



# **2D transformations**

**CS 600.361/600.461**

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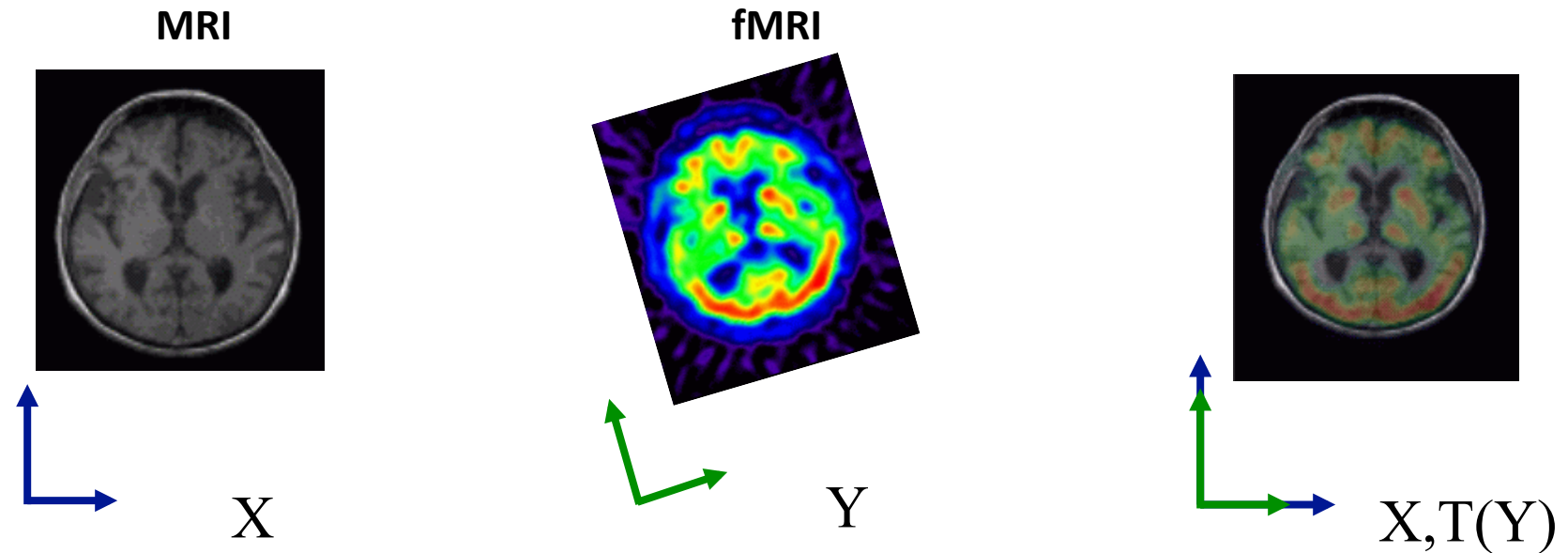


# Motivation: mosaics





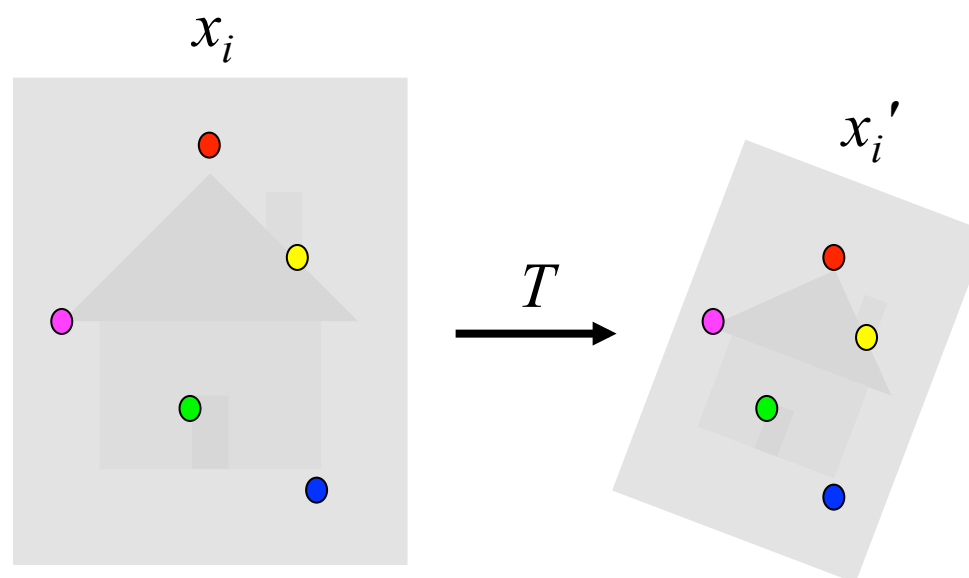
# Motivation: medical image registration





