Active Shape Models and Active Appearance Models

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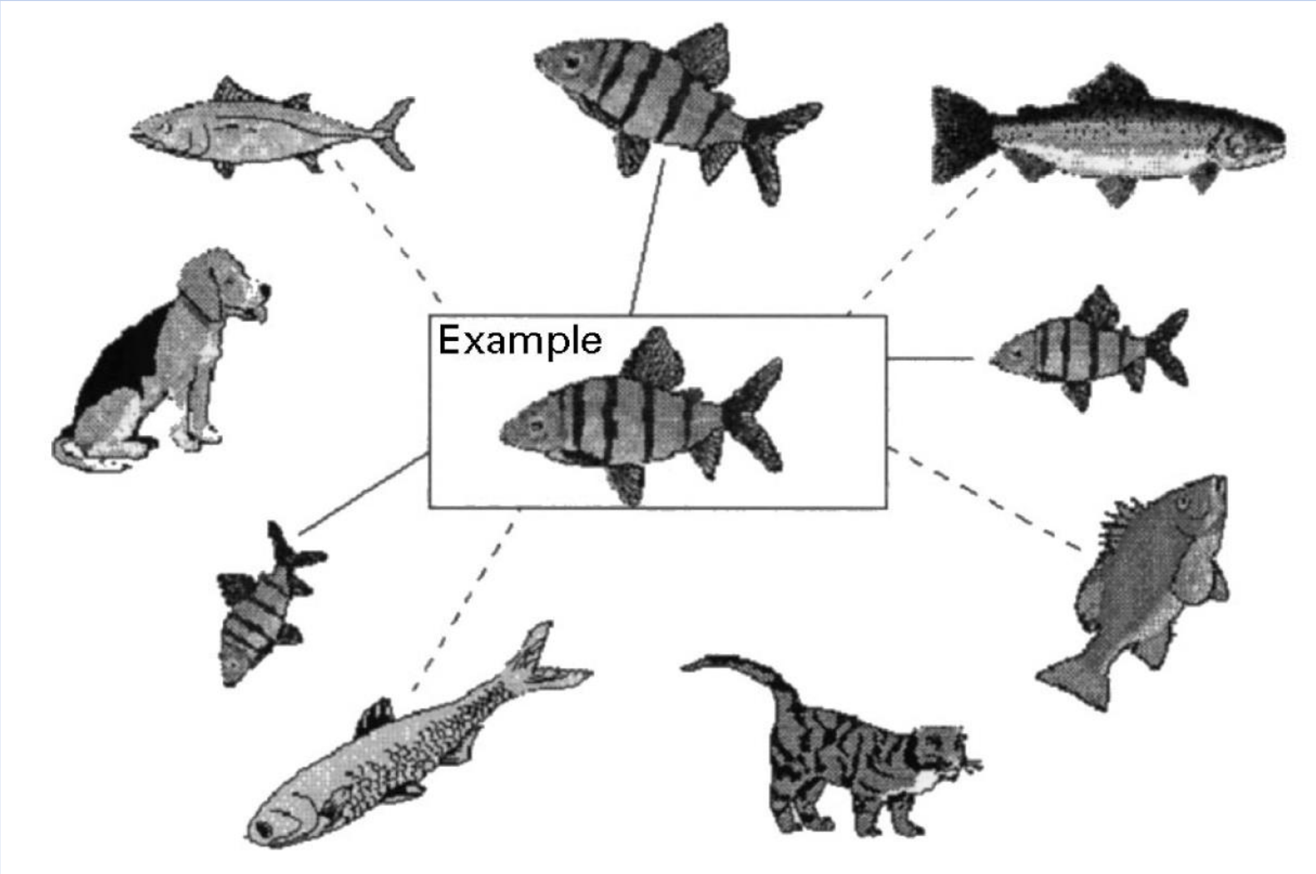
How to introduce **high-level knowledge** to regularize the segmentation problem?

- Similar pixels properties
- General high-level constraints
  - location and number of objects in images,
  - boundary smoothness, symmetry, etc.
- Model-guided segmentation and recognition



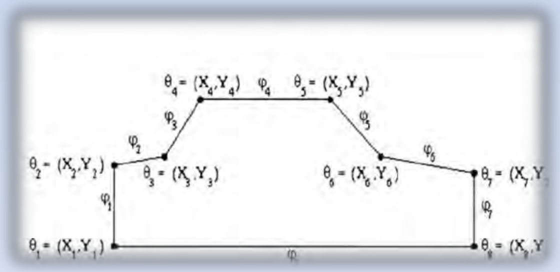

What can be done yet?!



Rigid vs. Non-rigid shape matching

Analytical Deformable Models

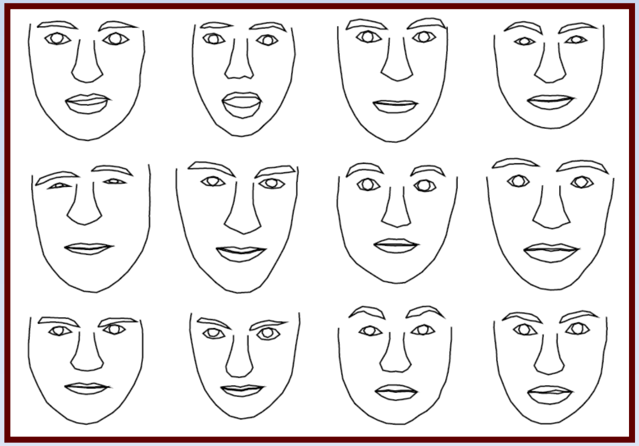
- Parameters defines explicitely the sizes and relationships between subparts of a shape
- Good inicialization is required
- Translation, orientation and scale should be known
- Initialization biases the converged configuration
- Shapes should be well-defined to be represented by a set of curves



Prototype-based Deformable Templates

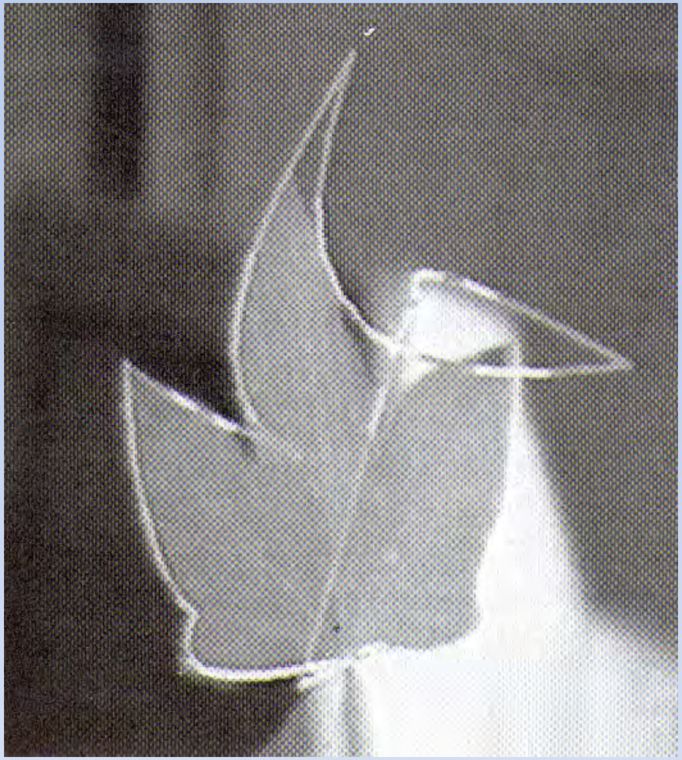
GENERAL: capable of generating any plausible example of the class that represents.

SPECIFIC: capable of generating just 'legal examples'



Prototype-based Deformable Templates

- Systematical generation of patterns from a class of shapes.
- A model template describes the overall architecture of the shape
- Parametric statistical mapping governs the random variations in the building blocks of the shape
- The prototype template can be obtained based on the prior knowledge or from training samples
- Parametric statistical mapping is chosen to reflect the particular deformations allowed in the application domain.

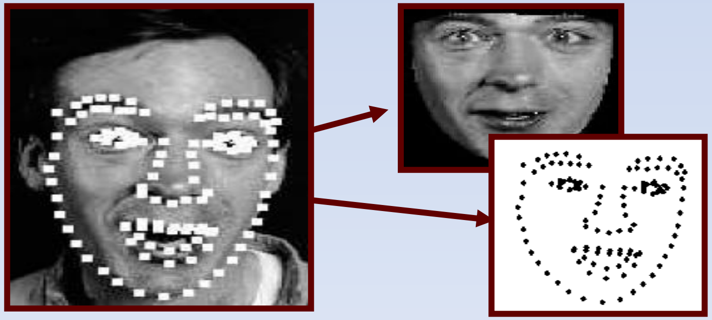


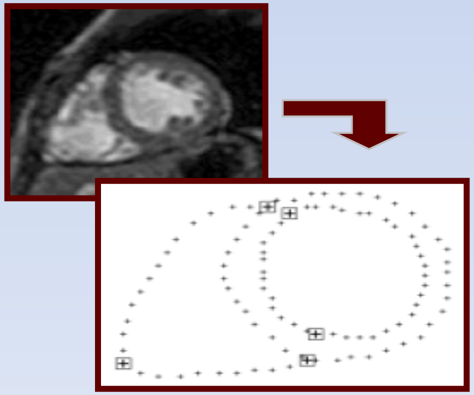
Need for shape spaces

Statistical Models

Properties:

- Few prior assumptions.
- Reflect variation appreciated in the training set.
- Can represent very complex objects and textures
- Expert knowledge captured in the annotation of training examples.
- Widely applicable.
- Compact representation.
- n-D space modeling. (2D, 3D)





Point Distribution Models

Aim: To build flexible models based on statistics of their point coordinates over a number of training shapes

$$x = \bar{x} + Pb$$

where $\bar{x}$ - mean position

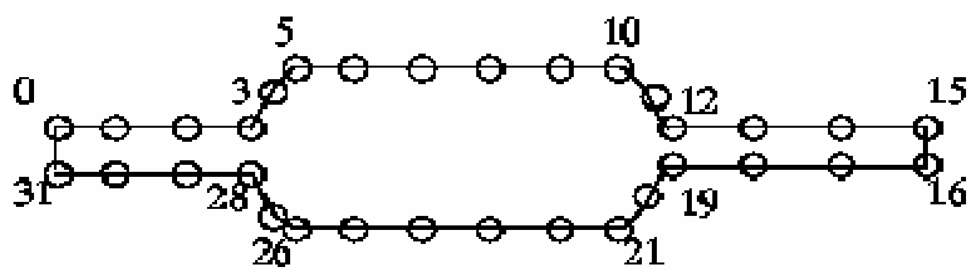
$P = (p1\ p2 \ldots p_t)$ -

matrix of first t modes

of variation

$b = (b1\ b2 \ldots b_t)^T$

vector of weights



Point Distribution Model (PDM)

From Tim Cootes

Capturing the statistics of an aligned shapes set

- Find the mean shape

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$$

- Find the deviations from the mean shape

$$dx_i = \bar{x} - x_i$$

- Find the covariance matrix

$$x = x + Pb$$

$$S = \frac{1}{N}\sum_{i=1}^{N} dx_i dx_i^{T}$$

$$x - x = Pb$$

- Find the eigenvectors and the eigenvalues of S

$$b = P^{T}(x - x)$$

$$p_k^{T} p_k = 1$$

Description in the shape space

- The modes of variation of the points of the shape are described by the eigenvectors of S

$$x = \bar{x} + Pb$$

- The shape is described by its weight vector b

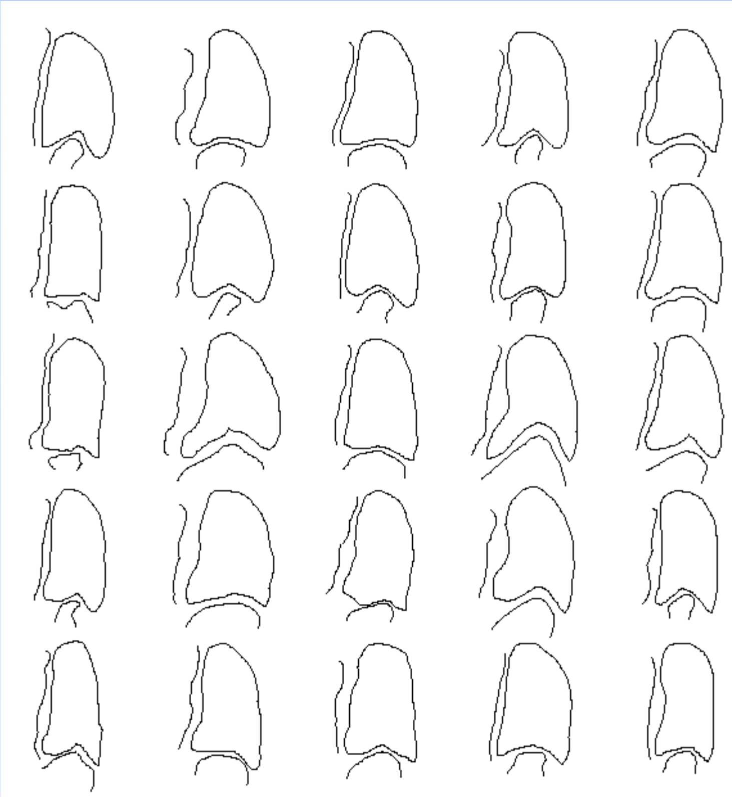
$$x - \bar{x} = Pb$$

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

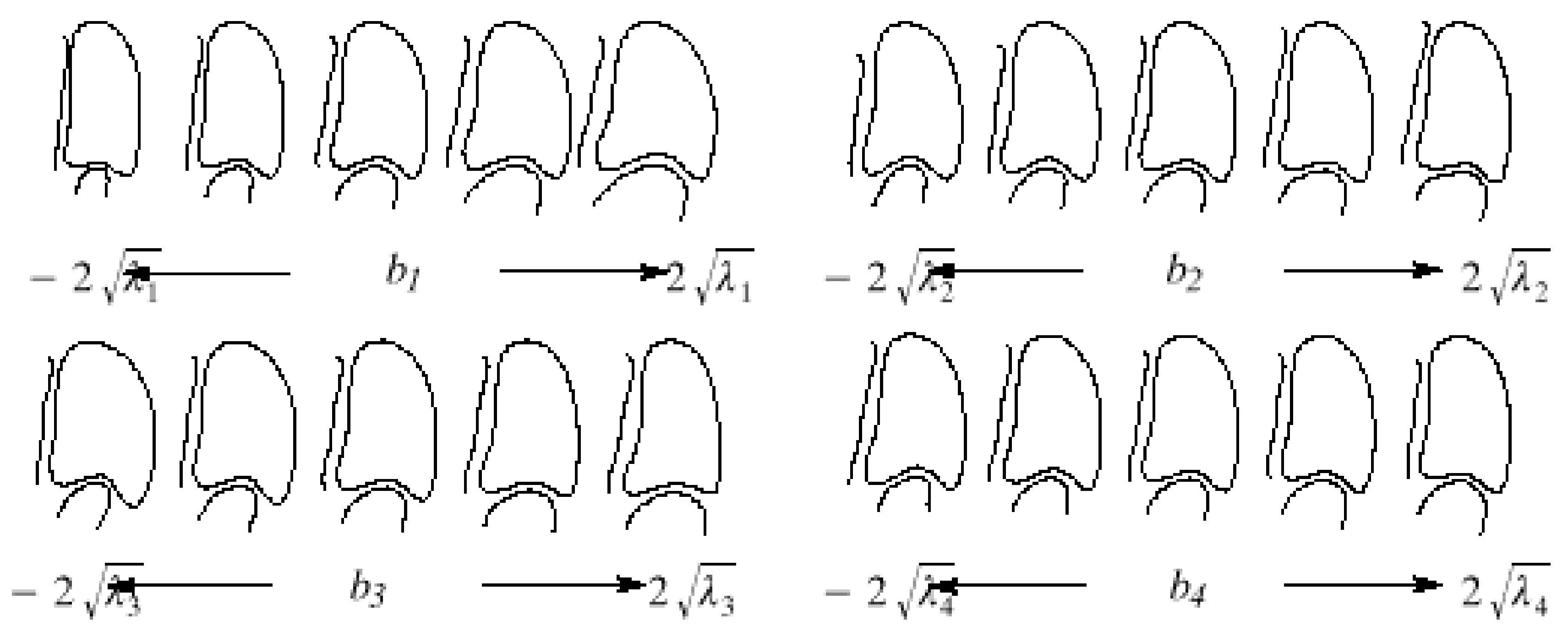
- The eigenvectors corresponding to the largest eigenvalue describe the most significant modes of variation in the training data

An example of shape variations

Echocardiogram with the ventricle at the top right and example of the ventricle shapes with 96 points and 66 examples.

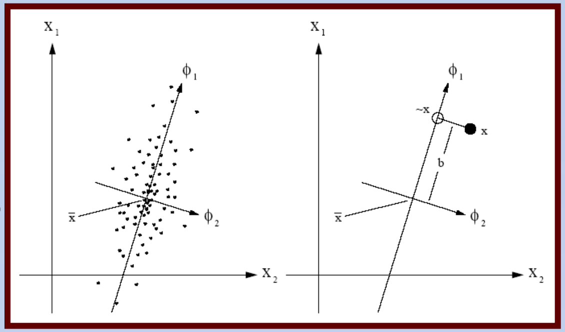


Most important eigenvectors



Dimension reduction of shape description

- The proportion of the total variance explained by each eigenvector is equal to the corresponding eigenvalue



How to calculate t: choose the smallest number

$$\sum_{k=1}^{t} \lambda_k$$

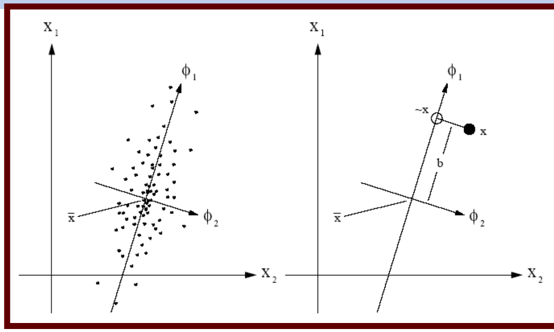
that explains a sufficiently large proportion of the total variance of variables

