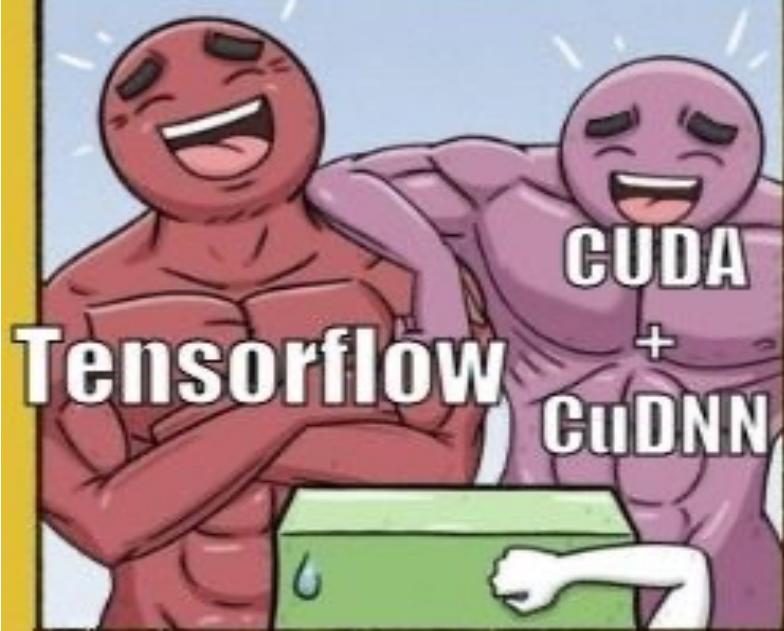
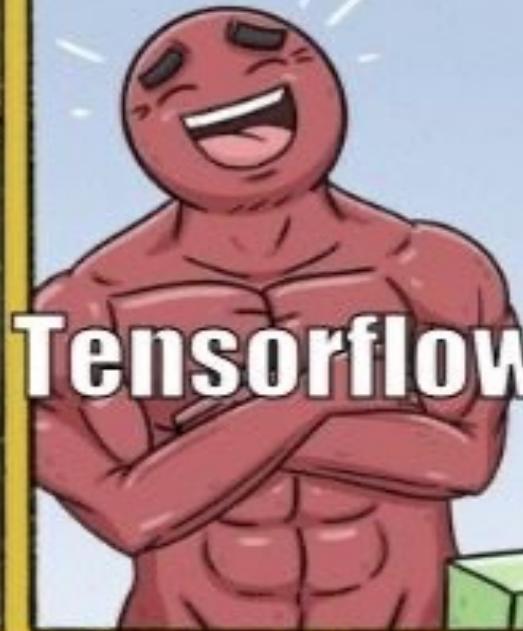
# Example of Data Annotations GUI



Oh look a repo with  
pretrained model! I wonder  
if I can just clone and use it



Tensorflow



# Image Transformations

**Transformation:** Transformation is a function.

A function that maps one set to another set after performing some operations.

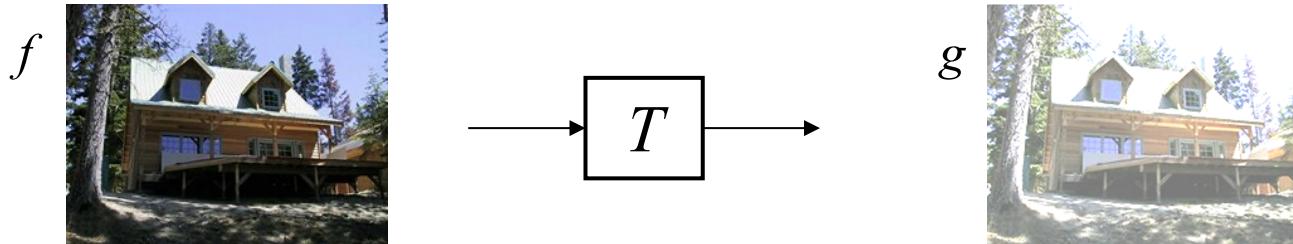
# Image Transformations



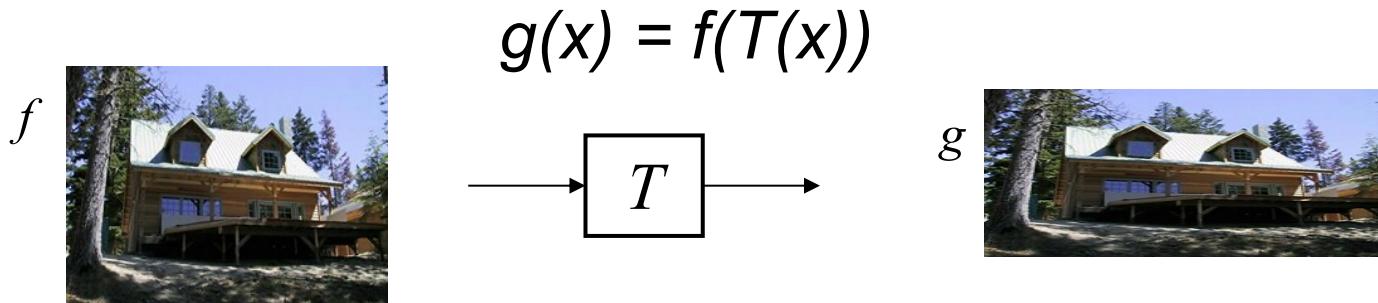
# Image Transformations

- image filtering: change ***range*** of image

$$\bullet g(x) = T(f(x))$$



- image warping: change ***domain*** of image



# Parametric (global) warping



translation



rotation



aspect



affine



perspective



cylindrical

# Parametric (global) warping

- Examples of parametric warps (**Image warping** is the process of digitally manipulating an image such that any shapes portrayed in the image have been significantly distorted):



translation



rotation



aspect



affine

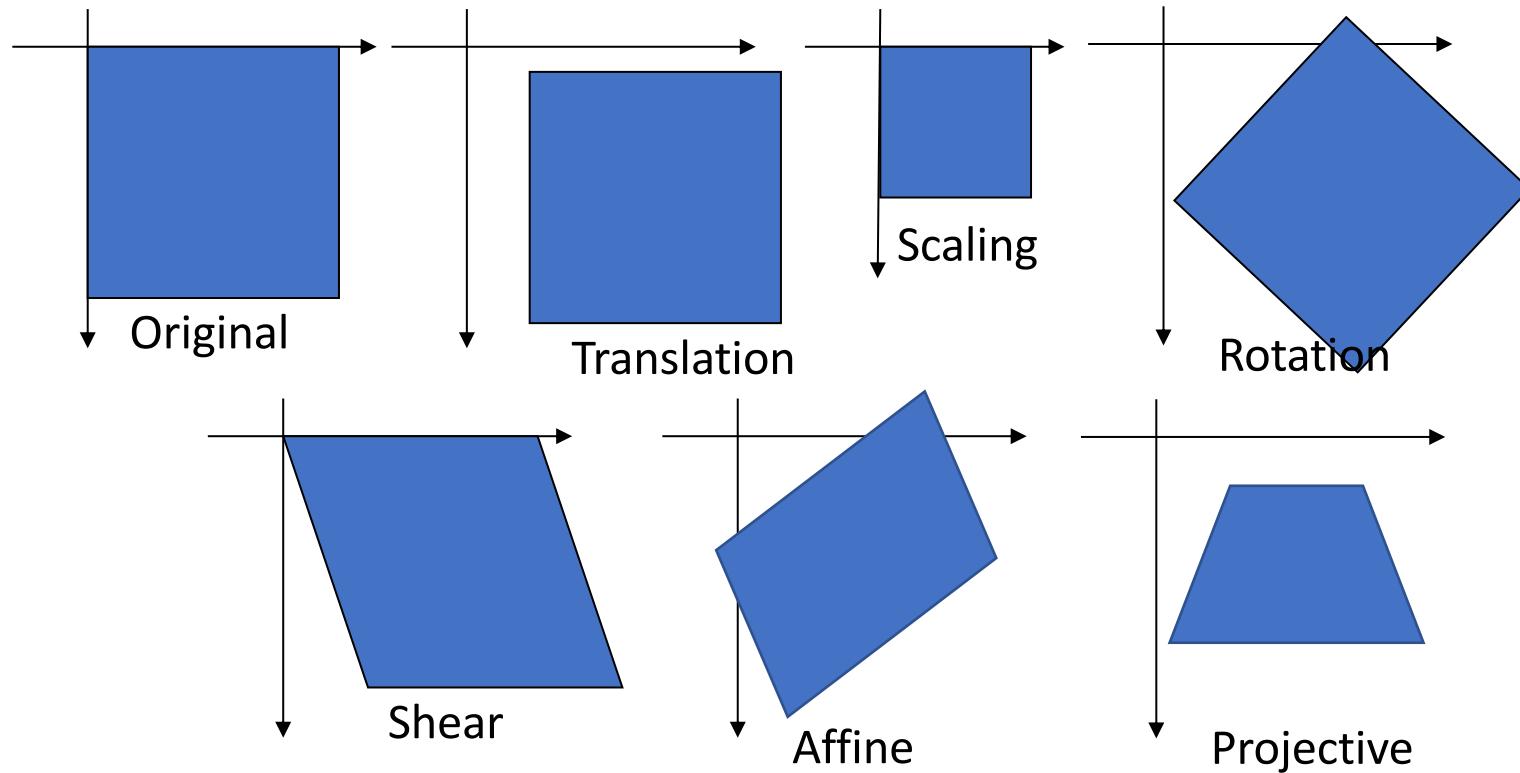


perspective



cylindrical

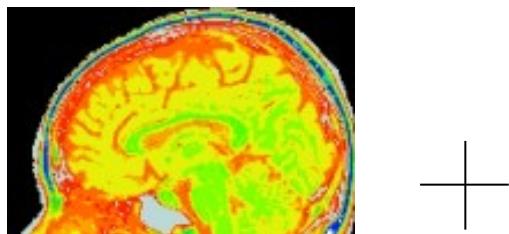
# 2-D Transformations



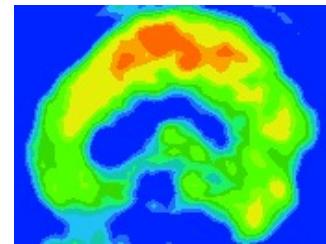
Then, What is Image Registration (formally)?

# Image Registration is a

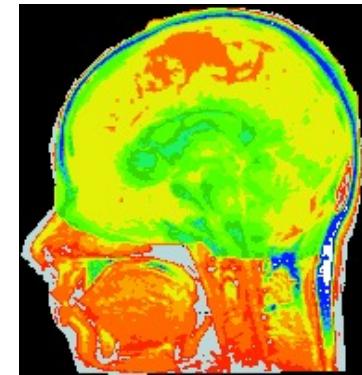
- **Spatial transform** that maps points from one image to corresponding points in another image
  - matching two images so that corresponding coordinate points in the two images correspond to the same physical region of the scene being imaged
  - Also referred to as image fusion, superimposition, matching or merge



+



=



MR

SPECT

registered

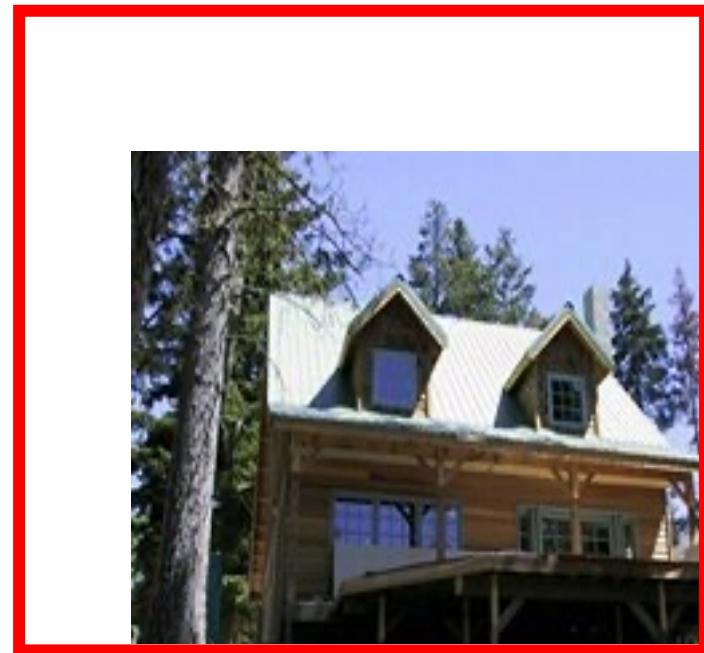
# 2-D Transformations



# 2-D Transformations



# 2-D Transformations



# 2-D Transformations



Original

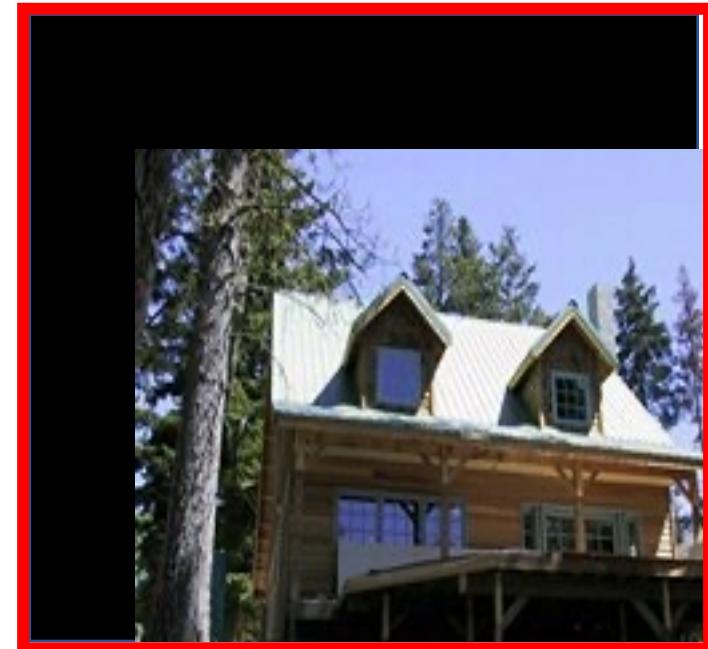


Translation

# 2-D Transformations



Original



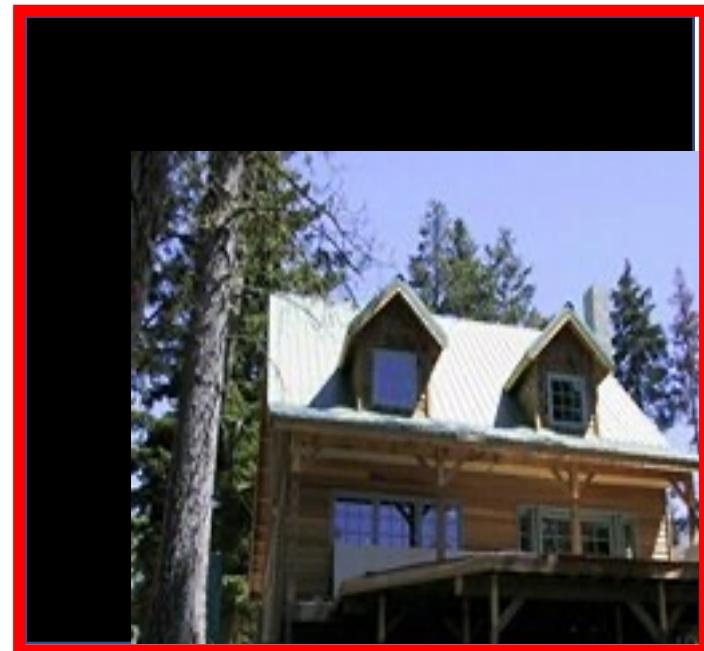
Translation

How much image translation has happened?

