Statistical Models of Shape and Appearance for Face Matching

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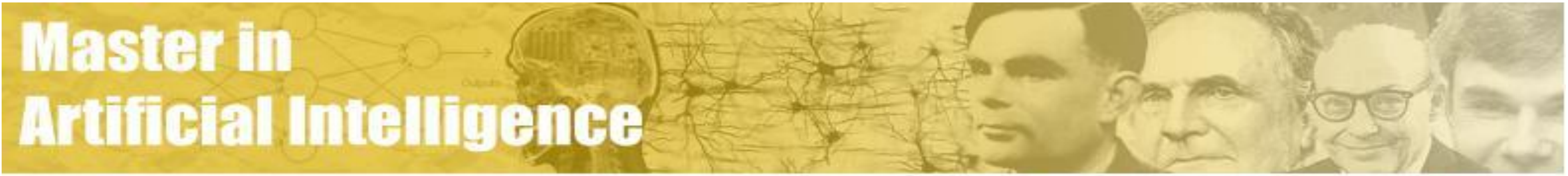

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Content

- Overview
- Statistical Shape Models
- Active Shape Models
- Statistical Appearance Models
- Active Appearance Models
- Comparison : ASM vs AAM
- Conclusion

OVERVIEW

Computer Vision

- Goal
  - Image understanding
- Challenge
  - Deformability of objects
- Statistic model-based approach
  - Shape model
  - Appearance model
  - Model matching
    - Image interpretation

Deformable Models

- Capable of generating any plausible example of the class they represent
- Only capable of generating legal examples

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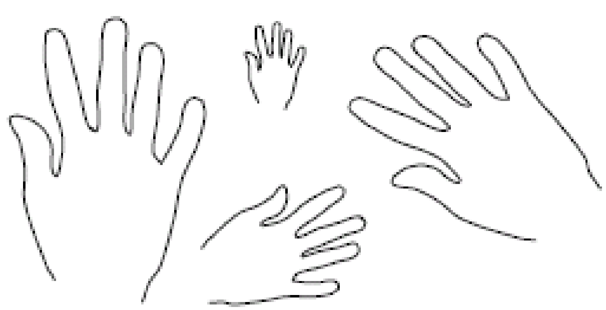
STATISTICAL SHAPE MODELS

Shapes

- The shape of an object is represented by a set of *n* points (**landmark points**) in any dimension.
- Invariance under some transformations
  - In 2-3 dimension – translation, rotation, scaling
  - Called similarity transformation



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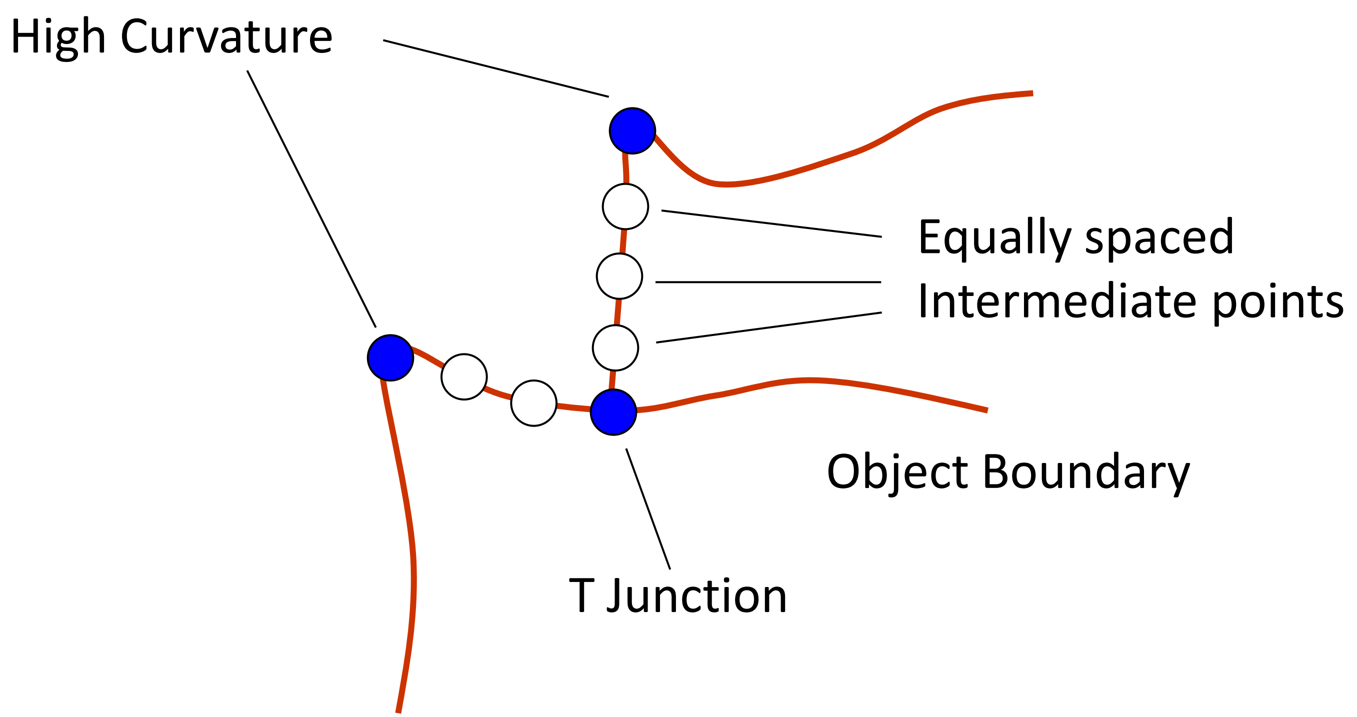
Hand-Annotated Training Set

- The training set typically comes from hand annotation of a set of training images

Suitable Landmarks



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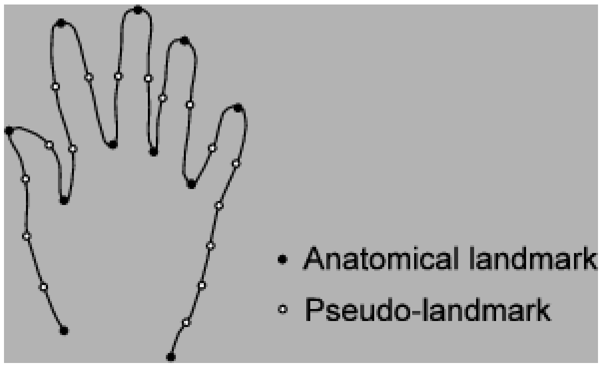
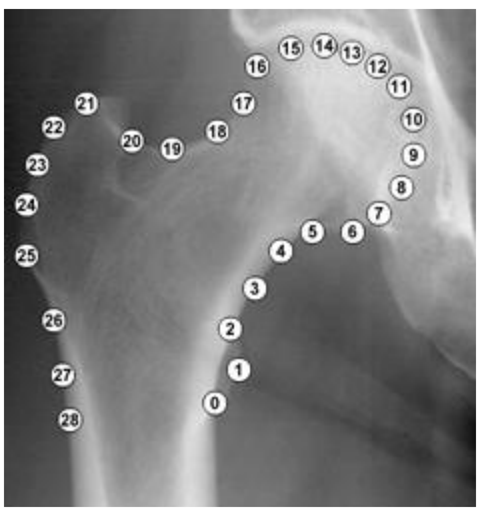
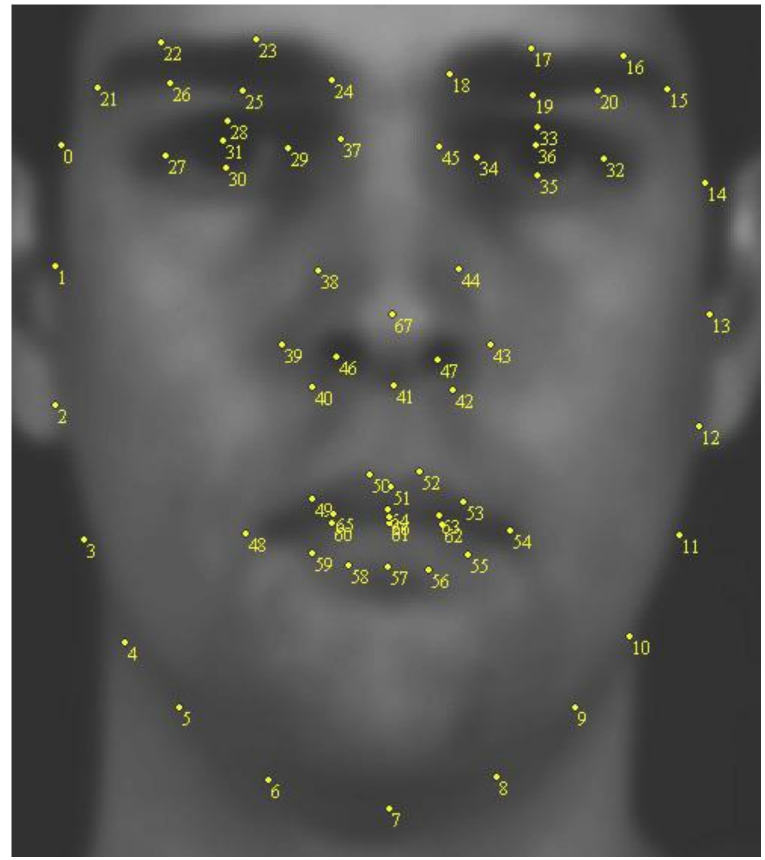
Suitable Landmarks







Training Set of Shape Vectors

- A *d*-dim shape with *n* landmarks is represented by a vector with *nd* elements.
- In a 2D-image with *n* landmark points, a shape vector **x** is

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

- The shape vectors in the training set should be in the same *coordinate frame*
  - Alignment of the training set is required

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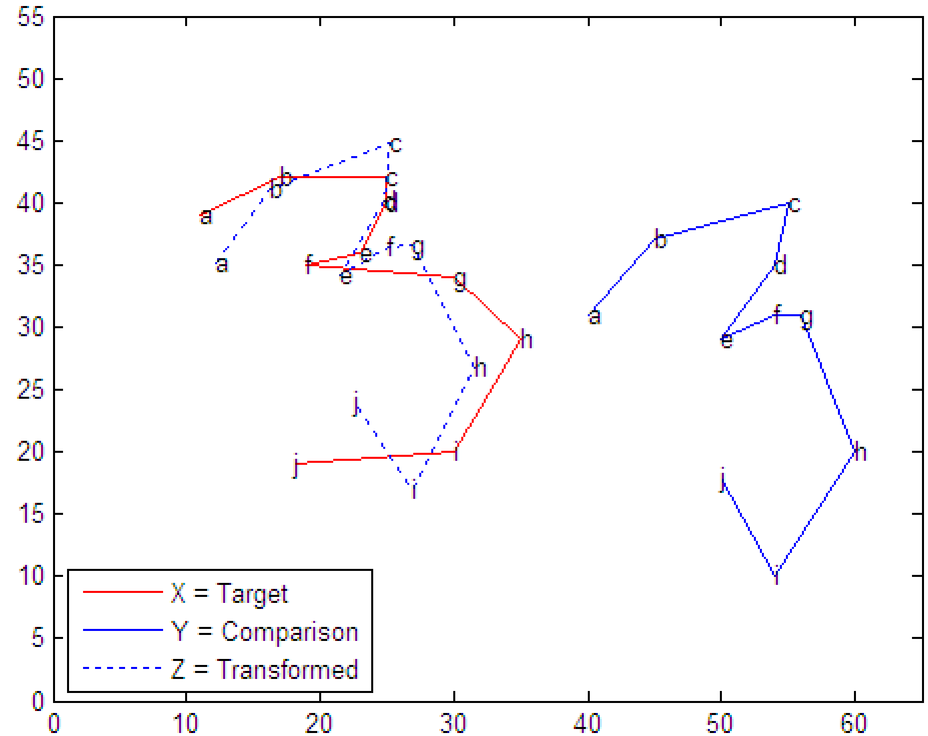
Aligning Shapes