# Alignment problem

- We have previously considered how to **fit a model to image evidence**
  - e.g., a line to edge points
- In alignment, we will **fit the parameters of some transformation** according to a set of matching feature pairs (“correspondences”).







# Parametric (global) warping

- Examples of parametric warps:



translation



rotation



aspect



affine



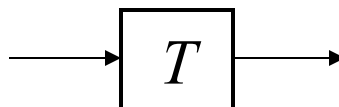
perspective



# 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  $\mathbf{p}$
  - can be described by just a few numbers (parameters)
- Let's represent  $T$  as a matrix:

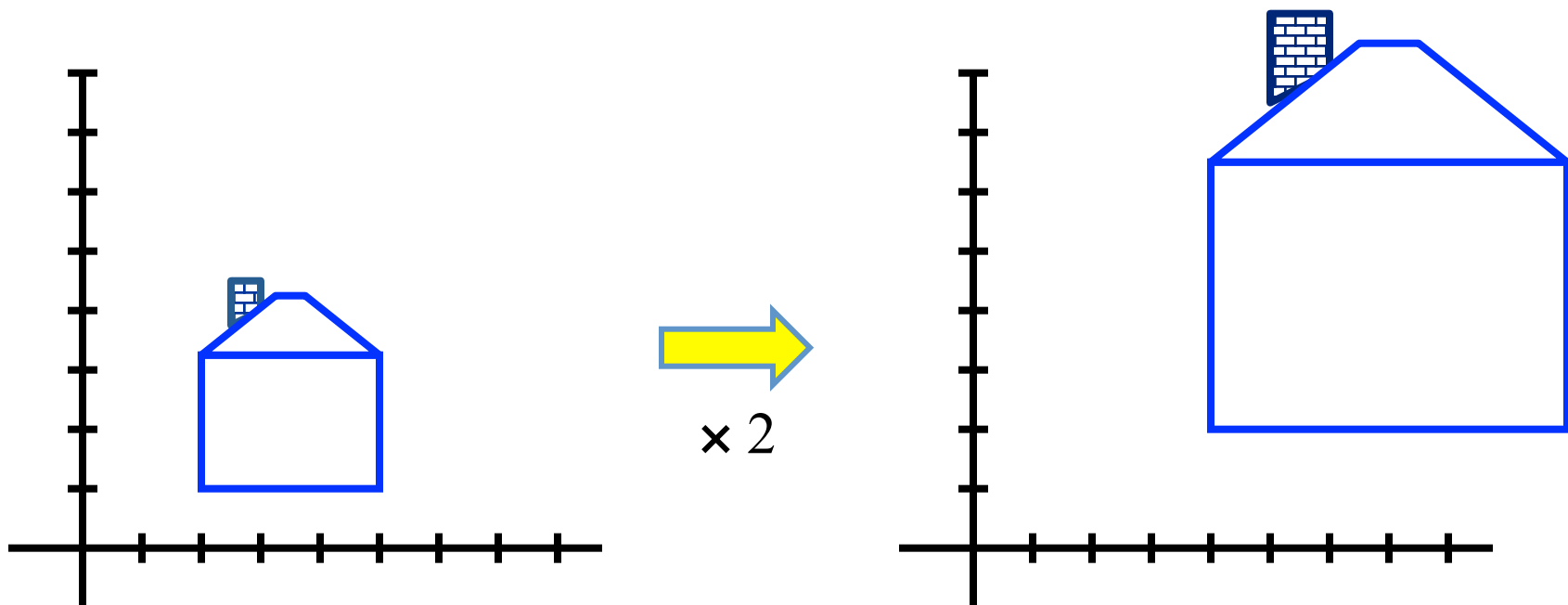
$$\mathbf{p}' = \mathbf{M}\mathbf{p}$$

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



# Scaling

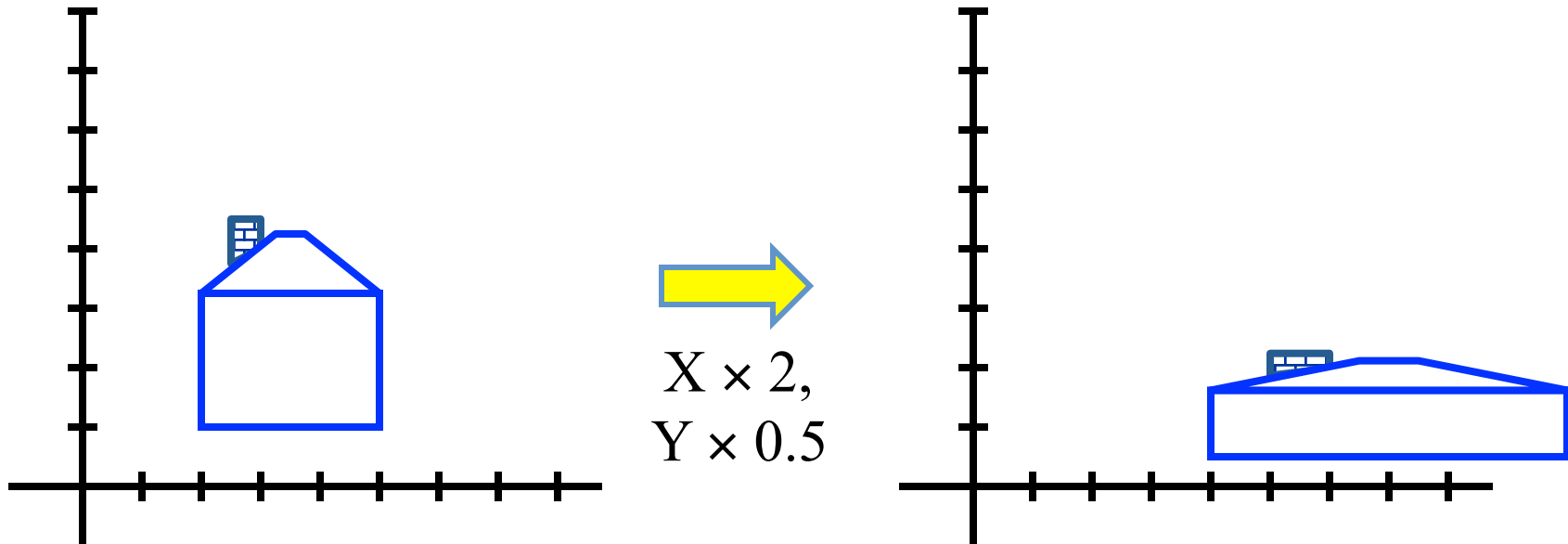
- *Scaling* a coordinate means multiplying each of its components by a scalar
- *Uniform scaling* means this scalar is the same for all components:





# 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 transformations can be represented with a 2x2 matrix?

2D Scaling?

$$x' = s_x * x$$

$$y' = s_y * y$$

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

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?

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

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

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



## What 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)?

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

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

2D Translation?

$$\mathbf{x}' = \mathbf{x} + \mathbf{t}_x$$

$$\mathbf{y}' = \mathbf{y} + \mathbf{t}_y$$

**NO!**



# 2D Linear Transformations

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

- Only linear 2D transformations can be represented with a 2x2 matrix.
- Linear transformations are combinations of ...
  - Scale,
  - Rotation,
  - Shear, and
  - Mirror





# Homogeneous coordinates

To convert to homogeneous coordinates:

$$(x, y) \Rightarrow \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

homogeneous image  
coordinates

Converting *from* homogeneous coordinates

$$\begin{bmatrix} x \\ y \\ w \end{bmatrix} \Rightarrow (x/w, y/w)$$



# Homogeneous coordinates

- Q: How can we represent 2d translation as a 3x3 matrix using homogeneous coordinates?

$$x' = x + t_x$$

$$y' = y + t_y$$

- A: Using the rightmost column:

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

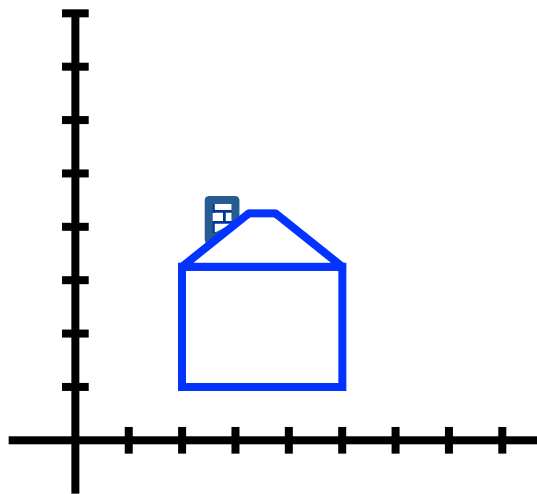


# Translation

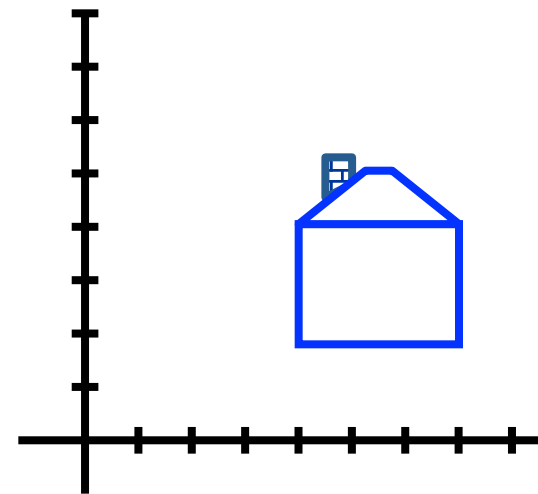
Homogeneous Coordinates



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



$$\begin{aligned} t_x &= 2 \\ t_y &= 1 \end{aligned}$$





# 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

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

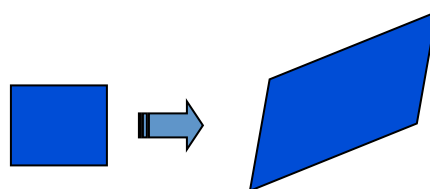
Shear



# 2D Affine Transformations

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

- Affine transformations are combinations of ...
  - Linear transformations, and
  - Translations
- Parallel lines remain parallel