# 2-D Transformations



Original



Translation

# 2-D Transformations



Original

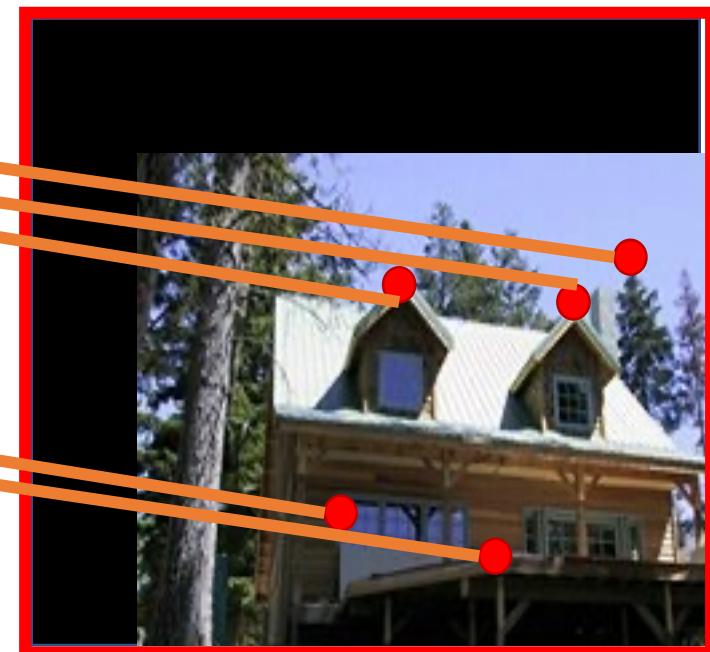


Translation

# 2-D Transformations

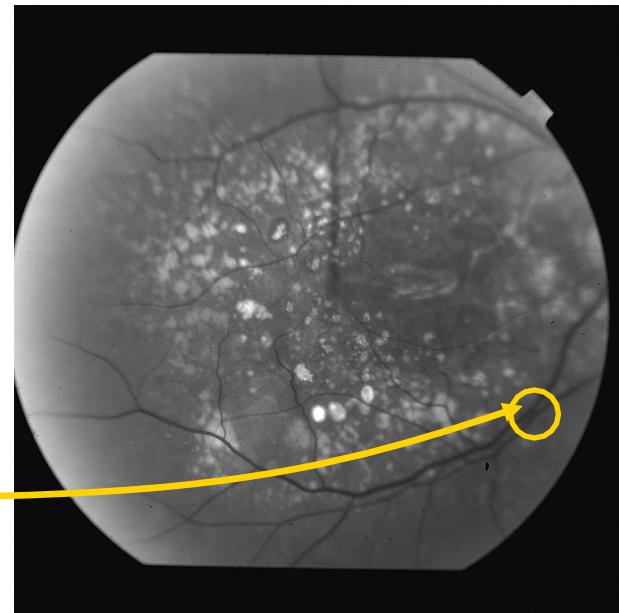
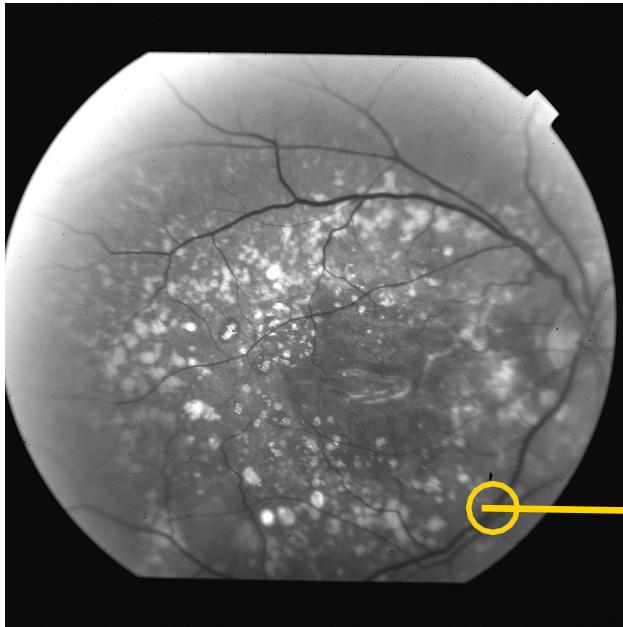


Original

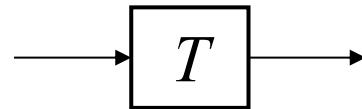


Translation

# Not an Easy Problem!!



# Parametric (global) warping



$$\mathbf{p} = (x, y)$$

$$\mathbf{p}' = (x', y')$$

- Transformation  $T$  is a coordinate-changing machine:

- $\mathbf{p}' = T(\mathbf{p})$

- What does it mean that  $T$  is global?

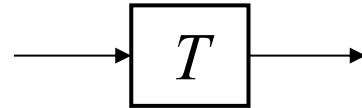
- Is the same for any point  $p$
  - can be described by just a few numbers (parameters)

- Let's represent a linear  $T$  as a matrix:

- $\mathbf{p}' = \mathbf{M}\mathbf{p}$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \mathbf{M} \begin{bmatrix} x \\ y \end{bmatrix}$$

# Parametric (global) warping



$$\mathbf{p} = (x, y)$$

$$\mathbf{p}' = (x', y')$$

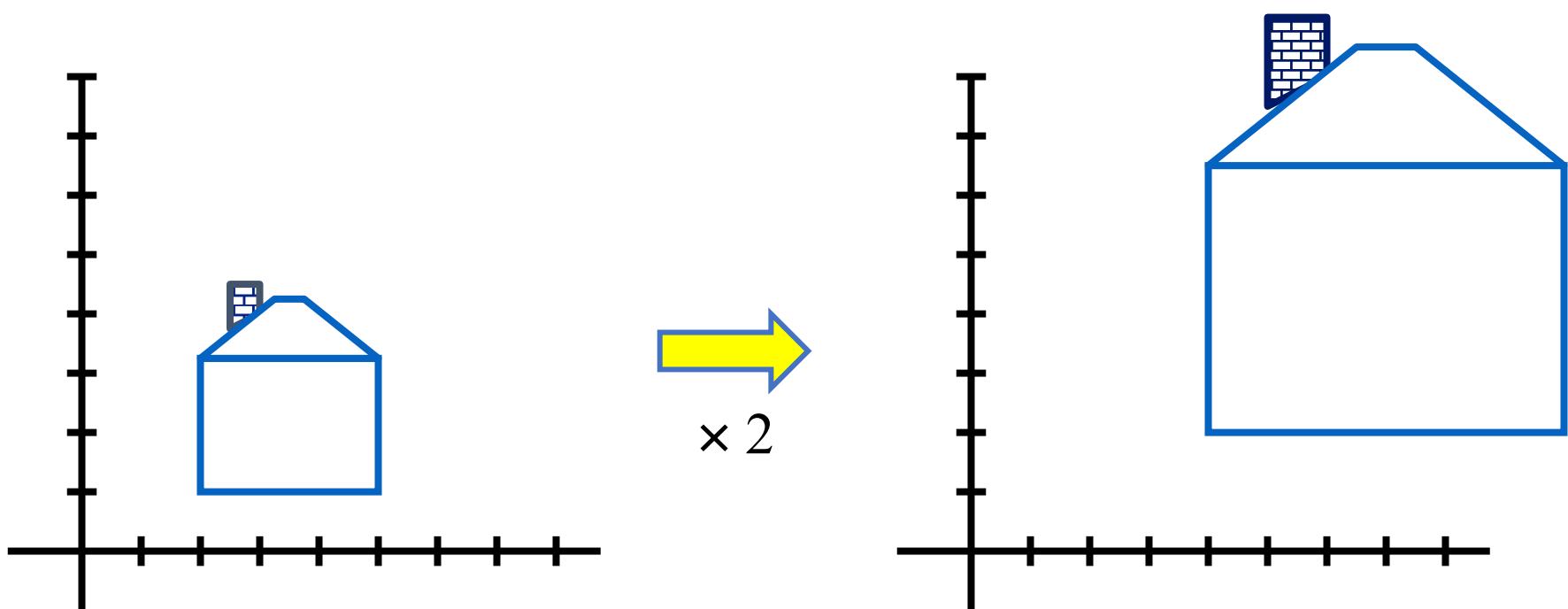
$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \mathbf{M} \begin{bmatrix} x \\ y \end{bmatrix}$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a_1 & a_2 \\ a_3 & a_4 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

↑  
Transformation  
Matrix

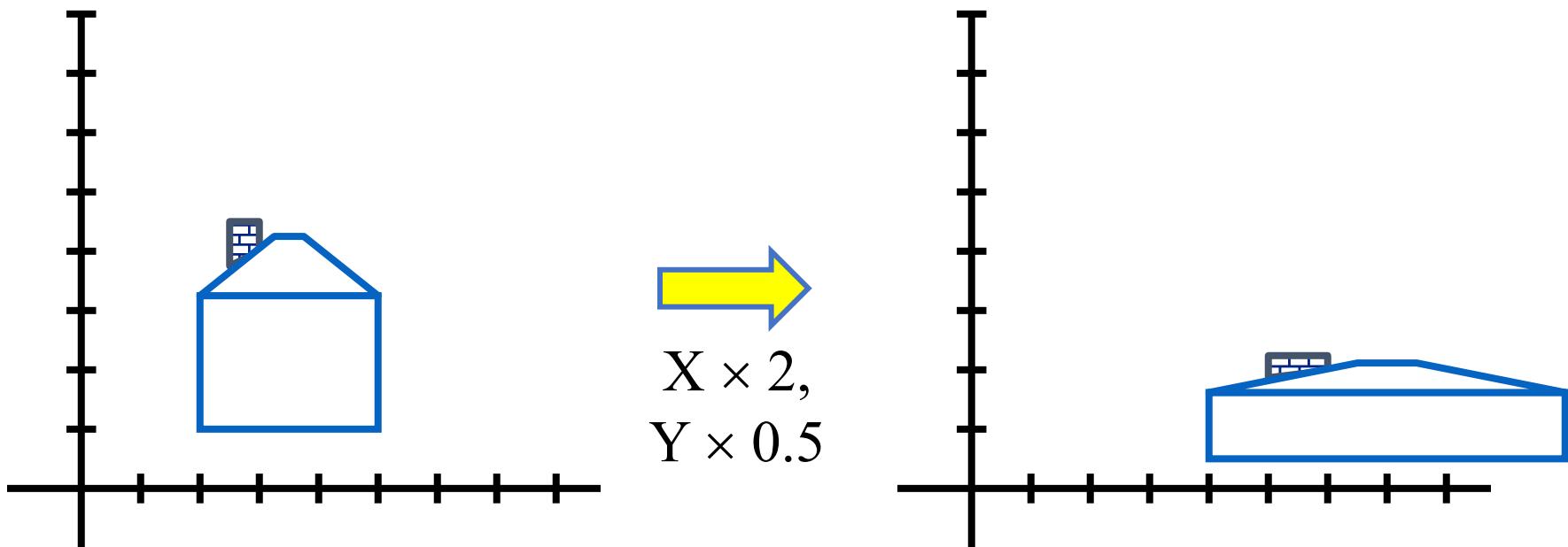
# Scaling

- *Scaling* a coordinate means multiplying each of its components by a scalar
- *Uniform scaling* means this scalar is the same for all components:



# Scaling

- *Non-uniform scaling*: different scalars per component:



# Scaling

- Scaling operation:

$$x' = ax$$

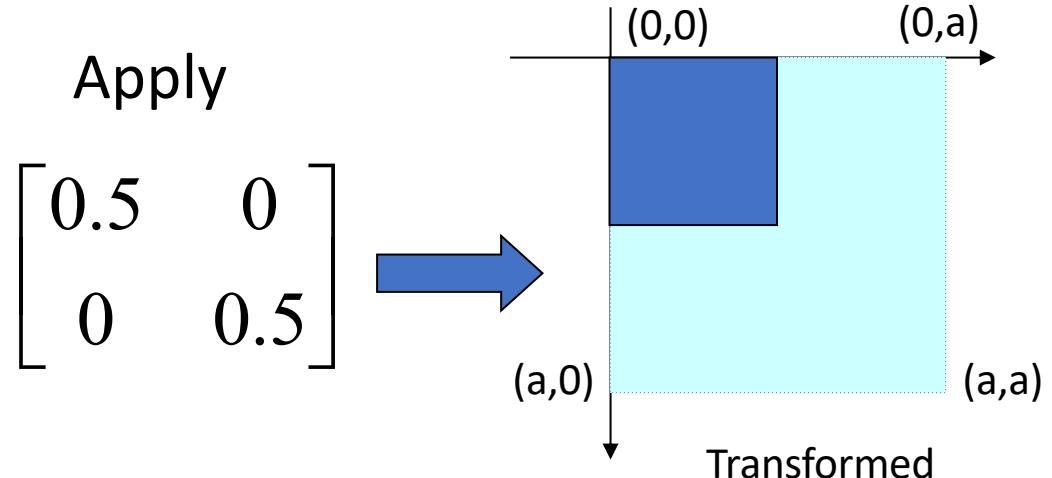
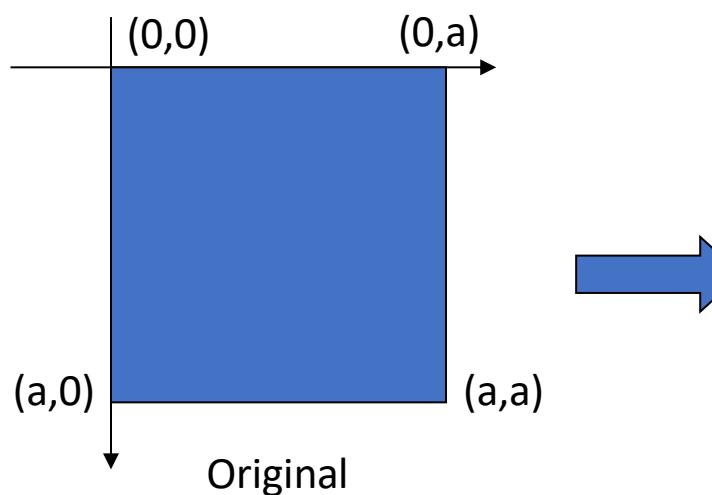
$$y' = by$$

- Or, in matrix form:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \underbrace{\begin{bmatrix} a & 0 \\ 0 & b \end{bmatrix}}_{\text{scaling matrix } S} \begin{bmatrix} x \\ y \end{bmatrix}$$

What's inverse of S?