Procrustes Analysis

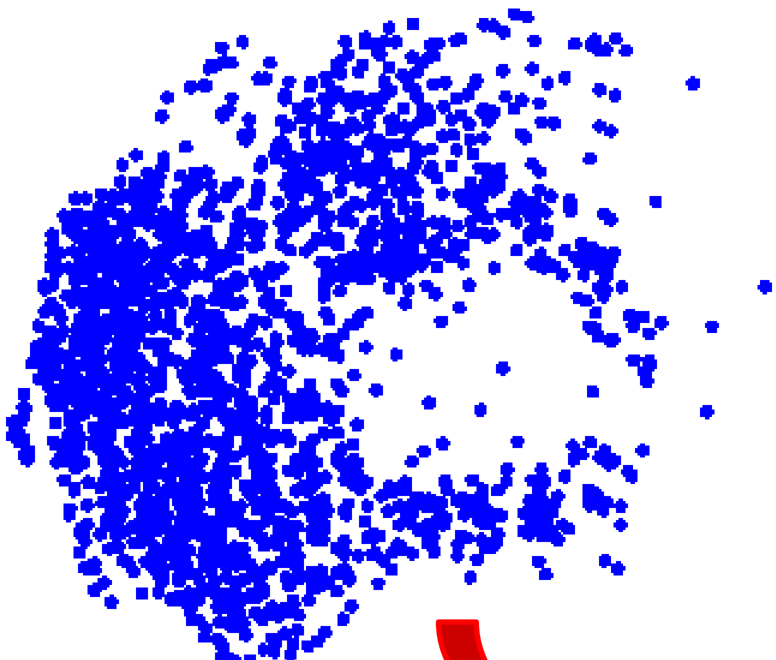
- Aligning Two Shapes:
- Find transformation T which minimizes

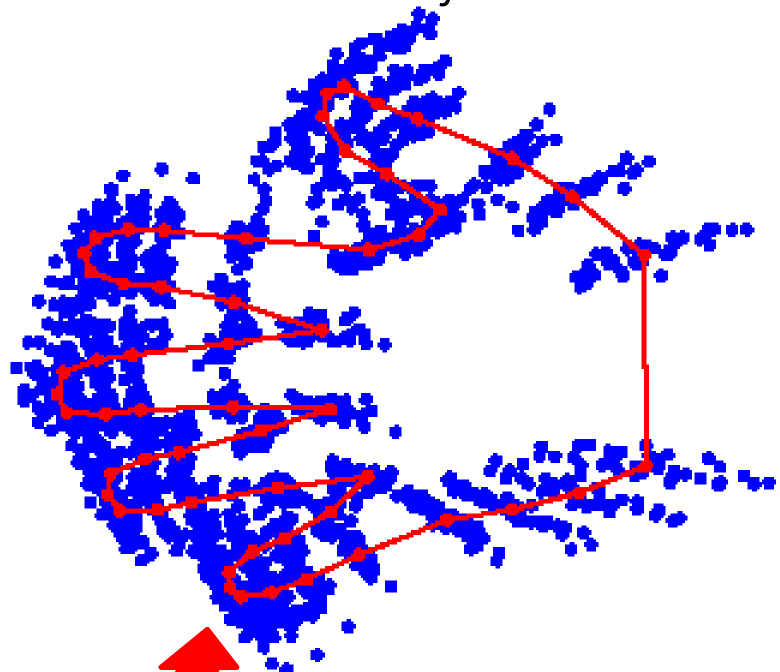
$$D = \left| \mathbf{x}_1 - T(\mathbf{x}_2) \right|^2$$



Aligning the Training Set

Coordinate frame

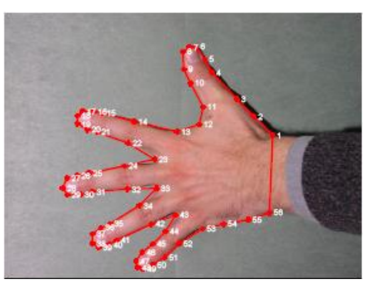


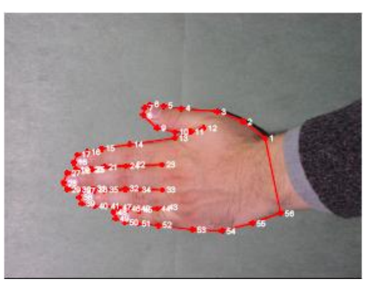


Unaligned shapes.

Procrustes Analysis

Aligned shapes with the mean given in red [1].





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Generalized Procrustes Analysis

- Aligning a set of shapes
- Find the transformations T_i which minimize:

$$D = \sum \left| \bar{\mathbf{x}} - T_i(\mathbf{x}_i) \right|^2$$

Alignment: Iterative Approach

1. Translate each example so that its centre of gravity is at the origin.
2. Choose one example as an initial estimate of the mean shape and scale so that $|\bar{\mathbf{x}}| = 1$.
3. Record the first estimate as $\bar{\mathbf{x}}_0$ to define the default reference frame.
4. Align all the shapes with the current estimate of the mean shape.
5. Re-estimate mean from aligned shapes.
6. Apply constraints on the current estimate of the mean by aligning it with $\bar{\mathbf{x}}_0$ and scaling so that $|\bar{\mathbf{x}}| = 1$.
7. If not converged, return to 4.

   (Convergence is declared if the estimate of the mean does not change significantly after an iteration)

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Alignment : Iterative Approach

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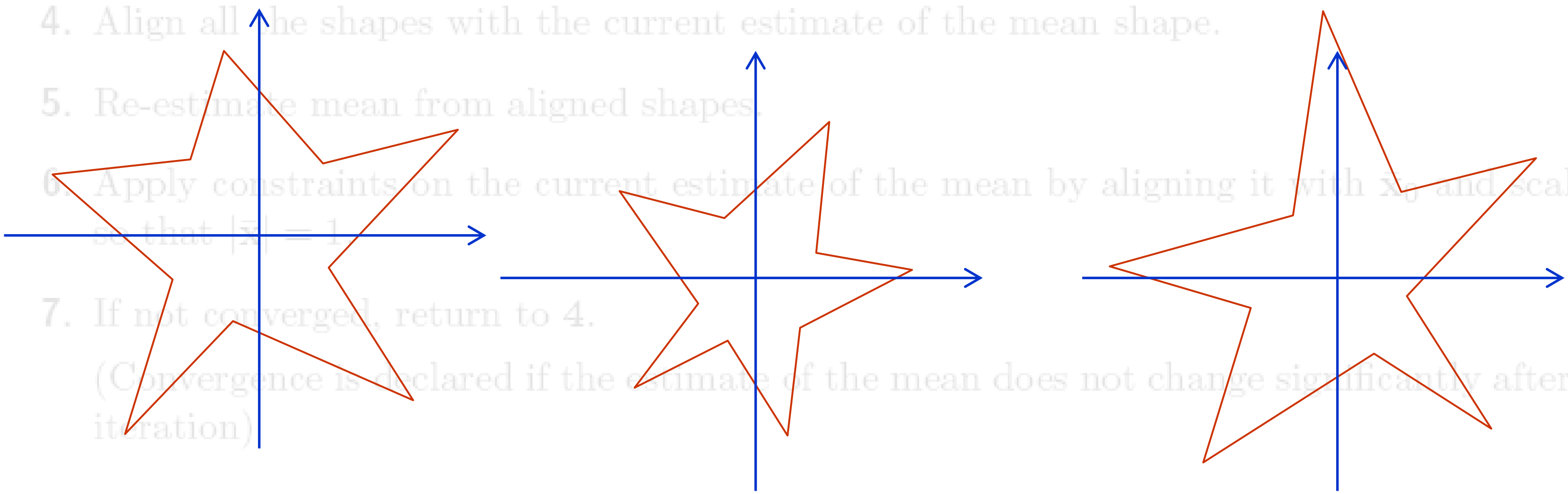

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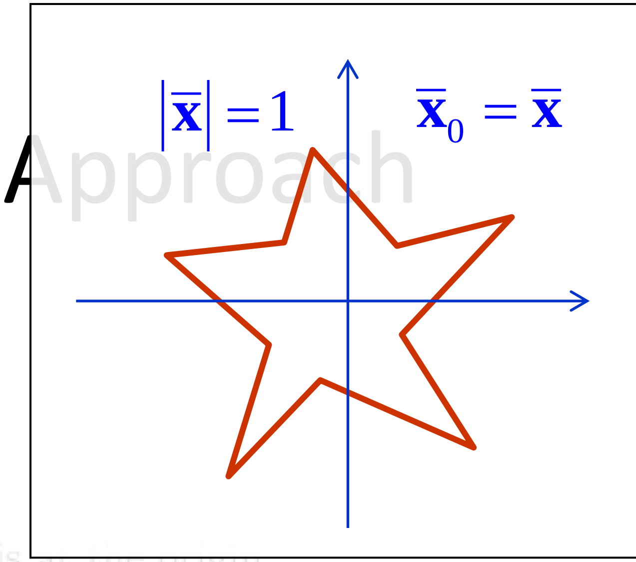
Alignment : Iterative Approach



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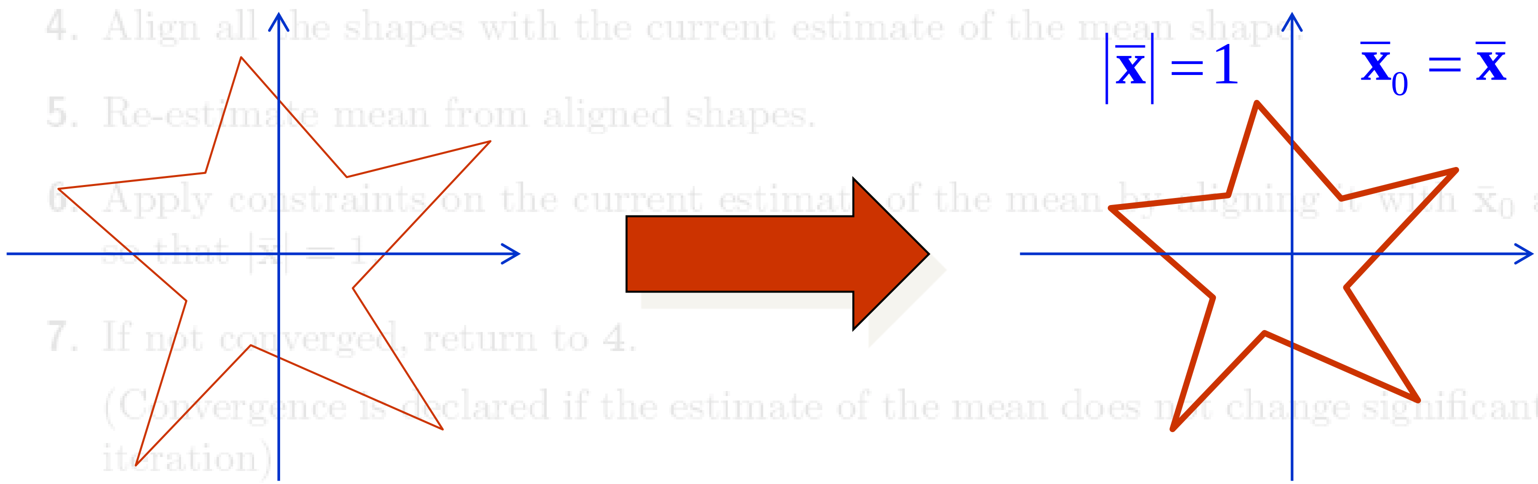
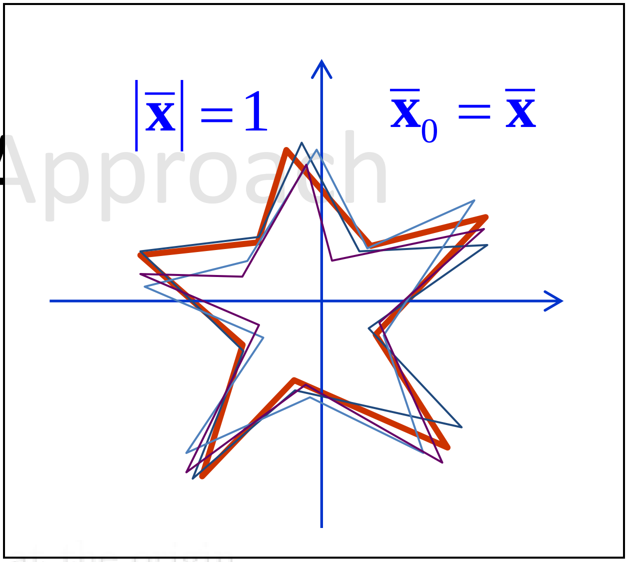