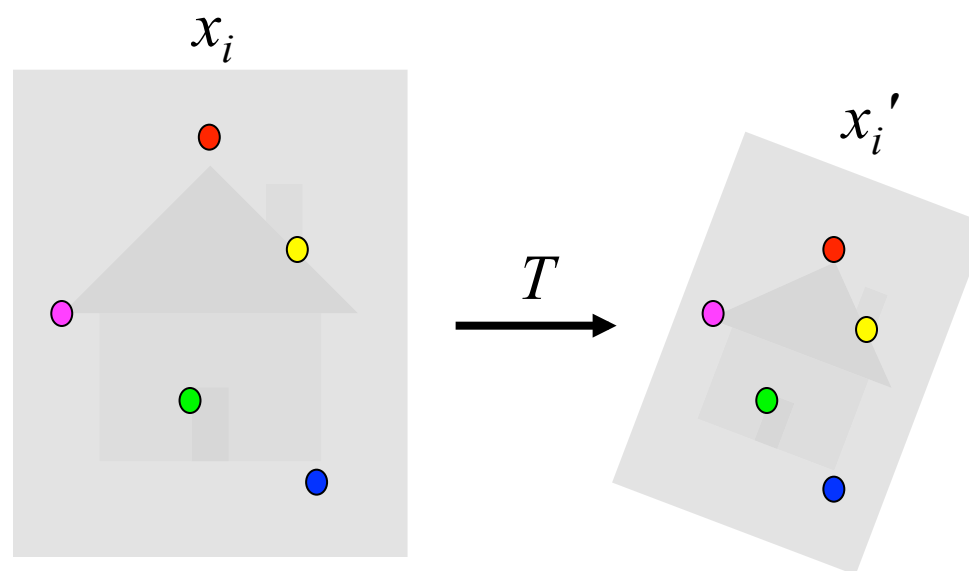


# 2D alignment



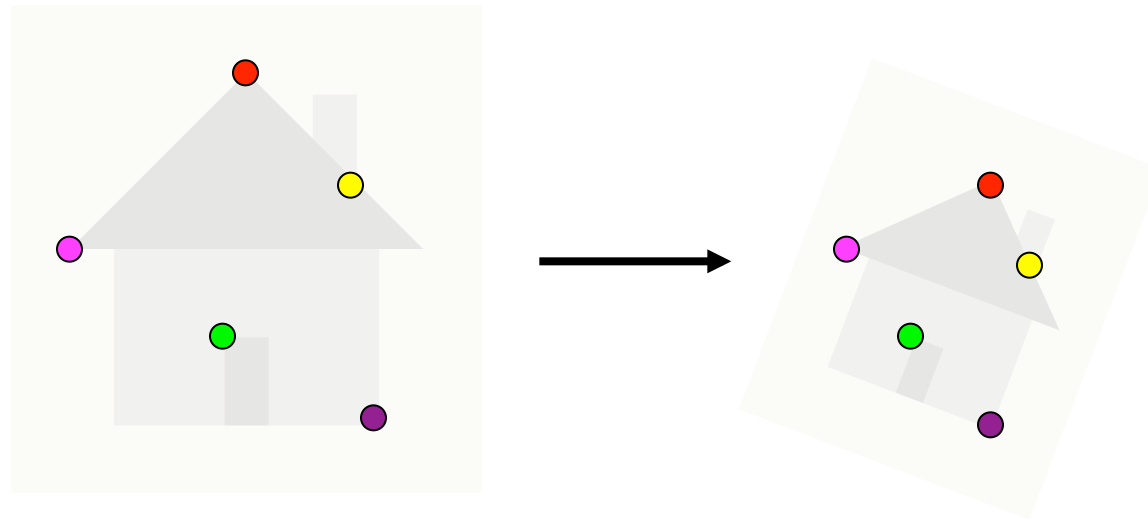
# Alignment problem

- We have previously considered how to **fit a model to image evidence**
  - e.g., a line to edge points
- In alignment, we will **fit the parameters of some transformation** according to a set of matching feature pairs (“correspondences”).





# Image alignment



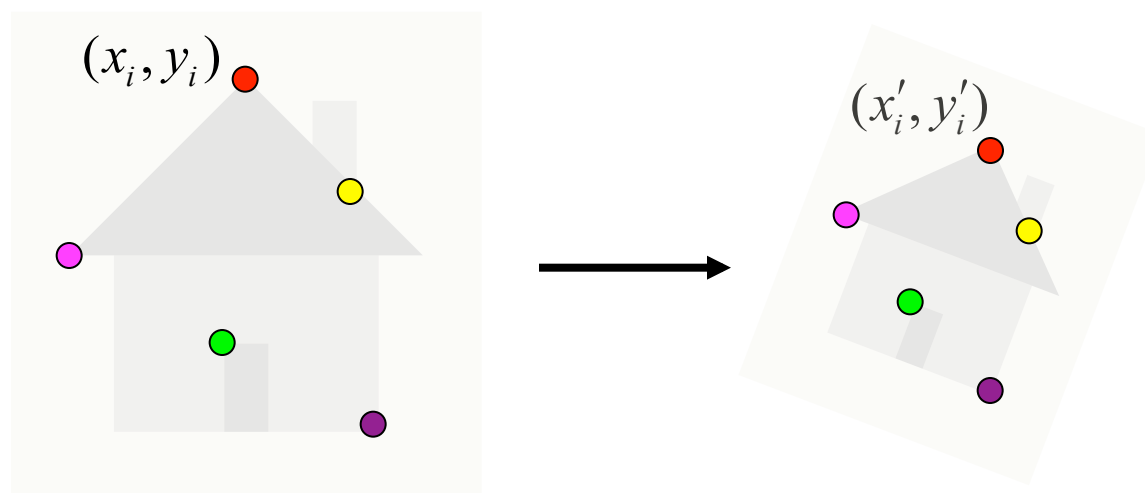
- Two broad approaches:
  - Direct (pixel-based) alignment
    - Search for alignment where most pixels agree
  - Feature-based alignment
    - Search for alignment where *extracted features* agree
    - Can be verified using pixel-based alignment