# Example



$$\begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix} \begin{bmatrix} a \\ a \end{bmatrix} = \begin{bmatrix} 0.5a \\ 0.5a \end{bmatrix}$$

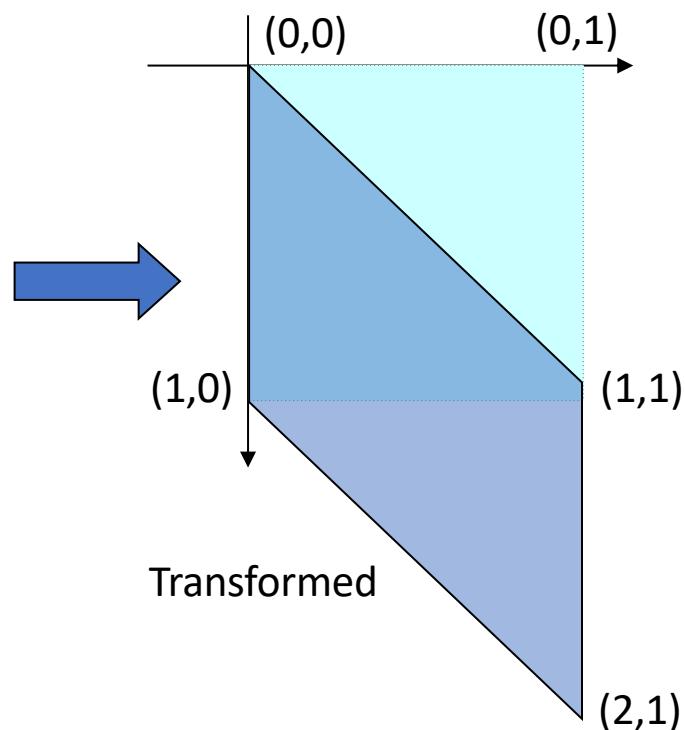
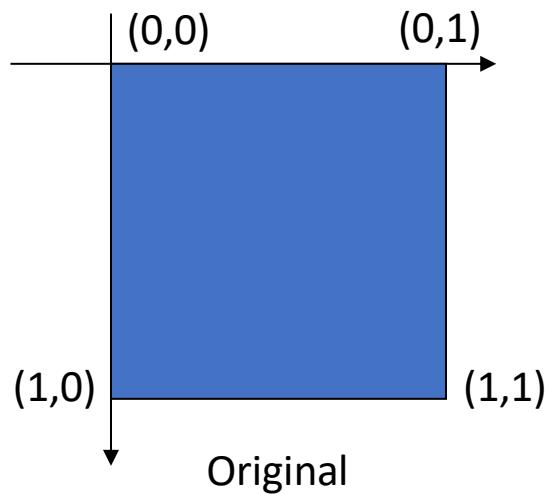
$$\begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix} \begin{bmatrix} a \\ 0 \end{bmatrix} = \begin{bmatrix} 0.5a \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 0.5 & 0 \\ 0 & 0.5 \end{bmatrix} \begin{bmatrix} 0.5a \\ 0.5a \end{bmatrix} = \begin{bmatrix} 0.25a \\ 0.25a \end{bmatrix}$$

# 2D Transformations

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a_1 & a_2 \\ a_3 & a_4 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Transformation  
Matrix



$$\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} = ?$$

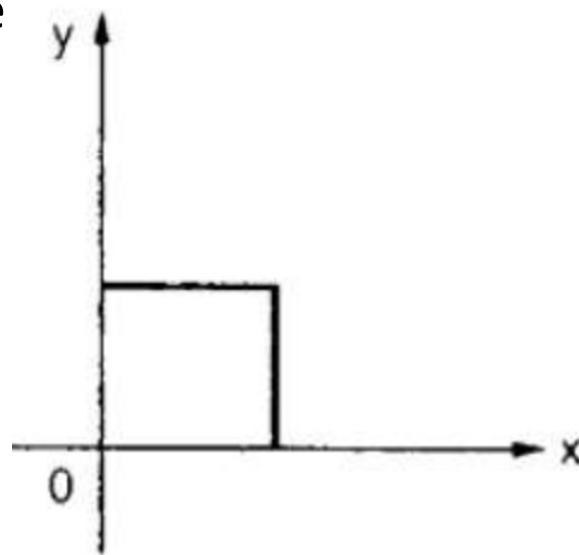
# Shear Transformation

- A transformation that slants the shape of an object is called the shear transformation.
- There are two shear transformations **X-Shear** and **Y-Shear**.
- One shifts X coordinates values and other shifts Y coordinate values.
- However; in both the cases only one coordinate changes its coordinates and other preserves its values.
- Shearing is also termed as **Skewing**.

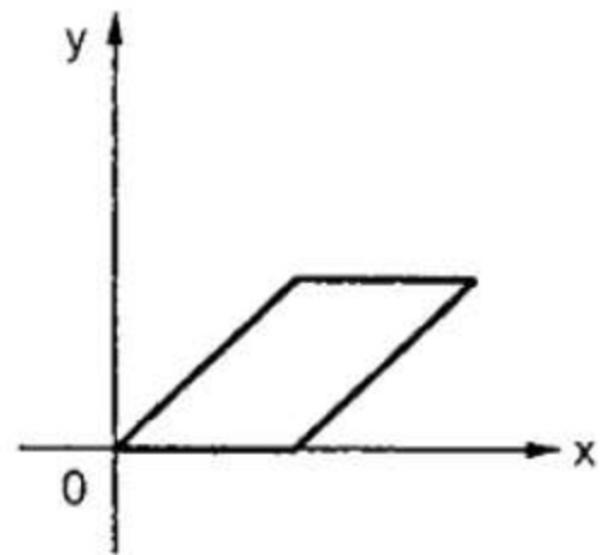
# Shear in x-direction

$$\begin{bmatrix} 1 & e \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x + ey \\ y \end{bmatrix}$$

- x-coordinate moves with an amount proportional to the y-coordinate



(a) Original object

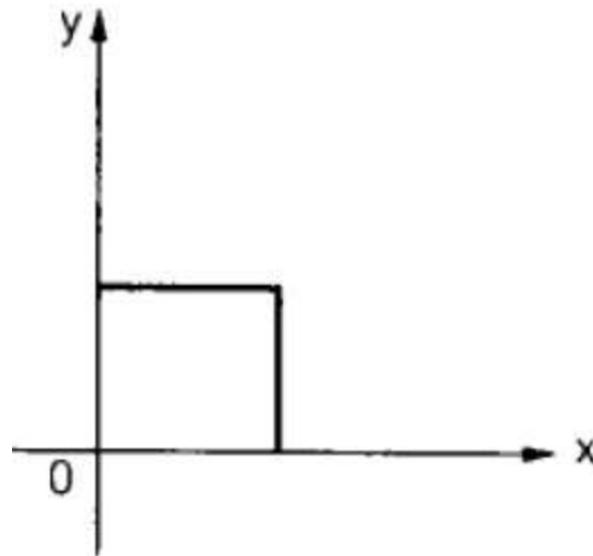


(b) Object after x shear

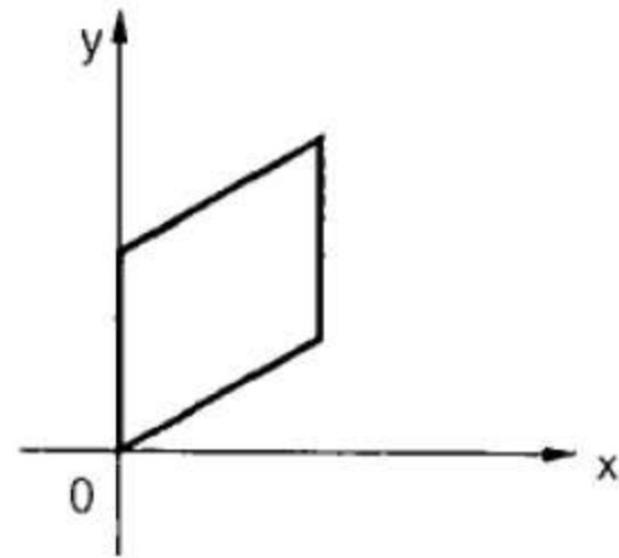
## Shear in y-direction

$$\begin{bmatrix} 1 & 0 \\ e & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x \\ ex + y \end{bmatrix}$$

- y-coordinate moves with an amount proportional to the x-coordinate

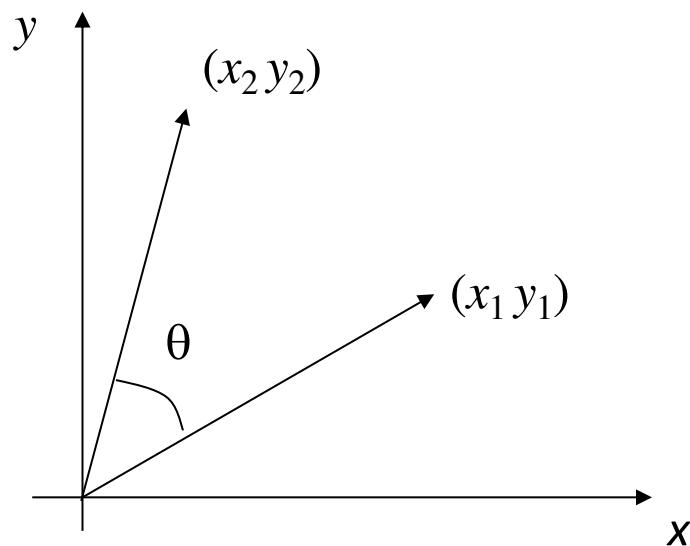


(a) Original object



(b) Object after y shear

# Rotation



- ▶ Task: Relate  $(x_2, y_2)$  to  $(x_1, y_1)$

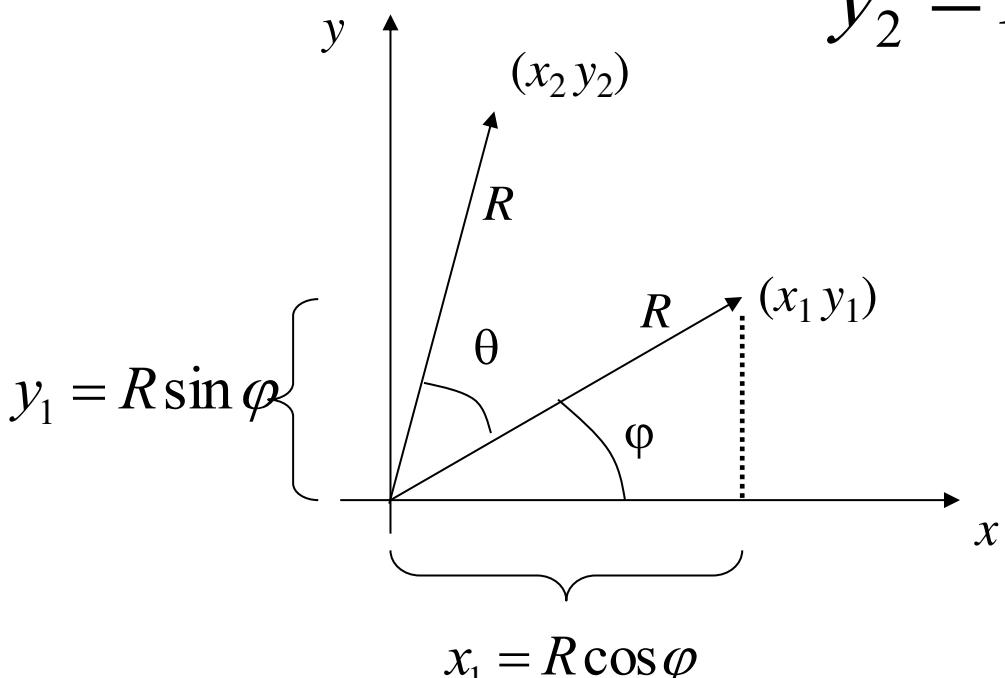
# Rotation

$$x_2 = R \cos(\theta + \varphi)$$

$$y_2 = R \sin(\theta + \varphi)$$

$$x_2 = R \cos \theta \cos \varphi - R \sin \theta \sin \varphi$$

$$y_2 = R \sin \theta \cos \varphi + R \cos \theta \sin \varphi$$



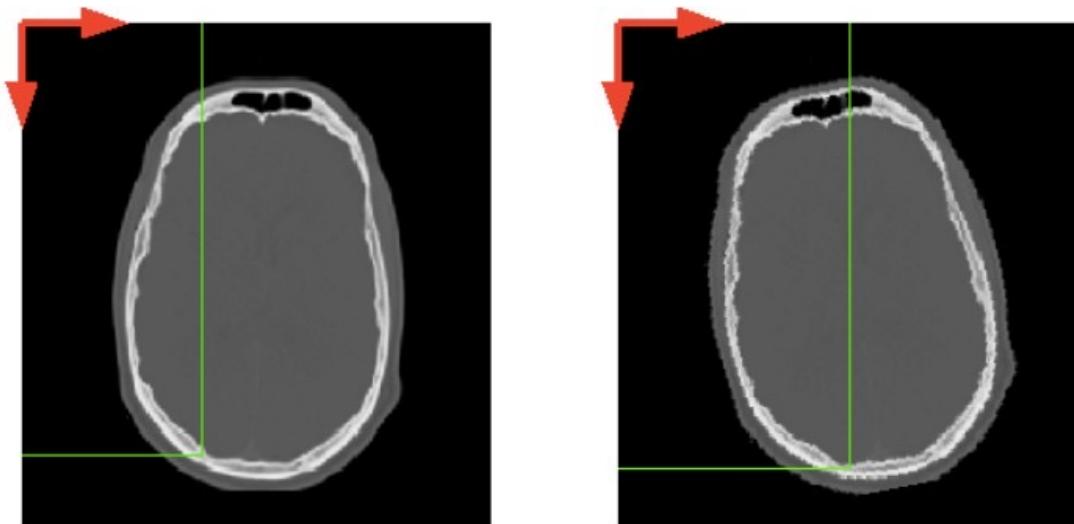
$$x_2 = x_1 \cos \theta - y_1 \sin \theta$$

$$y_2 = x_1 \sin \theta + y_1 \cos \theta$$

$$\begin{bmatrix} x_2 \\ y_2 \end{bmatrix} = \underbrace{\begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}}_{R} \begin{bmatrix} x_1 \\ y_1 \end{bmatrix}$$

**R is rotation by  $\theta$  counterclockwise about origin**

## Rigid Registration - Rotation



One parameter, the angle  $\theta$ :

$$\mathbf{R} = \begin{bmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

# 2-D Rotation

- This is easy to capture in matrix form:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \underbrace{\begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix}}_{\mathbf{R}} \begin{bmatrix} x \\ y \end{bmatrix}$$

- 

- What is the inverse transformation?