Alignment : Iterative Approach



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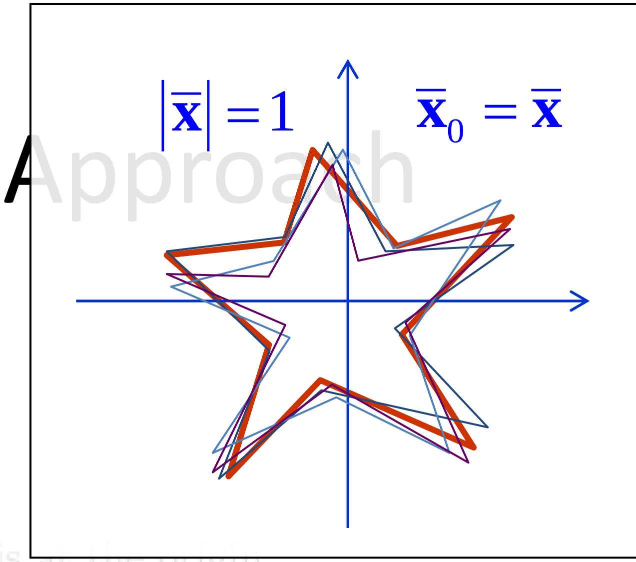

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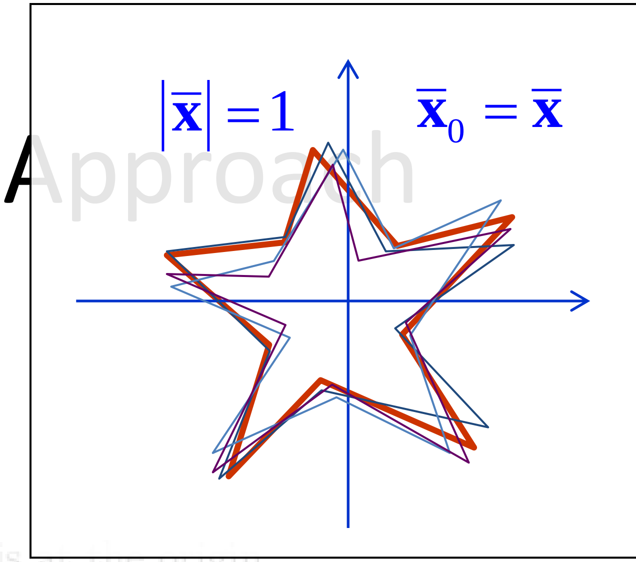

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Modeling Shape Variation

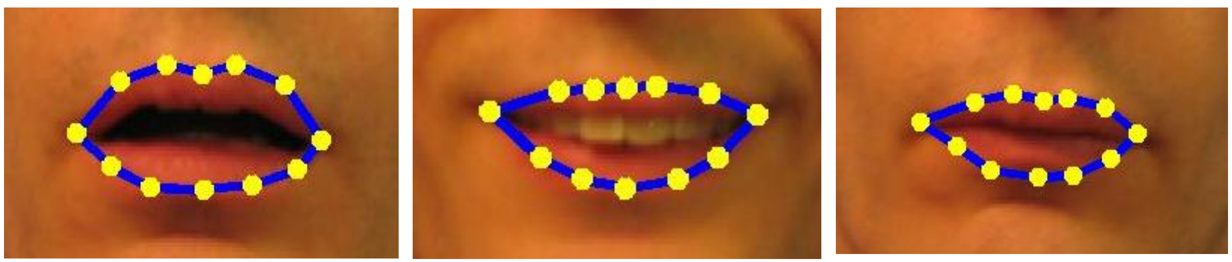
- Parametric Shape Model: **Point Distribution Model**

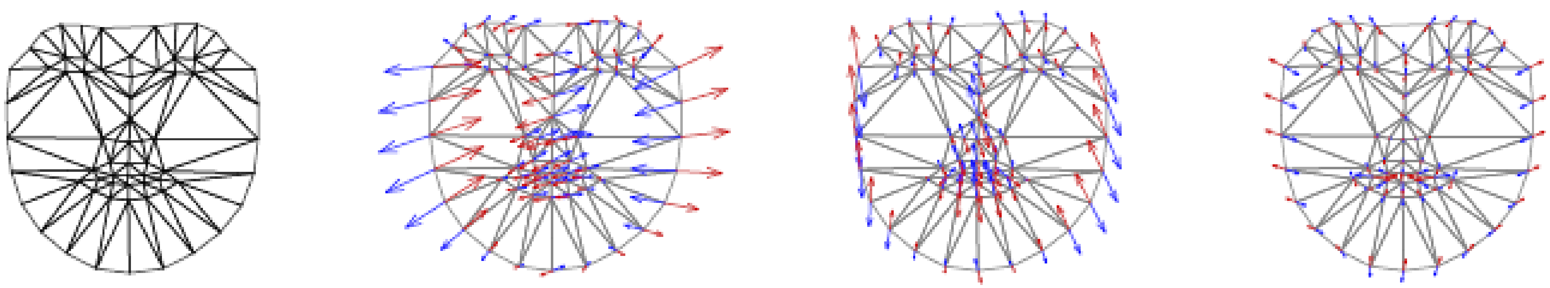
$$\mathbf{x} = M(\mathbf{b}) \qquad \mathbf{b}: \text{prameter vector}$$

- Estimate the distribution of **b**
  - Generating new shapes
  - Examining new shapes (plausibility)

PCA

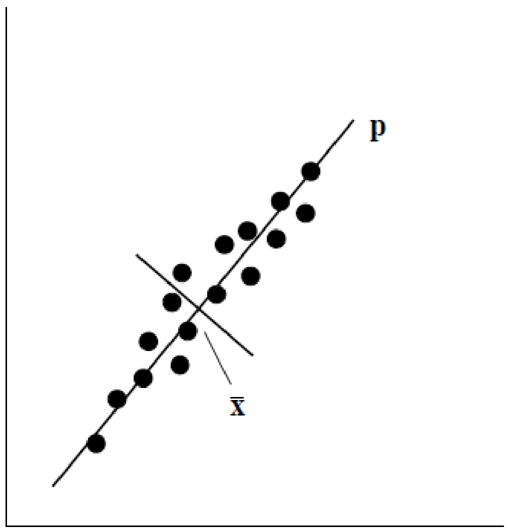
- Estimate variations with respect to the mean



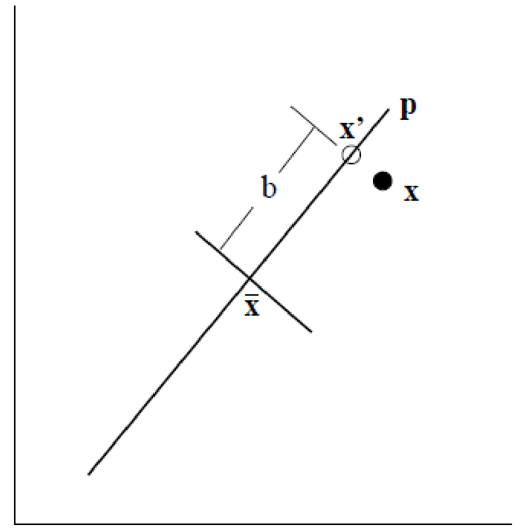


s_0 s_1 s_2 s_3

PCA



Applying a PCA to a set of 2D vectors.
p is the principal axis.



Any point x can be approximated by the nearest point on the line, x'.

PCA

1. Compute the mean

$$\bar{\mathbf{x}} = \frac{1}{s}\sum_{i=1}^{s}\mathbf{x}_i$$

2. Compute the covariance matrix

$$\mathbf{S} = \frac{1}{s-1}\sum_{i=1}^{s}(\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T$$

3. Compute the eigenvectors, ϕ_i and corresponding eigenvalues λ_i of **S** s.t. $\lambda_1 \geq \lambda_2 \geq \cdots$

$$\mathbf{\Phi} = \left[\phi_1 \,|\, \phi_2 \,|\cdots|\, \phi_t\right]$$

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Choice of Number of Modes (t = ?)

$$\mathbf{\Phi} = \left[\phi_1 \mid \phi_2 \mid \cdots \mid \phi_t \right]$$

- Let f_v be the proportion of the total variation one wishes to explain (e.g., 98%)
- Total variance $V_T = \Sigma\lambda_i$ is the sum of all eigenvalues, assuming $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_T$
- Then, we can chose the smallest t s.t.

$$\sum_{i=1}^{t} \lambda_i \geq f_v$$

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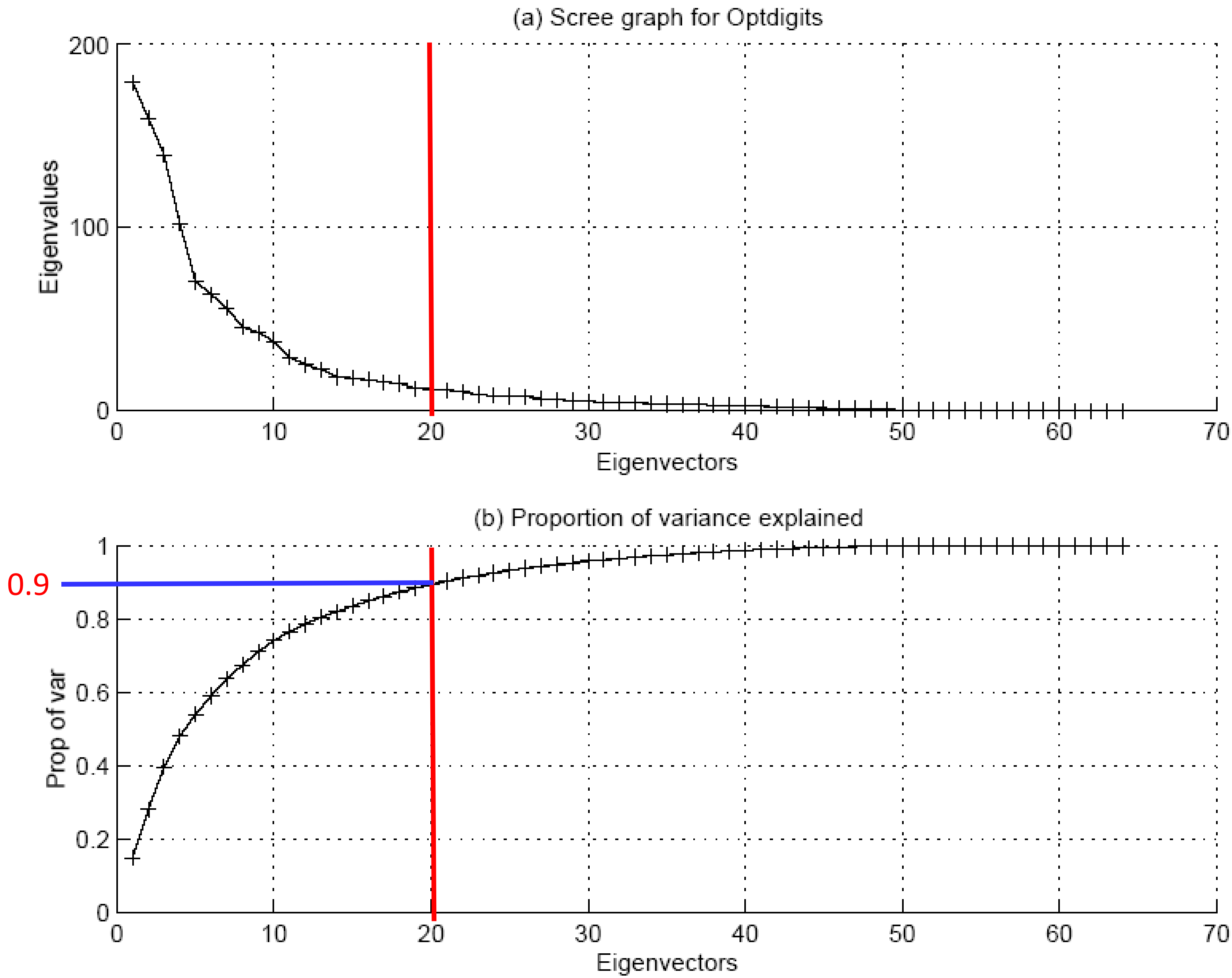