# Fitting an affine transformation

- Assuming we know the correspondences, how do we get the transformation?



$$\begin{bmatrix} x'_i \\ y'_i \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix}$$



# An aside: Least Squares Example

- Say we have a set of data points  $(X_1, X'_1), (X_2, X'_2), (X_3, X'_3),$  etc.  
(e.g. person's height vs. weight)
- We want a nice compact formula (a line) to predict  $X'$ s from  $X$ s:  $Xa + b = X'$
- We want to find  $a$  and  $b$
- How many  $(X, X')$  pairs do we need?

$$X_1 a + b = X'_1$$

$$X_2 a + b = X'_2$$

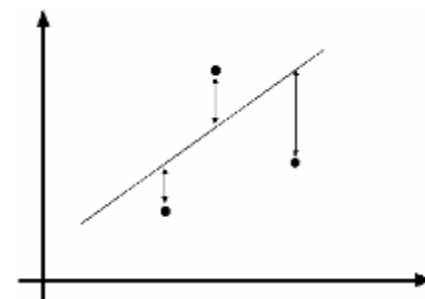
$$\begin{bmatrix} X_1 & 1 \\ X_2 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} X'_1 \\ X'_2 \end{bmatrix} \quad Ax=B$$

- What if the data is noisy?

$$\begin{bmatrix} X_1 & 1 \\ X_2 & 1 \\ X_3 & 1 \\ \dots & \dots \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} X'_1 \\ X'_2 \\ X'_3 \\ \dots \end{bmatrix}$$

overconstrained

$$\min \|Ax - B\|^2$$

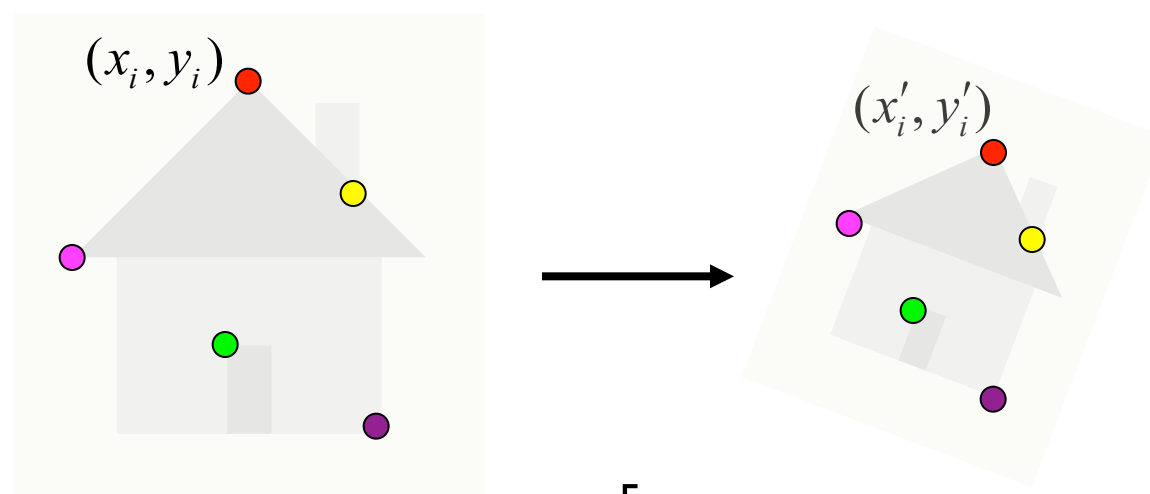


Source: Alyosha Efros



# Fitting an affine transformation

- Assuming we know the correspondences, how do we get the transformation?



$$\begin{bmatrix} x'_i \\ y'_i \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix}$$