- Rotation by  $-\theta$
- For rotation matrices

[**prove it**]

$$\mathbf{R}^{-1} = \mathbf{R}^T$$

# 2x2 Matrices

- What types of transformations can be represented with a 2x2 matrix?

2D Identity?

$$x' = x$$

$$y' = y$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

2D Scale around (0,0)?

$$x' = s_x * x$$

$$y' = s_y * y$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

# 2x2 Matrices

- What types of transformations can be represented with a 2x2 matrix?

2D Rotate around (0,0)?

$$x' = \cos \Theta * x - \sin \Theta * y$$

$$y' = \sin \Theta * x + \cos \Theta * y$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos \Theta & -\sin \Theta \\ \sin \Theta & \cos \Theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

2D Shear?

$$x' = x + sh_x * y$$

$$y' = sh_y * x + y$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & sh_x \\ sh_y & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

# 2x2 Matrices

- What types of transformations can be represented with a 2x2 matrix?

2D Mirror about Y axis?

$$\begin{aligned}x' &= -x \\y' &= y\end{aligned}$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

2D Mirror over (0,0)?

$$\begin{aligned}x' &= -x \\y' &= -y\end{aligned}$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

# 2x2 Matrices

- What types of transformations can be represented with a 2x2 matrix?

## 2D Translation?

$$\begin{aligned}x' &= x + t_x \\y' &= y + t_y\end{aligned}\quad \text{NO!}$$

Only linear 2D transformations  
can be represented with a 2x2 matrix

# All 2D Linear Transformations

- Linear transformations are combinations of ...

- Scale,
- Rotation,
- Shear, and
- Mirror

- Properties of linear transformations:

- Origin maps to origin
- Lines map to lines
- Parallel lines remain parallel
- Ratios are preserved
- Closed under composition

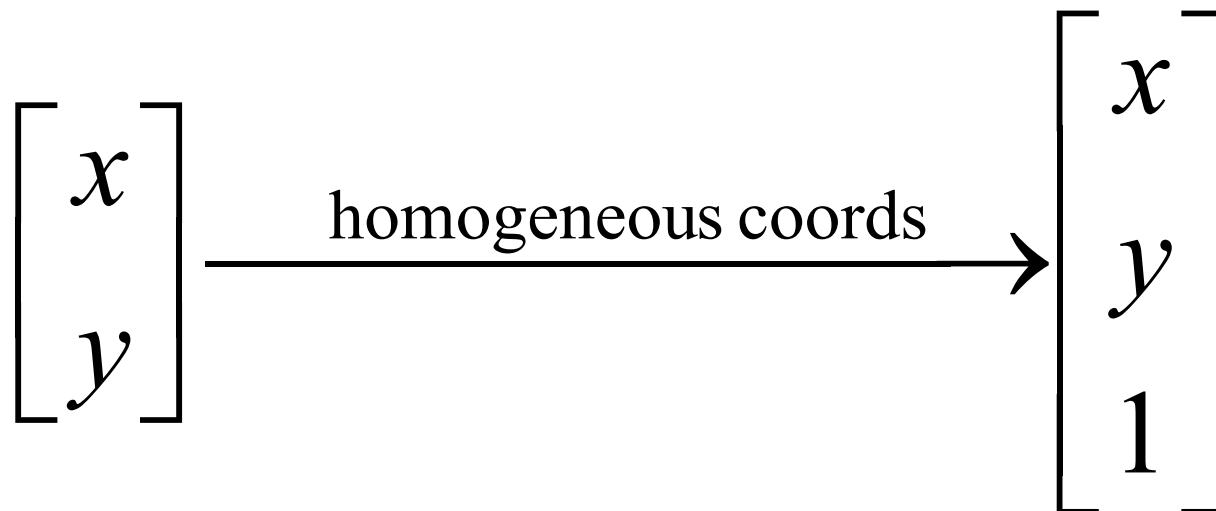
$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} e & f \\ g & h \end{bmatrix} \begin{bmatrix} i & j \\ k & l \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

# Homogeneous Coordinates

- ***Homogeneous coordinates***

- represent coordinates in 2 dimensions with a 3-vector



# Homogeneous Coordinates

- Q: How can we represent translation as a 3x3 matrix?

$$x' = x + t_x$$

$$y' = y + t_y$$

- A: Using the rightmost column:

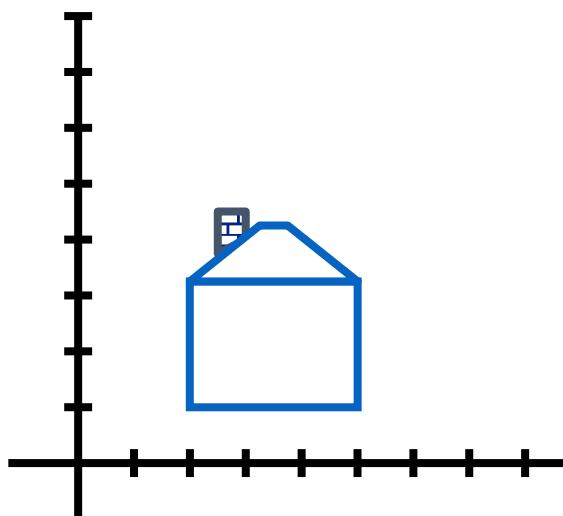
$$\text{Translation} = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix}$$

# Translation

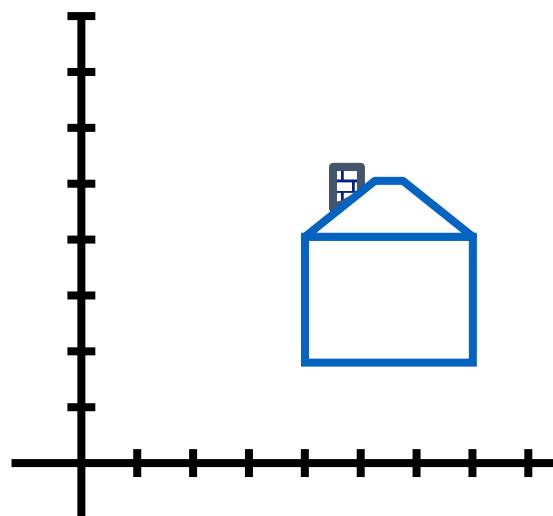
- Example of translation

## Homogeneous Coordinates

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



$$t_x = 2$$
$$t_y = 1$$



# Basic 2D Transformations

- Basic 2D transformations as 3x3 matrices

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

Translate

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} s_x & 0 & 0 \\ 0 & s_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Scale

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\Theta & -\sin\Theta & 0 \\ \sin\Theta & \cos\Theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Rotate

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & sh_x & 0 \\ sh_y & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Shear

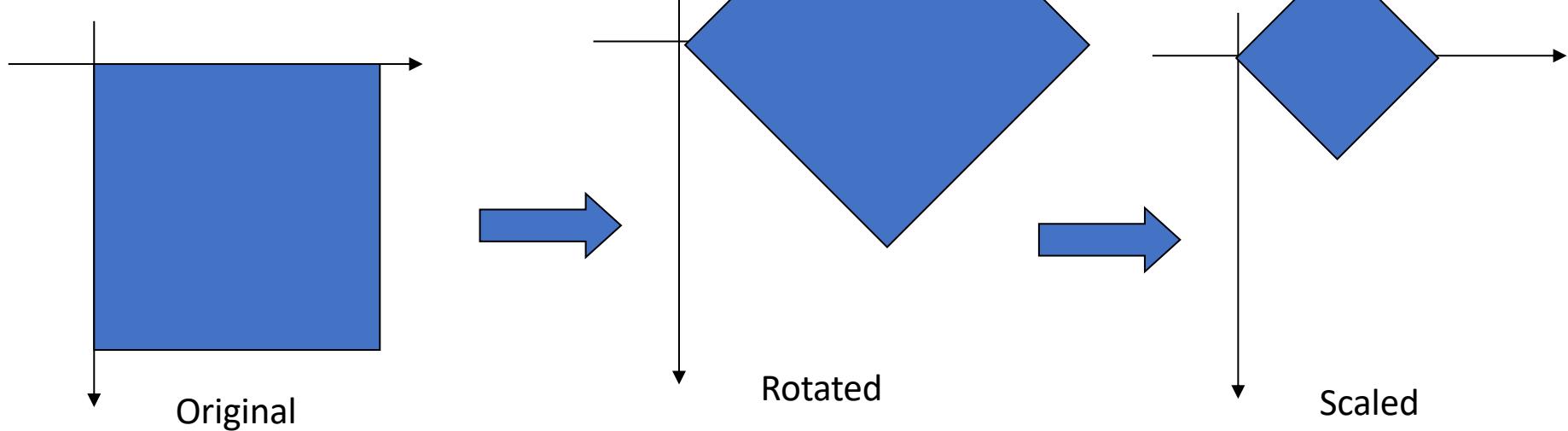
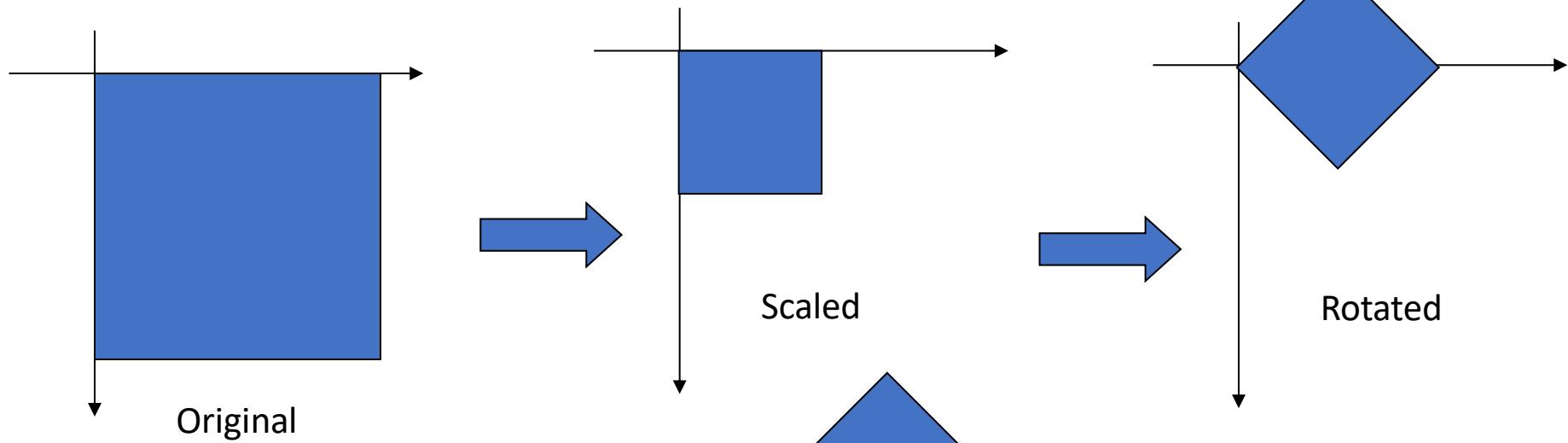
# Matrix Composition

- Transformations can be combined by matrix multiplication

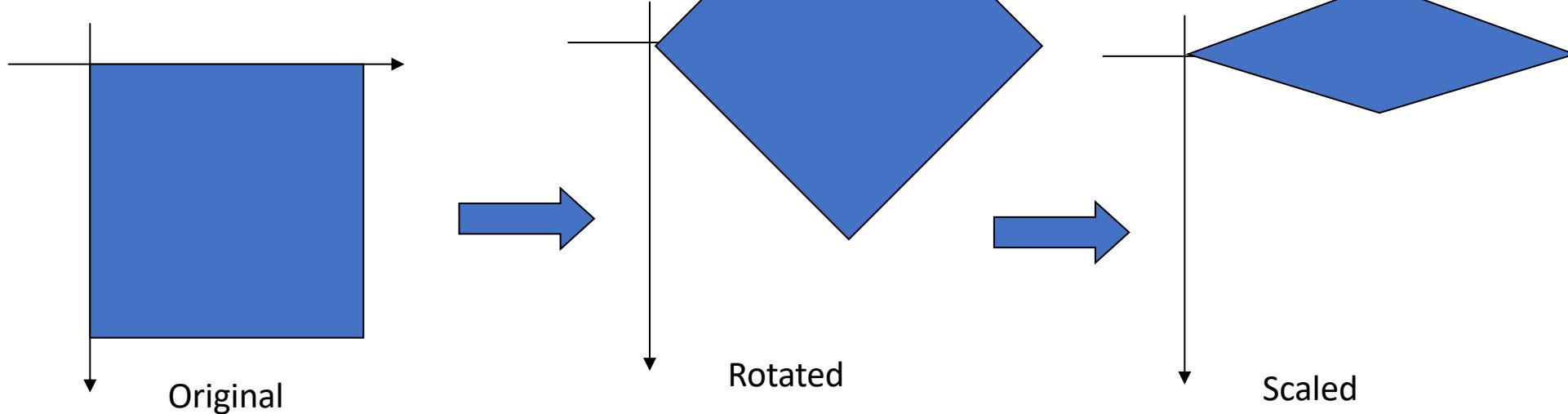
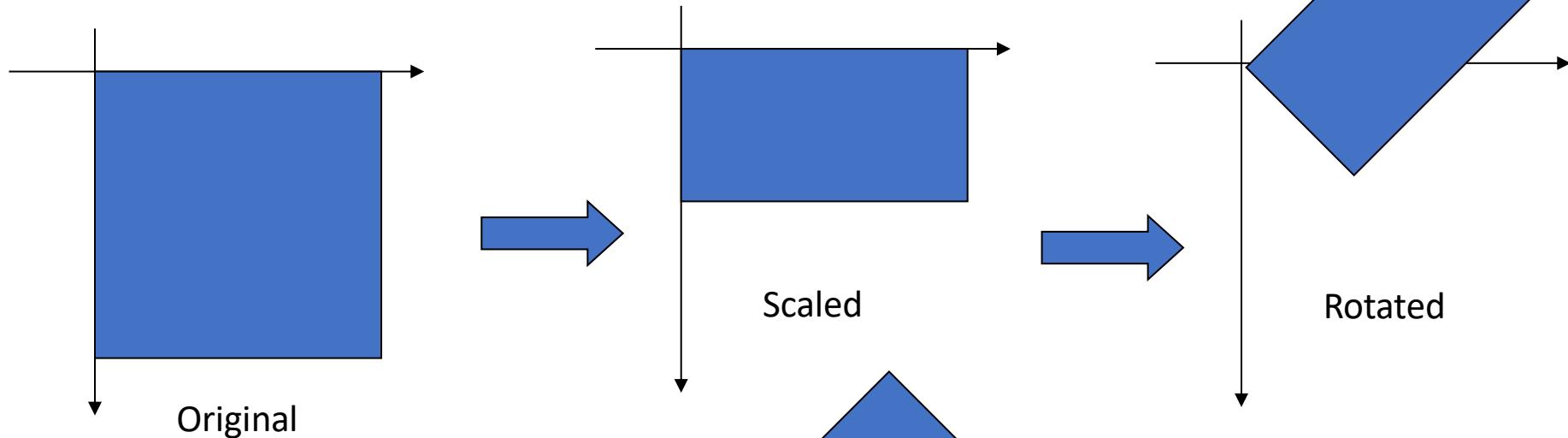
$$\begin{bmatrix} x' \\ y' \\ w' \end{bmatrix} = \left( \begin{bmatrix} 1 & 0 & tx \\ 0 & 1 & ty \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos \Theta & -\sin \Theta & 0 \\ \sin \Theta & \cos \Theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} sx & 0 & 0 \\ 0 & sy & 0 \\ 0 & 0 & 1 \end{bmatrix} \right) \begin{bmatrix} x \\ y \\ w \end{bmatrix}$$