(a) Scree graph for Optdigits
Eigenvalues
200
100
0
0
10
20
30
40
50
60
70
Eigenvectors
(b) Proportion of variance explained
Prop of var
1
0.9
0.8
0.6
0.4
0.2
0
0
10
20
30
40
50
60
70
Eigenvectors

Shape Approximation

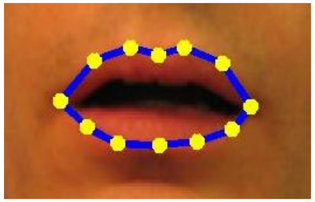
$$\mathbf{\Phi} = \left[\phi_1 \mid \phi_2 \mid \cdots \mid \phi_t \right]$$

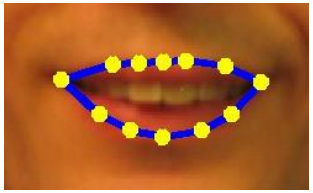
$$\mathbf{x} \approx \bar{\mathbf{x}} + \mathbf{\Phi}\boxed{\mathbf{b}}$$

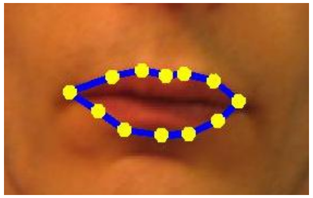
parameter vector of deformable model

mean shape

a plausible shape







$$\mathbf{b} = \mathbf{\Phi}^T(\mathbf{x} - \bar{\mathbf{x}})$$

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Shape Approximation

$$\mathbf{\Phi} = \left[\phi_1 \mid \phi_2 \mid \cdots \mid \phi_t \right]$$

$$\mathbf{x} \approx \bar{\mathbf{x}} + \mathbf{\Phi}\boxed{\mathbf{b}}$$

parameter vector of deformable model

$$\mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_t \end{bmatrix}$$ with $-3\sqrt{\lambda_i} \leq b_i \leq 3\sqrt{\lambda_i}$

The generated shape is similar to those in training set (plausible).

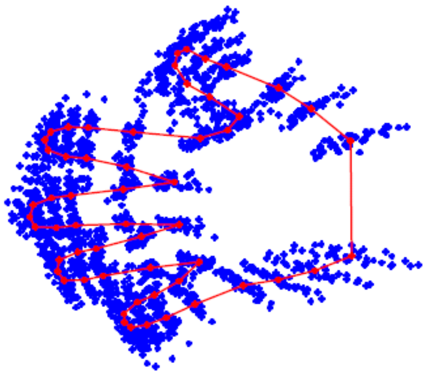
Generating Plausible Shapes

$$\mathbf{\Phi} = \left[\phi_1 \mid \phi_2 \mid \cdots \mid \phi_t \right]$$

$$\mathbf{x} = \bar{\mathbf{x}} + \underbrace{\mathbf{\Phi b}}$$

Variations are modeled as

linear combinations of eigenvectors



Generating Plausible Shapes

$$\boldsymbol{\Phi} = \left[\phi_1 \mid \phi_2 \mid \cdots \mid \phi_t \right]$$

$$\mathbf{x} = \bar{\mathbf{x}} + \boldsymbol{\Phi}\boxed{\mathbf{b}}$$

parameter vector of deformable model

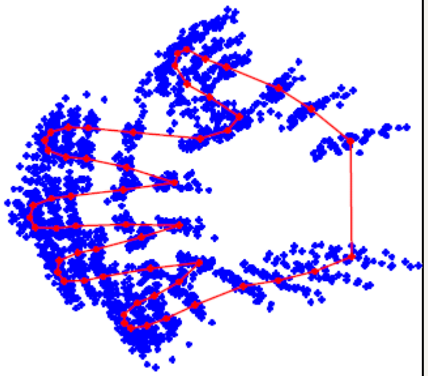
$$\mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_t \end{bmatrix}$$

Assumption :

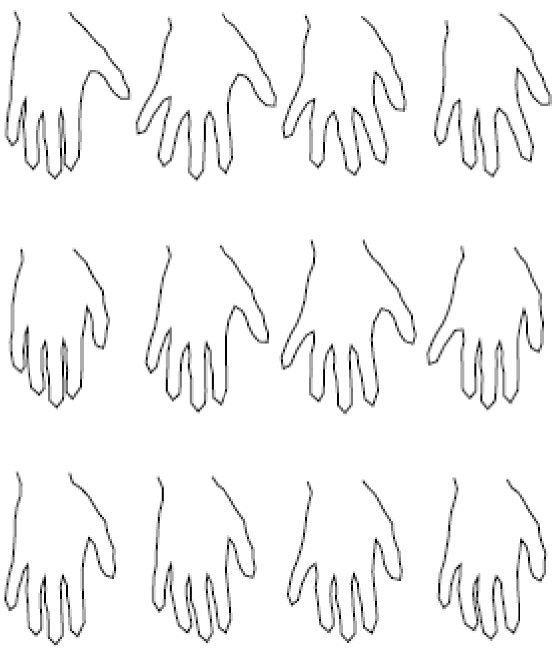
b_i's are independent and Gaussian

Two options:

- Hard limits on independent b_i's or
- Constrain **b** in a hyperellipsoid

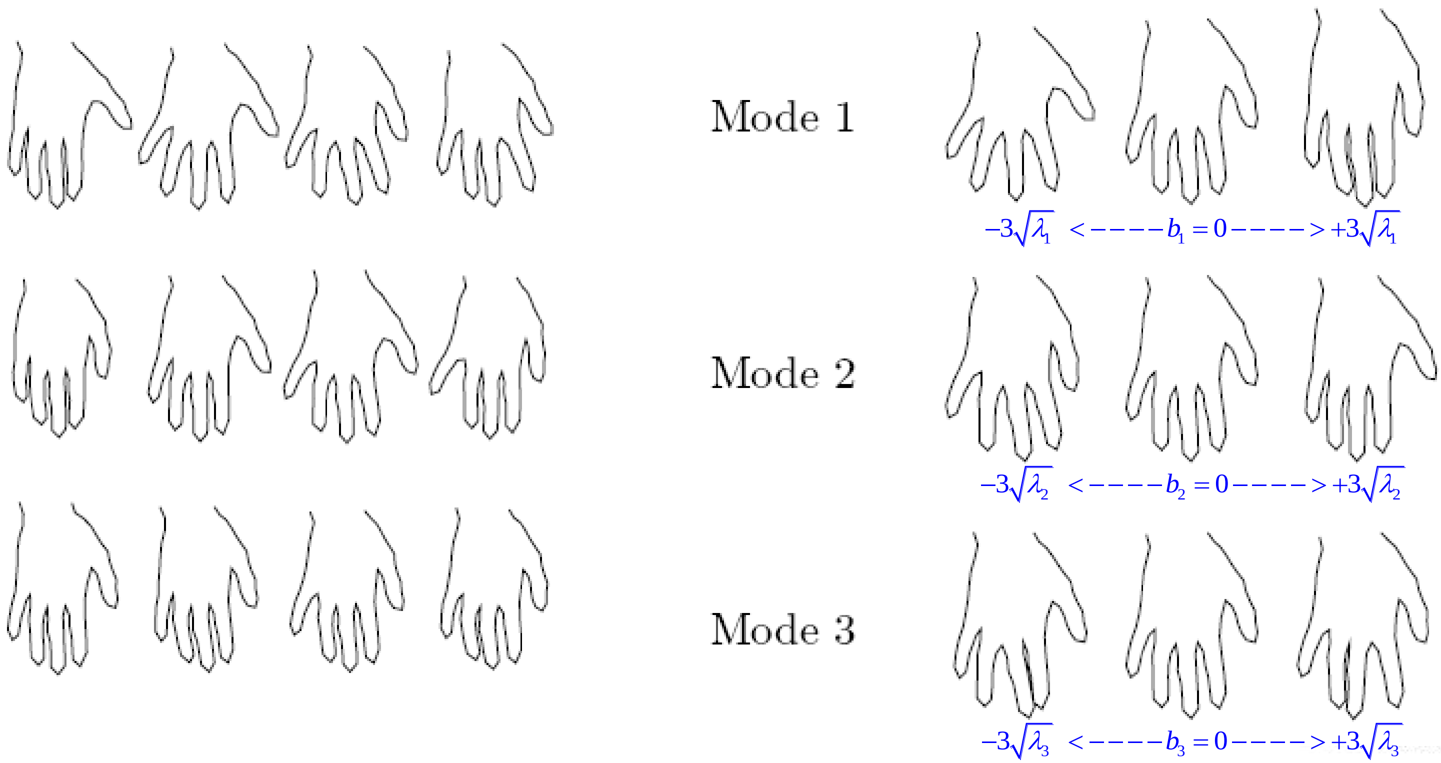


Examples of Shape Models



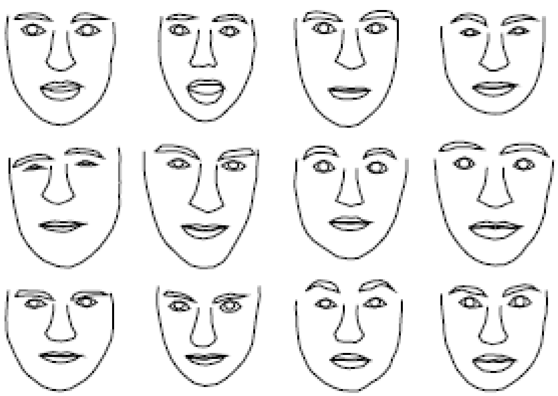
- Some members in the training set (18 hands)
- Each is represented by 72 landmark points

Examples of Shape Models



Examples of Shape Models

- Some members in the training set (300 faces)
- Each is represented by 133 landmark points



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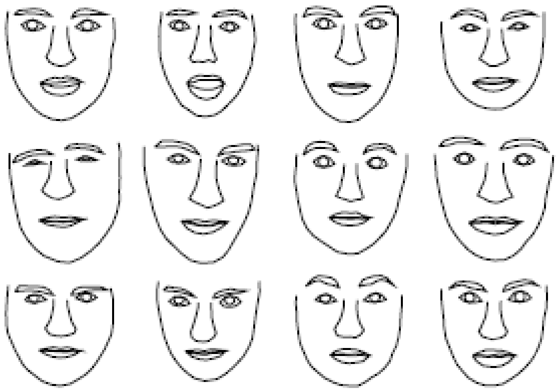
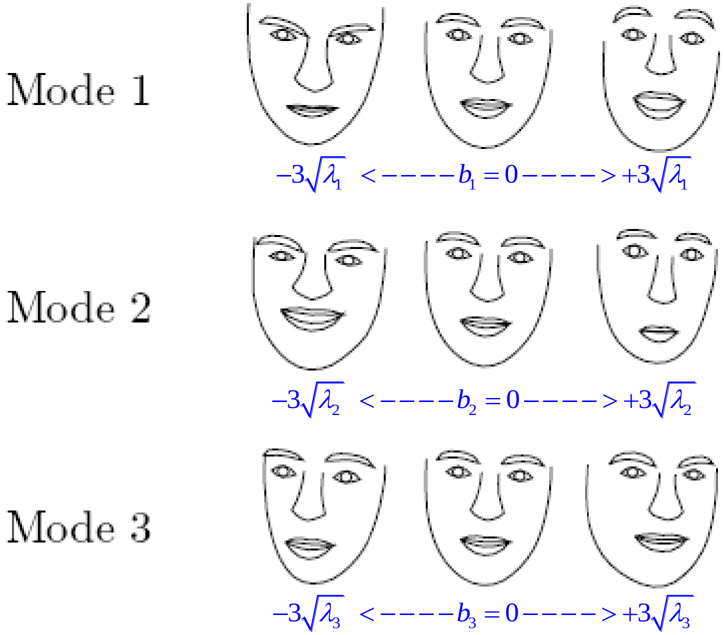
Examples of Shape Models





