Statistical Shape Models

Maria A. Zuluaga

UCL Centre for Medical Image Computing, London

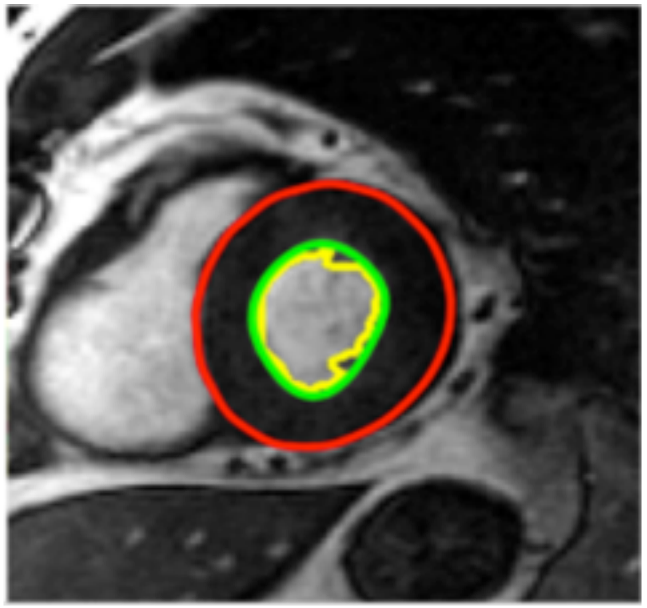
January 29, 2015

Outline

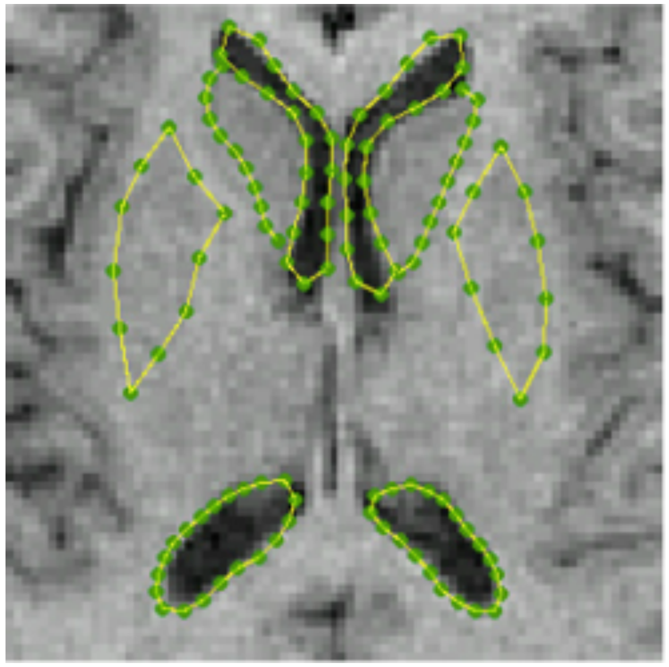
- **Motivation**
- Statistical Shape Models
- Statistical Appearance Models
- Active Shape Models
- Active Appearance sModels
- New approaches
- Summary

Motivation: Why study shape?

- Most structures of clinical interest have a characteristic shape and location relative to other structures.

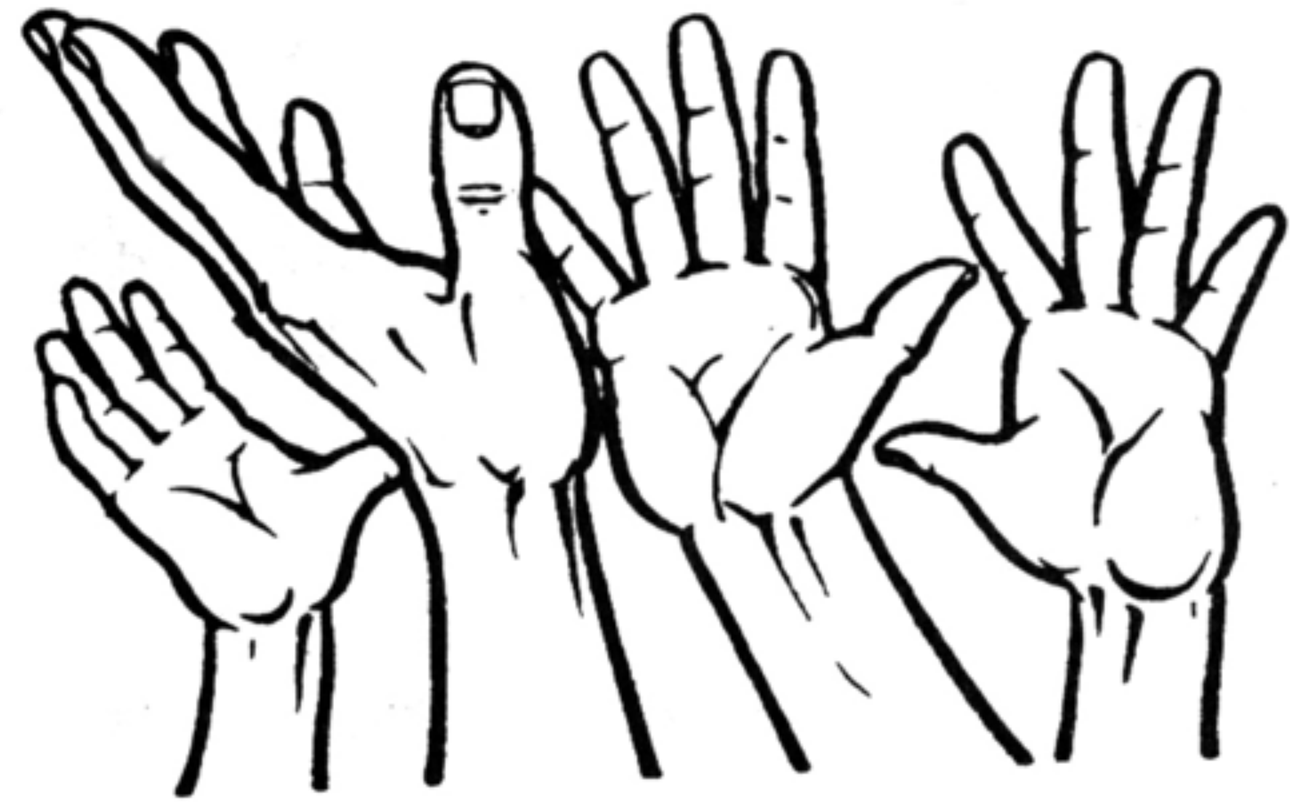


- The shape and relative positioning of the appearance of anatomical objects is set out within an atlas.



Motivation: Why study shape?

- Across a normal population, instances vary in size but also in shape.
- However, the key features of the shape are kept.

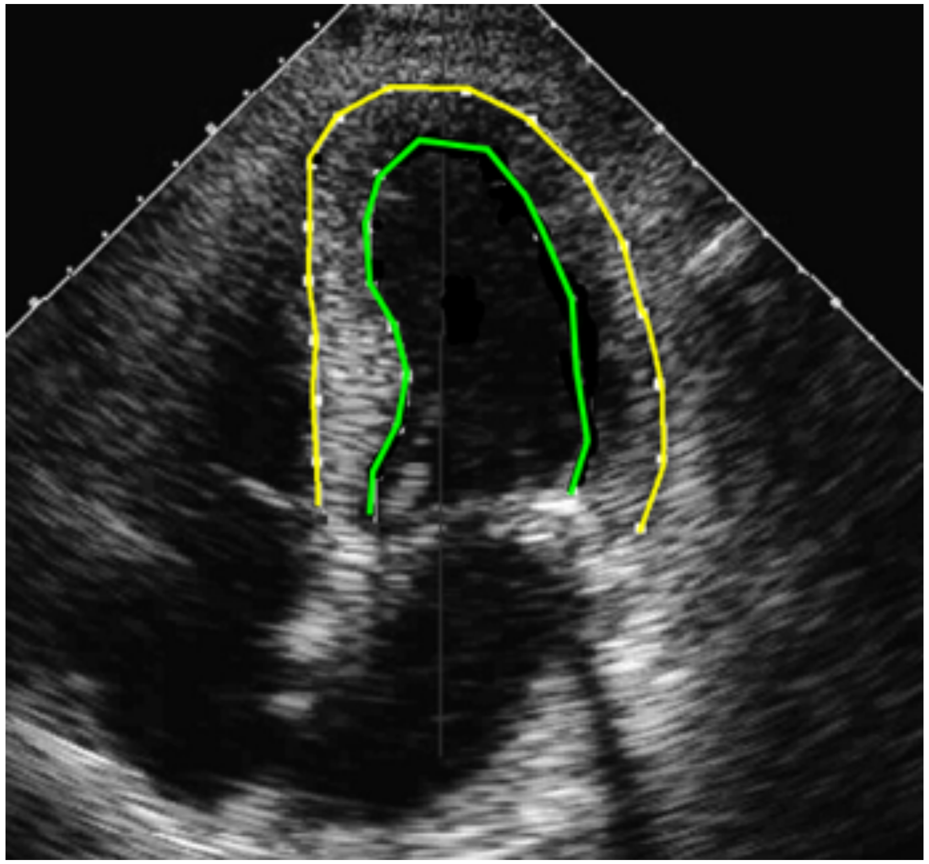


- Abnormal shape variations often characterize a disease.

Motivation

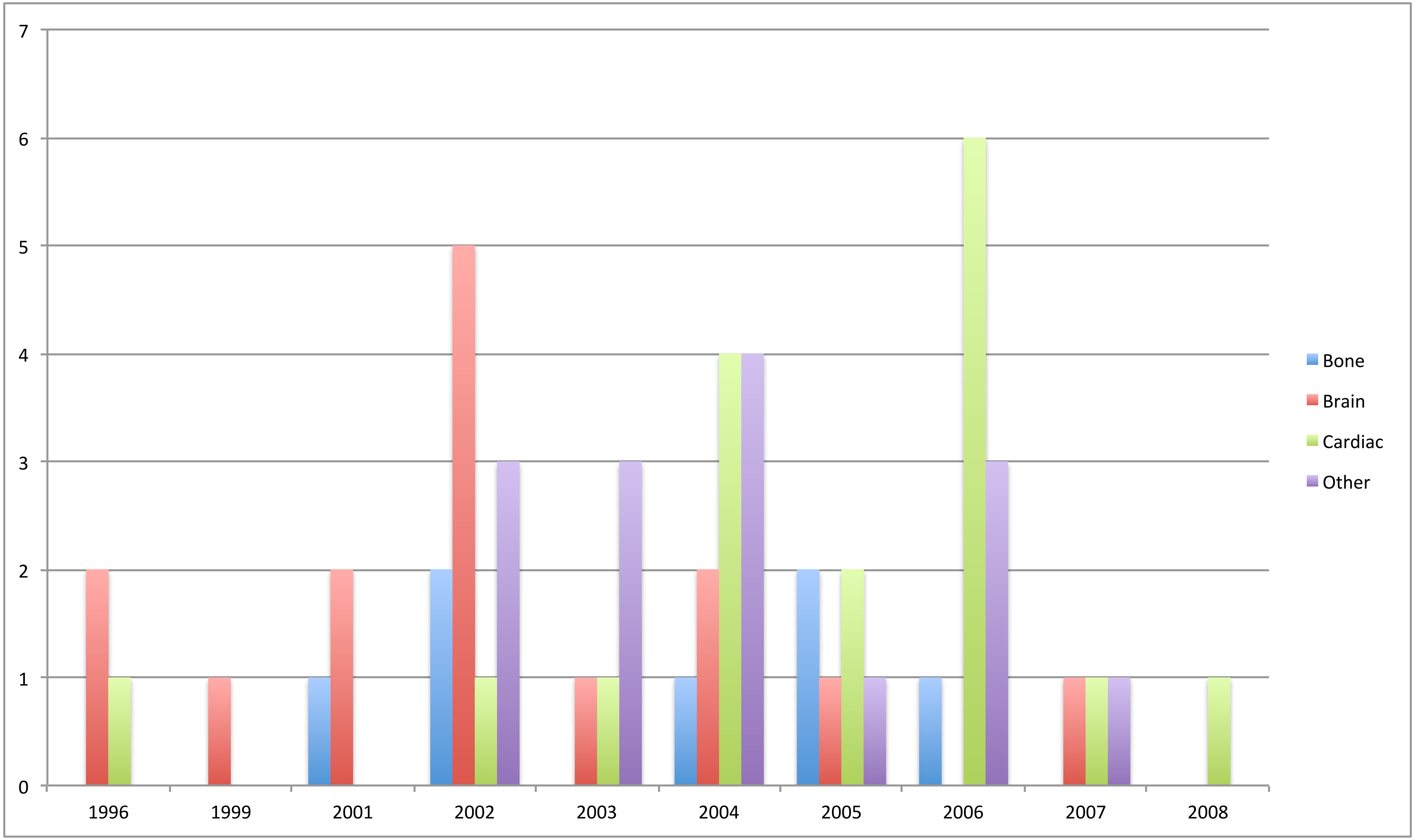
- Make use of a priori knowledge on **shape** to infer information contained within the images.