$\mathbf{p}' = T(t_x, t_y) R(\Theta) S(s_x, s_y) \mathbf{p}$

# Order of Transformations



# Order of Transformations



# Order of Transformations

- In general  $\mathbf{AB} \neq \mathbf{BA}$
- However, in specific cases, this might hold true
- In the previous example, if  $s_x = s_y$ , then order of transformations does not matter

# Inverse Transformations

- Inverse transformation should ‘undo’ the effect of the original transformation
- Simply taking the matrix inverse will work

$$\mathbf{A}\mathbf{A}^{-1} = \mathbf{I}$$

- Inverse Transforms

$$\begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cancel{1/s_x} & 0 & 0 \\ 0 & \cancel{1/s_y} & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & -t_x \\ 0 & 1 & -t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & -e_x & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

- Remember that when inverting concatenation of transforms, their order reverses

$$(\mathbf{ABC})^{-1} = \mathbf{C}^{-1}\mathbf{B}^{-1}\mathbf{A}^{-1}$$

# Hierarchy of Transformation Groups

- Translation

$$\mathbf{x}' = \begin{bmatrix} \mathbf{I}_{2 \times 2} & \mathbf{t} \end{bmatrix}_{2 \times 3} \bar{\mathbf{x}} \quad \begin{aligned} x' &= x + t_x \\ y' &= y + t_y \end{aligned}$$

- Rigid Body Transformation

$$\mathbf{x}' = \begin{bmatrix} \mathbf{R} & \mathbf{t} \end{bmatrix}_{2 \times 3} \bar{\mathbf{x}} \quad \begin{aligned} x' &= x \cos \theta - y \sin \theta + t_x \\ y' &= x \sin \theta + y \cos \theta + t_y \end{aligned}$$

- Similarity

$$\mathbf{x}' = \begin{bmatrix} s\mathbf{R} & \mathbf{t} \end{bmatrix}_{2 \times 3} \bar{\mathbf{x}} \quad \begin{aligned} x' &= sx \cos \theta - sy \sin \theta + t_x \\ y' &= sx \sin \theta + sy \cos \theta + t_y \end{aligned}$$

# Hierarchy of Transformation Groups

- Translation

$$x' = x + t_x$$

$$y' = y + t_y$$

- Rigid Body Transformation

$$x' = x \cos \theta - y \sin \theta + t_x$$

$$y' = x \sin \theta + y \cos \theta + t_y$$

- Similarity

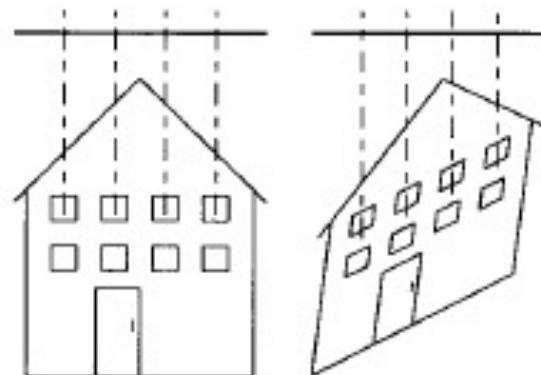
$$x' = sx \cos \theta - sy \sin \theta + t_x$$

$$y' = sx \sin \theta + sy \cos \theta + t_y$$

# Affine Transformations

- Affine transformations are combinations of ...
  - Linear transformations rotation, scaling, shear, and
  - Translations
- Properties of affine transformations:
  - Origin does not necessarily map to origin
  - Lines map to lines
  - Parallel lines remain parallel
  - Ratios are preserved

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



(ORIGINAL)

(AFFINE)

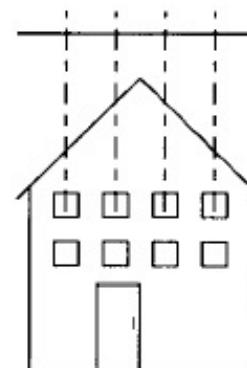
# Projective Transformations

- Projective transformations ...
- 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
  - Models change of basis
  - Simulates out of plane rotations

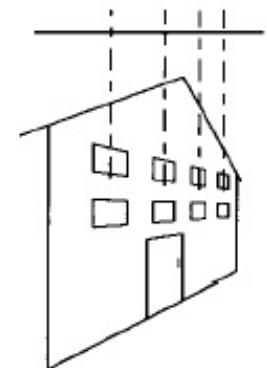
$$\mathbf{x}' = \begin{bmatrix} a_{00} & a_{01} & a_{02} \\ a_{10} & a_{11} & a_{12} \\ a_{20} & a_{21} & a_{22} \end{bmatrix} \bar{\mathbf{x}}$$

$$x' = \frac{a_{00}x + a_{01}y + a_{02}}{a_{20}x + a_{21}y + a_{22}}$$

$$y' = \frac{a_{10}x + a_{11}y + a_{12}}{a_{20}x + a_{21}y + a_{22}}$$

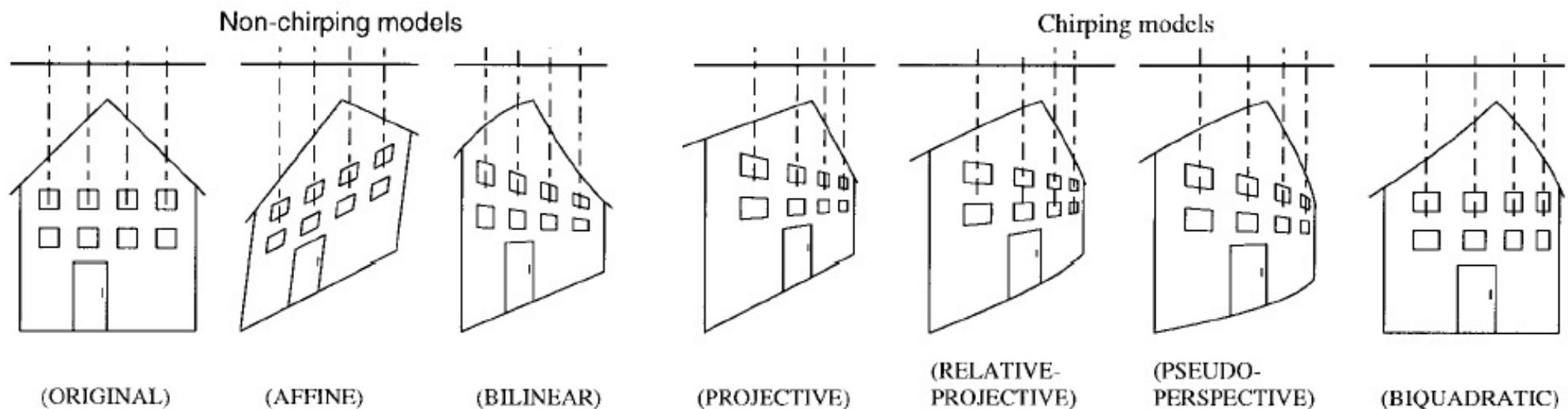


(ORIGINAL)



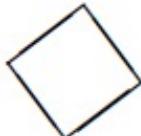
(PROJECTIVE)

# Displacement Models



Ref: Steve Mann & Rosalind W. Picard, “Video Orbits of the Projective Group: A simple approach to featureless estimation of parameters”, IEEE Trans. on Image Processing, Vol. 6, No. 9, September 1997

# Hierarchy of 2D Transformations

Transformation	Matrix	# DoF	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	

# Basic 2D transformations

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Scale

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & \alpha_x \\ \alpha_y & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Shear

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos \Theta & -\sin \Theta \\ \sin \Theta & \cos \Theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Rotate

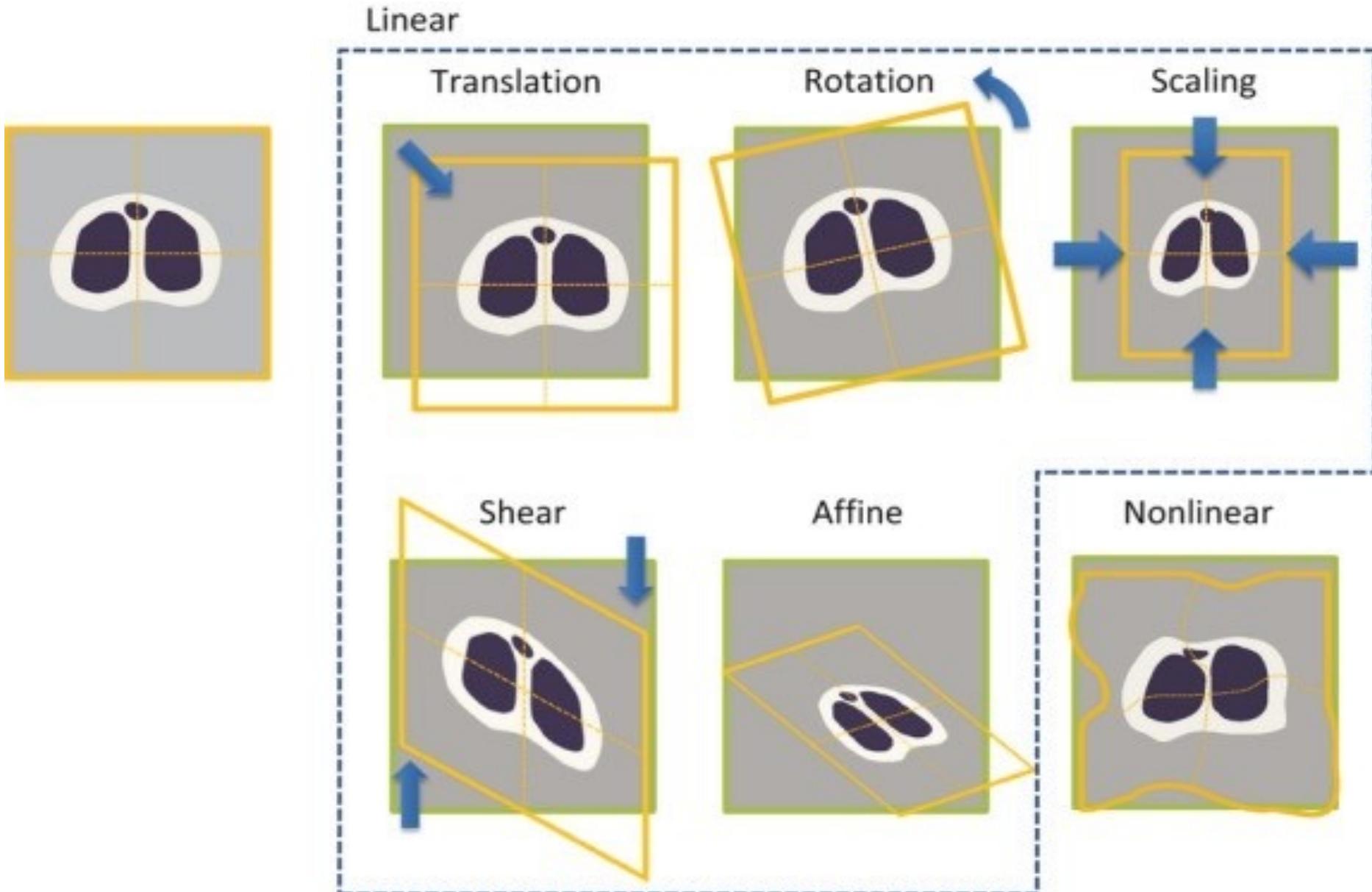
$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Translate