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Similar Transformation

$$T_{X_t,Y_t,s,\theta}\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} X_t \\ Y_t \end{pmatrix} + \begin{pmatrix} s\cos\theta & s\sin\theta \\ -s\sin\theta & s\cos\theta \end{pmatrix}\begin{pmatrix} x \\ y \end{pmatrix}$$

$$\mathbf{x} = T_{\underbrace{X_t,Y_t}_{\text{Translation}},\,s,\,\theta}\big(\underbrace{\bar{\mathbf{x}} + \mathbf{\Phi b}}_{\text{A shape of the model}}\big)$$

A shape of the model

Rotation

Scale

Translation

Pose parameters

Similar Transformation

A shape in an image

Fitting a Model to New Points in a Image

$$T_{X_t,Y_t,s,\theta}\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} X_t \\ Y_t \end{pmatrix} + \begin{pmatrix} s\cos\theta & s\sin\theta \\ -s\sin\theta & s\cos\theta \end{pmatrix}\begin{pmatrix} x \\ y \end{pmatrix}$$

$$\mathbf{x} = T_{X_t,Y_t,s,\theta}(\bar{\mathbf{x}} + \mathbf{\Phi b})$$

Given a set of new image points **Y**, find **b** and pose parameters so as to minimize:

$$|Y - T_{X_t,Y_t,s,\theta}(\bar{\mathbf{x}} + \mathbf{\Phi b})|^2$$

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Fitting a Model to New Points in a Image

Minimize $|Y - T_{X_t, Y_t, s, \theta}(\bar{\mathbf{x}} + \mathbf{\Phi b})|^2$

1. Initialise the shape parameters, $\mathbf{b}$, to zero
2. Generate the model instance $\mathbf{x} = \bar{\mathbf{x}} + \Phi \mathbf{b}$
3. Find the pose parameters (X_t, Y_t, s, θ) which best map $\mathbf{x}$to $\mathbf{Y}$
4. Invert the pose parameters and use to project $\mathbf{Y}$ into the model co-ordinate frame:

$$\mathbf{y} = T^{-1}_{X_t, Y_t, s, \theta}(\mathbf{Y})$$

5. Project $\mathbf{y}$ into the tangent plane to $\bar{\mathbf{x}}$ by scaling by $1/(\mathbf{y}.\bar{\mathbf{x}})$.
6. Update the model parameters to match to $\mathbf{y}$

$$\mathbf{b} = \Phi^T(\mathbf{y} - \bar{\mathbf{x}})$$

7. Apply constraints on $\mathbf{b}$
8. If not converged, return to step 2.

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Fitting a Model to New Points in a Image

Minimize $|Y - T_{X_t,Y_t,s,\theta}(\bar{\mathbf{x}} + \boldsymbol{\Phi}\mathbf{b})|^2$

1. Initialize the shape parameters, b, to zero.
2. Generate the model instance $\bar{\mathrm{x}} = \mathrm{x} + \Phi\,\mathrm{b}$
3. Find the pose parameters (X_t, Y_t, s, θ) which best map x to Y.
4. Invert the pose parameters and use to project Y into the model coordinate frame:

$$\mathrm{y} = T^{-1}_{X_t,Y_t,s,\theta}(Y)$$

5. Scale y
6. Update the model parameters to match to y

$$b = \Phi^T(\mathrm{y} - \bar{\mathrm{x}})$$

7. Apply constraints on b
8. If not converged, return to step 2.

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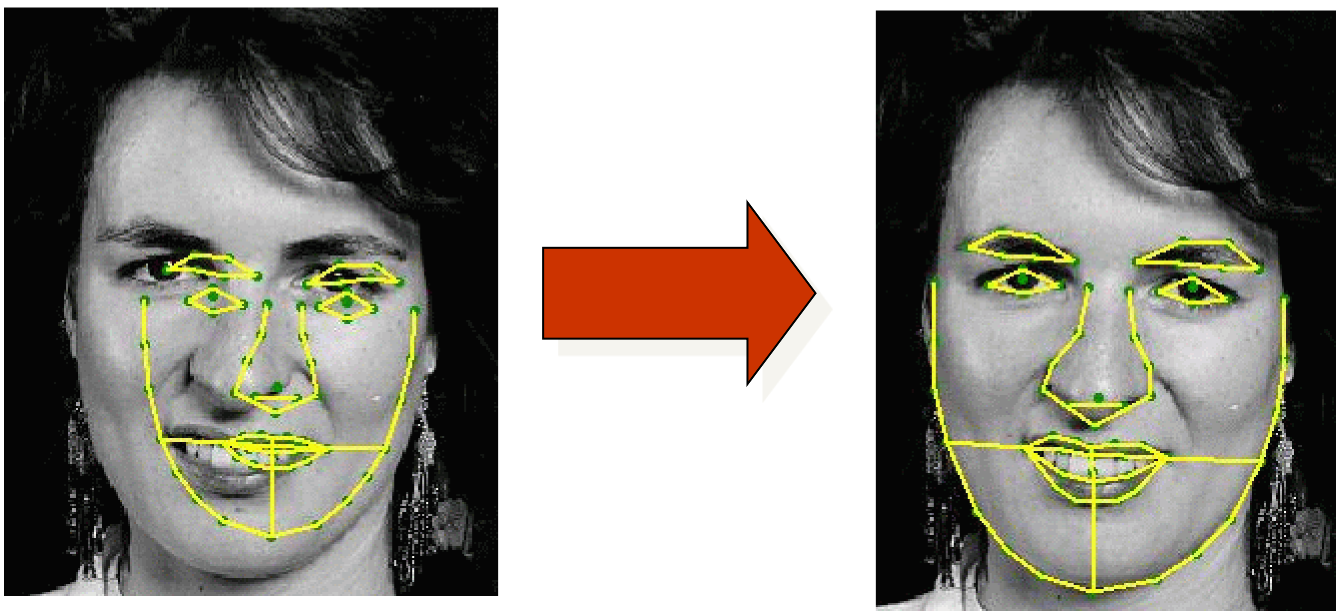
ACTIVE SHAPE MODELS

Goal

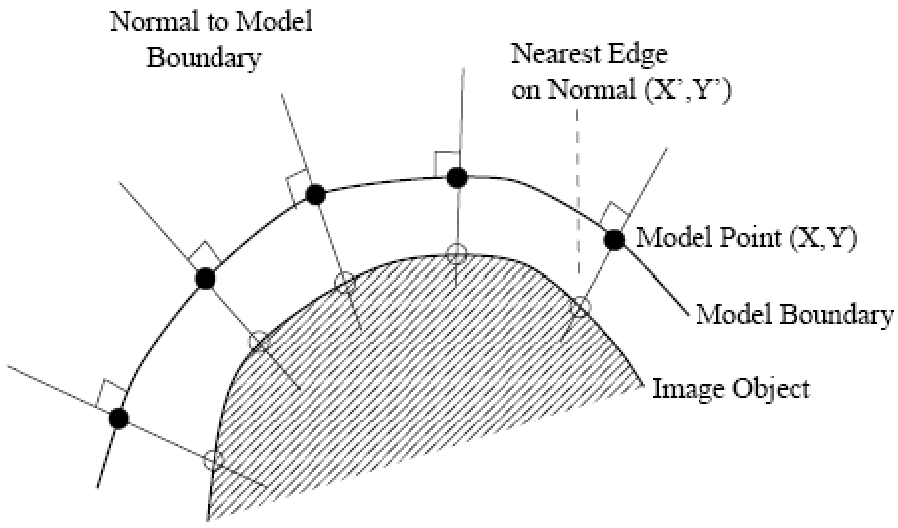
- Given a rough starting approximation,
- Fit an instance of a model to the image

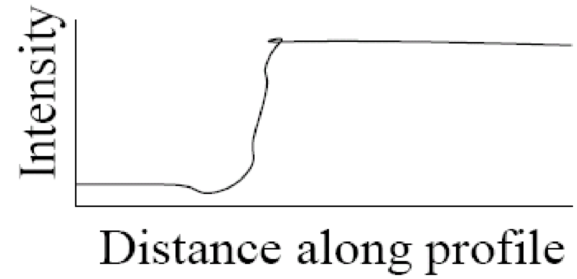


Iterative Approach

- Iteratively improving the fit of the instance, **X**, to an image proceeds as follows:

  1. Examine a region of the image around each point $\mathbf{X}_i$ to find the best nearby match for the point $\mathbf{X}_i'$





Look along normals through each model point to find the best local match for the model of the image appearance at that point (eg strongest nearby edge)

1. Examine a region of the image around each point $\mathbf{X}_i$ to find the best nearby match for the point $\mathbf{X}_i'$

• The above method is applicable if model points are edges

• The best approach is to examine the local structures of model points (to be discussed)

Iterative Approach

- Iteratively improving the fit of the instance, **X**, to an image proceeds as follows:

1. Examine a region of the image around each point $\mathbf{X}_i$ to find the best nearby match for the point $\mathbf{X}_i'$
2. Update the parameters (X_t, Y_t, s, θ, $\mathbf{b}$) to best fit the new found points **X**
3. Repeat until convergence

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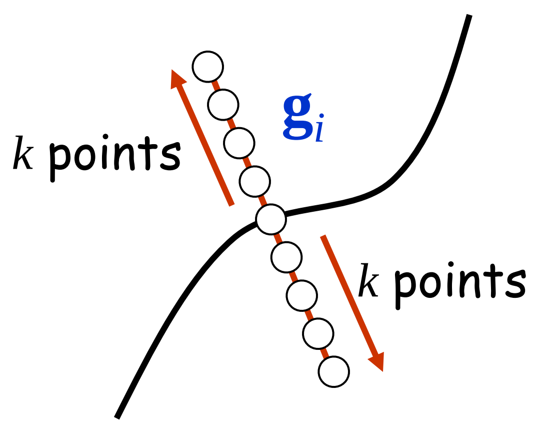
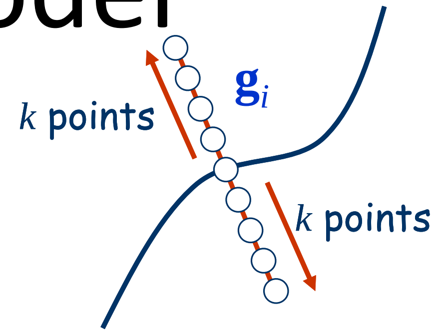
Modeling Local Structure

- Sample the derivative along a profile, *k* pixels on either side of a model point, to get a vector $\mathbf{g}_i$ of the $2k$+1 points



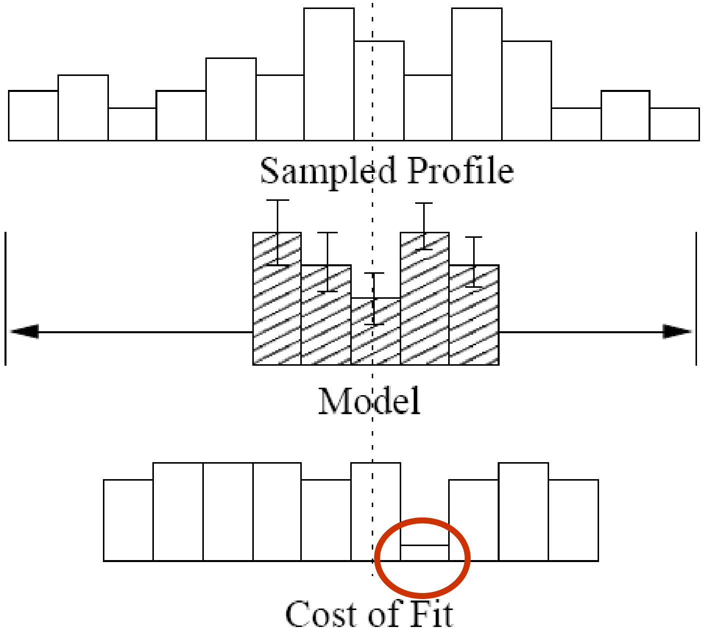
Using Local Structure Model



- Sample a profile m pixels either side of the current point ($m>k$)