T. F. Cootes, C. J. Taylor, D. H. Cooper, and J. Graham. Training models of shape from sets of examples. BMVC 1992



Courtesy of CAMPAR (Garching Germany)

Motivation:Evolution in Medical Imaging



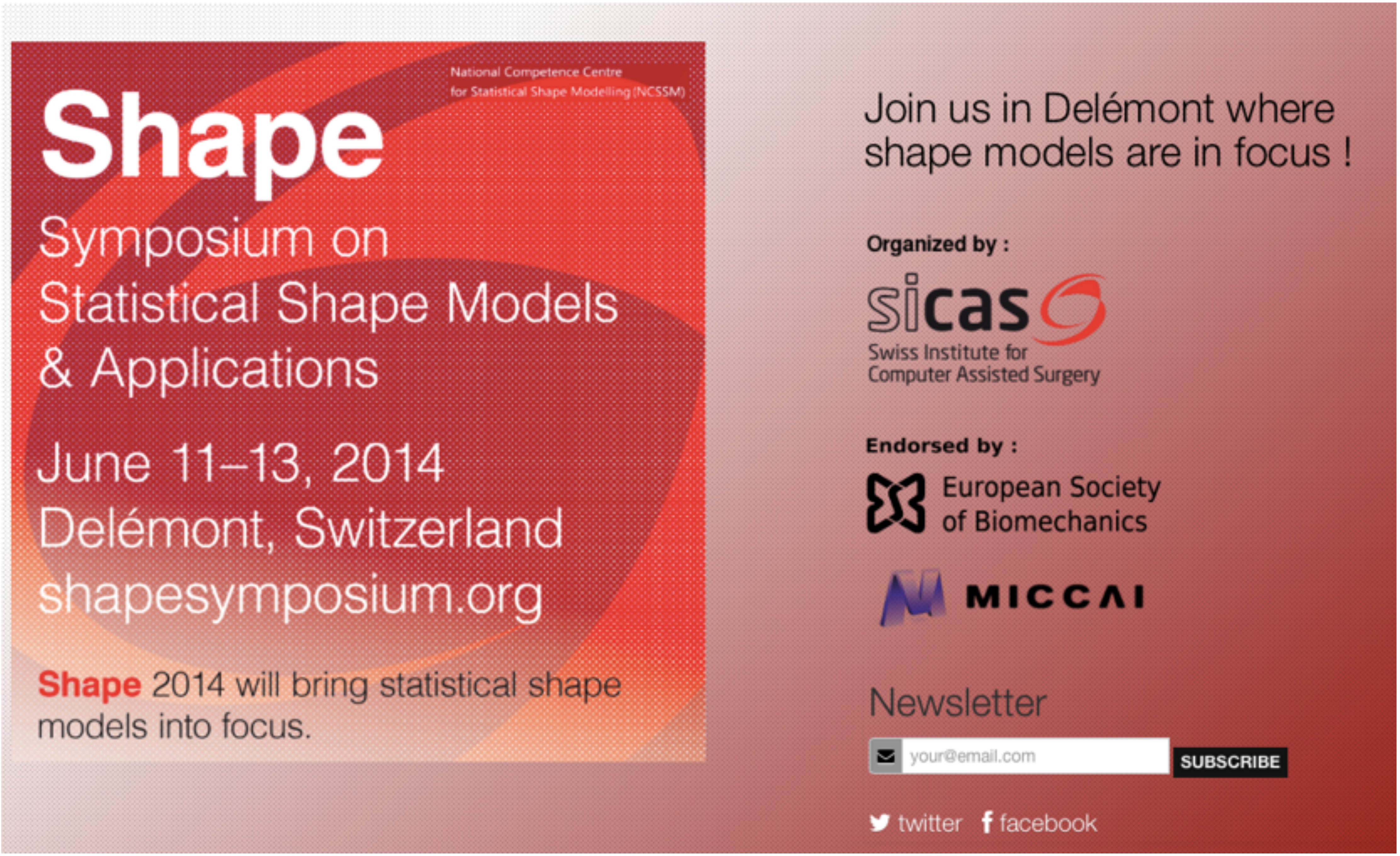
Heimann et al., MedIA, 2009

Motivation:Evolution in Medical Imaging

Authors	Object(s) of interest	Correspondences	Application
Shape analysis			
Paulsen et al. (2002, 2003)	Ear canal	Mesh-to-mesh	Correlation to gender
Styner et al. (2003, 2004)	Hippocampus	SPHARM	Correlation to schizophrenia
Davies et al. (2003)	Hippocampus	Optimization	Correlation to schizophrenia
Csernansky et al. (2004)	Thalamus	Volume-to-volume	Correlation to schizophrenia
Kim et al. (2005)	Hippocampus	Mesh-to-volume	Correlation to schizophrenia
Bansal et al. (2007)	Hippocampus, amygdala	Volume-to-volume	Correlation to attention deficit/ hyperactivity disorder
Thompson et al. (2004)	Hippocampus, ventricles	Man + Param	Correlation to Alzheimer disease
Styner et al. (2003)	Brain ventricles	SPHARM	Correlation to twins
Ferrarini et al. (2007)	Brain ventricles	Mesh-to-mesh	Correlation to aging
Wang et al. (2003)	Cortical surface	Mesh-to-mesh	Correlation to neurologic and psychiatric disorders
Shape extrapolation			
Fleute et al. (1999)	Femur	Mesh-to-mesh	Extrapolate geometry from sparse 3D data for surgery
Chan et al. (2003)	Femur	Volume-to-volume	Extrapolate geometry from sparse 3D data for surgery
Zheng et al. (2005), Rajamani et al. (2007)	Femoral heads	Optimization	Extrapolate geometry from sparse 3D data for surgery
Barratt et al. (2008)	Femur and pelvis	Volume-to-volume	Extrapolate geometry from US point data for surgery
Other applications			
Subsol et al. (1998)	Crest lines on skull	Mesh-to-mesh	Assess mandible deformation under craniofacial disease
Andresen et al. (2000)	Mandible	Mesh-to-mesh	Model mandible growth
Blackall et al. (2001)	Liver	Volume-to-volume	Model deformation caused by breathing
Rueckert et al. (2003)	Brain	Volume-to-volume	Register landmarks to new subjects
Rao et al. (2008)	Deep brain structures	Volume-to-volume	Correlate different brain structures for shape prediction
Lee et al. (2005)	Levator ani	Optimization	Optimal scan planning
Deligianni et al. (2006)	Bronchial tree	Feature points	Model breathing motion for bronchoscopy simulation
Sierra et al. (2006)	Uterus	Man + Subdivision	Generate variable scenes for surgery simulator

Heimann et al., MedIA, 2009

Motivation: Community



Motivation: Community

Challenges »

Shape Challenge 2014

Shape 2014 - Statistical Shape Model Challenge

Information about the evaluation are now available. Scroll down to read the instructions. For now, you can download the challenge set consisting of 59 liver segmentations.

Acknowledgments

The provided liver segmentations are part of the training data from the "VISCERAL Organ Segmentation and Landmark Detection Challenge" at the IEEE International Symposium on Biomedical Imaging (ISBI) in May 1st, 2014 in Beijing, China. For more information on the ongoing VISCERAL Anatomy Benchmark series, please visit www.visceral.eu (which should also be acknowledged by citation, footnote, or other suitable means in any publication using any part of its dataset).

Please reference the Virtual Skeleton Database in your work as:

View online plain text as END as RIS as BibTex Mendeley CiteULike

Registration

- You have to use your institutional email address for the registration.
- Select the Shape2014 Research Unit during registration.

Data download
Workshop: Jun 11, 2014
Associated with: Shape 2014

Shape 2014 - Statistical Shape Model Challenge

The Shape Symposium hosts the first Grand Challenge in Statistical Shape Modeling. The task is to build a model of the liver from a set of segmented training datasets.

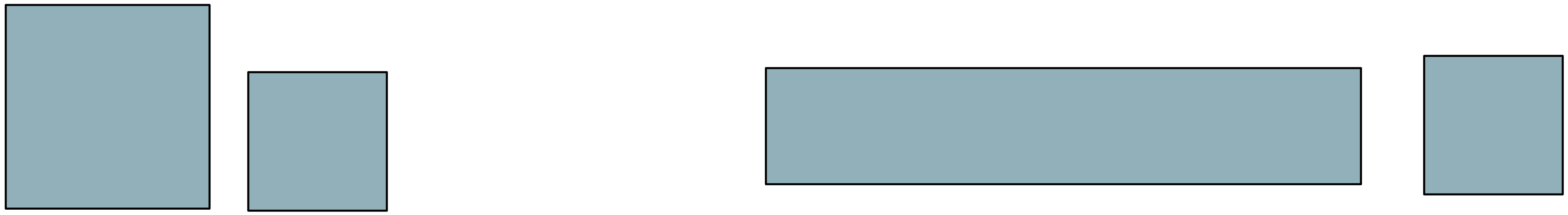
It is possible to learn shape models and its variation to infer information contained in images

Outline

- Motivation
- **Statistical Shape Models**
- Statistical Appearance Models
- Active Shape Models
- Active Appearance Models
- New approaches
- Summary

SSM: What is a shape?

Geometric information that remains when location, scale and rotational effects removed.
-Kendall



Geometric information that is invariant to a particular set of transformations.

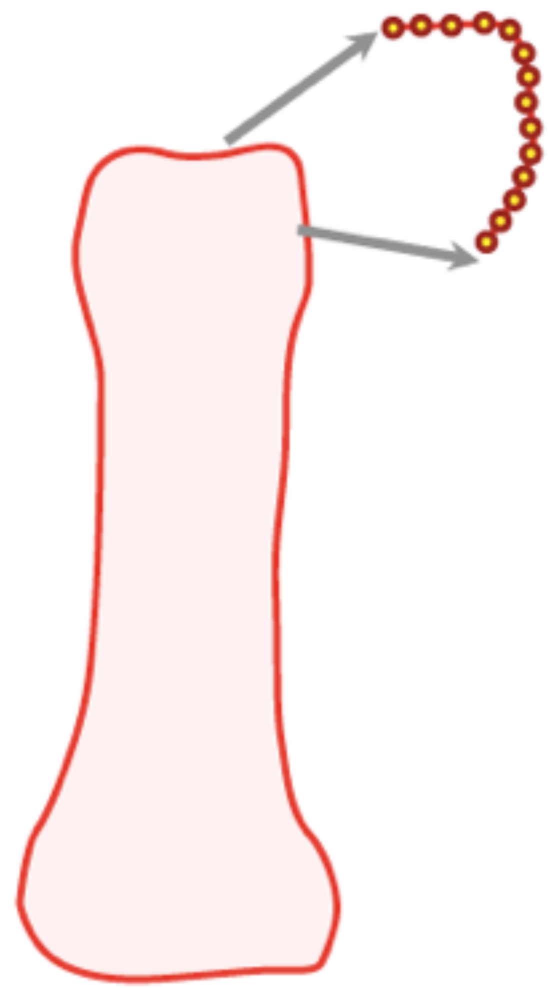
SSM: How we represent shape?