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

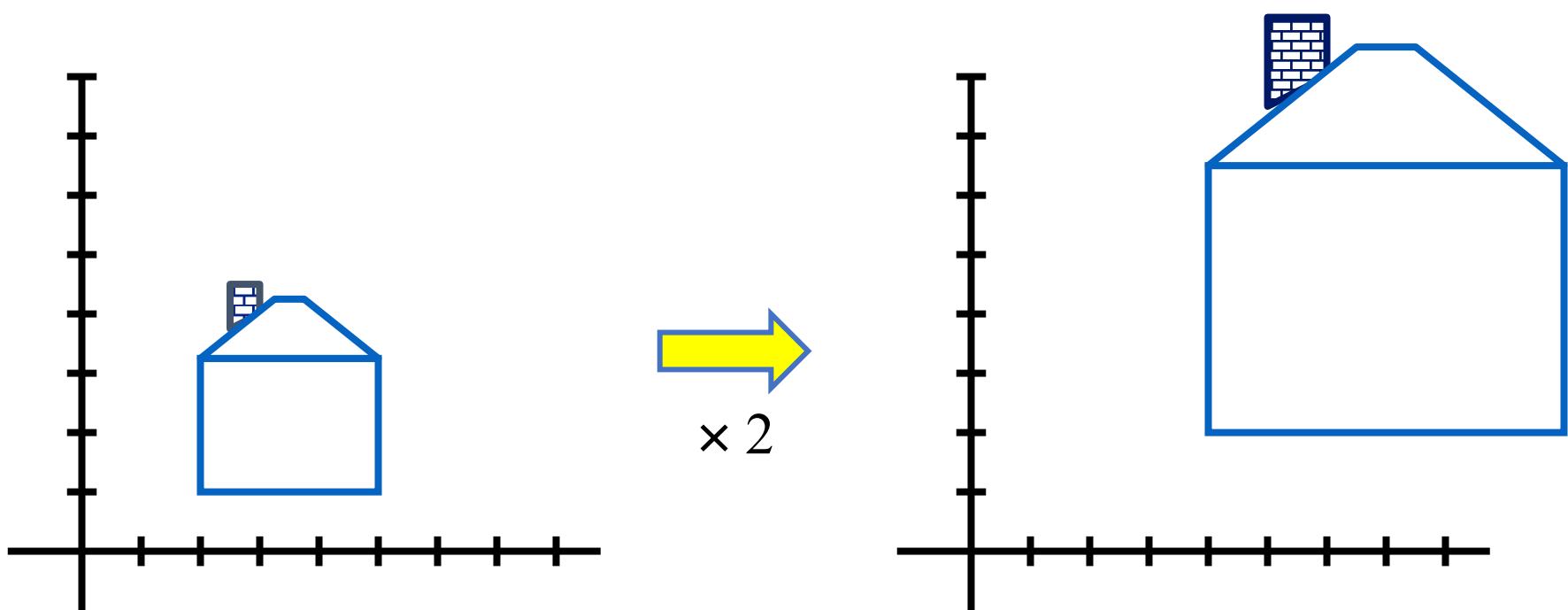
Affine

Affine is any combination of translation, scale, rotation, shear



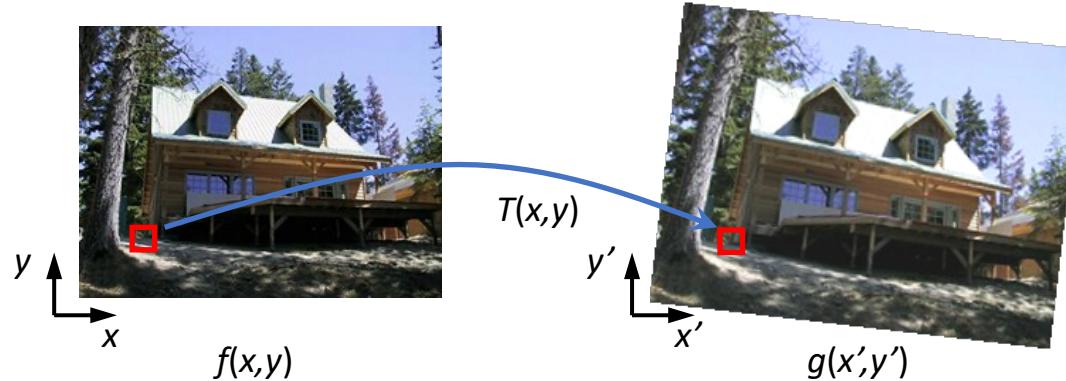
# Scaling

- *Scaling* a coordinate means multiplying each of its components by a scalar
- *Uniform scaling* means this scalar is the same for all components:



# Image warping

Image Warping is application of transformation such that it changes 'spatial' configuration of an image

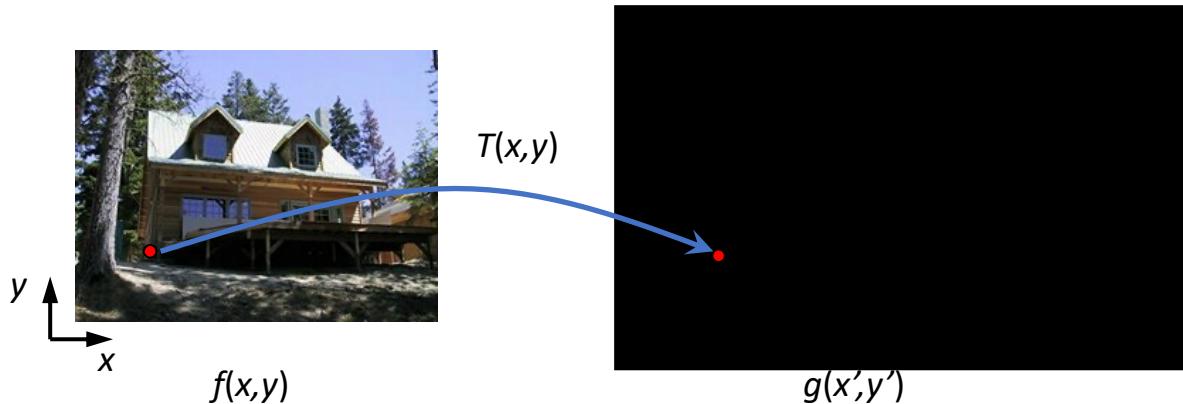


- Given a coordinate transform  $(x',y') = h(x,y)$  and a source image  $f(x,y)$ , how do we compute a transformed image  $g(x',y') = f(T(x,y))$ ?

# Warping

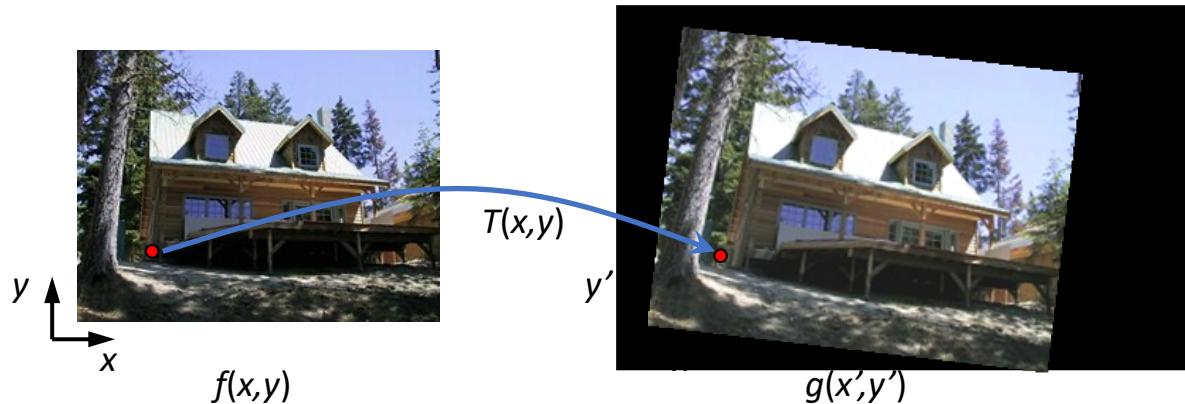
- Inputs:
  - Image X
  - Affine Transformation  $A = [a_1 \ a_2 \ b_1 \ a_3 \ a_4 \ b_2]^T$
- Output:
  - Generate  $X'$  such that  $X' = AX$
- Obvious Process:
  - For each pixel in X
  - Apply transformation
  - At that location in  $X'$ , put the same color as at the original location in X
- Problems?

# Forward warping



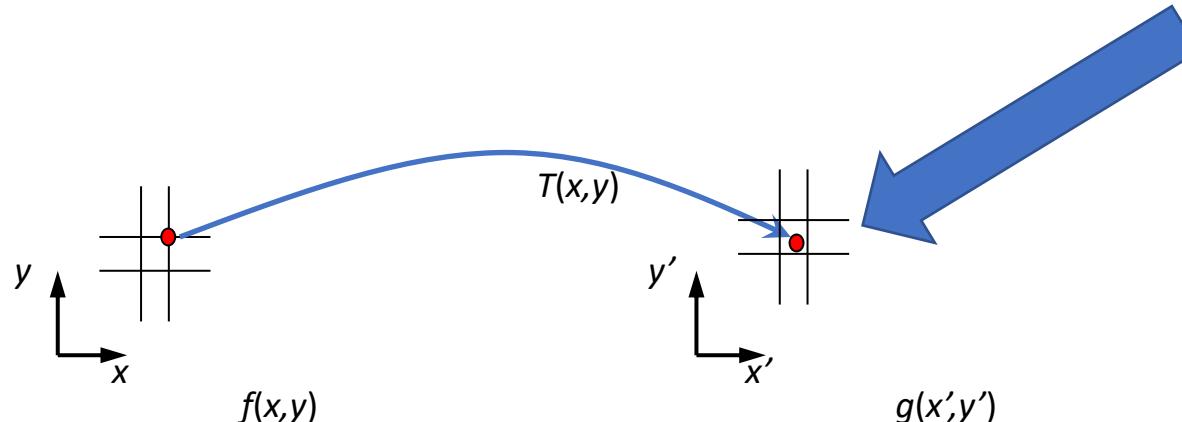
- Send each pixel  $f(x,y)$  to its corresponding location
    - $(x',y') = T(x,y)$  in the second image
- Q: what if pixel lands “between” two pixels?

# Forward warping



- Send each pixel  $f(x,y)$  to its corresponding location
    - $(x',y') = T(x,y)$  in the second image
- Q: what if pixel lands “between” two pixels?

# Forward warping



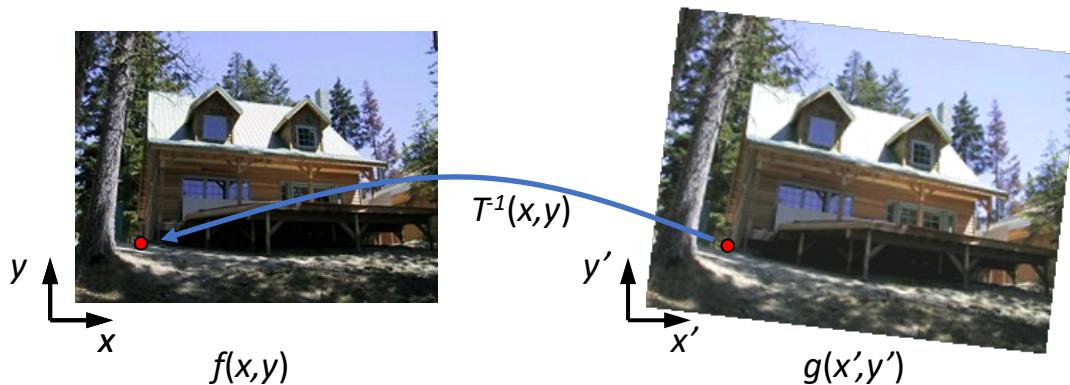
- Send each pixel  $f(x, y)$  to its corresponding location
- $(x', y') = T(x, y)$  in the second image

Q: what if pixel lands “between” two pixels?

A: distribute color among neighboring pixels  $(x', y')$

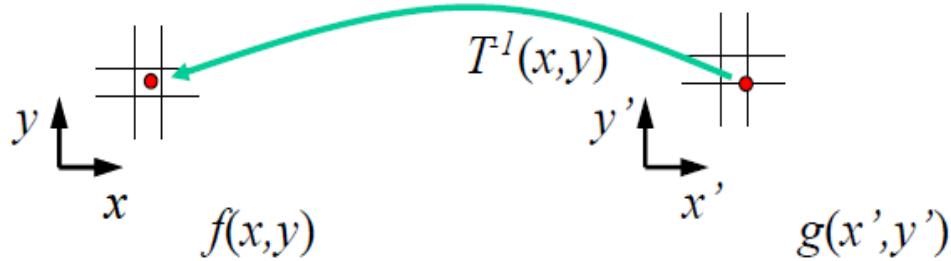
– Known as “splatting” NOT A SIMPLE TASK

# Inverse warping



- Get each pixel  $g(x',y')$  from its corresponding location
    - $(x,y) = T^{-1}(x',y')$  in the first image
- Q: what if pixel comes from “between” two pixels?

# Inverse Mapping



Get each pixel  $g(x',y')$  from its corresponding location  
 $(x,y) = T^{-1}(x',y')$  in the first image

Q: what if pixel comes from “between” two pixels?

A: *Interpolate* color value from neighbors

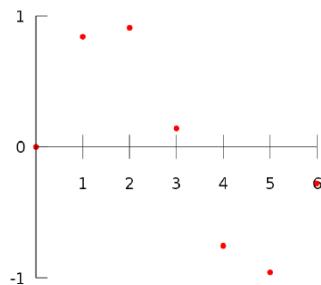
- nearest neighbor, bilinear, Gaussian, bicubic

# Interpolations

## Interpolation

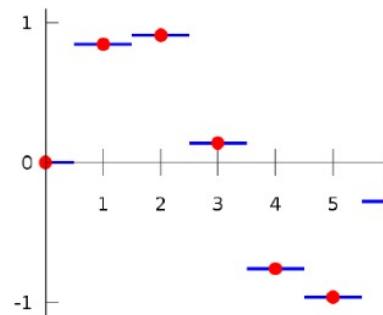
---

**interpolation** is a method of constructing new data points within the range of a discrete set of known data points.

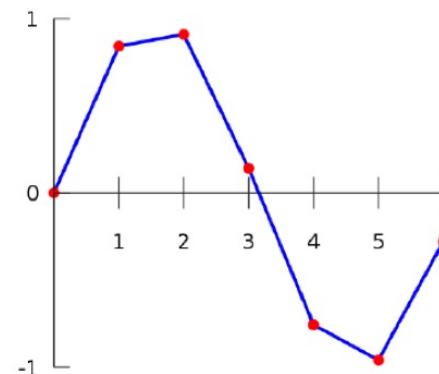


# Interpolations

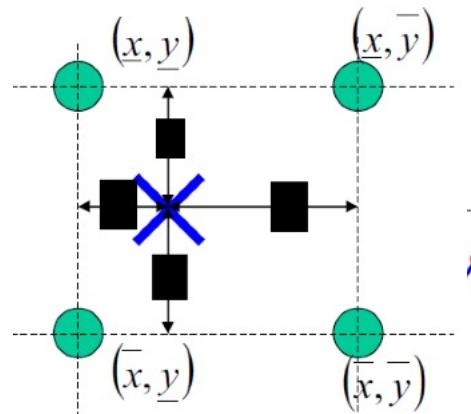
- Nearest Neighbor Interpolations



- Linear Interpolation

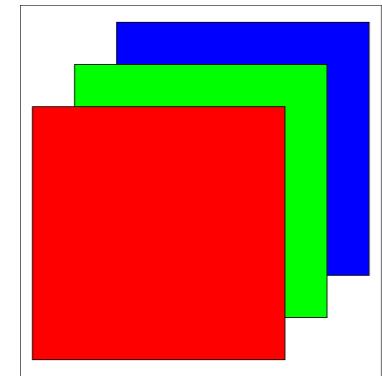


- 2D Bilinear Interpolation



# Warping Color Images

- Same as applying to Gray Scale Images
- Since Color images consists of
  - More than one 2D matrix
  - In case of RGB image
    - Apply transformation to each layer separately
  - Bilinear Interpolation
    - Also applied separately



# 2D Transformation & Image Registration

- **Definition:** A mapping from one 2D coordinate system to another
- Also called
  - spatial transformation,
  - geometric transformation,
  - warp
- **Image Registration:** Process of transforming two images so that same features overlap

---

# Recovering the best transformation

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

# Recovering Best Affine Transformation

---

- Given two images with unknown transformation between them...