- Test quality of fit at $2(m–k)+1$ positions

- Chose the one which gives the best match



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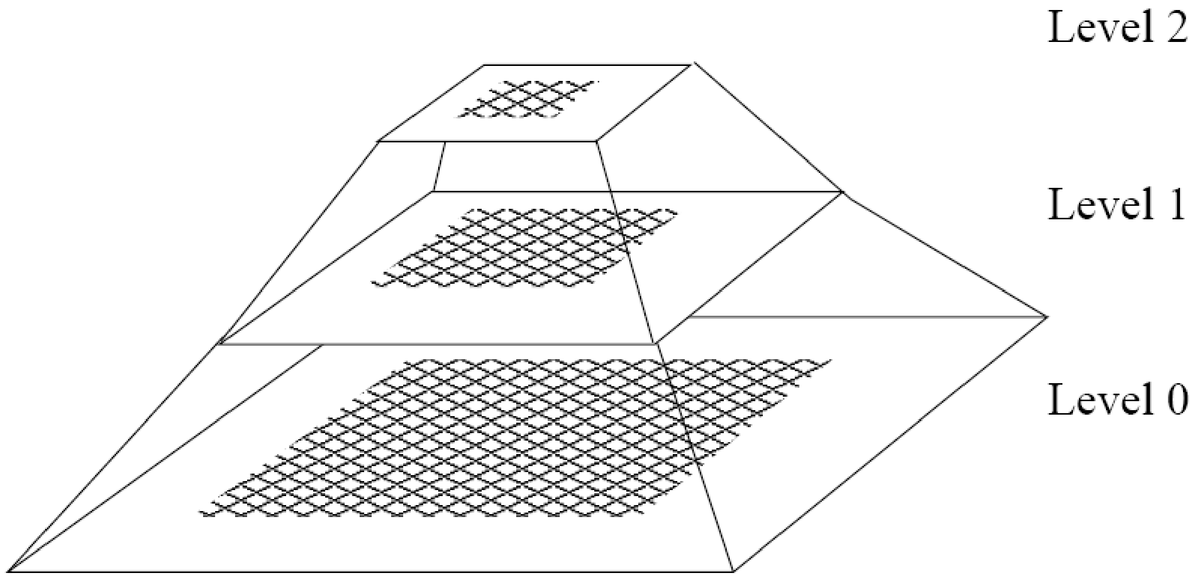
Statistical Models of Grey-Level Profiles

Performance improvement: Multi-resolution implementation coarse-to-fine approach

- We start searching on a coarse level of a Gaussian image pyramid, and progressively refine.
- This leads to much faster, more accurate and more robust search.



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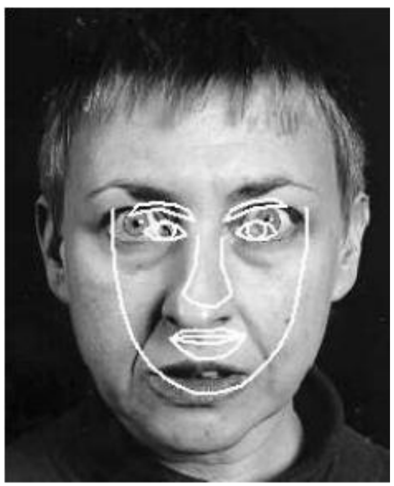
Examples of Search



Initial

After 2 iterations

After 6 iterations

After 18 iterations

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Examples of Search

Initial | After 2 iterations | After 20 Iterations

Poor Starting Point

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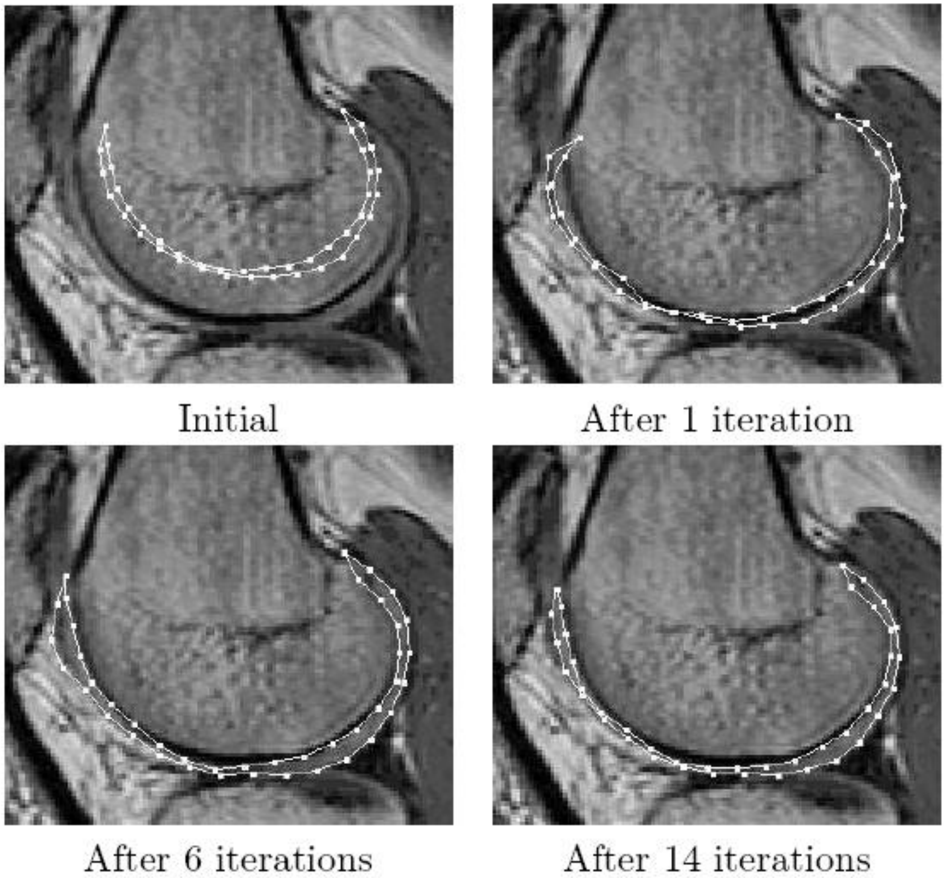
Examples of Search



Search using ASM of cartilage on an MR image of the knee

STATISTICAL MODELS OF APPEARANCE

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Appearance

- Statistical Shape Model models the shape change of an object
- Construct a similar statistical model to represented the **intensity variation across a region**
- Use:
  - Shape
  - Texture
    - ‘Texture’ means pattern of intensities across an image patch.

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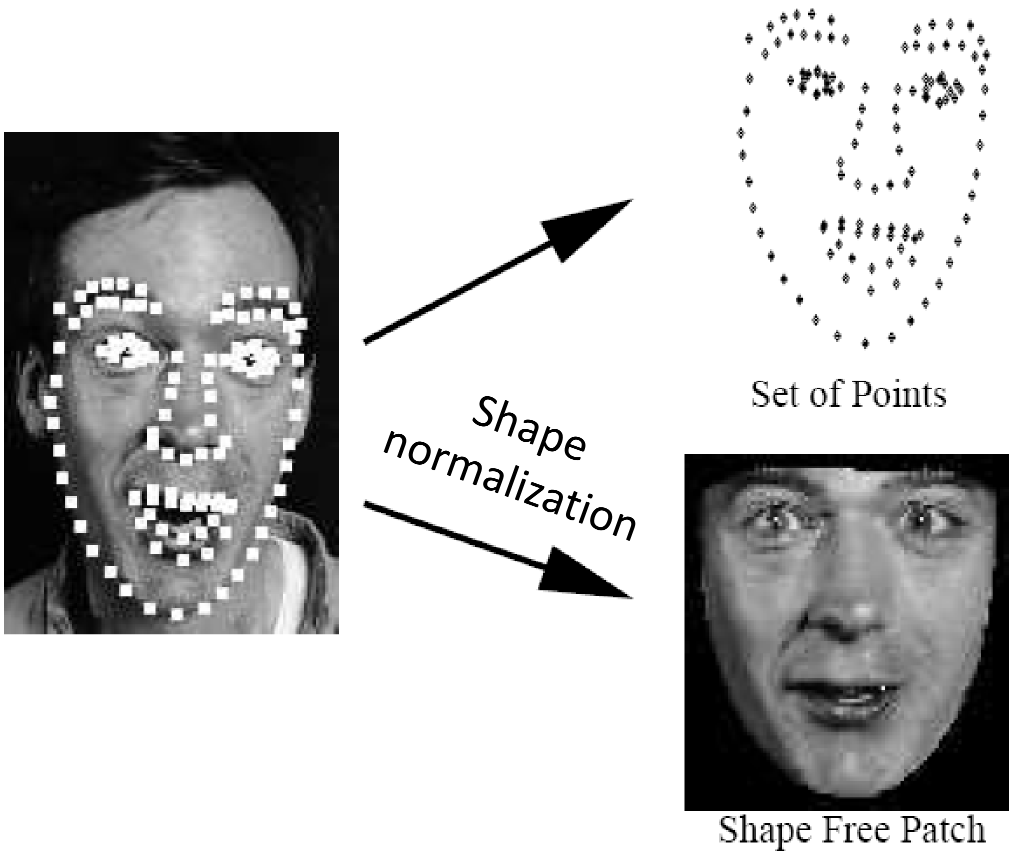
Appearance Model



shape variance

texture variance

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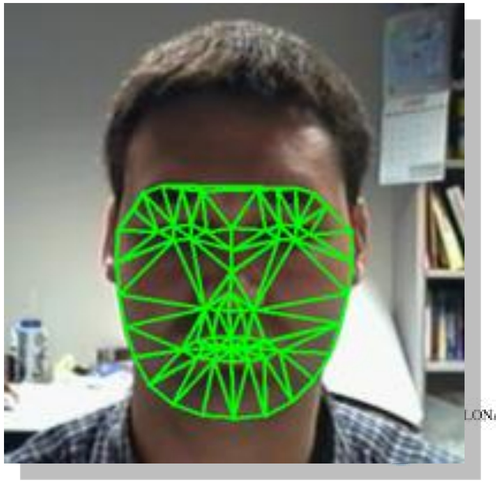
Shape Normalization

- Remove spurious texture variations due to shape differences

- Warp each image to match control points with the mean image
  - triangulation algorithm



PCA

After shape and intensity normalization, and by applying PCA to the normalised data we obtain a linear model:

$$\mathbf{g} = \bar{\mathbf{g}} + \mathbf{P}_g \mathbf{b}_g$$

$\mathbf{b}_g$: a set of grey-level parameters

$\mathbf{P}_g$: a set of orthogonal *modes of variation*

$\bar{\mathbf{g}}$: mean normalized grey-level vector

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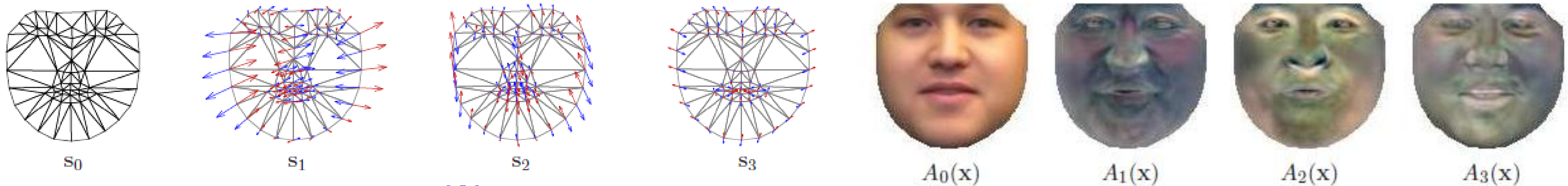
Combined Appearance Model



$$\mathbf{b}_s = \mathbf{P}_s^T(\mathbf{x} - \overline{\mathbf{x}})$$ — Shape parameters

$$\mathbf{b}_g = \mathbf{P}_g^T(\mathbf{g} - \overline{\mathbf{g}})$$ — Appearance parameters

