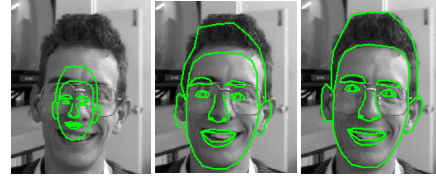


CSE 586, Spring 2010 Advanced Computer Vision Procrustes Shape Analysis

Credits

lots of slides are due to



Lecture material from Tim Cootes University of Manchester.
For more info, see <http://www.isbe.man.ac.uk/~bim/>
(includes code for exploring active shape/appearance models).

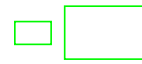
Overview

Statistical Shape Models: a method of modelling shape and shape variation

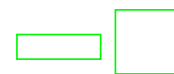
Active Shape Models: an active contour method with constraints on shape

Shape

- Need to model the variability in shape
- What is shape?
 - Geometric information that remains when location, scale and rotational effects removed (Kendall)



Same Shape



Different Shape

Shape

- More generally
 - Shape is the geometric information invariant to a particular class of transformations
- Transformations:
 - Euclidean (translation + rotation)
 - Similarity (translation+rotation+scaling)
 - Affine
 - Projective

Shape

Shapes	Euclidean	Similarity	Affine	Projective
	✓			
		✓		
			✓	
				✓

Shape Models

- We will represent the shape using a set of points
- We will model the variation by computing the PDF of the distribution of shapes in a training set (Gaussian)
- This allows us to generate new shapes similar to the training set

Point-based Shape Models

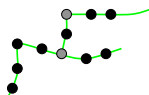
- Require labeled training images
 - point “landmarks” represent correspondences



e.g. point 23 is always right corner of mouth

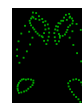
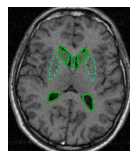
Suitable Landmarks

- Define correspondences
 - Well defined corners
 - ‘T’ junctions
 - Easily located biological landmarks
 - Use additional points along boundaries to define shape more accurately



Building Shape Models

- For each example



$$\mathbf{x} = (x_1, y_1, \dots, x_n, y_n)^T$$

note, we are considering only 2D points here, but the approach generalizes to nD.

Statistical Shape Models

- Given a set of shapes:
- Align shapes into common frame
 - Procrustes analysis
- Estimate shape distribution $p(\mathbf{x})$
 - Single gaussian often sufficient
 - Mixture models sometimes necessary

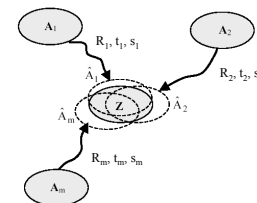
Procrustes Analysis

Procrustes Analysis



Align one shape with another (not symmetric)

General Procrustes Analysis



Align a set of shapes with respect to some unknown “mean” shape (independent of ordering of shapes)

Why "Procrustes"?



<http://www.procrustes.nl/gif/illustr.gif>

Aligning Two Shapes

- Procrustes analysis:
 - Find transformation which minimises
- $$|\mathbf{x}_1 - T(\mathbf{x}_2)|^2$$
- T is a particular type of transformation that you want "shape" to be invariant to

Go to board. Insert my handwritten notes here.

Aligning Two Shapes

- Procrustes analysis:
 - Find transformation which minimises

$$|\mathbf{x}_1 - T(\mathbf{x}_2)|^2$$

- If T is a similarity transformation, the resulting shapes have
 - Identical center of mass
 - approximately the same scale and orientation

Steps in Similarity Alignment

Given a set of K points: **Configuration**

Translation normalization: **Centered Configuration**
(center of mass at origin)

Scale normalization: **Pre-shape**
(divide by Sqrt of SSQ centered coordinates)

Rotation normalization: **Shape**
(rotate to alignment with ref shape)

Aligning Pre-Shapes by Rotation

Sketch:

A, B are two Kx2 preshapes, R is unknown rotation

Want to minimize $\|(AR - B)^2\|$ subject to $R^T R = I$

After some manipulation, we get

$$(A^T B)(A^T B)^T = R (A^T B)^T (A^T B) R^T$$

Note, both sides are symmetric and have same eigenvalues. This is a job for SVD!

Aligning Pre-Shapes by Rotation

Sketch continued:

$$\underbrace{(A^T B)(A^T B)^T}_{\text{SVD}} = R \underbrace{(A^T B)^T (A^T B)}_{\text{SVD}} R^T$$

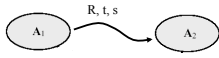
$$V D V^T = R W D W^T R^T$$

$$\text{So... } V = R W$$

$$\text{and therefore } R = V W^T$$

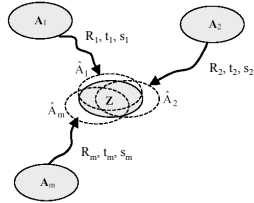
Recall:

Procrustes Analysis



Align one shape with another
(not symmetric)

General Procrustes Analysis



Align a set of shapes with respect to some unknown "mean" shape
(independent of ordering of shapes)

Aligning a Set of Shapes

- Generalised Procrustes Analysis
 - Find the transformations T_i which minimise

$$\sum | \mathbf{m} - T_i(\mathbf{x}_i) |^2$$

- Where $\mathbf{m} = \frac{1}{n} \sum T_i(\mathbf{x}_i)$
- Under the constraint that $|\mathbf{m}| = 1$

Aligning Shapes : Algorithm

- Normalise all so center of mass is at origin, and size=1
- Let $\mathbf{m} = \mathbf{x}_1$
- Align each shape with \mathbf{m} (via a rotation)
- Re-calculate $\mathbf{m} = \frac{1}{n} \sum T_i(\mathbf{x}_i)$
- Normalise \mathbf{m} to default size, orientation
- Repeat until convergence