$$\begin{bmatrix}$$

$$\begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} \end{bmatrix}$$

-> Rewrite into the form  $Ax = B$ , where  $x$  is the vector of parameters



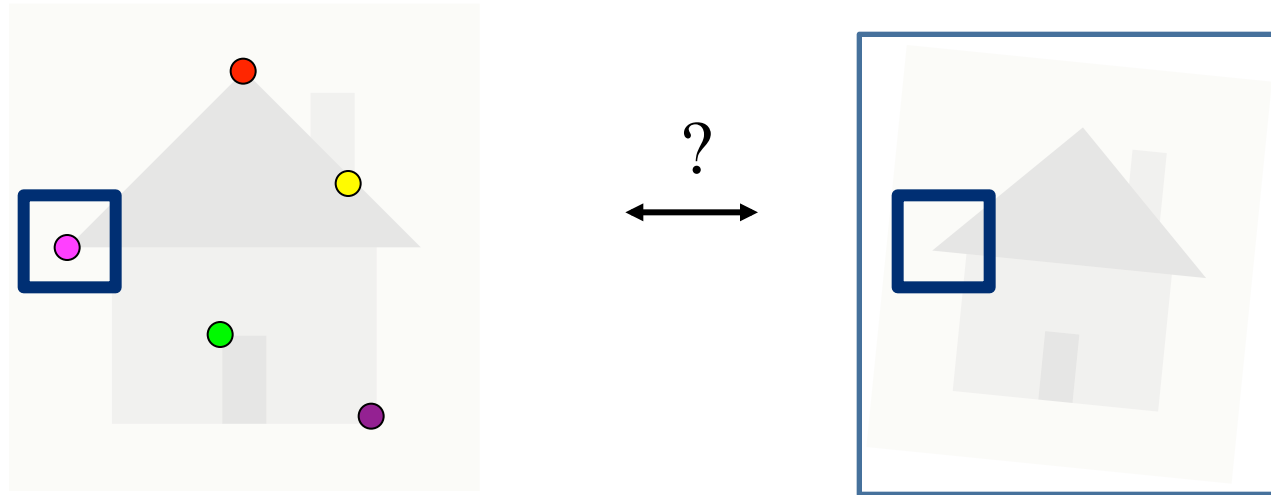
# Fitting an affine transformation

$$\begin{bmatrix} \dots & & & & & \\ x_i & y_i & 0 & 0 & 1 & 0 \\ 0 & 0 & x_i & y_i & 0 & 1 \\ \dots & & & & & \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} \dots \\ x'_i \\ y'_i \\ \dots \end{bmatrix}$$

- How many matches (correspondence pairs) do we need to solve for the transformation parameters?
- Once we have solved for the parameters, how do we compute the coordinates of the corresponding point for  $(x_{new}, y_{new})$ ?



# What **are** the correspondences?



- Points selected manually
- Features matched automatically  
*e.g., use Harris corners, or more robust detectors/descriptors that we will define later in the class*
- Chicken and egg problem !  
*RANSAC will be used to remove the outliers*



# Least squares minimization

(Board)



# Singular Value Decomposition (SVD)

- Given any  $m \times n$  real matrix  $\mathbf{A}$ , algorithm to find matrices  $\mathbf{U}$ ,  $\mathbf{V}$ , and  $\mathbf{D}$  such that

$$\mathbf{A} = \mathbf{U} \mathbf{D} \mathbf{V}^T$$

$\mathbf{U}$  is  $m \times m$  and orthogonal

$\mathbf{D}$  is  $m \times n$  and diagonal

$\mathbf{V}$  is  $n \times n$  and orthogonal

$$d_1 \geq d_2 \geq \dots \geq d_p \geq 0 \quad \text{for } p = \min(m, n)$$

$$\begin{pmatrix} \mathbf{A} \end{pmatrix} = \begin{pmatrix} \mathbf{U} \begin{pmatrix} d_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & d_p \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \mathbf{V}^T \end{pmatrix}$$



# Method 1

- Linear least-squares solution to an overdetermined full-rank set of linear equations

## Objective

Find the least-squares solution to the  $m \times n$  set of equations  $A\mathbf{x} = \mathbf{b}$ , where  $m > n$  and  $\text{rank } A = n$ .

## Algorithm

- Find the SVD  $A = UDV^T$ .
- Set  $\mathbf{b}' = U^T \mathbf{b}$ .
- Find the vector  $\mathbf{y}$  defined by  $y_i = b'_i / d_i$ , where  $d_i$  is the  $i$ -th diagonal entry of  $D$ .
- The solution is  $\mathbf{x} = V\mathbf{y}$ .





# Conclusion

- Today
  - Corners
  - 2D transformations
  - 2D alignment (affine)
  - LS minimization
- Next time
  - More on LS minimization
  - RANSAC for 2D alignment
  - Homographies
  - Mosaics