Since there may be correlations between the shape and texture variations, we apply a further PCA to the data as follows. For each example we generate the concatenated vector:

$$\mathbf{b} = \begin{pmatrix} \mathbf{W}_s \mathbf{b}_s \\ \mathbf{b}_g \end{pmatrix} = \begin{pmatrix} \mathbf{W}_s \mathbf{P}_s^T(\mathbf{x} - \overline{\mathbf{x}}) \\ \mathbf{P}_g^T(\mathbf{g} - \overline{\mathbf{g}}) \end{pmatrix}$$

Combined Appearance Models

A diagonal matrix of weights to accommodate the difference in units between the shape and grey models

$$\mathbf{b} = \begin{pmatrix} \mathbf{W}_s \mathbf{b}_s \\ \mathbf{b}_g \end{pmatrix} = \begin{pmatrix} \mathbf{W}_s \mathbf{P}_s^T (\mathbf{x} - \bar{\mathbf{x}}) \\ \mathbf{P}_g^T (\mathbf{g} - \bar{\mathbf{g}}) \end{pmatrix}$$

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PCA for Combined Vectors

$$\mathbf{b} = \begin{pmatrix} \mathbf{W}_s \mathbf{b}_s \\ \mathbf{b}_g \end{pmatrix} = \begin{pmatrix} \mathbf{W}_s \mathbf{P}_s^T (\mathbf{x} - \overline{\mathbf{x}}) \\ \mathbf{P}_g^T (\mathbf{g} - \overline{\mathbf{g}}) \end{pmatrix} \rightarrow \mathbf{b} = \mathbf{P}_c \mathbf{c}$$

eigenvectors from applying PCA on **b**'s

appearance parameters controlling both the **shape** and **grey-levels** of the model

Shape & Grey-Level Reconstruction

$$\mathbf{b} = \begin{pmatrix} \mathbf{W}_s \mathbf{b}_s \\ \mathbf{b}_g \end{pmatrix} = \begin{pmatrix} \mathbf{W}_s \mathbf{P}_s^T (\mathbf{x} - \overline{\mathbf{x}}) \\ \mathbf{P}_g^T (\mathbf{g} - \overline{\mathbf{g}}) \end{pmatrix}$$

$$\begin{pmatrix} \mathbf{W}_s \mathbf{P}_s^T (\mathbf{x} - \overline{\mathbf{x}}) \\ \mathbf{P}_g^T (\mathbf{g} - \overline{\mathbf{g}}) \end{pmatrix} = \mathbf{b} = \mathbf{P}_c \mathbf{c} = \begin{pmatrix} \mathbf{P}_{cs} \\ \mathbf{P}_{cg} \end{pmatrix} \mathbf{c}$$

$$\mathbf{x} = \overline{\mathbf{x}} + \mathbf{P}_s \mathbf{W}_s^{-1} \mathbf{P}_{cs} \mathbf{c} = \overline{\mathbf{x}} + \mathbf{Q}_s \mathbf{c}$$

$$\mathbf{g} = \overline{\mathbf{g}} + \mathbf{P}_g \mathbf{P}_{cg} \mathbf{c} = \overline{\mathbf{g}} + \mathbf{Q}_g \mathbf{c}$$

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Appearance Reconstruction

Given appearance parameter **c**

→ Generate shape-free gray-level image **g**

→ warp **g** to the shape described by **x**

$$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{P}_s \mathbf{W}_s^{-1} \mathbf{P}_{cs} \mathbf{c} = \bar{\mathbf{x}} + \mathbf{Q}_s \mathbf{c}$$

$$\mathbf{g} = \bar{\mathbf{g}} + \mathbf{P}_g \mathbf{P}_{cg} \mathbf{c} = \bar{\mathbf{g}} + \mathbf{Q}_g \mathbf{c}$$

Review: Combined Appearance Models

How to obtained $\mathbf{W}_s$?

a diagonal matrix of weights to accommodate the difference in units between the shape and grey models

$$\mathbf{b} = \begin{pmatrix} \mathbf{W}_s \mathbf{b}_s \\ \mathbf{b}_g \end{pmatrix} = \begin{pmatrix} \mathbf{W}_s \mathbf{P}_s^T (\mathbf{x} - \overline{\mathbf{x}}) \\ \mathbf{P}_g^T (\mathbf{g} - \overline{\mathbf{g}}) \end{pmatrix}$$

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Choice of Shape Parameter Weights

- Method1 —— Displace each element of $\mathbf{b}_s$ from its optimum value and observe change in $\mathbf{g}$ for each training example
  - The RMS change gives elements in W

The choice of $\mathbf{W}_s$ is relatively insensitive

ratio of the total intensity variation to the total shape variation

$$\mathbf{b} = \begin{pmatrix} \mathbf{W}_s \mathbf{b}_s \\ \mathbf{b}_g \end{pmatrix} = \begin{pmatrix} \mathbf{W}_s \mathbf{P}_s^T (\mathbf{x} - \overline{\mathbf{x}}) \\ \mathbf{P}_g^T (\mathbf{g} - \overline{\mathbf{g}}) \end{pmatrix}$$

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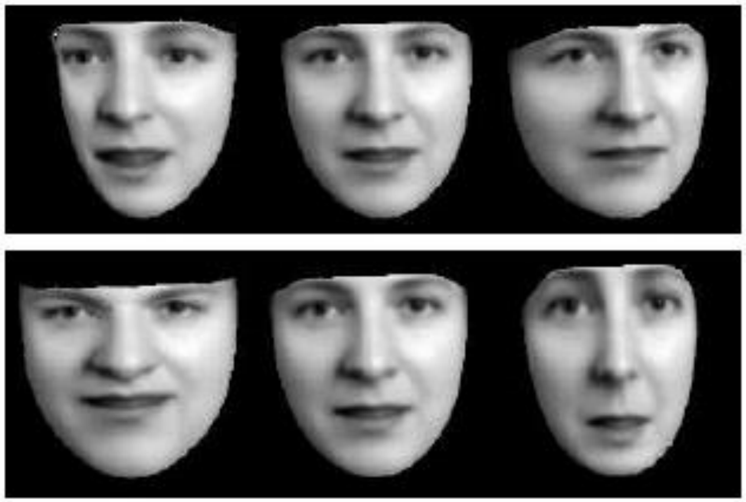
Choice of Shape Parameter Weights

- Method1 — Displace each element of $\mathbf{b}_s$ from its optimum value and observe change in $\mathbf{g}$ for each training example
  - The RMS change gives elements in $\mathbf{W}_s$
- Method2 — $\mathbf{W}_s = r\mathbf{I}$ where r^2 is the ratio of the total intensity variation to the total shape variation

$$\mathbf{b} = \begin{pmatrix} \mathbf{W}_s \mathbf{b}_s \\ \mathbf{b}_g \end{pmatrix} = \begin{pmatrix} \mathbf{W}_s \mathbf{P}_s^T (\mathbf{x} - \bar{\mathbf{x}}) \\ \mathbf{P}_g^T (\mathbf{g} - \bar{\mathbf{g}}) \end{pmatrix}$$

Example: Facial Appearance Model



First two modes of shape variation (± 3 sd)

First two modes of grey-level variation (± 3 sd)

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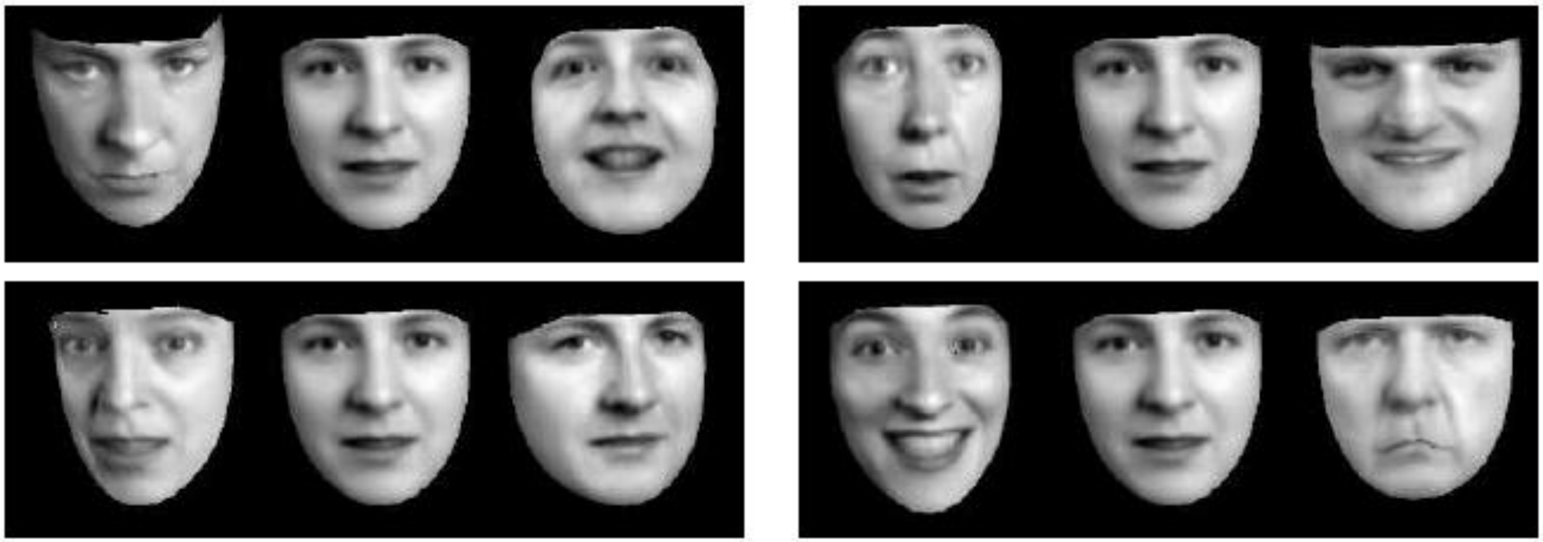
Example: Facial Appearance Model



First four modes of appearance variation (±3 sd)

Approximating a New Example

Given a new image, labeled with a set of landmarks, to generate an approximation with the model.

Approx.

Approximating a New Example

Given a new image, labelled with a set of landmarks, to generate an approximation with the model.

- Obtain $\mathbf{b}_s$ and $\mathbf{b}_g$
- Obtain $\mathbf{b}$
- Obtain $\mathbf{c}$
- Apply $$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{P}_s \mathbf{W}_s^{-1} \mathbf{P}_{cs} \mathbf{c}$$ $$\mathbf{g} = \bar{\mathbf{g}} + \mathbf{P}_g \mathbf{P}_{cg} \mathbf{c}$$
- Inverting gray level normalization by $\mathbf{g}_{im} = \alpha \mathbf{g} + \beta \mathbf{1}$
- Applying pose to the points
- Projecting the gray level vector to the image

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ACTIVE APPEARANCE MODELS

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Disadvantages of ASM

- Only uses shape constraints (together with some information about the image structure near the landmarks) for search.

- Incapable of generating photo-realistic **synthetic image**

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Goal of AAM

- Given a rough starting approximation of an appearance model, to fit it within an image

Using an Iterative Model Refinement.