- Point distribution model

A shape is represented by a set of points (features) each of which is a k-dim vector. In the simplest case, k=2

The m feature points are stacked into a vector of length km for each shape

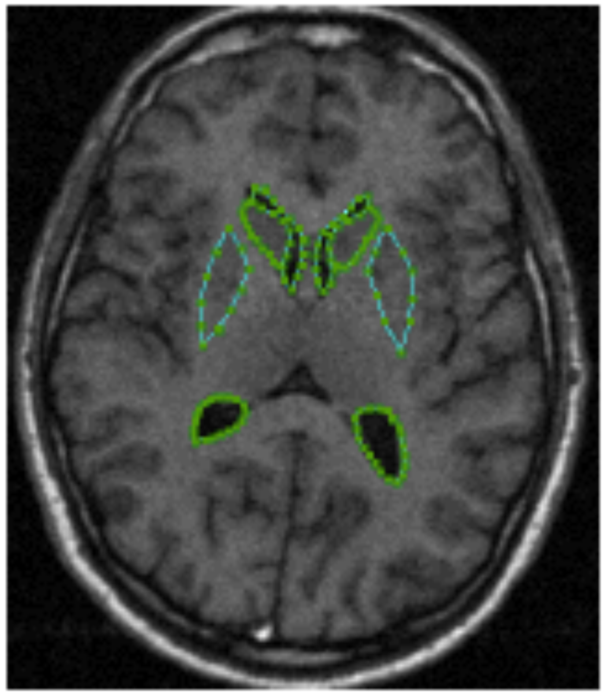
$$\mathbf{x}_i = \begin{pmatrix} x_1 \\ y_1 \\ x_2 \\ y_2 \\ \vdots \\ x_m \\ y_m \end{pmatrix}$$

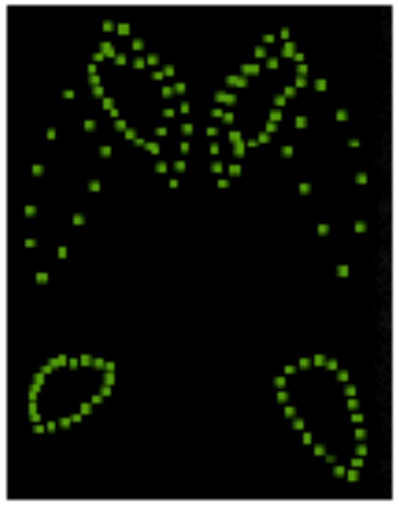


Credit: G. Langs

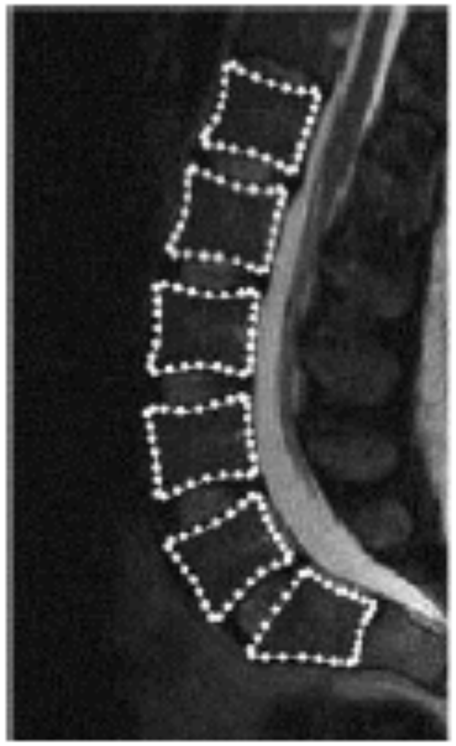
Point distribution model: Examples

$$\mathbf{x}_i = \begin{pmatrix} x_1 \\ y_1 \\ x_2 \\ y_2 \\ \vdots \\ x_m \\ y_m \end{pmatrix}$$



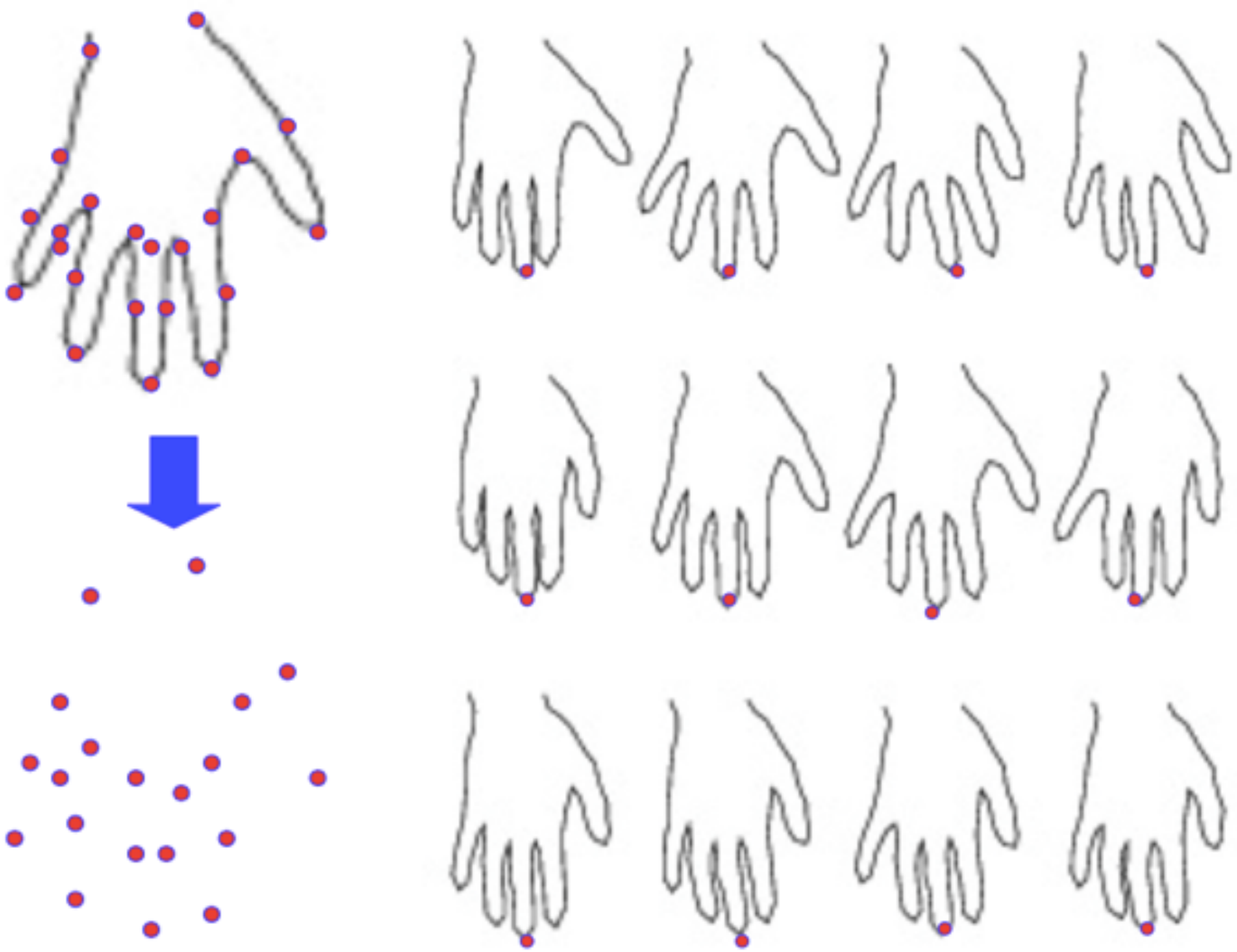


Cootes, Active shape tutorial



Characterizing the Shape of the Lumbar Spine Using an Active Shape Model: Reliability and Precision of the Method
Meakin, et al
Department of Radiology, University of Aberdeen, Foresterhill, Aberdeen, UK

Point distribution model: Requirements



Credit: T. Cootes

$\mathbf{X}^1{}_{14}, \mathbf{X}^2{}_{14}, \ldots, \mathbf{X}^{12}{}_{14}$

- Features should correspond between shapes

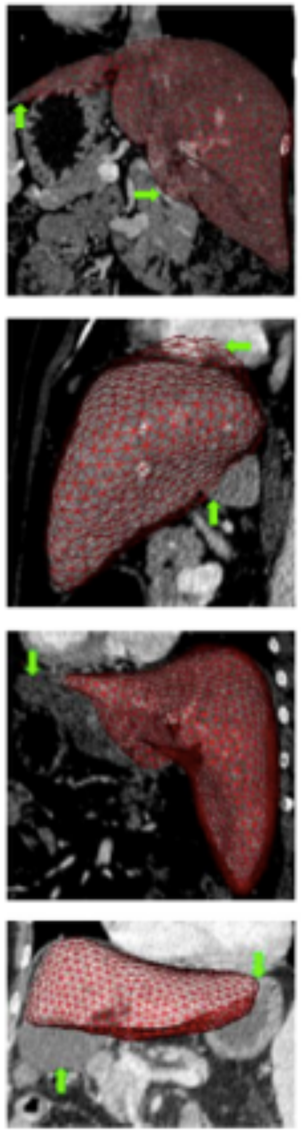
- Well defined corners
- Junctions
- Easy to locate biological landmarks

- Extra points along boundaries for higher accuracy.

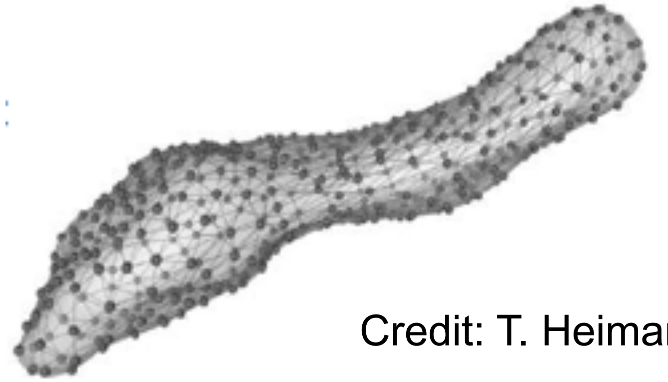
Point distribution model

- How do we get the points?
  - Manual annotation.
  - If the number of training samples is too big, an (semi) automated method is desirable.

Landmarks on all training shapes have to be located at corresponding positions



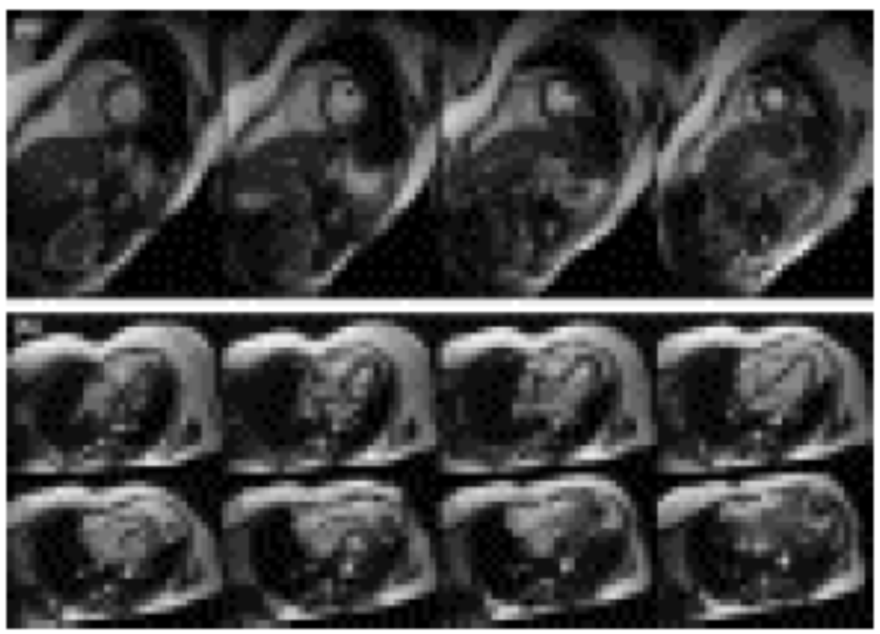
Wang et al. 2015



Credit: T. Heimann

SSM: Alignment

- What do we have up to now?