- Compute the values for  $[a_1 \dots a_6]$

# Recovering Best Affine Transformation

---

Input: we are given some correspondences

Output: Compute  $a_1 - a_6$  which relate the images



This is an optimization problem... Find the 'best' set of parameters, given the input data

Source: updated from Sohaib Khan, LUMS

---

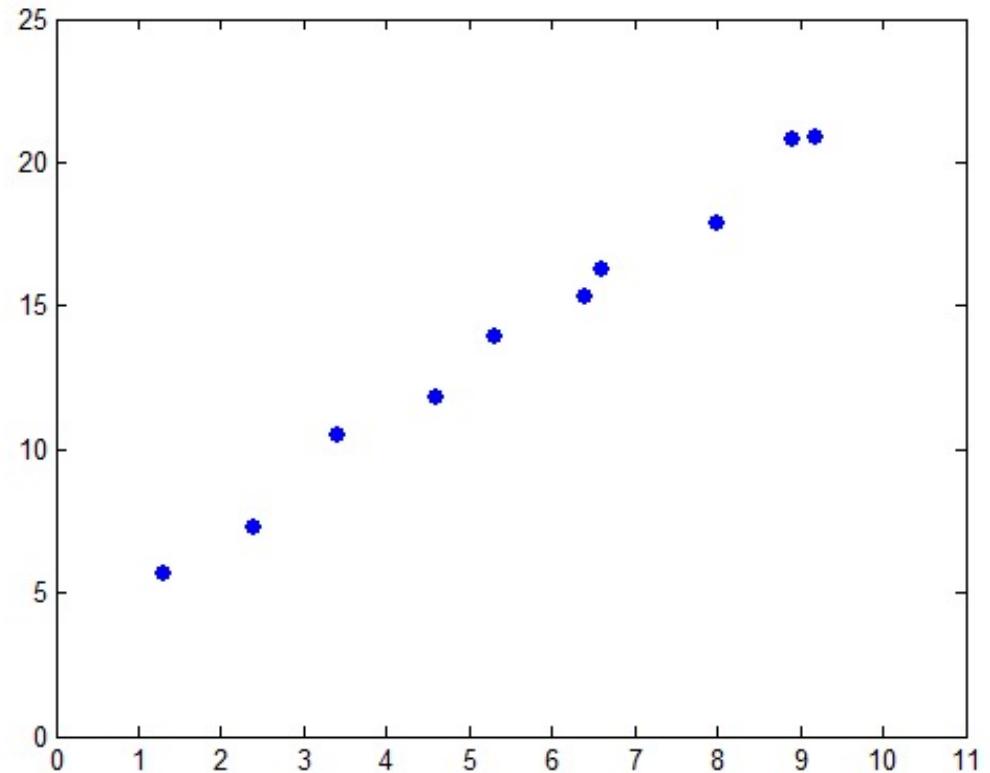
**HM (a):**  
Why we need 3 points for six variables?

# Parameter Optimization: Least Squared Error Solutions

---

Let us first consider the ‘simpler’ problem of fitting a line to a set of data points...

x	y
1.3	5.7
2.4	7.3
3.4	10.5
4.6	11.8
5.3	13.9
6.6	16.3
6.4	15.3
8.0	17.9
8.9	20.8
9.2	20.9



Equation of best fit line ?

# Line Fitting: Least Squared Error Solution

---

Step 1: Identify the model

- Equation of line:  $y = mx + c$

Step 2: Set up an error term which will give the goodness of every point with respect to the (unknown) model

- Error induced by  $i^{\text{th}}$  point:

- $e_i = mx_i + c - y_i$

- Error for whole data:  $E = \sum_i e_i^2$

- $E = \sum_i (mx_i + c - y_i)^2$

Step 3: Differentiate Error w.r.t. parameters, put equal to zero and solve for minimum point

HM (b):

Differentiate Error w.r.t. parameters, put equal to zero and solve for minimum point

# Recovering Best Affine Transformation

---

Input: Set of correspondences

- Image 1:  $(x_i, y_i)$    Image 2:  $(x'_i, y'_i)$



# Recovering Best Affine Transformation

---

## Least Squares Error Solution

- Is the solution (i.e. set of parameters  $a_1 \dots a_6$ ) such that the sum of the square of error in each corresponding point is as minimum as possible
- No other set of parameters exists that may have a lower error (in the squared error sense)

# Recovering Best Affine Transformation

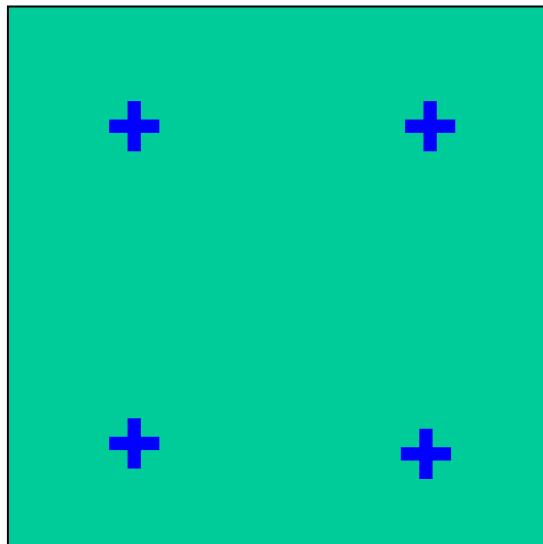


Image 1

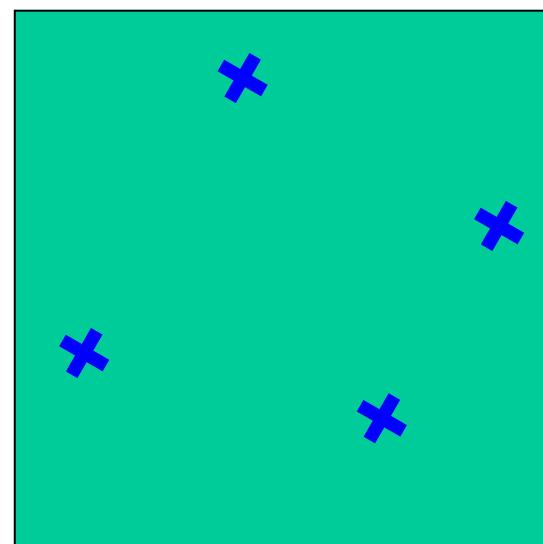
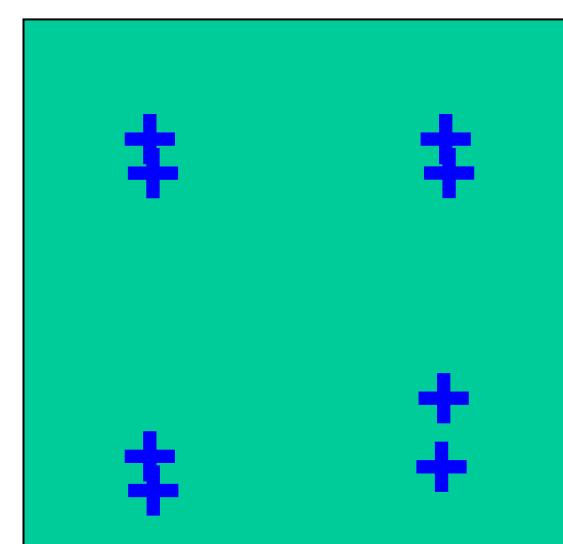


Image 2



Overlap of points  
after recovering the  
transformation

We can try to find the set of parameters in which the  
**error** is minimum

# Least Squares Error Solution

$$\begin{bmatrix} x_j^* \\ y_j^* \\ 1 \end{bmatrix} = \begin{bmatrix} a_1 & a_2 & a_3 \\ a_4 & a_5 & a_6 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x'_j \\ y'_j \\ 1 \end{bmatrix}$$

( $x_j^*, y_j^*$ )

( $x_j, y_j$ )

$$E(a_1, a_2, a_3, a_4, a_5, a_6) = \sum_{j=1}^n (x_j^* - x_j)^2 + (y_j^* - y_j)^2$$

$$E(\mathbf{a}) = \sum_{j=1}^n ((a_1 x'_j + a_2 y'_j + a_3 - x_j)^2 + (a_4 x'_j + a_5 y'_j + a_6 - y_j)^2)$$

# Least Squares Error Solution

---

$$E(\mathbf{a}) = \sum_{j=1}^n ((a_1 x_j + a_2 y_j + a_3 - x'_j)^2 + (a_4 x_j + a_5 y_j + a_6 - y'_j)^2)$$

Minimize  $E$  w.r.t.  $\mathbf{a}$

Compute  $\frac{\partial E}{\partial a_i}$ , put equal to zero, solve simultaneously

$$\begin{bmatrix} \sum_j x_j^2 & \sum_j x_j y_j & \sum_j x_j & 0 & 0 & 0 \\ \sum_j x_j y_j & \sum_j y_j^2 & \sum_j y_j & 0 & 0 & 0 \\ \sum_j x_j & \sum_j y_j & \sum_j 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sum_j x_j^2 & \sum_j x_j y_j & \sum_j x_j \\ 0 & 0 & 0 & \sum_j x_j y_j & \sum_j y_j^2 & \sum_j y_j \\ 0 & 0 & 0 & \sum_j x_j & \sum_j y_j & \sum_j 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \\ a_6 \end{bmatrix} = \begin{bmatrix} \sum_j x_j x'_j \\ \sum_j y_j x'_j \\ \sum_j x'_j \\ \sum_j x_j y'_j \\ \sum_j y_j y'_j \\ \sum_j y'_j \end{bmatrix}$$

# Least Squares Error Solution

$$E(\mathbf{a}) = \sum_{j=1}^n ((a_1 x_j + a_2 y_j + a_3 - x'_j)^2 + (a_4 x_j + a_5 y_j + a_6 - y'_j)^2)$$

Minimize  $E$  w.r.t.  $\mathbf{a}$

Compute  $\frac{\partial E}{\partial a_i}$ , put equal to zero, solve simultaneously

$$\begin{bmatrix} \sum_j x_j^2 & \sum_j x_j y_j & \sum_j x_j & 0 & 0 & 0 \\ \sum_j x_j y_j & \sum_j y_j^2 & \sum_j y_j & 0 & 0 & 0 \\ \sum_j x_j & \sum_j y_j & \sum_j 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sum_j x_j^2 & \sum_j x_j y_j & \sum_j x_j \\ 0 & 0 & 0 & \sum_j x_j y_j & \sum_j y_j^2 & \sum_j y_j \\ 0 & 0 & 0 & \sum_j x_j & \sum_j y_j & \sum_j 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \\ a_6 \end{bmatrix} = \begin{bmatrix} \sum_j x_j x'_j \\ \sum_j y_j x'_j \\ \sum_j x'_j \\ \sum_j x_j y'_j \\ \sum_j y_j y'_j \\ \sum_j y'_j \end{bmatrix}$$

HM (c):  
How?

# Recovering Best Affine Transformation (alternate way)

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$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} a_1 & a_2 & a_3 \\ a_4 & a_5 & a_6 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} x & y & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x & y & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \\ a_6 \end{bmatrix} = \begin{bmatrix} x' \\ y' \end{bmatrix}$$

# Recovering Best Affine Transformation

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Given three pairs of corresponding points, we get 6 equations

$$\begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_1 & y_1 & 1 \\ x_2 & y_2 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_2 & y_2 & 1 \\ x_3 & y_3 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_3 & y_3 & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \\ a_6 \end{bmatrix} = \begin{bmatrix} x_1' \\ y_1' \\ x_2' \\ y_2' \\ x_3' \\ y_3' \end{bmatrix}$$

$$\mathbf{Ax}=\mathbf{B}$$

$$\mathbf{x}=\mathbf{A}^{-1}\mathbf{B}$$

# Recovering Best Affine Transformation

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What if we knew four corresponding points?

We should be able to utilize the additional information

$$\begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_1 & y_1 & 1 \\ x_2 & y_2 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_2 & y_2 & 1 \\ x_3 & y_3 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_3 & y_3 & 1 \\ x_4 & y_4 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_4 & y_4 & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \\ a_6 \end{bmatrix} = \begin{bmatrix} x_1' \\ y_1' \\ x_2' \\ y_2' \\ x_3' \\ y_3' \\ x_4' \\ y_4' \end{bmatrix}$$

# Recovering Best Affine Transformation

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$$\mathbf{Ax} = \mathbf{B}$$

Cannot take inverse  
directly

$$\begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_1 & y_1 & 1 \\ x_2 & y_2 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_2 & y_2 & 1 \\ x_3 & y_3 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_3 & y_3 & 1 \\ x_4 & y_4 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_4 & y_4 & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \\ a_6 \end{bmatrix} = \begin{bmatrix} x_1' \\ y_1' \\ x_2' \\ y_2' \\ x_3' \\ y_3' \\ x_4' \\ y_4' \end{bmatrix}$$

# Pseudo inverse

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For an over-constrained linear system

$$Ax = B$$

$A$  has more rows than columns

Multiply by  $A^T$  on both sides

$$A^T A x = A^T B$$

$A^T A$  is a square matrix of as many rows as  $x$

We can take its inverse

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

Pseudo-inverse gives the least squares error solution! [Proof?]