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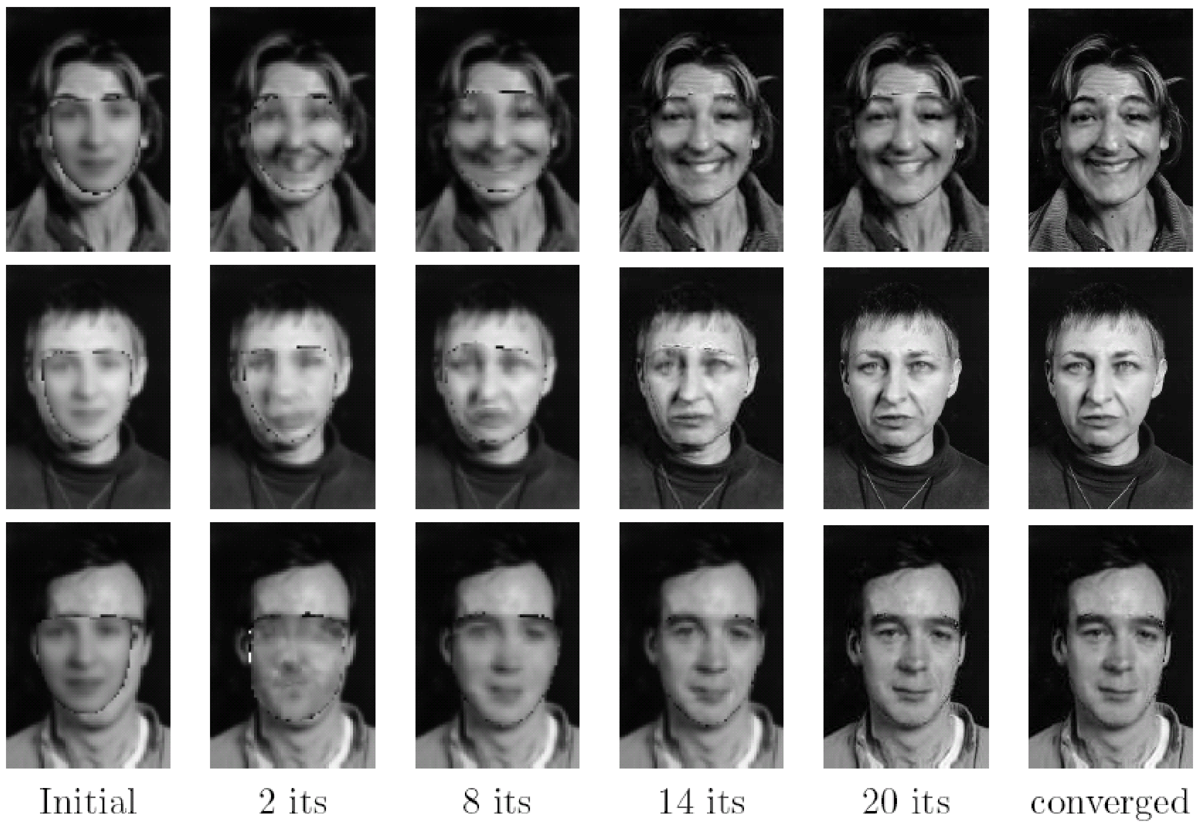
Examples of AAM Search



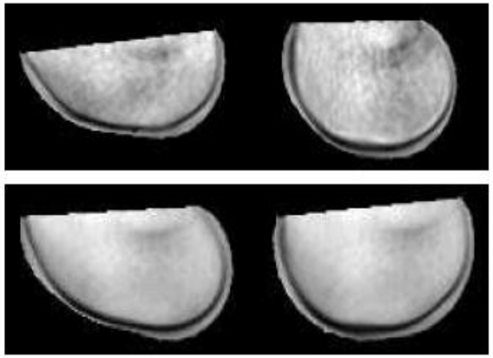
Reconstruction (left) and original (right) given original landmark points

Examples of AAM Search

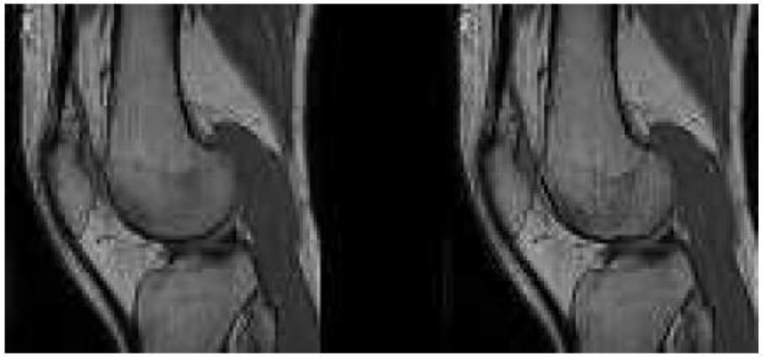


Multi-Resolution search from displaced position

Examples of AAM Search



First two modes of appearance variation of knee model



Best fit of knee model to new image given landmarks

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Examples of AAM Search

Multi-Resolution search from displaced position

COMPARISON : ASM VS AAM

Key Differences

- ASM only uses models of the image texture in the **small** regions around each landmark point
- ASM searches **around** current position, , typically along profiles normal to the boundary.
- ASM seeks to minimize the distance between **model points** and corresponding **image points**

- AAM uses a model of appearance of the **whole** region
- AAM only samples the image **under** current position
- AAM seeks to minimize the difference of the **synthesized image** and **target image**

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Experiment Data

- Two data sets :
  - 72 brain slices, 133 landmark points
- Training data set
  - Brain : 400, leave-one-brain-experiments

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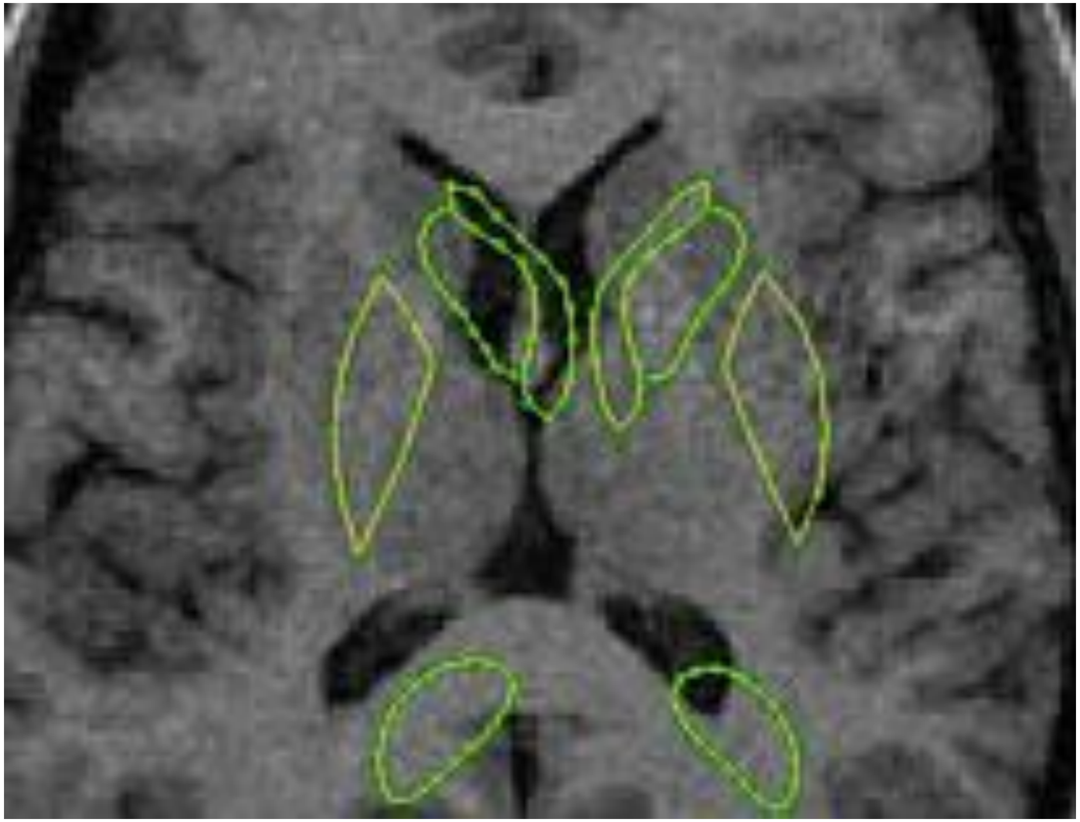
Segmentation of Brain Structures in MRI



http://personalpages.manchester.ac.uk/staff/timothy.f.cootes/Models/brain_search.html

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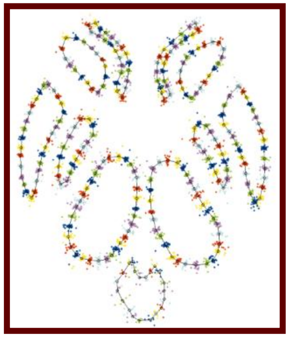
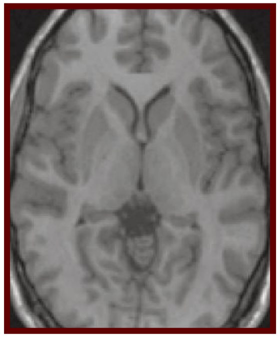
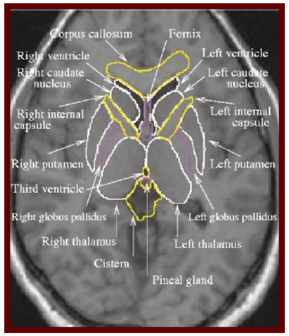
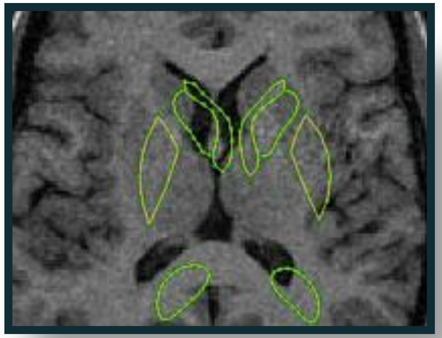
Image Interpretation with AAM

- When a labeled model is fitted to an image to be interpreted, it automatically gets labeled just by transfer:









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Conclusion

- ASM searches around the current location, along profiles, so one would expect them to have larger capture range
- ASM takes only the shape into account
- AAM can work well with a much smaller number of landmarks as compared to ASM

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References

[1] Mikkel B. Stegmann and David Delgado Gomez. *A Brief Introduction to Statistical Shape Analysis*, Technical University of Denmark, Lyngby, 2002.

[2] Matthew James Francis Cairns. *An Investigation into the use of 3D Computer Graphics for Forensic Facial Reconstruction*, Glasgow University, 2000.

[3] T. F. Cootes and C. J. Taylor *Statistical Models of Appearance for Computer Vision. Report.*

[4] Iain Matthews and Simon Baker, *Active Appearance Models Revisited.* IJCV 2004.

http://aimm02.cse.ttu.edu.tw/class_2009_1/PR/Lecture%208/Statistical%20Models%20of%20Appearance%20for%20Computer%20Vision.ppt.

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Matlab Codes for ASM and AAM

1. http://www.mathworks.com/matlabcentral/fileexchange/32704-icaam-inverse-compositional-active-appearance-models (Used in the practicum)
2. http://www.isbe.man.ac.uk/val/asmtk/ASMInfoSheet.html (p-files)
3. http://www.mathworks.com/matlabcentral/fileexchange/26706-active-shape-model-asm-and-active-appearance-model-aam (No face training images included)
4. http://www.cs.sfu.ca/~hamarneh/software/asm/ (No training images included)

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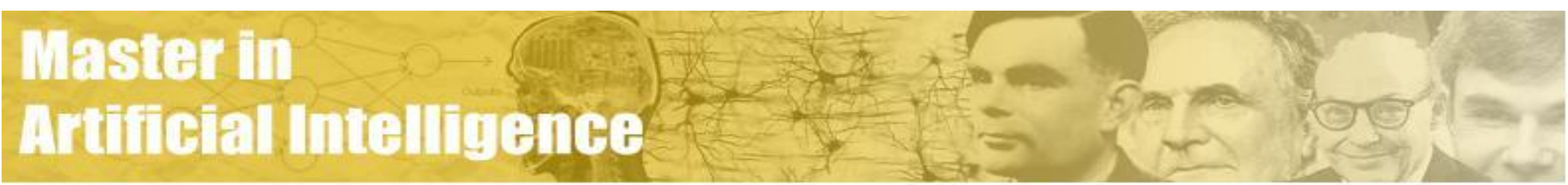
C++ codes

1. https://github.com/kylemcdonald/FaceTracker (OpenCV library)
2. http://www.milbo.users.sonic.net/stasm/ (OpenCV library)
3. http://www.isbe.man.ac.uk/~bim/software/am_tools_doc/index.html (VXL library)
4. http://humansensing.cs.cmu.edu/intraface/ (Matlab/C++)

Statistical Models of Shape and Appearance for Face Matching

Laura Igual

BCN Perceptual Computing Lab



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