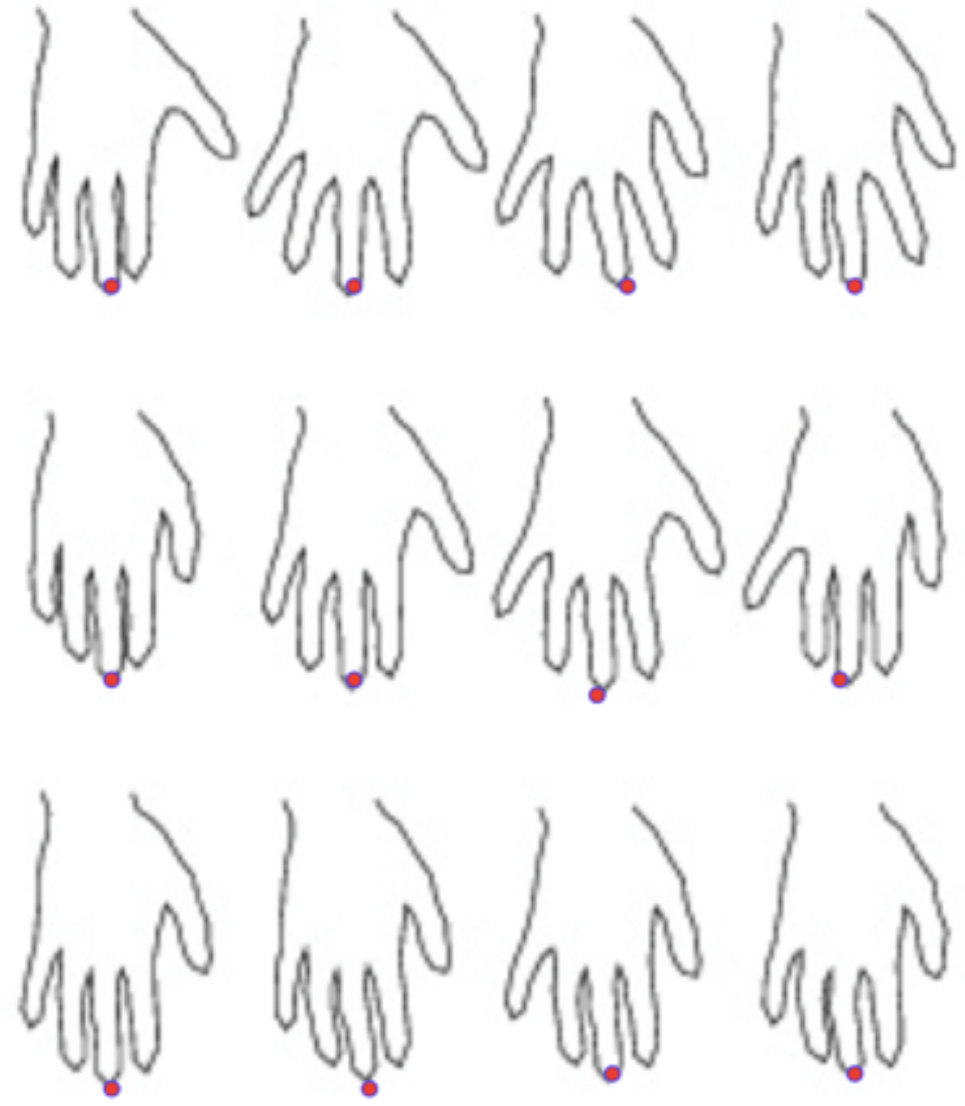
Training set

We will assume that landmark correspondence is a solved issue. We won't address it.

Optimal Statistical Deformable Surface Models
P Horkaew and GZ Yang, IPMI 2003

SSM: Alignment

- All shapes need to be in the same coordinate system.
- Different from landmark correspondence.
- The most common approach is the generalised Procustes alignment (Gower, 1975 and Goodall 1991).



Alignment: Procustes myth

Procustes bed

Procustes, son of Poseidon, had an iron bed in which he invited every passer-by to spend the night. The guests were “**forced**” to fit into the bed exactly.

Procustes analysis is the process of performing a **shape-preserving** Eucledian transformation to a set of shapes.

Generalised Procustes Analysis (GPA)

1. Arbitrarily choose a reference shape.

2. Superimpose all instances to the reference shape.

3. Compute the mean shape (from all shapes).

4. If the Procustes distance between the mean and the reference is above a threshold, set the mean to be the reference and go to 2.

GPA: Detailed

1. Arbitrarily choose a reference shape.

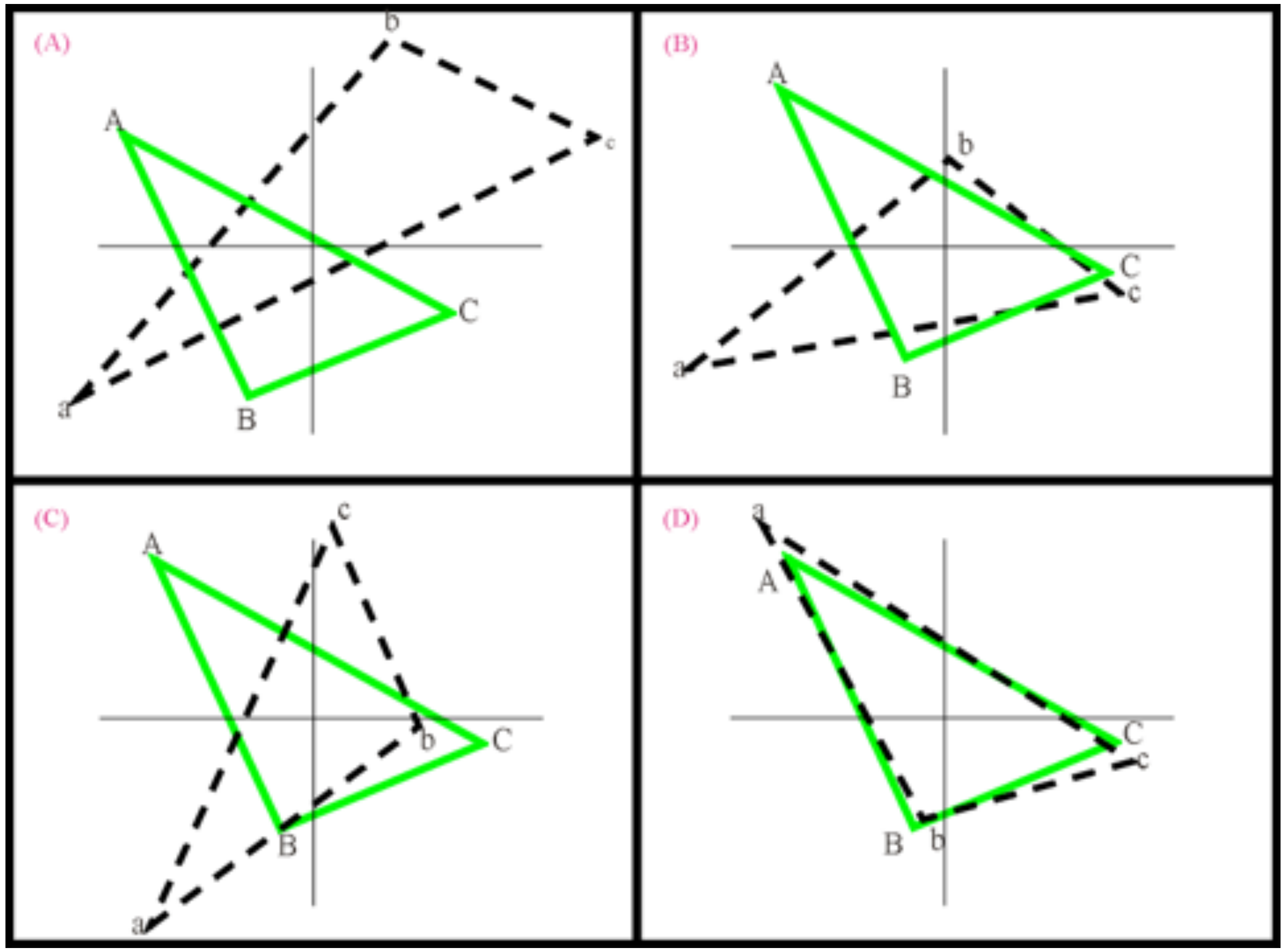
$$\mathbf{m} = \mathbf{x}_1 \qquad |\mathbf{m}| = 1$$

2. Superimpose all instances to the reference shape (B).

3. Compute the mean shape (from all shapes).

$$\mathbf{m} = \frac{1}{n}\sum T_i(\mathbf{x}_i)$$

4. If the Procustes distance between the mean and the reference is above a threshold, set the mean to be the reference and go to 2.



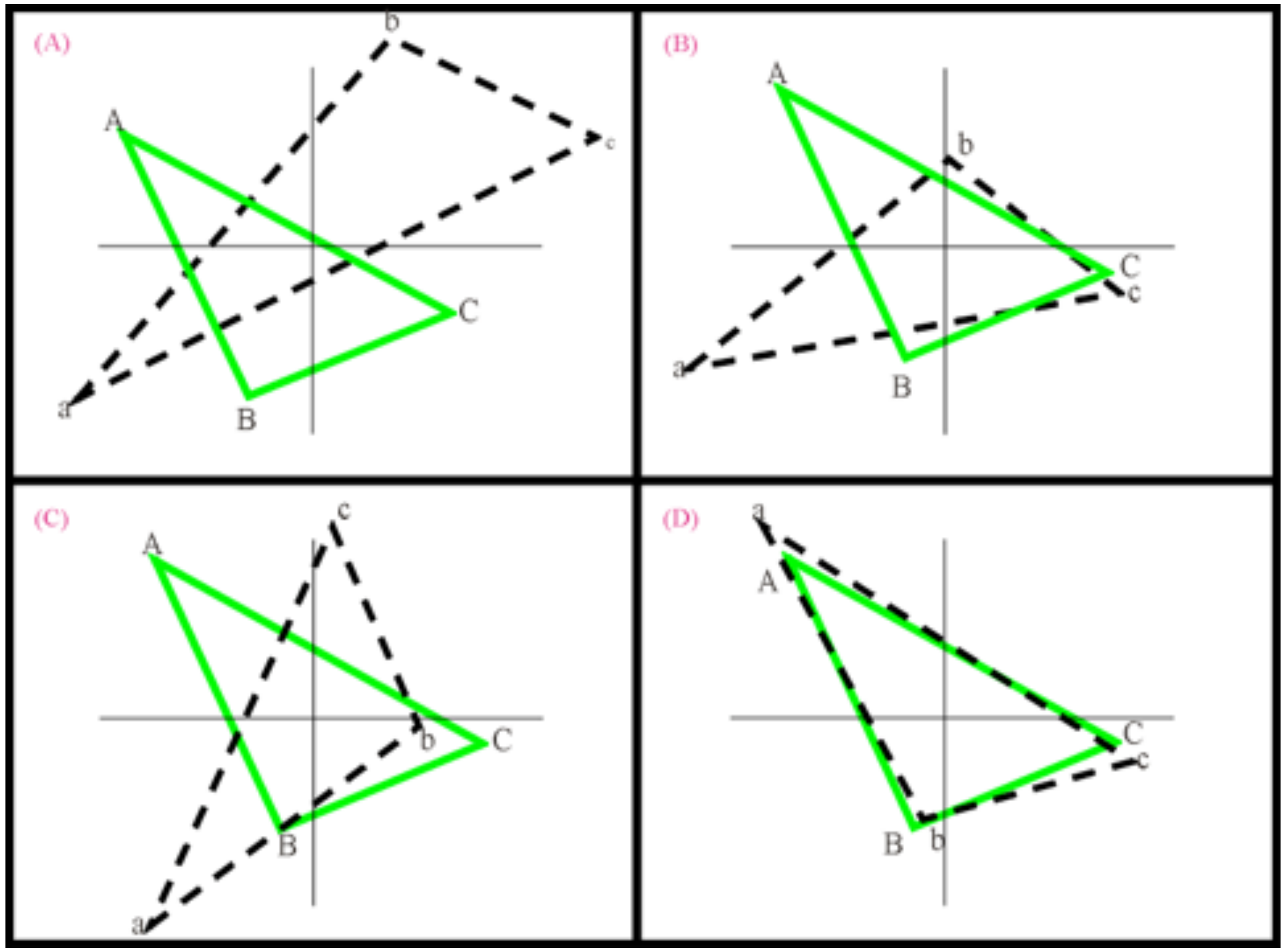
$$\sum |\mathbf{m} - T_i(\mathbf{x}_i)|^2$$

GPA: Alignment algorithm

- Normalise all so that CoG is at origin.
- Let **m** = x_1
- Align each shape with **m**.
- Recalculate **m**.
- Normalize **m.**
- Repeat until convergence.