- Most of the variation can be explained by a small number of nodes t<<2n

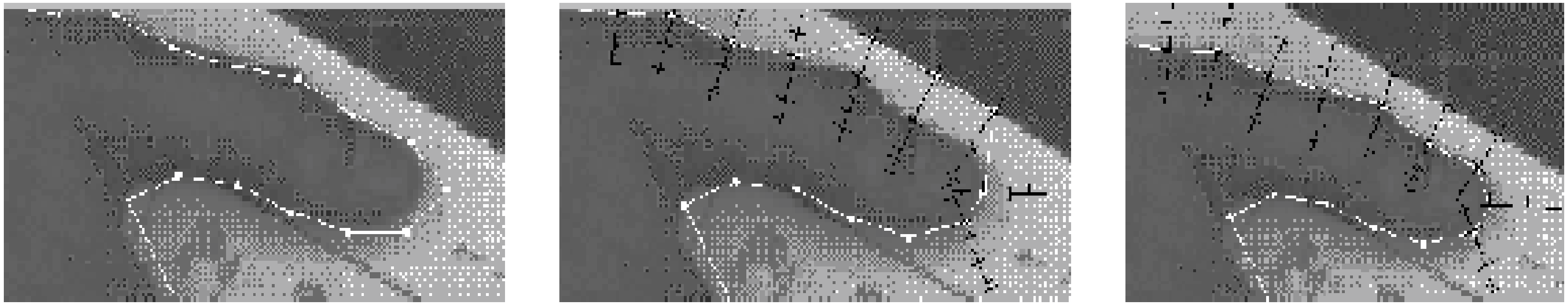
$$\lambda_T = \sum_{k=1}^{2n} \lambda_k$$

Assuring plausible shapes

$$D_m = \sum_{i=1}^{t} \left(\frac{b_i^2}{\lambda_i}\right) \leq D_{max}$$



Weight normalization: $b_i \to b_i \frac{D_{max}}{D_m} \; i = 1, \ldots t$



Segmentation of articulated objects by PDM (reprint from H. Cootes, 1992)

Using the PDM as a Local Optimiser

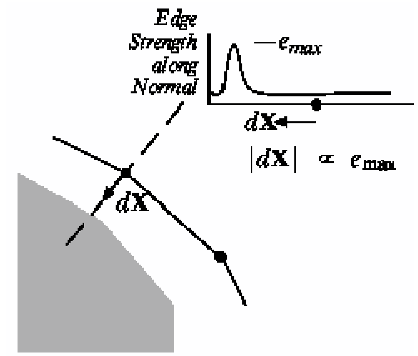
$$x + \partial x = x + P(b + \partial b)$$

$$x = x + Pb \quad \Rightarrow$$

$$\partial x = P\partial b \Rightarrow \partial b = P^T \partial x$$

- Determining displacement along normal to the boundary proportional to maximum edge strength

$$\delta X = (\delta X_0, \delta Y_0, \delta X_1, \ldots)^T$$

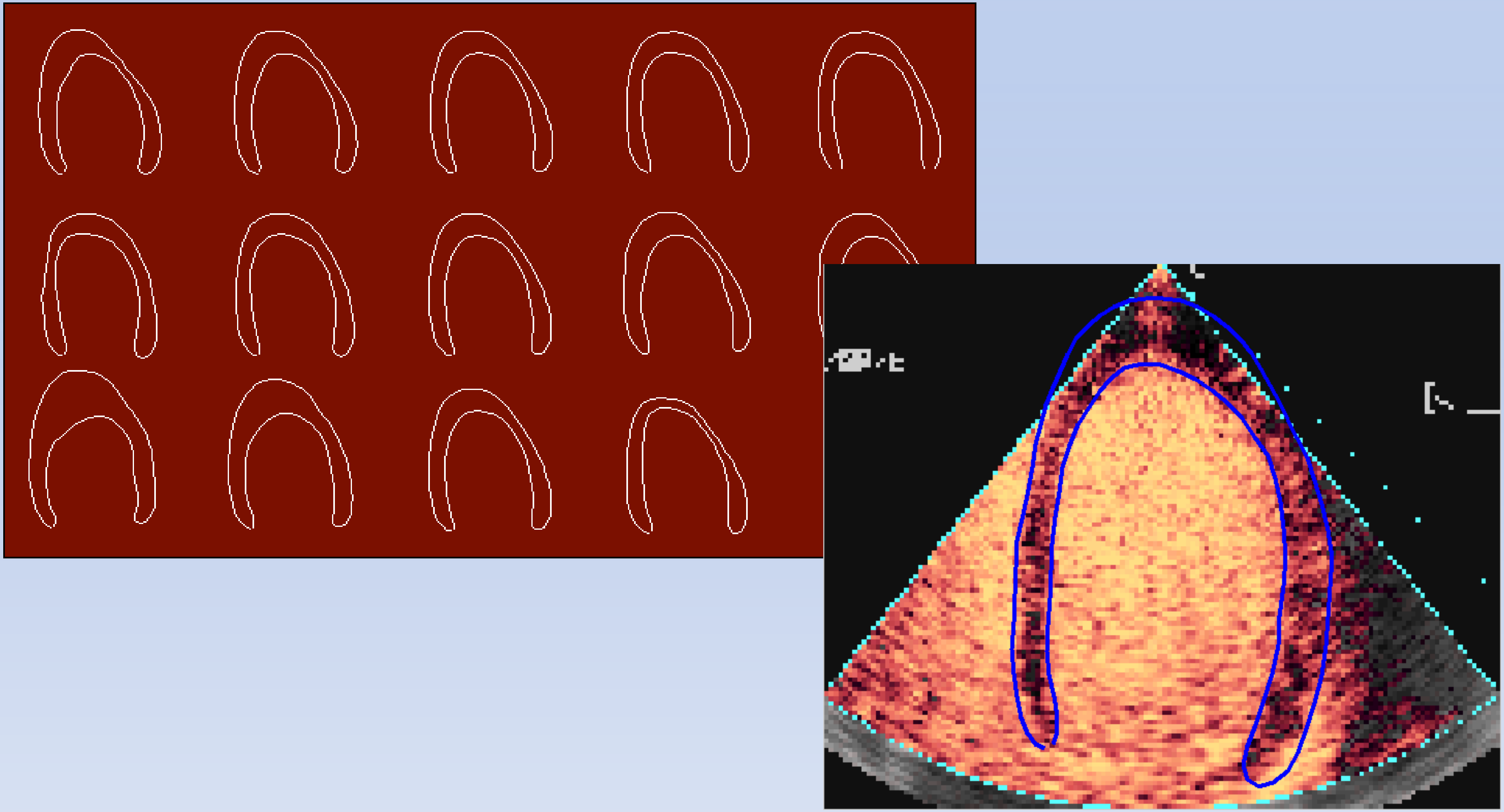


Suggested movement of labelled points (reprint from H. Cootes, 1992)

- Adjusting pose variables: $(\delta X_c, \delta Y_c)$, $\delta\theta$, $(1 + \delta s)$

- Shape parameter adjustment $\delta b = P^T \delta x$

Segmentation by Active Shape Models



Examples of ASM segmentation

Statistical Models of Appearance

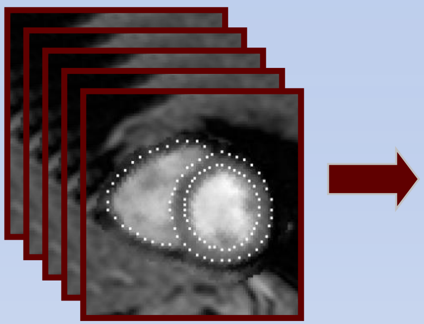
We do not use shape alone when identifying objects in real life. While object shapes provide a mental boundary where an object can exist in 3D space, they are not exclusively the only metric that we use to recognize objects.

Next logical step is to model the appearance of an entire shape.

Combined Models

Since there may be correlations between the shape and texture variations, a combined model is obtained by applying PCA over the model parameters:

$$\left\{d^i\right\}_{i=1}^N$$



Shape params.

Texture params.

$$\left\{b^i\right\}_{i=1}^N$$

$$e^i = \left\{\begin{pmatrix} b^i \\ d^i \end{pmatrix}\right\}_{i=1}^N$$

PCA

$$e = P_c c$$

Combined model: ***c*** parameter controlls shape and texture variation.

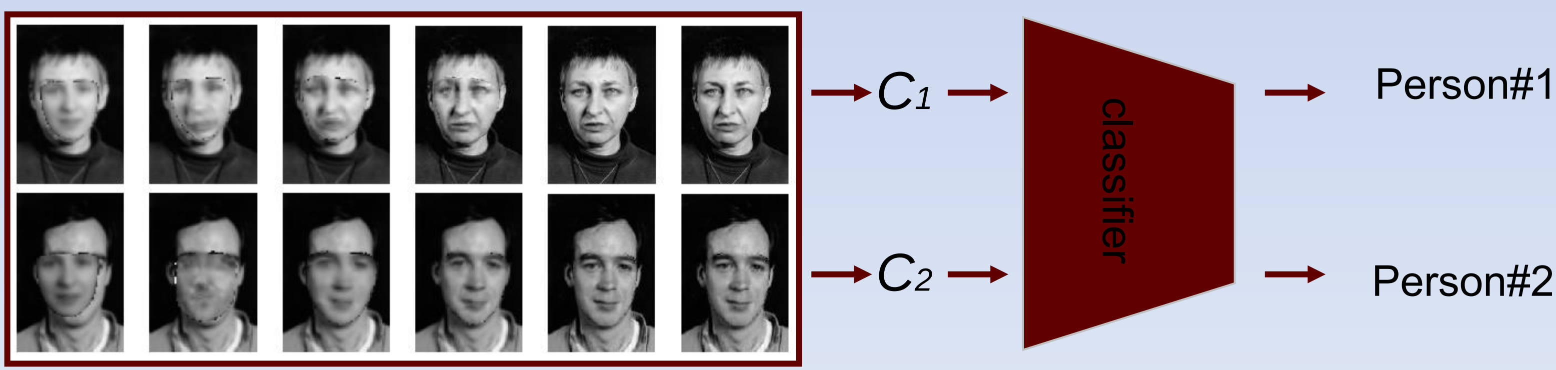
$$\boxed{\begin{aligned} X &= \overline{X} + \Phi P_{cs} c \\ G &= \overline{G} + \Psi P_{cg} c \end{aligned}}$$

$$P_c = \begin{pmatrix} P_{cs} \\ P_{cg} \end{pmatrix}$$

Image Interpretation with AAM

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

- All models have a relativelly small number of parameters. If we learn which parameters correspond to typical images, then an input image can be interpreted just by fitting a model and classifying its associated parameters:



Segmentation by Active Appearance Models

Examples of AAM segmentation

Combined Models

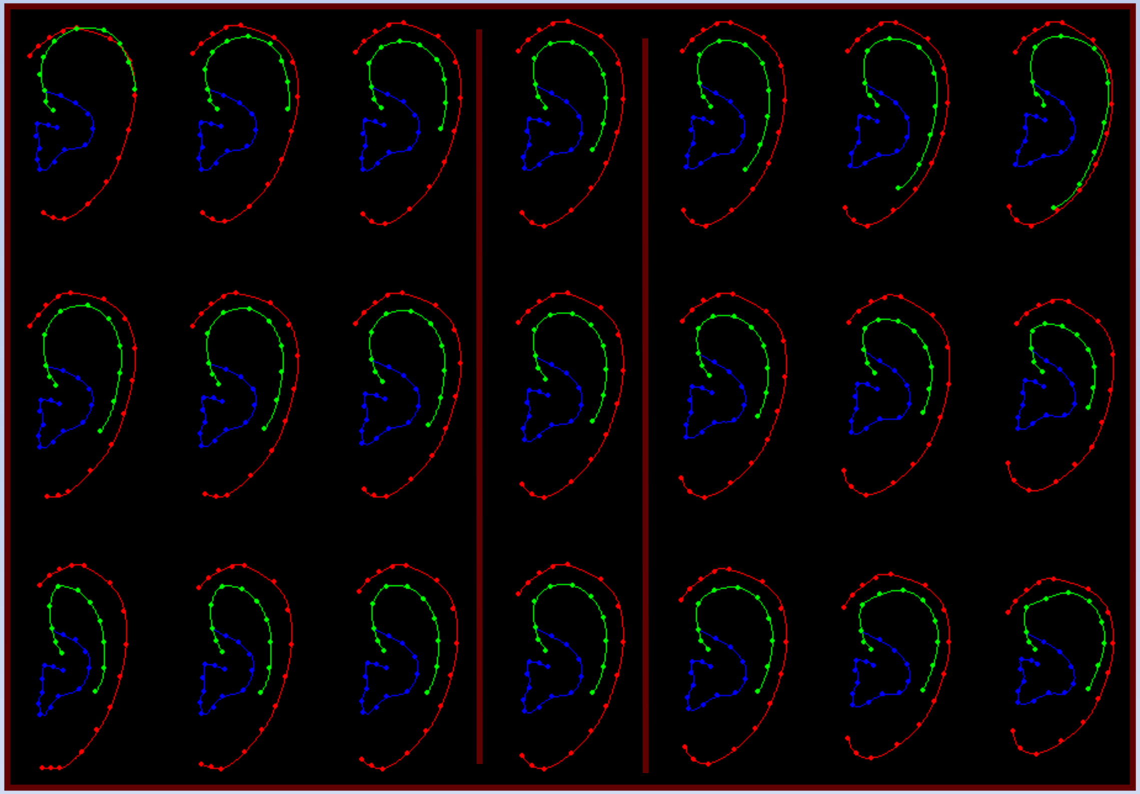
- Training set: 60 left ears
- Num. Landmarks:
  - 15 $\rightarrow$ external contour
  - 13 $\rightarrow$ internal contour
  - 12 $\rightarrow$ internal detail

Combined Models

Mode#1

Mode#2

Mode#3



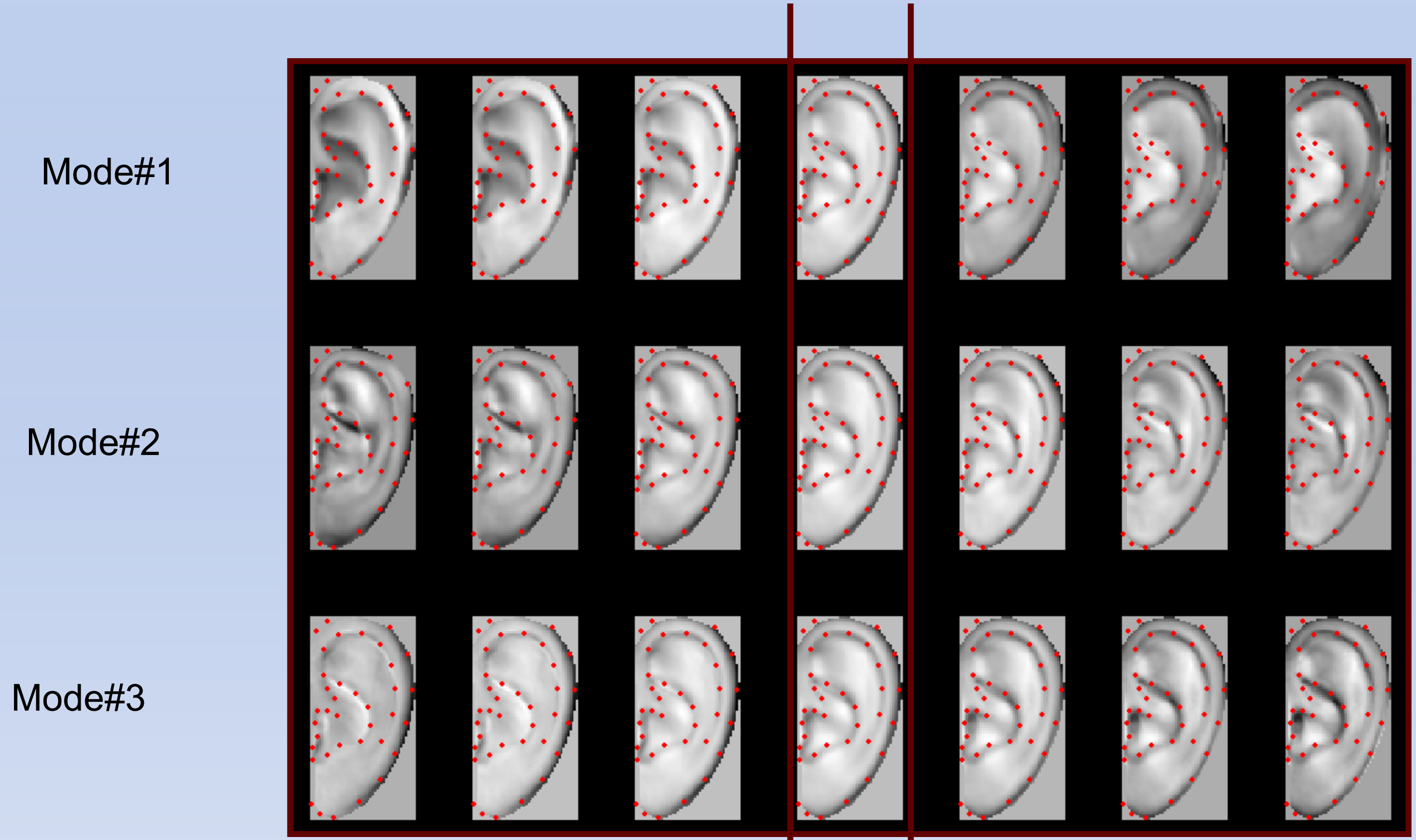
Shape model:

Original dimension → 40

Reduced dimension → 20

Variation explained → 97.66%

Combined Models



Texture model: Original dimension → 3434

Reduced dimension → 40

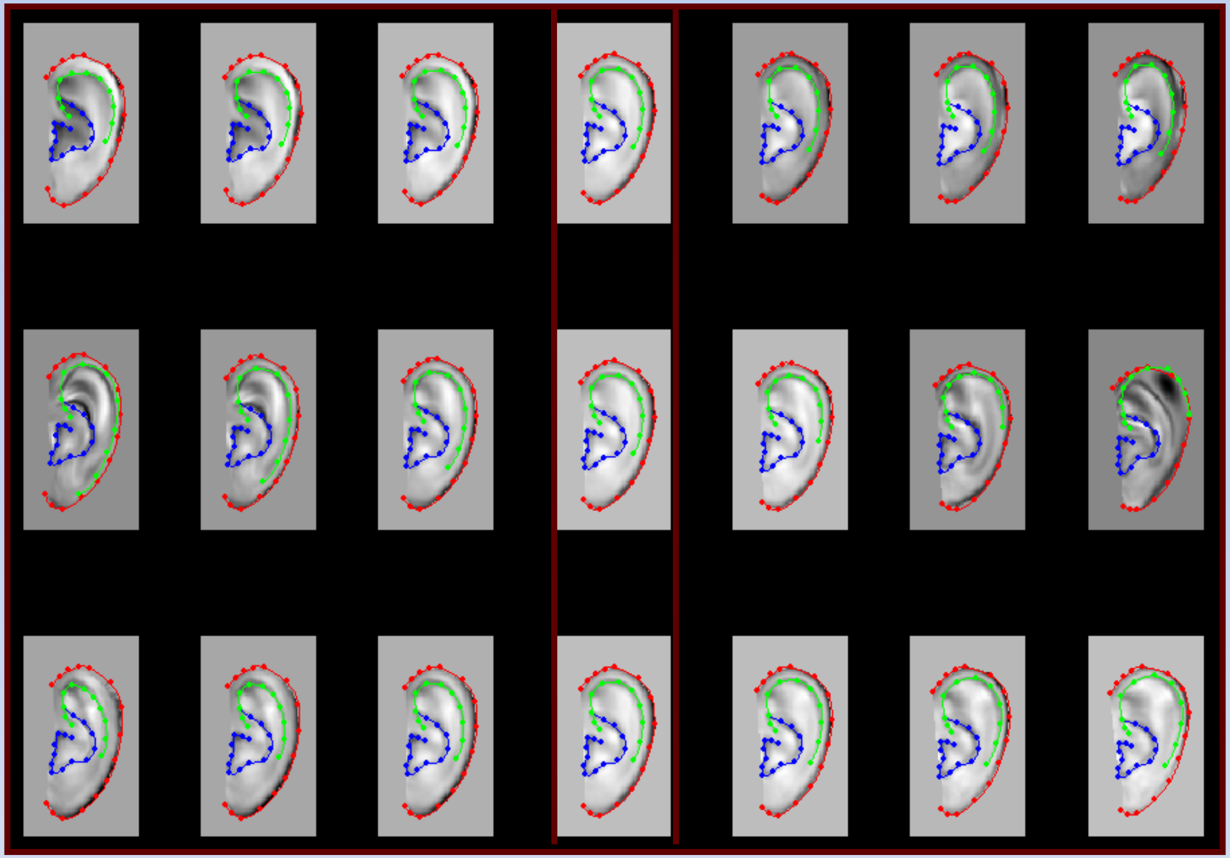
Variation explained → 97%

Combined Models

Mode#1

Mode#2

Mode#3



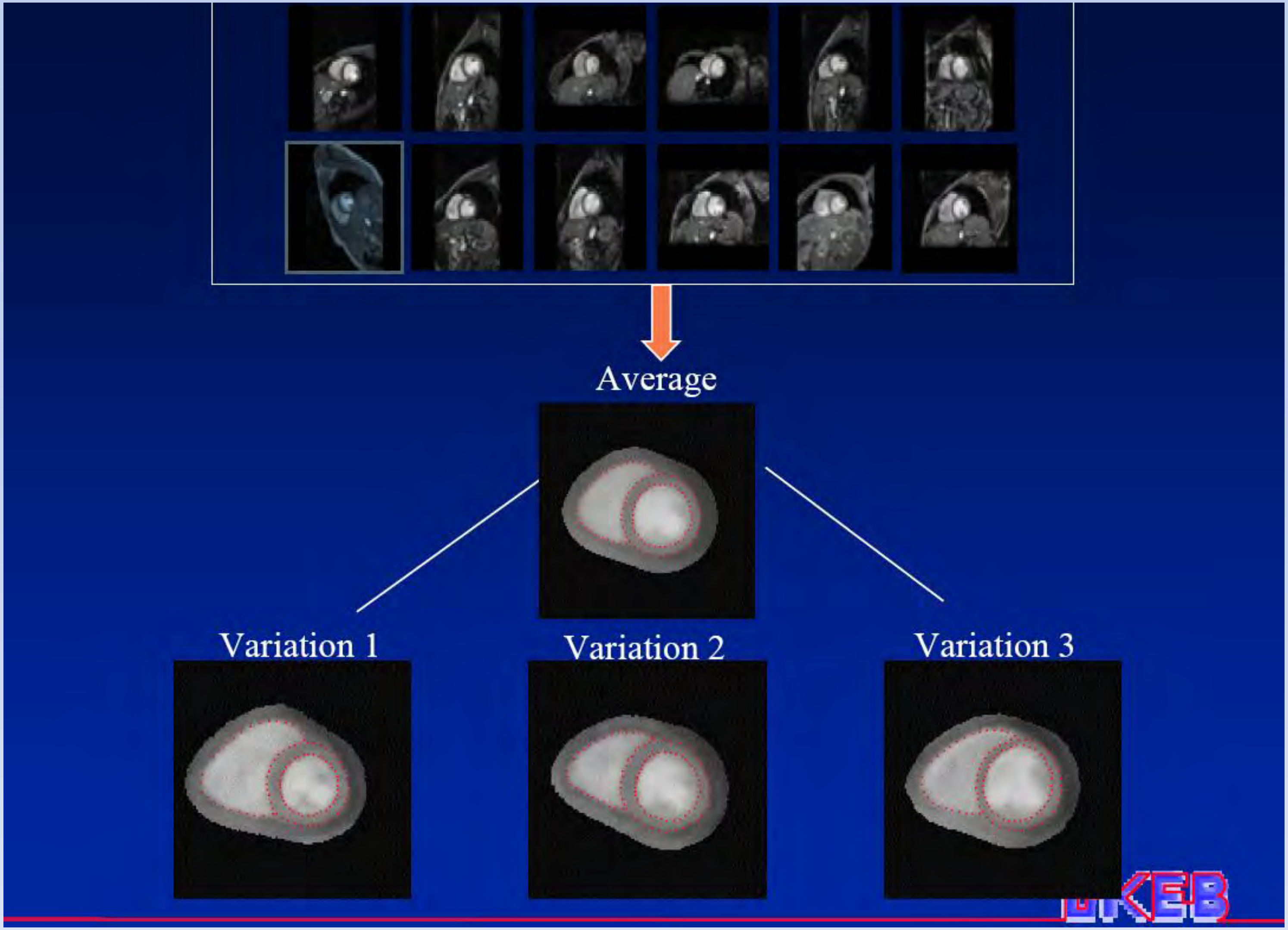
Combined model:

Original dimension → 60

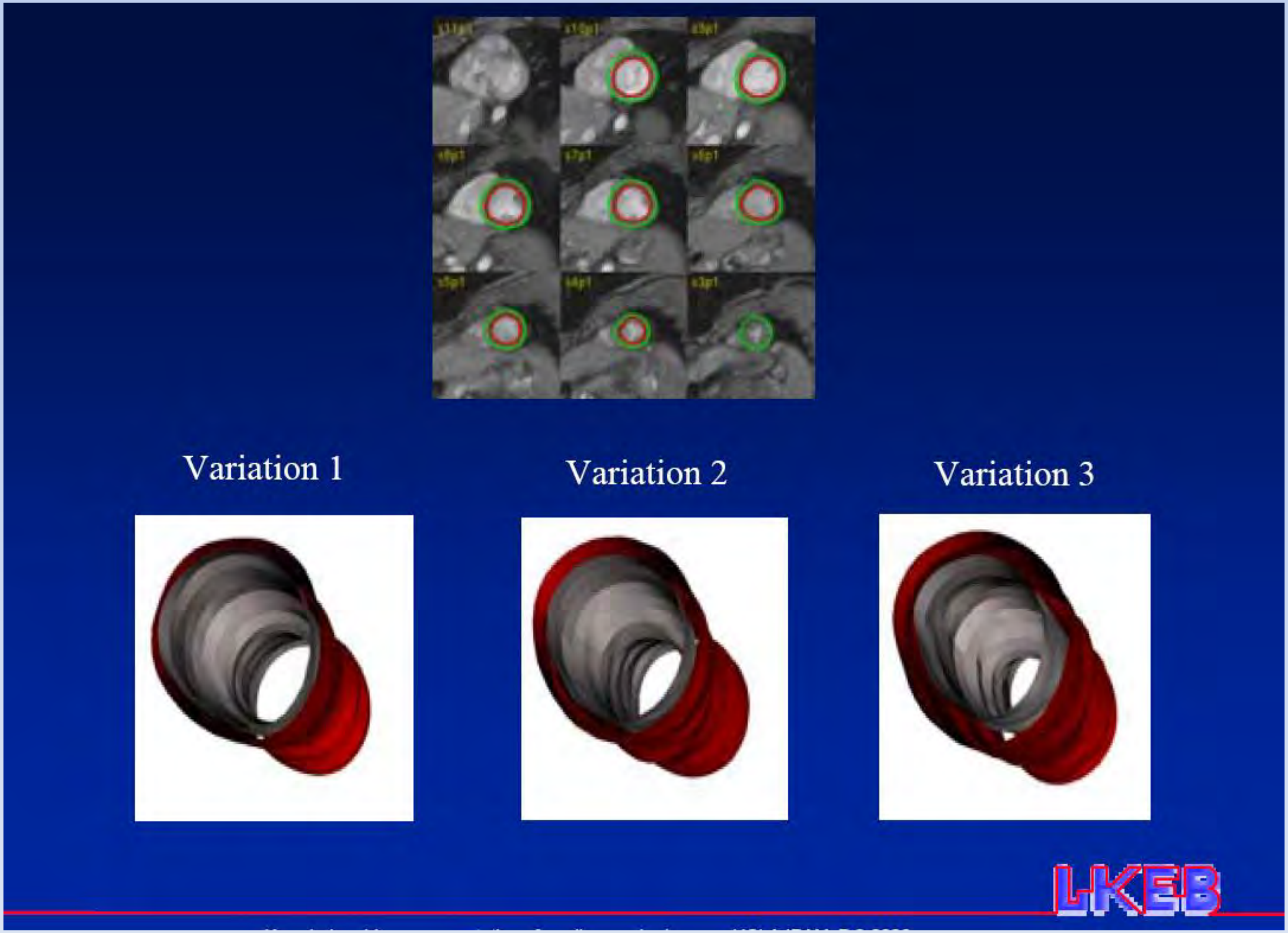
Reduced dimension → 30

Variation explained → 96%

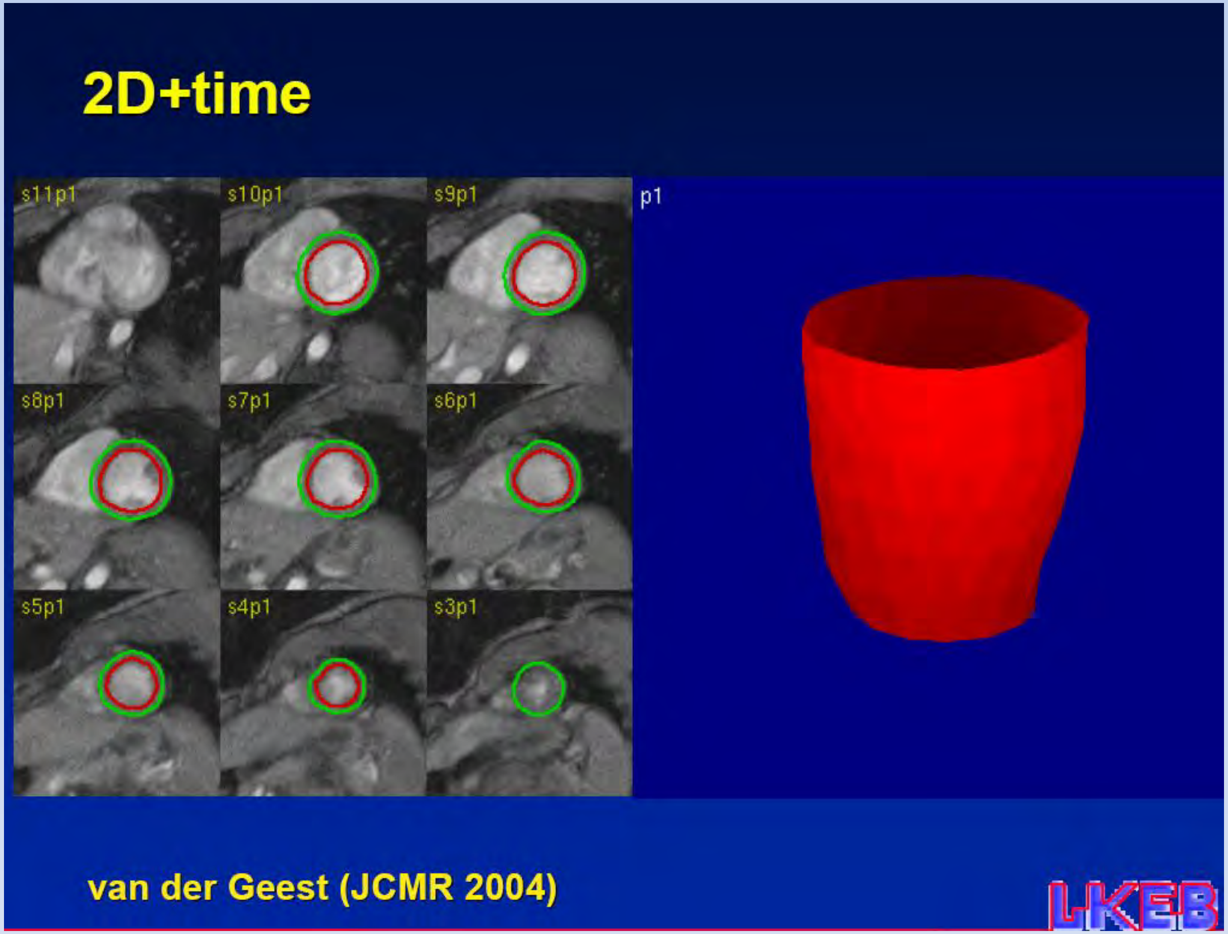
Application of ASM to Medical Imaging



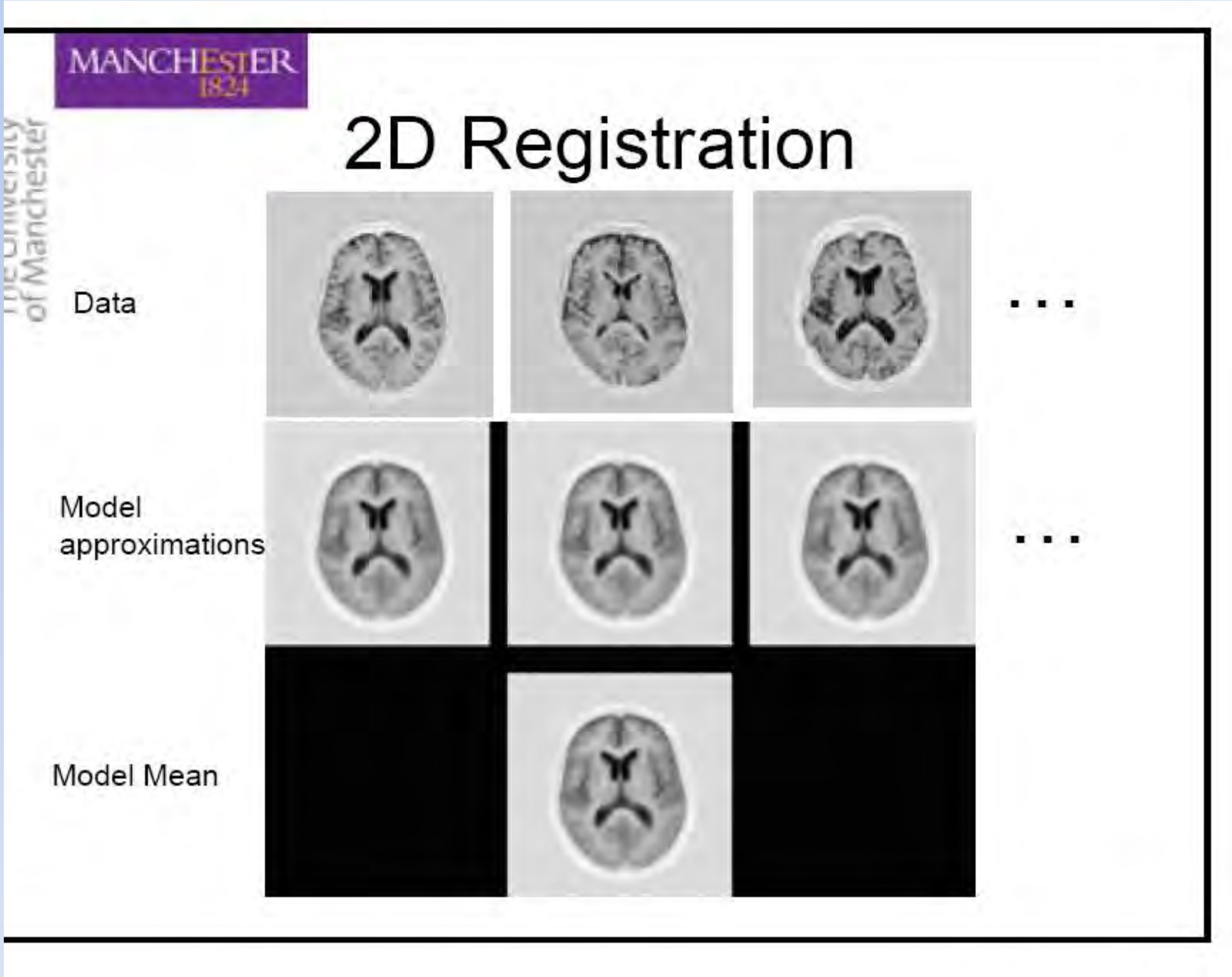
Application of ASM to Medical Imaging



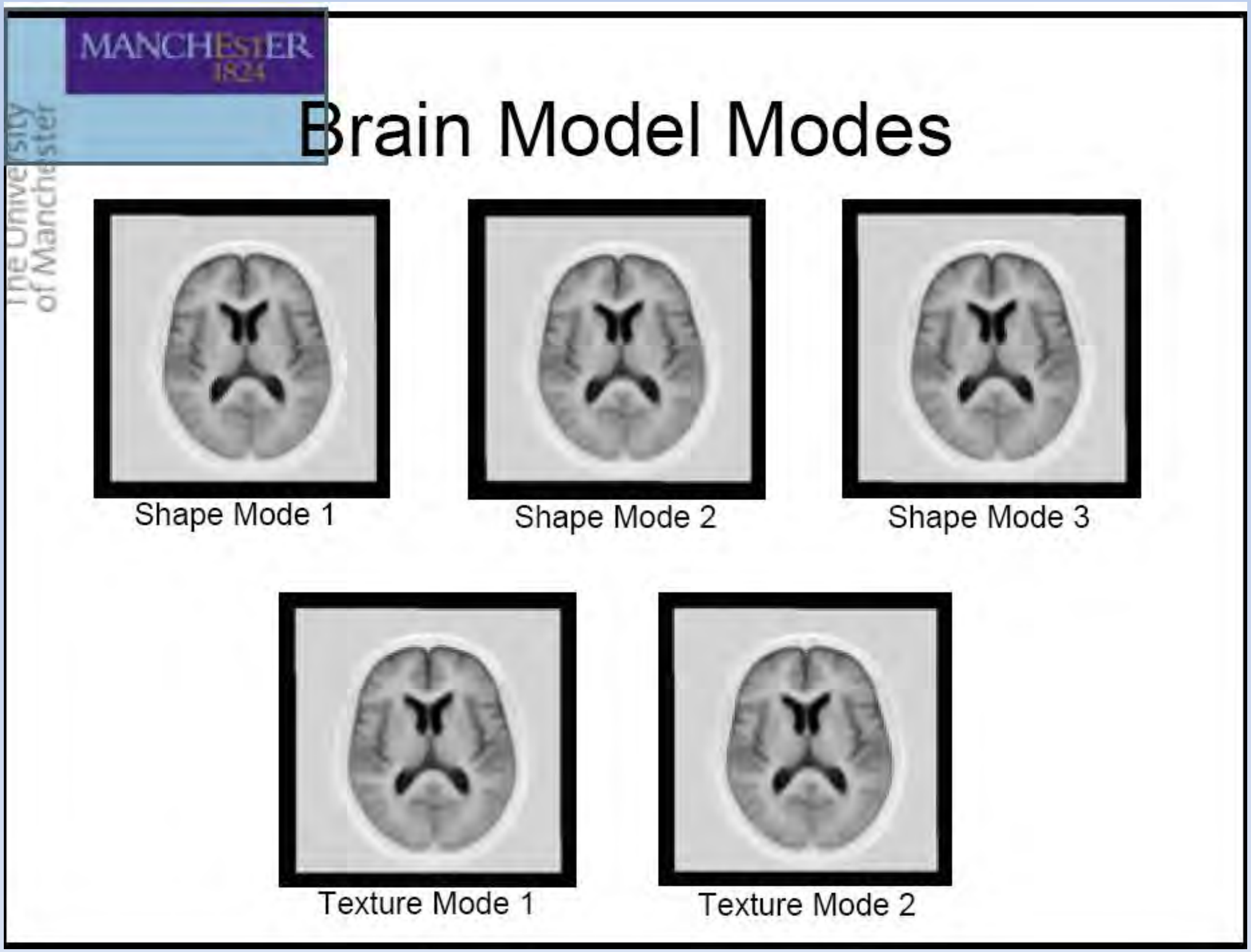
Application of ASM to Medical Imaging



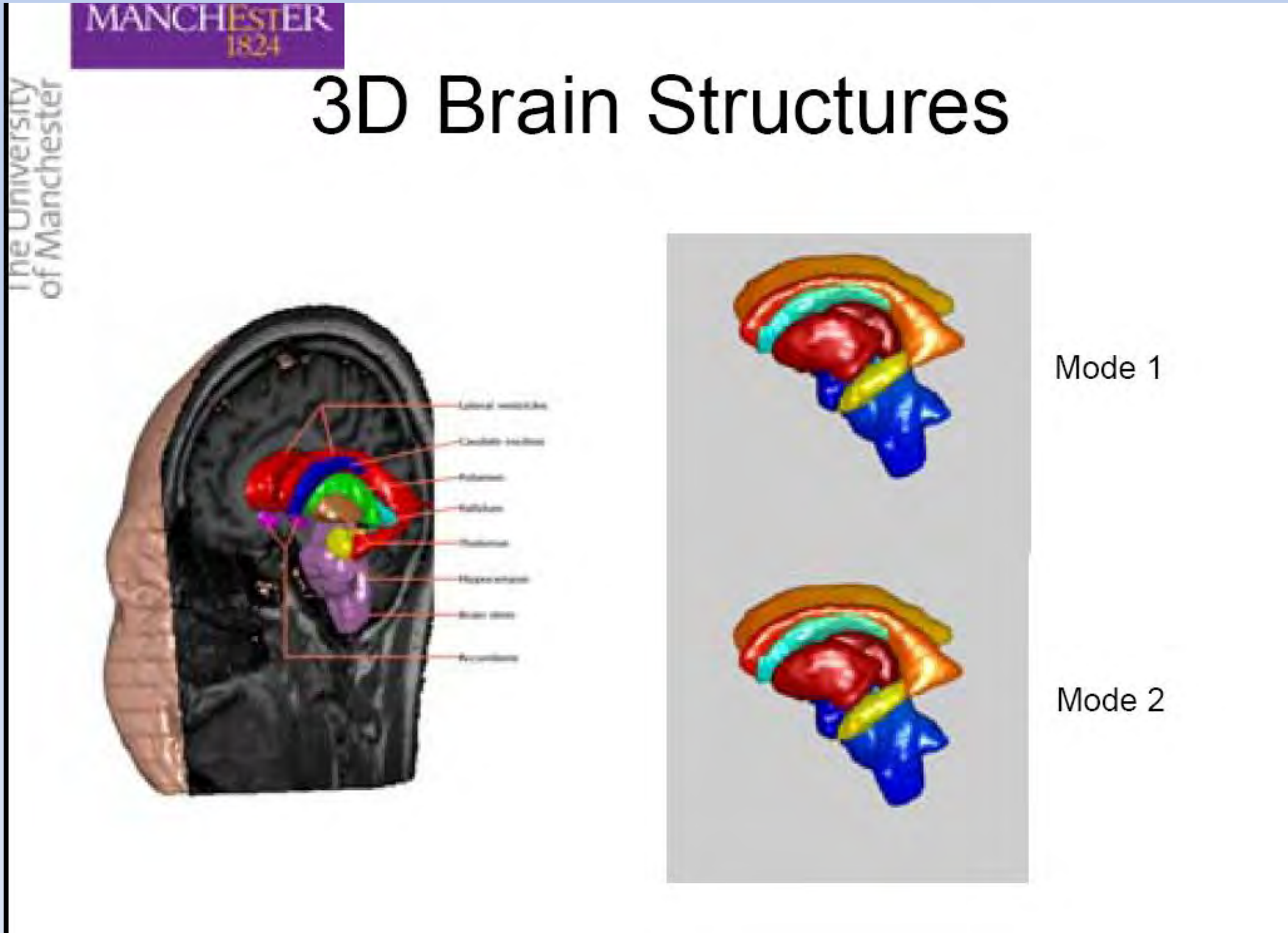
2D Registration



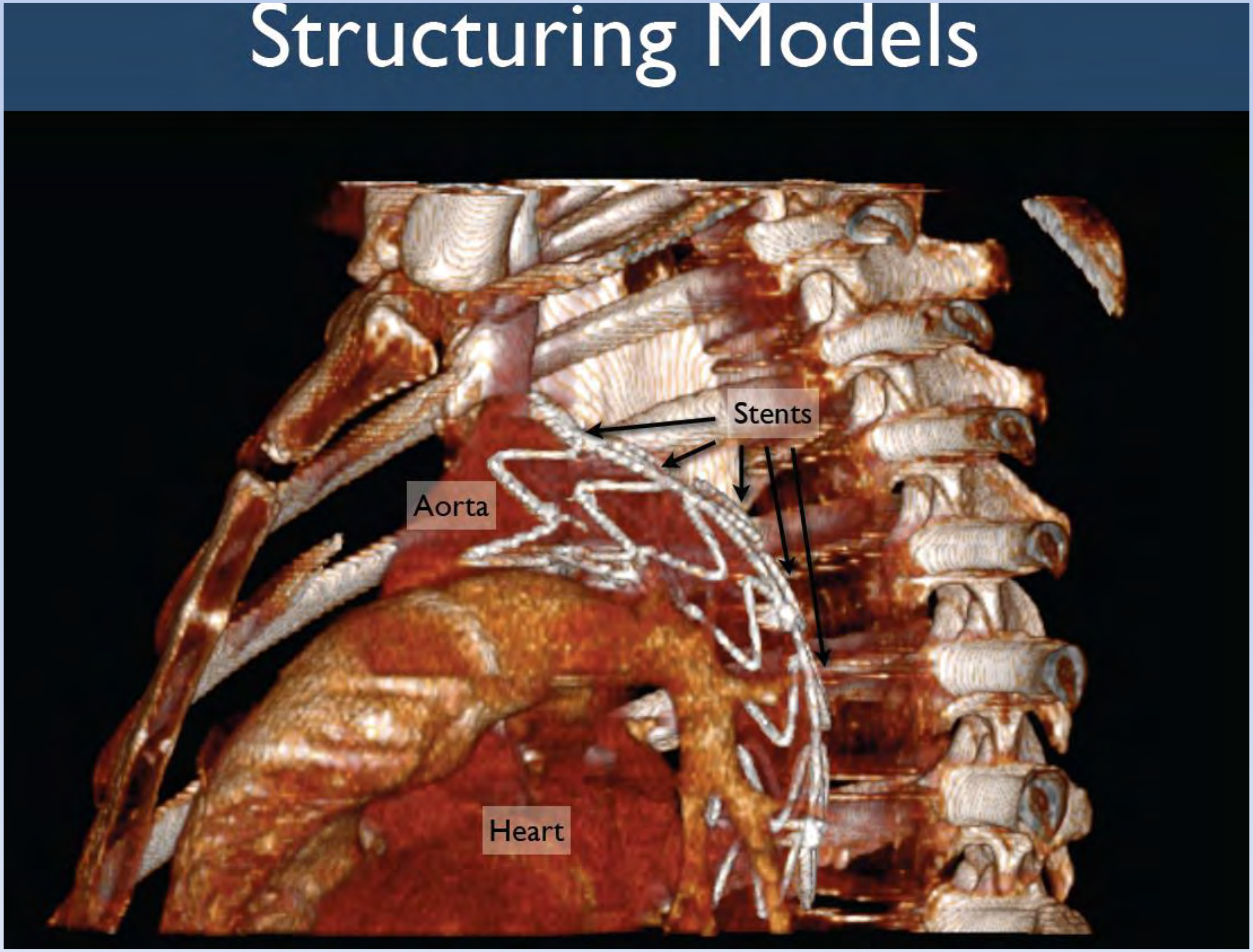
Brain Model Modes



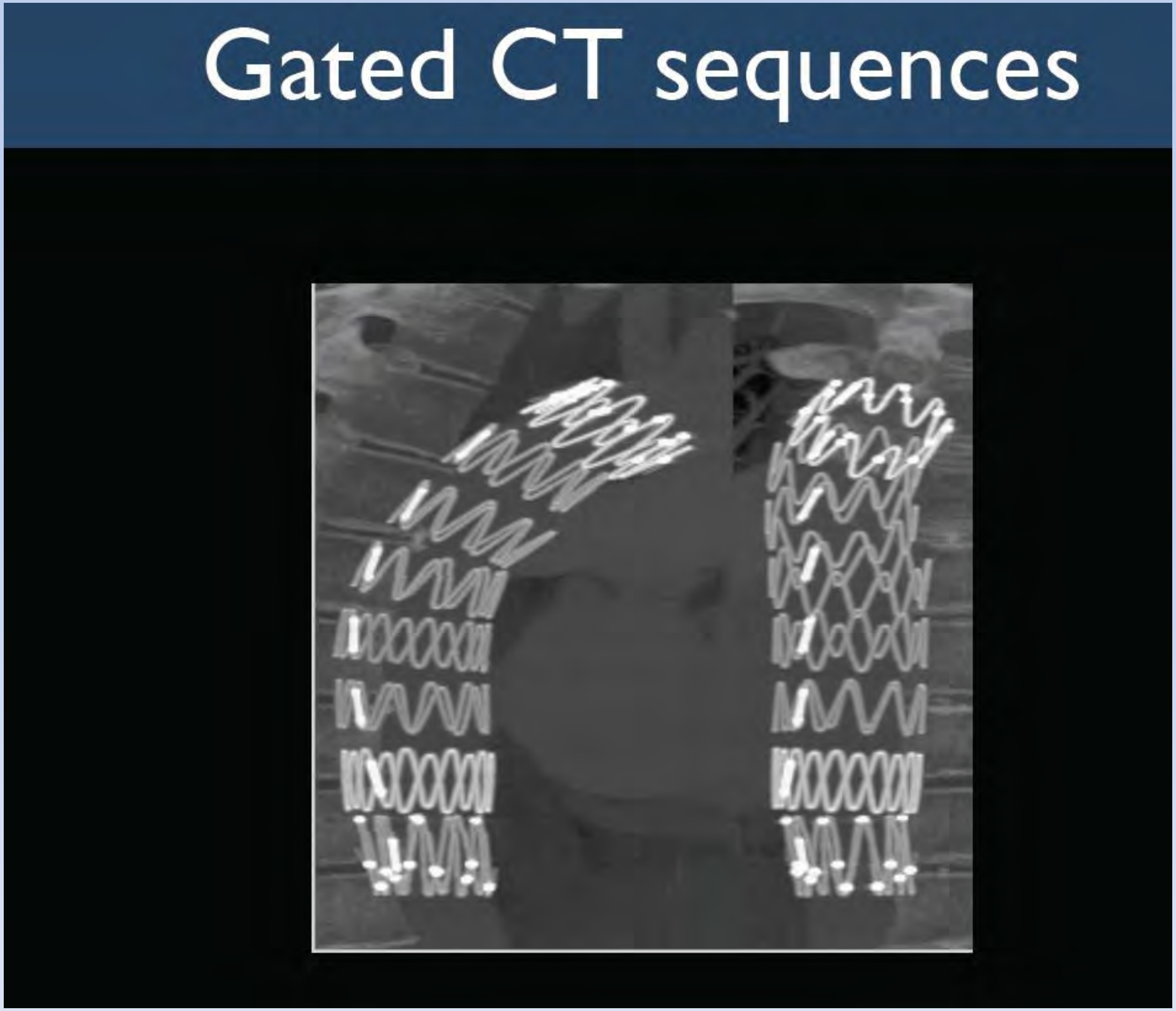
Model Evolution



Structuring models

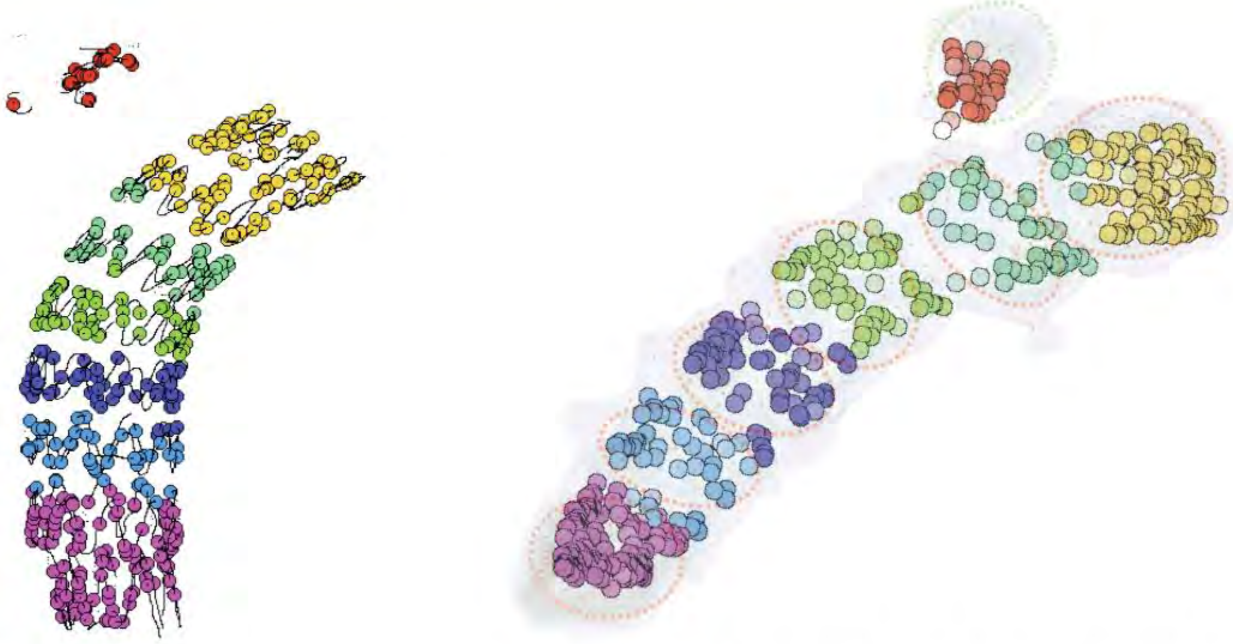


Gated CT sequence



Structure of the deformation