# Recovering Best Affine Transformation

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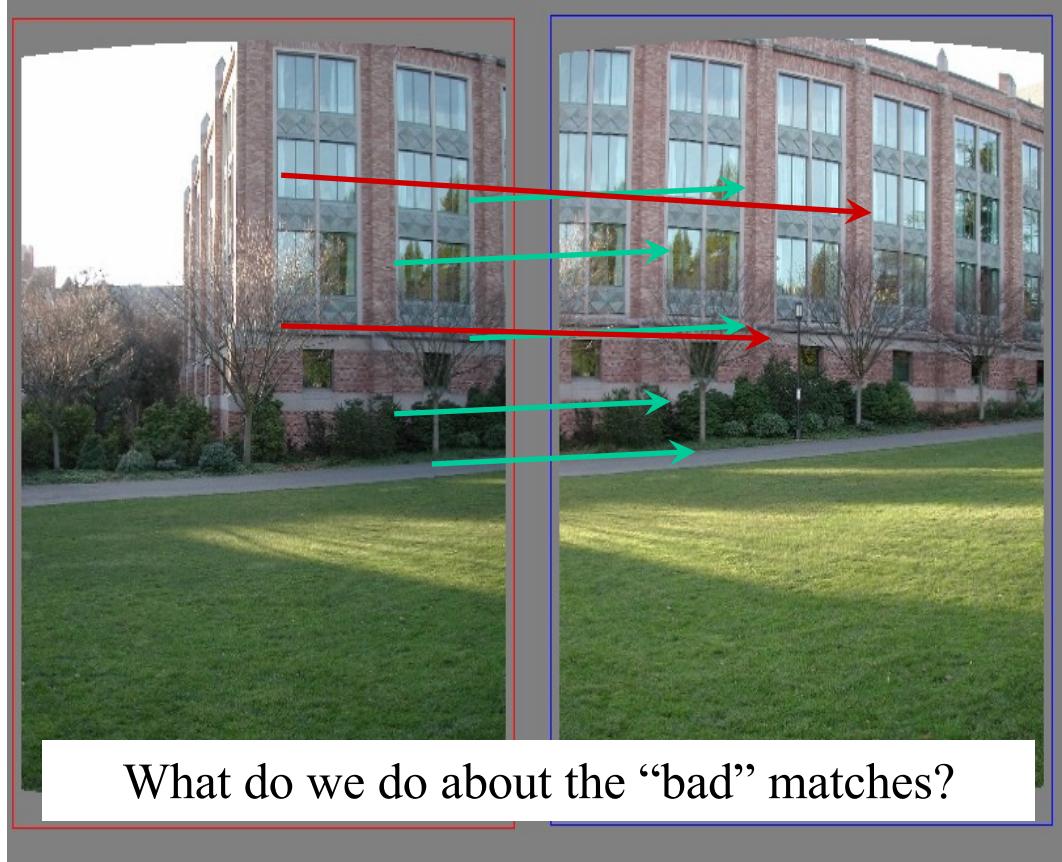
- In general, we may be given  $n$  correspondences
- Concatenate  $n$  correspondences in  $A$  and  $B$
- $A$  is  $2n \times 6$
- $B$  is  $2n \times 1$
- Solve using Least Squares
- $x = (A^T A)^{-1} A^T B$

# RANSAC Algorithm

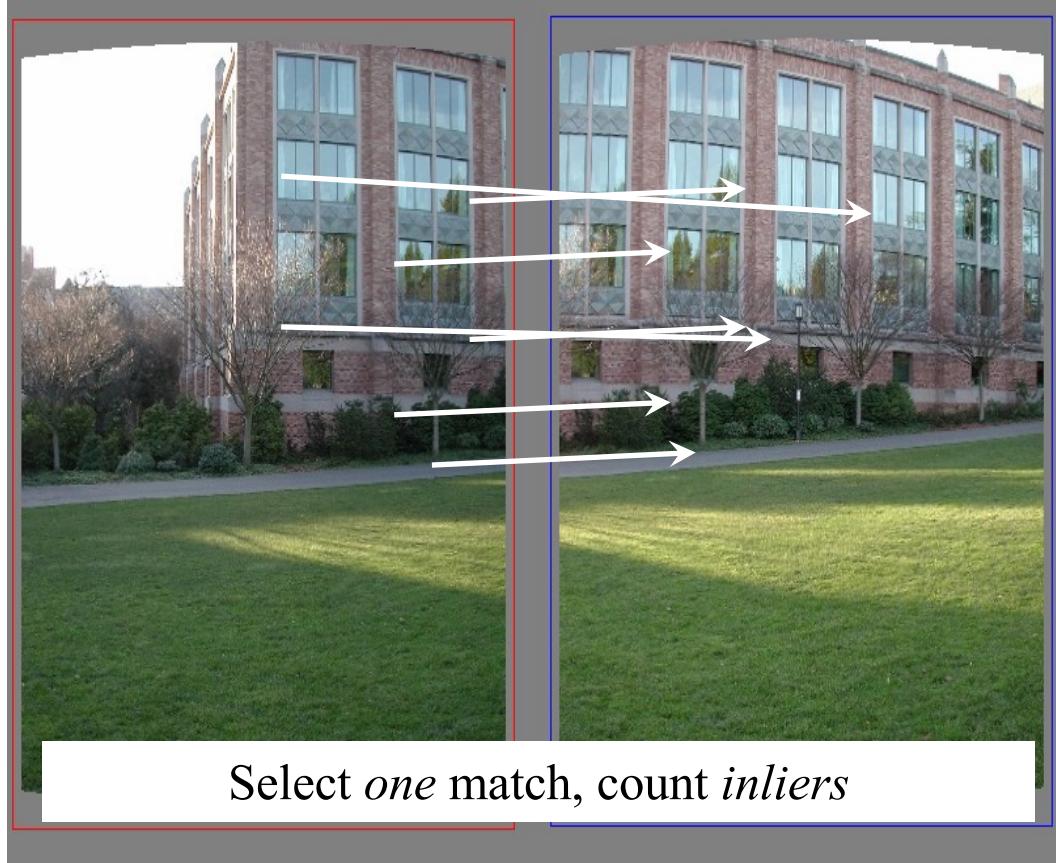
- “Random Sample Consensus”
  - Can be used to find inliers for any type of model fitting
- Widely used in computer vision
- Requires two parameters:
  - The number of trials  $N$  (how many do we need?)
  - The agreement threshold (how close does an inlier have to be?)

*Fischler, M. A., & Bolles, R. C. 1981. Random sampling consensus: A paradigm for model fitting with applications to image analysis and automated cartography. Communications of the Association for Computing Machinery, 24(26), 381–395.*

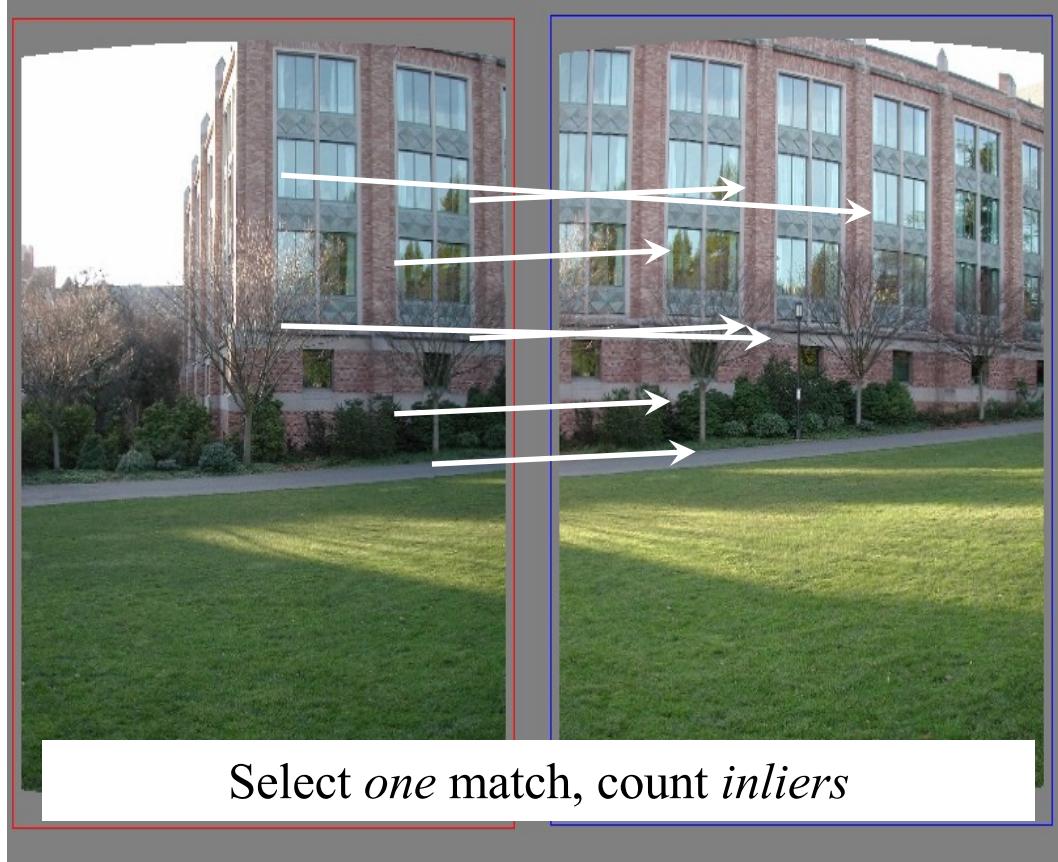
# Matching features



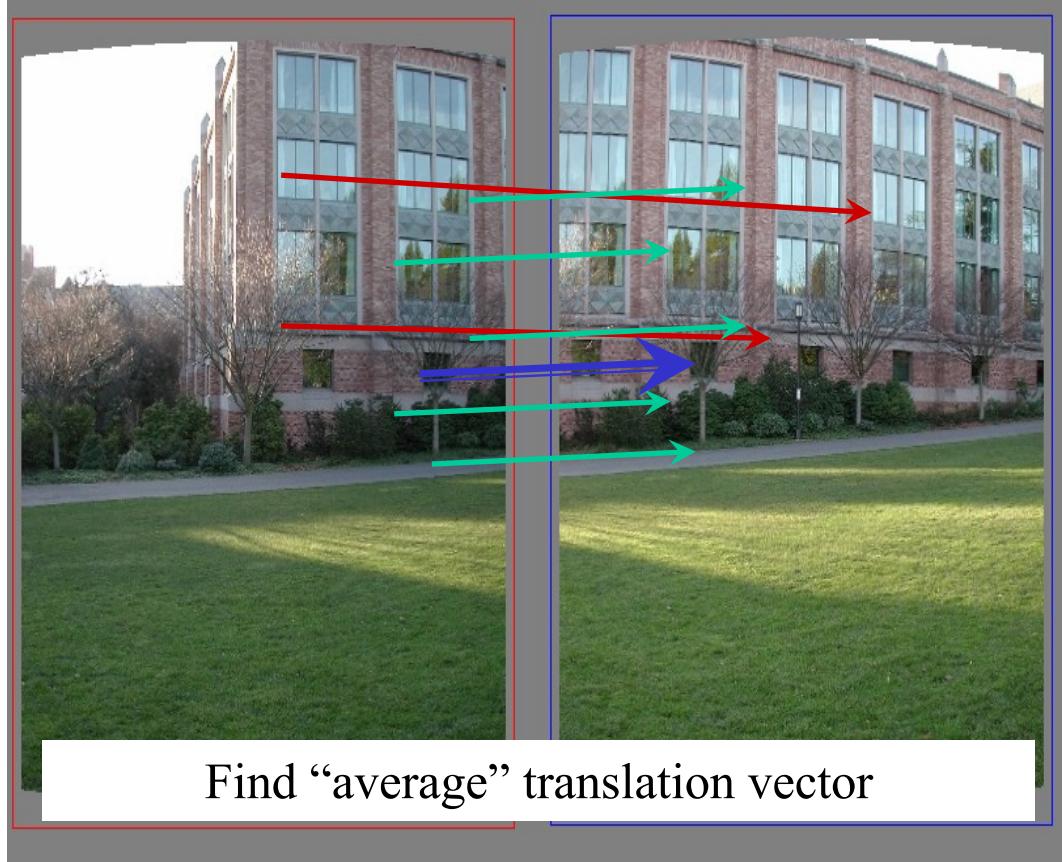
# Random Sample Consensus



# Random Sample Consensus



# Least squares fit

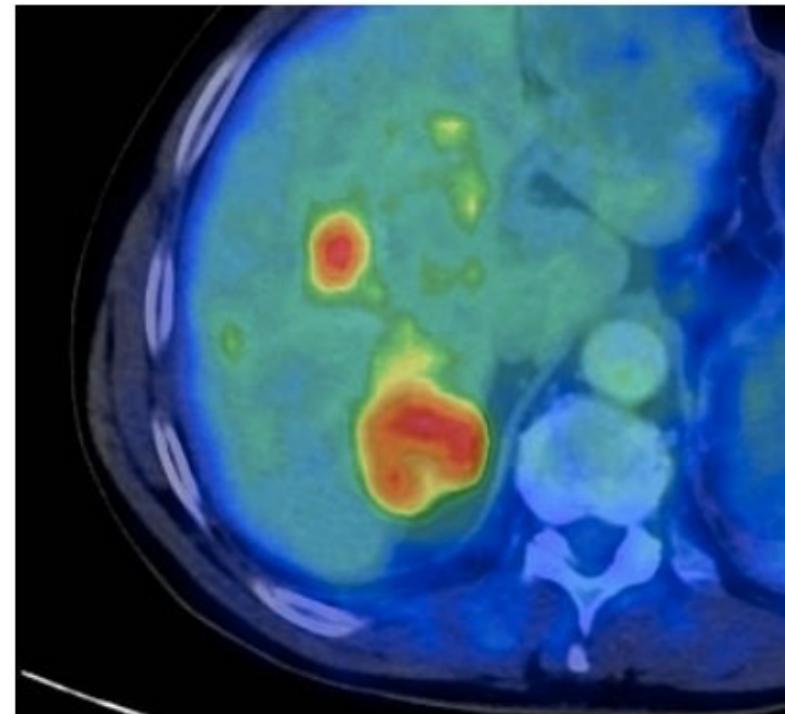
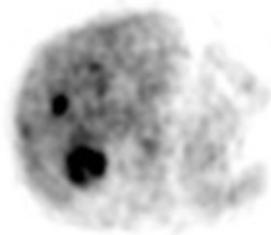


Fusion of information = registration plus combination in a single representation: PET/CT

CT



PET



Deformable fusion- PET shows increased metabolism in lesions identified on CT, consistent with active tumour growth rather than necrosis post-radiotherapy

# Slide Credits

- Jayaram K. Udupa, MIPG of University of Pennsylvania, PA.
- P. Suetens, Fundamentals of Medical Imaging, Cambridge Univ. Press.
- N. Bryan, Intro. to the science of medical imaging, Cambridge Univ. Press.
- CAP 5415 Computer Vision (Fall 2016) Lecture Presentations
- Computer Vision (Lecture Presentations) by Dr. Mohsen Ali