Alignment: Output

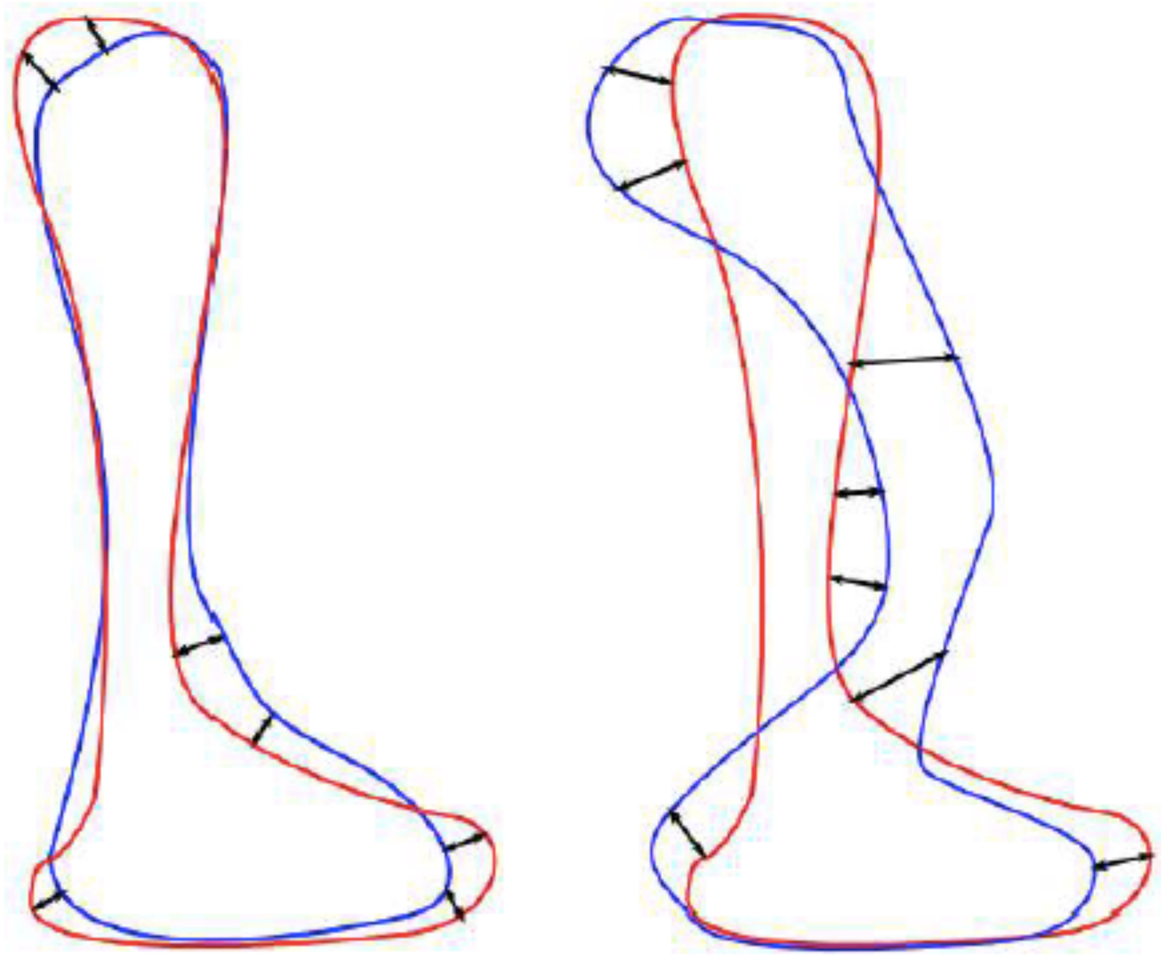
- Resulting shapes should:
  - Have same CoG.
  - Have approx. same scale and orientation.



GPA: Drawbacks

- Sensible to outliers.
- Can lead to non-linearities between shapes.

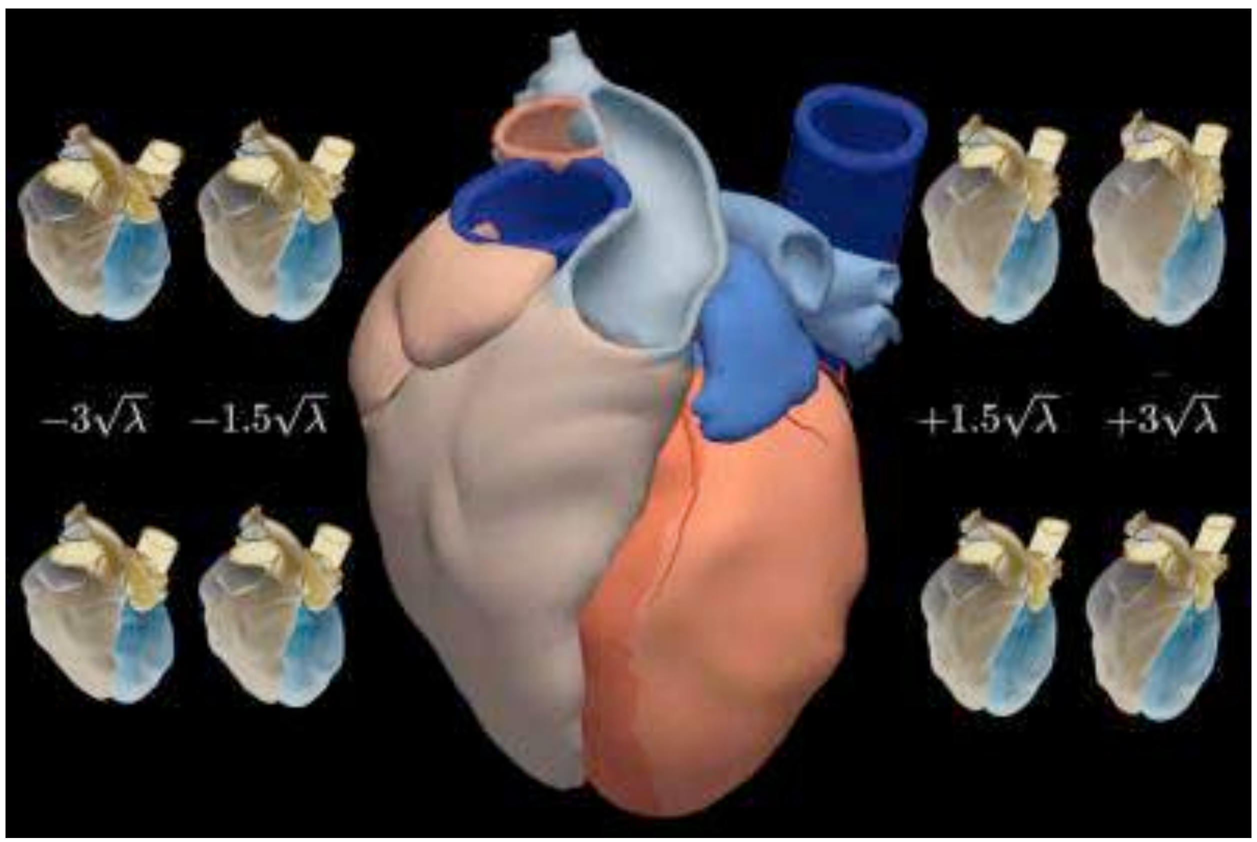
State of the art work tries to cope with this kind of problems.



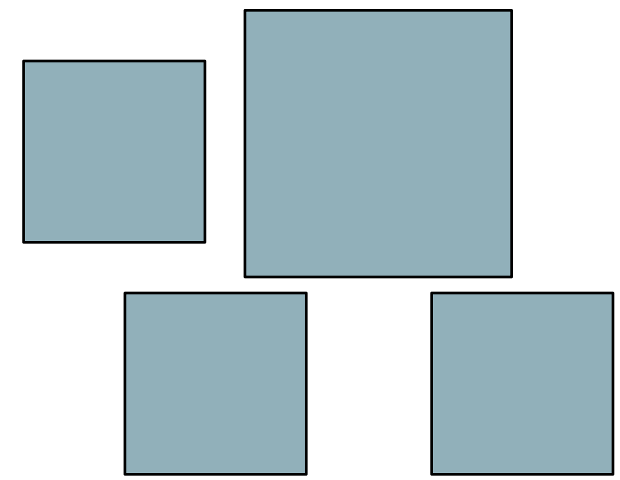
Credit: T. Heimann

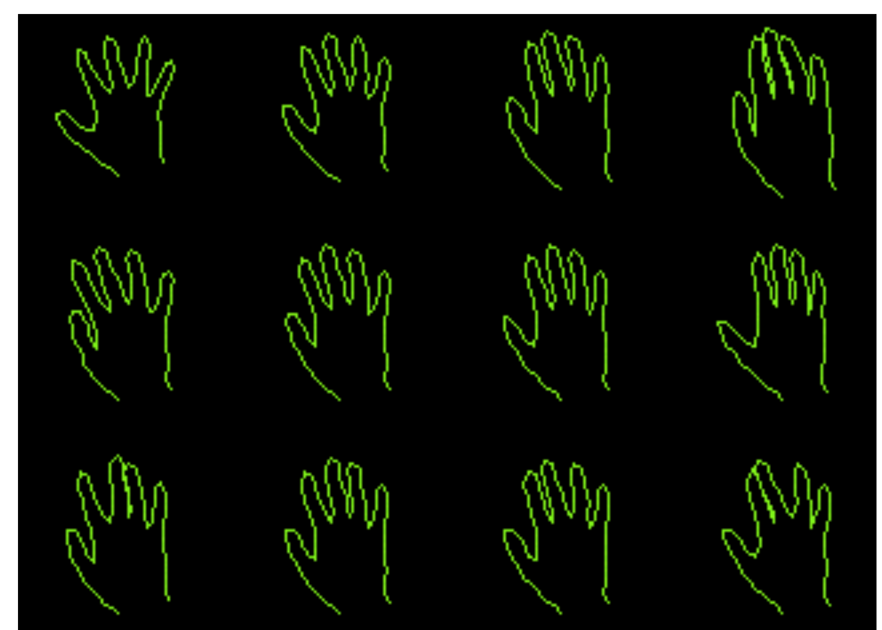
SSM: Model building/learning

- **Goal:** Build a model that captures a priori knowledge on the shape of a particular set of structures.