Structure of the deformation



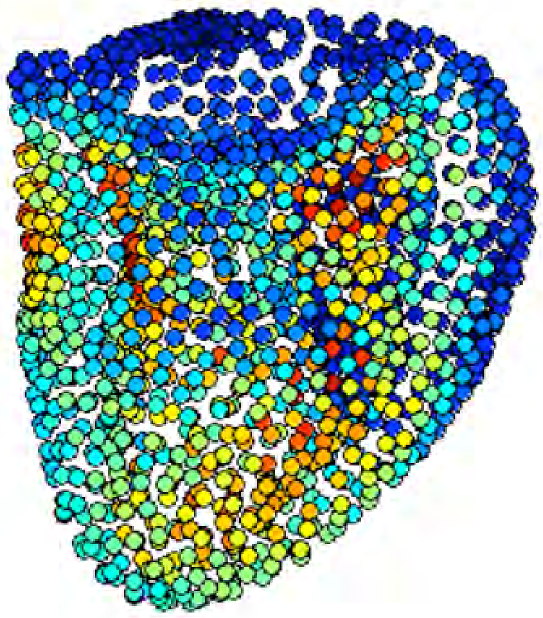
Landmarks

Landmarks in the model map

[Langs et al CVPR'08]

Model representation

- The density in the model map indicates redundancy in the deformation behavior
- We can use this to find an efficient parameterization of the model
  - Many landmarks for complex deformation
  - Few landmarks for simple deformation



Summarizing Active Shape Models

- Segmentation of non-rigid objects by PDM (reprint from H. Cootes, 1992)
- Captures the statistics of family of shapes
- Compact representation
- Not necessity for a continuous curve
- Global refinement segmentation technique
- Fast, useful for industrial vision tasks, facial and medical image analysis
- Allows incorporating grey-value and texture of landmarks
- Needs an initial estimation of pose parameters and correspondence of points

Summary

+ ASM and AAM represents an elegant way to learn statistics of shape and appearance and recover only objects from the same family of shapes

+ Global deformation method

+ Integrates shape and appearance (texture, colour, filters, etc.

+ Specially useful for medical imaging since often atlas are available.

+ Multiple applications

- Needs large training set

- Training sets should be aligned.

- Thank you ☺