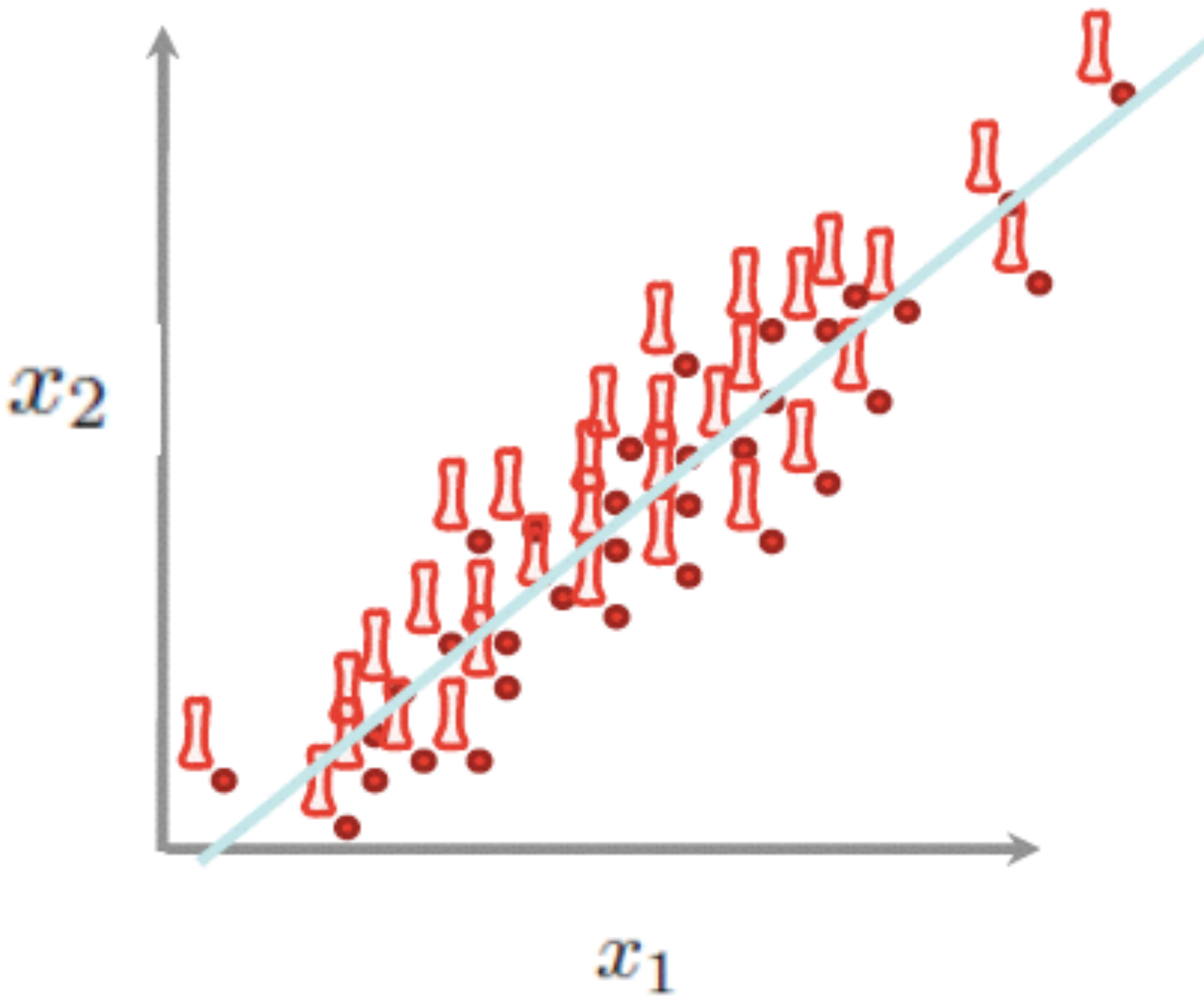
scienceblog.com





T. Cootes tutorial

SSM: Model Learning

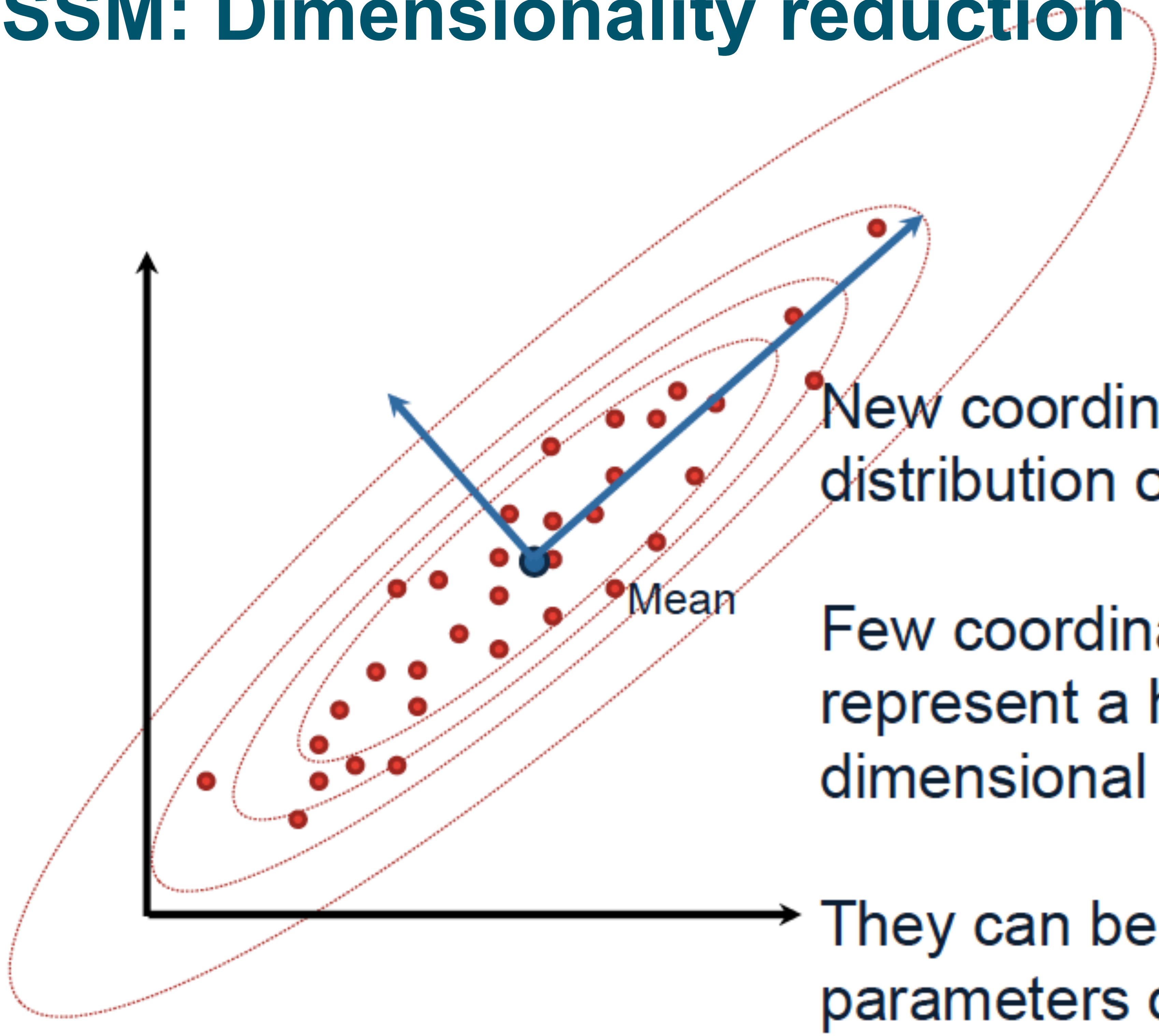


Credit G. Langs

$$\mathbf{x}_i = \begin{pmatrix} x_1 \\ y_1 \\ x_2 \\ y_2 \\ \vdots \\ x_m \\ y_m \end{pmatrix}$$

Project the data into a lower dimensional space that better represents the variation

SSM: Dimensionality reduction



New coordinates reflect the distribution of the data.

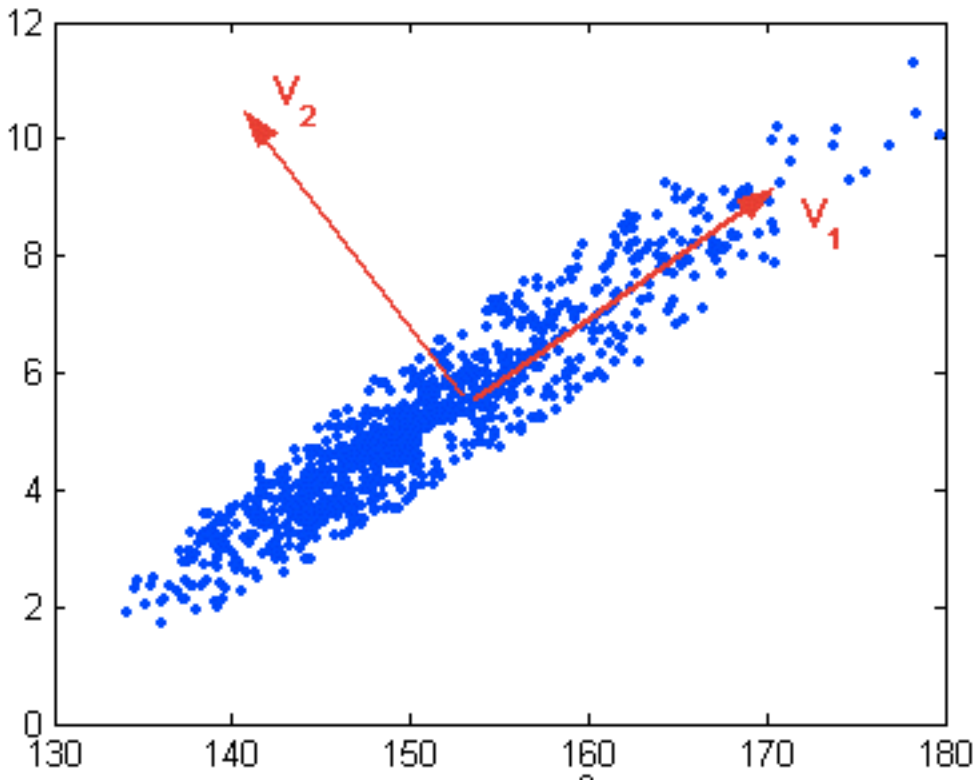
Few coordinates suffice to represent a high dimensional vector

They can be viewed as parameters of a model

Slice credit: G. Langs

SSM: Model learning & Dim. reduction

- Principal Component Analysis



- Compute eigenvectors of covariance,S.

- Eigenvectors : main directions

- Eigenvalue : variance along eigenvector

SSM: Principal component analysis

1. Compute the mean of the data: $$\bar{\mathbf{x}} = \frac{1}{M}\sum_{i=1}^{M}\mathbf{x}_i$$

2. Compute the covariance of the data:
$$\mathbf{S} = \frac{1}{M-1}\sum_{i}(\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T$$

3. Compute the eigenvectors $\mathbf{e}_i$ and eigenvalues of **S**, sorted in decreasing order of eigenvalue.

4. Remove the small eigenvalues, retaining most of the variation.
$$\sum_{i=1}^{t}\lambda_i \geq 0.98\sum_{i}^{M}\lambda_i$$

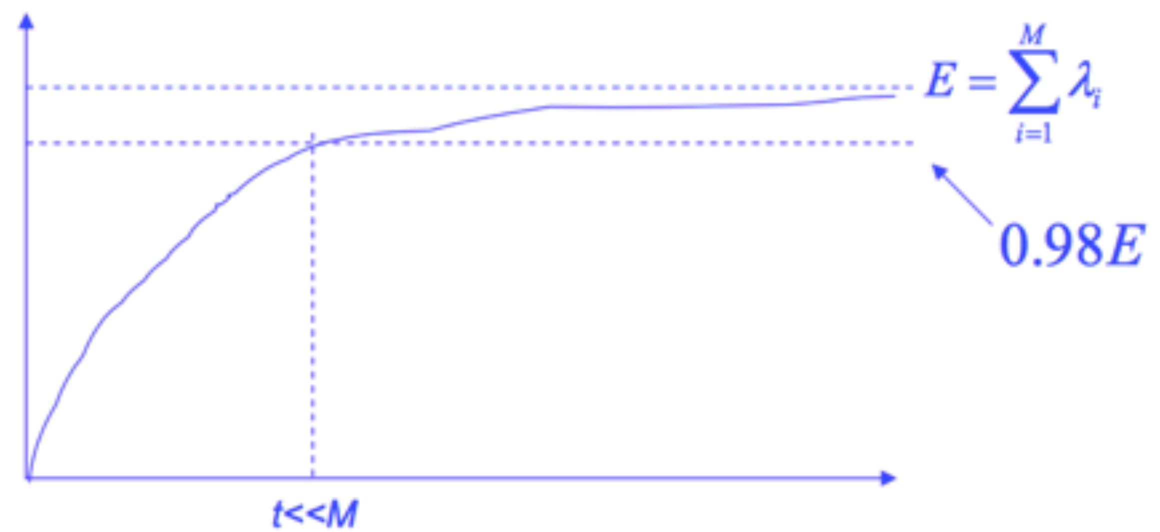
SSM: Principal Components Analysis

5. Construct matrix **P** using the top t eigenvectors:

$$\mathbf{P} = [\mathbf{e}_1 | \mathbf{e}_2 | \mathbf{e}_3 | \ldots | \mathbf{e}_t]$$

6. Any shape instance **X** can be described by the linear combination:

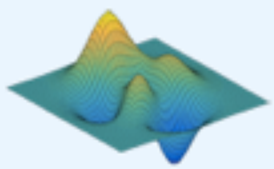
$$\mathbf{X} = \bar{\mathbf{X}} + \mathbf{P}\mathbf{b}$$



Courtesy: Sir M. Brady

PCA: How to?

New to MATLAB? See resources for Getting Started.



New MATLAB Graphics System

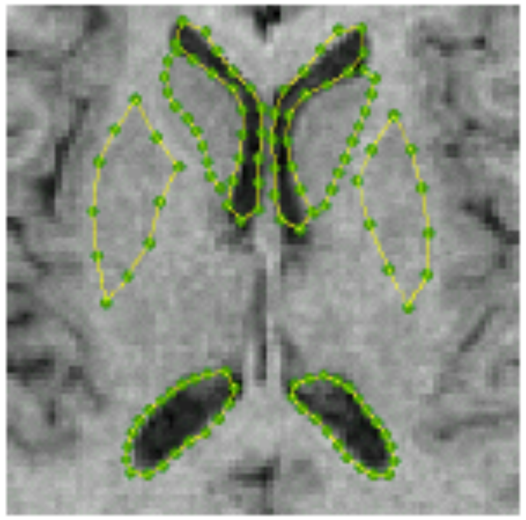
MATLAB R2014b introduces a new MATLAB graphics system, with new default colors, fonts, and styles, and many new features. Some existing code may need to be revised to work in this version of MATLAB.

Learn more

```
>> help pca
pca Principal Component Analysis (pca) on raw data.
   COEFF = pca(X) returns the principal component coefficients for the N
   by P data matrix X. Rows of X correspond to observations and columns to
   variables. Each column of COEFF contains coefficients for one principal
   component. The columns are in descending order in terms of component
   variance (LATENT). pca, by default, centers the data and uses the
   singular value decomposition algorithm. For the non-default options,
   use the name/value pair arguments.

   [COEFF, SCORE] = pca(X) returns the principal component score, which is
   the representation of X in the principal component space. Rows of SCORE
   correspond to observations, columns to components. The centered data
   can be reconstructed by SCORE*COEFF'.

   [COEFF, SCORE, LATENT] = pca(X) returns the principal component
   variances, i.e., the eigenvalues of the covariance matrix of X, in
   LATENT.

   [COEFF, SCORE, LATENT, TSQUARED] = pca(X) returns Hotelling's T-squared
   statistic for each observation in X. pca uses all principal components
   to compute the TSQUARED (computes in the full space) even when fewer
   components are requested (see the 'NumComponents' option below). For
   TSQUARED in the reduced space, use MAHAL(SCORE,SCORE).

   [COEFF, SCORE, LATENT, TSQUARED, EXPLAINED] = pca(X) returns a vector
   containing the percentage of the total variance explained by each
   principal component.

   [COEFF, SCORE, LATENT, TSQUARED, EXPLAINED, MU] = pca(X) returns the
   estimated mean.
```

SSM: Model learning

$$\mathbf{x} \approx \bar{\mathbf{x}} + \mathbf{P}\mathbf{b}$$



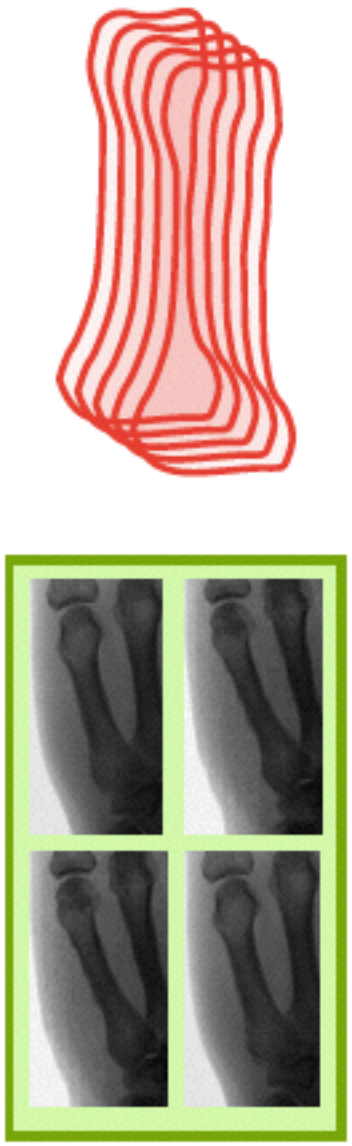
Labeled brain
MR image

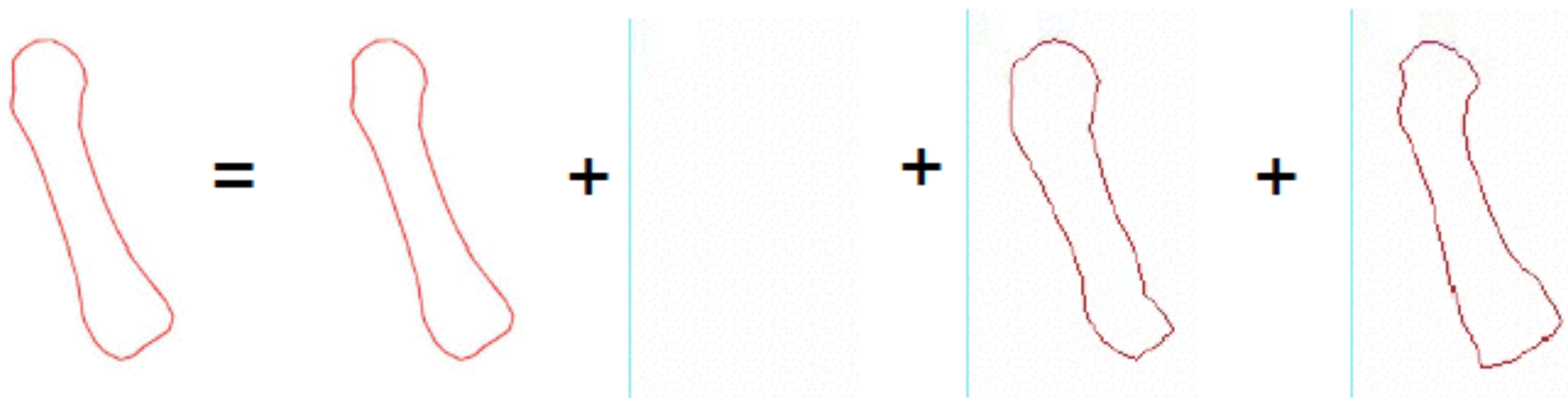
Varying the most significant parameter b1

Varying the second most significant parameter b2

T. Cootes, Statistical Shapes tutorial

SSM: Model Learning

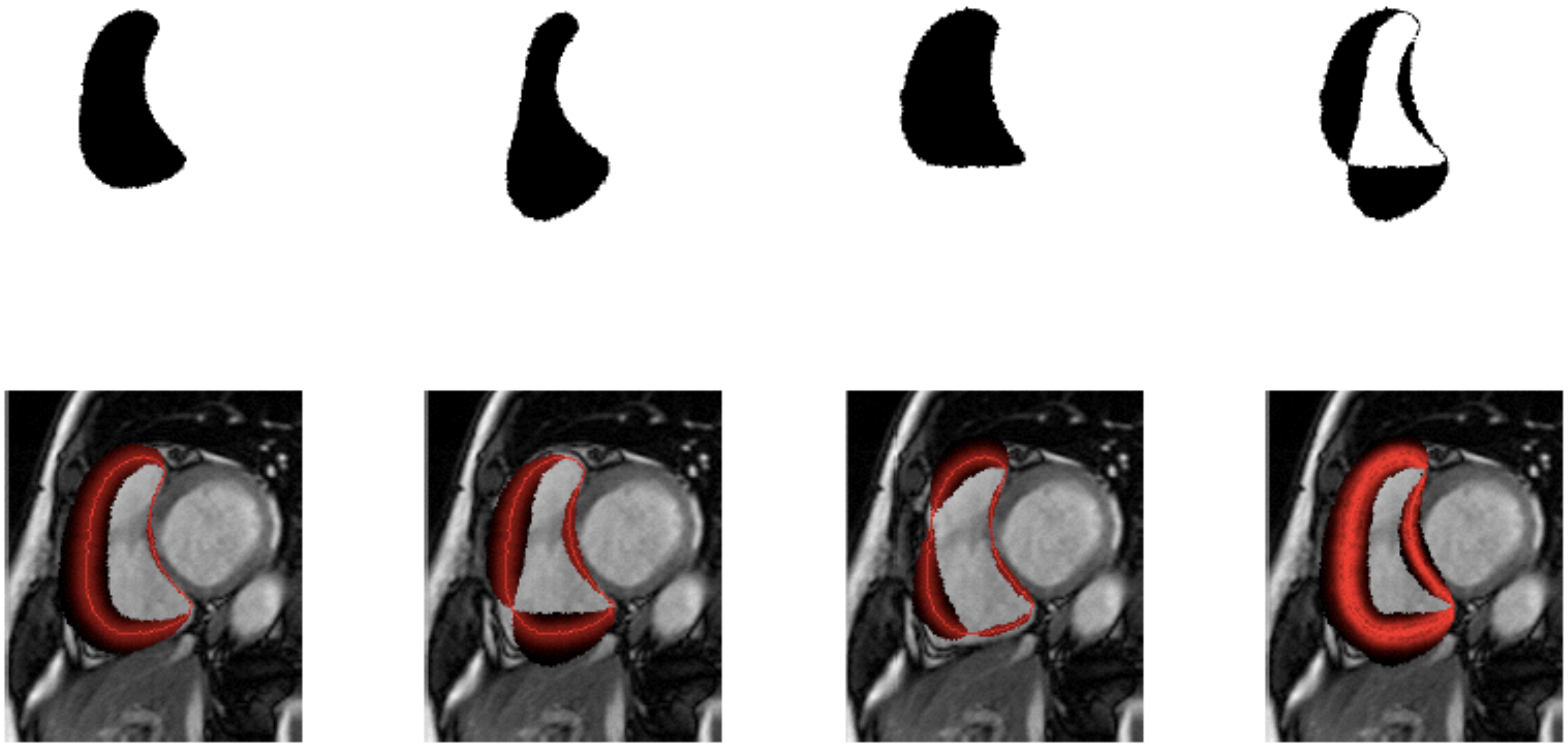




$$\mathbf{x}_{new} = \hat{\mathbf{m}} + b_1\mathbf{e}_1 + b_2\mathbf{e}_2 + b_3\mathbf{e}_3$$

Credit G. Langs

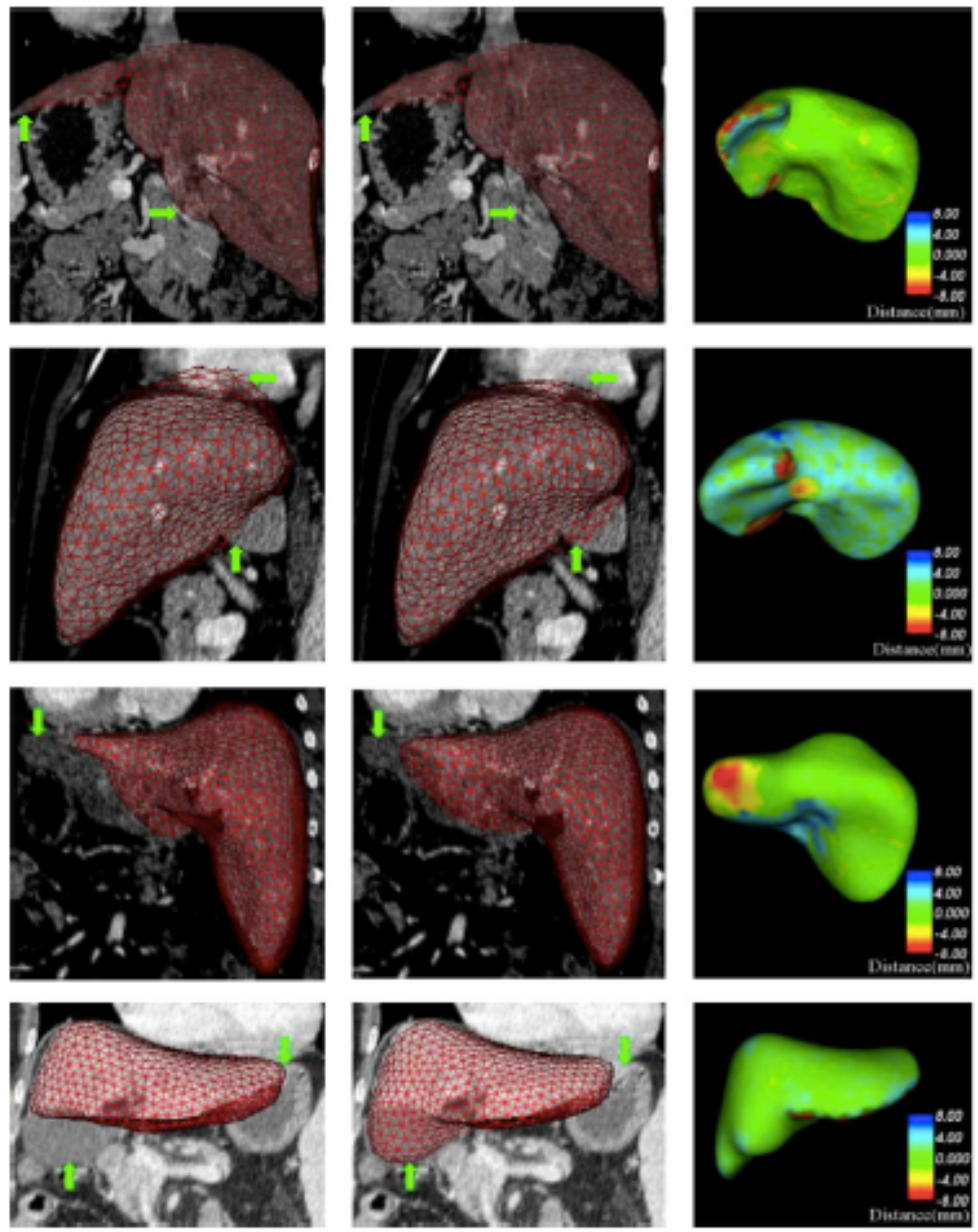
SSM: Model learning



Grosjean et al. RV Segmentation Challenge, 2012.

SSM: Model Learning

Wang et al, 2015

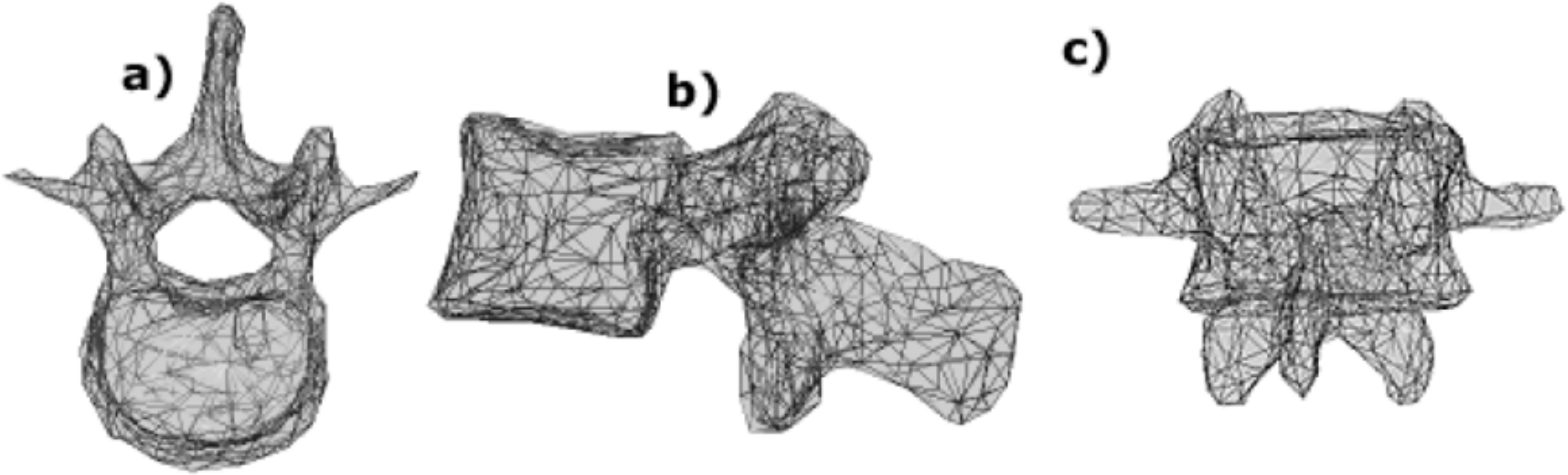


(a) input shape

(b) PCA shape prior

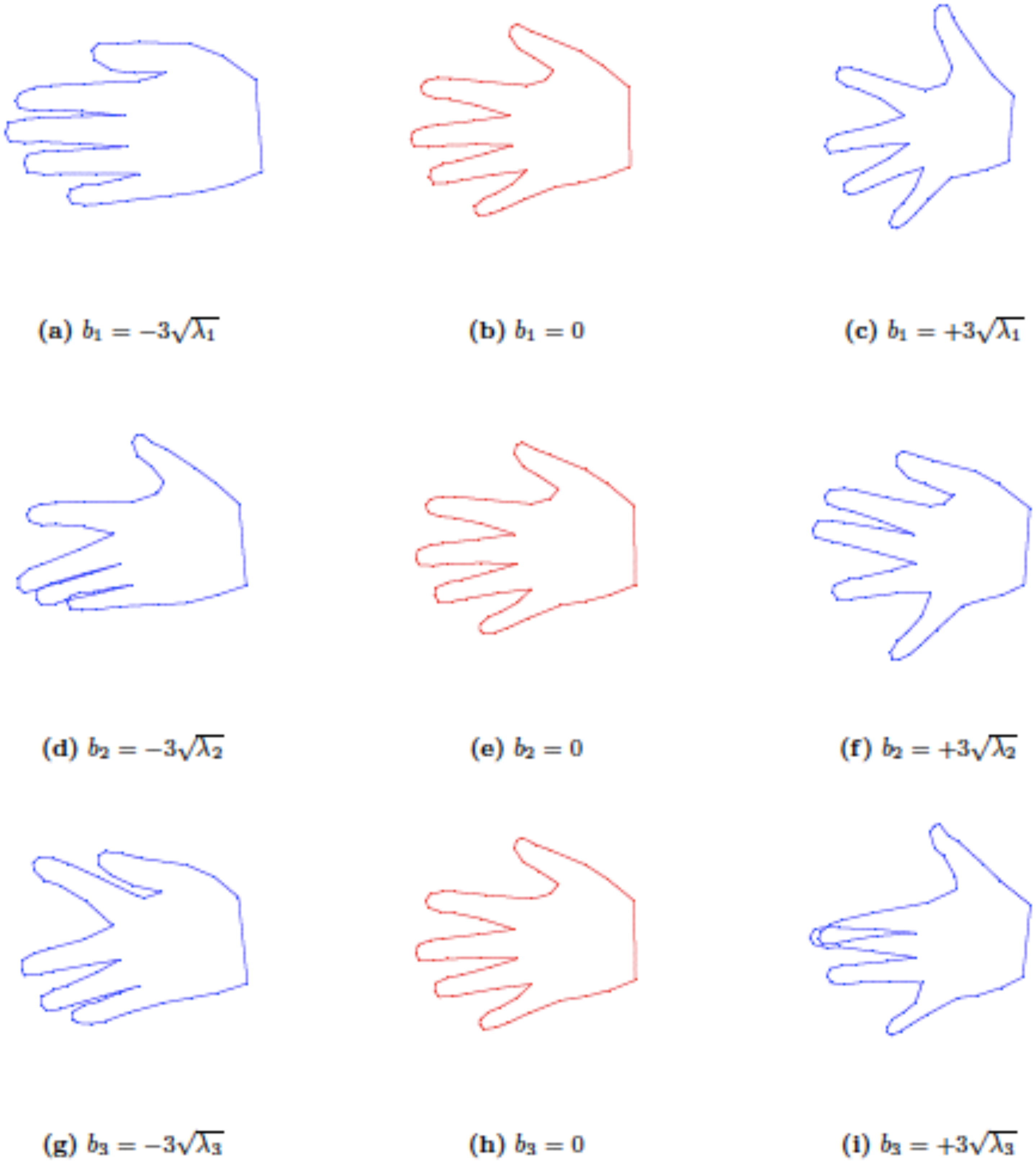
(c) error of PCA shape prior

SSM: Model Learning



Vrtovec et al, 2003.

SSM: b parameters



(a) $b_1 = -3\sqrt{\lambda_1}$ (b) $b_1 = 0$ (c) $b_1 = +3\sqrt{\lambda_1}$

(d) $b_2 = -3\sqrt{\lambda_2}$ (e) $b_2 = 0$ (f) $b_2 = +3\sqrt{\lambda_2}$

(g) $b_3 = -3\sqrt{\lambda_3}$ (h) $b_3 = 0$ (i) $b_3 = +3\sqrt{\lambda_3}$

Credit T. Cootes

Outline

- Motivation
- Statistical Shape Models
- **Statistical Appearance Models**
- Active Shape Models
- Appearance Shape Models
- New approaches
- Summary

Statistical Appearance Models

- Shape models represent variation through geometric features.
  - What about the image itself?

- Eigen-models can represent texture variation.

- **Goal:** Combine shape and texture information into a statistical model.

Statistical Appearance Model: How?

- Proceed as with the SSM.
  - Extract shape vectors.
  - Align.
  - Build shape model.

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

$$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{P}_s \mathbf{b}_s$$

Credit T. Cootes

Statistical Appearance Model: How?

Credit T. Cootes

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

Warp to mean shape

Texture, $\mathbf{g}$

- Then, for each sample
  - Warp to mean shape
  - Extract texture vector **g**.
  - Build eigen-model

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

Statistical Appearance Model: How?

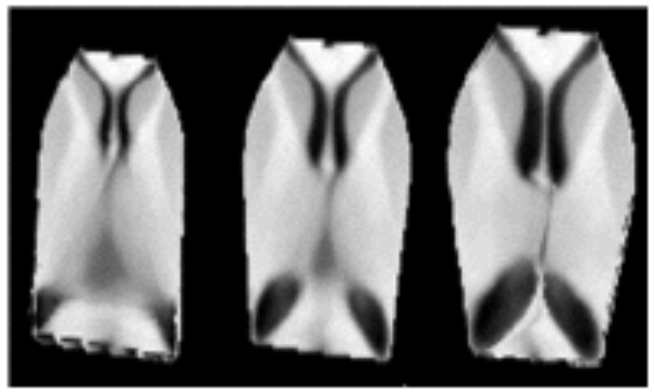
- Things that need to be addressed:
  - Warping (**not addressed**).
  - Learning correlations between shape and texture.

For further details:

T. Cootes and C.J. Taylor, 2004. Statistical Models of Appearance for Computer Vision, Tutorial

An example

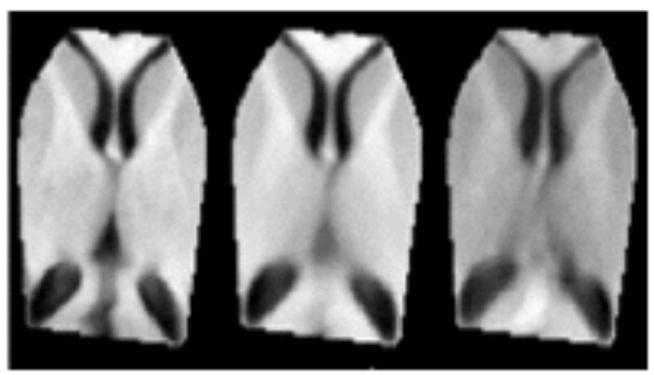
Shape variation, texture fixed



$$x \approx \bar{x} + P_s b_s$$

vary b_s

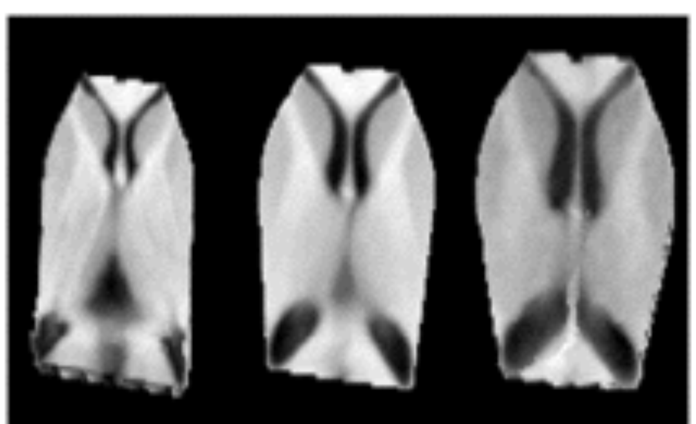
Texture variation, shape fixed



$$g \approx \bar{g} + P_g b_g$$

vary b_g

Shape and texture correlated



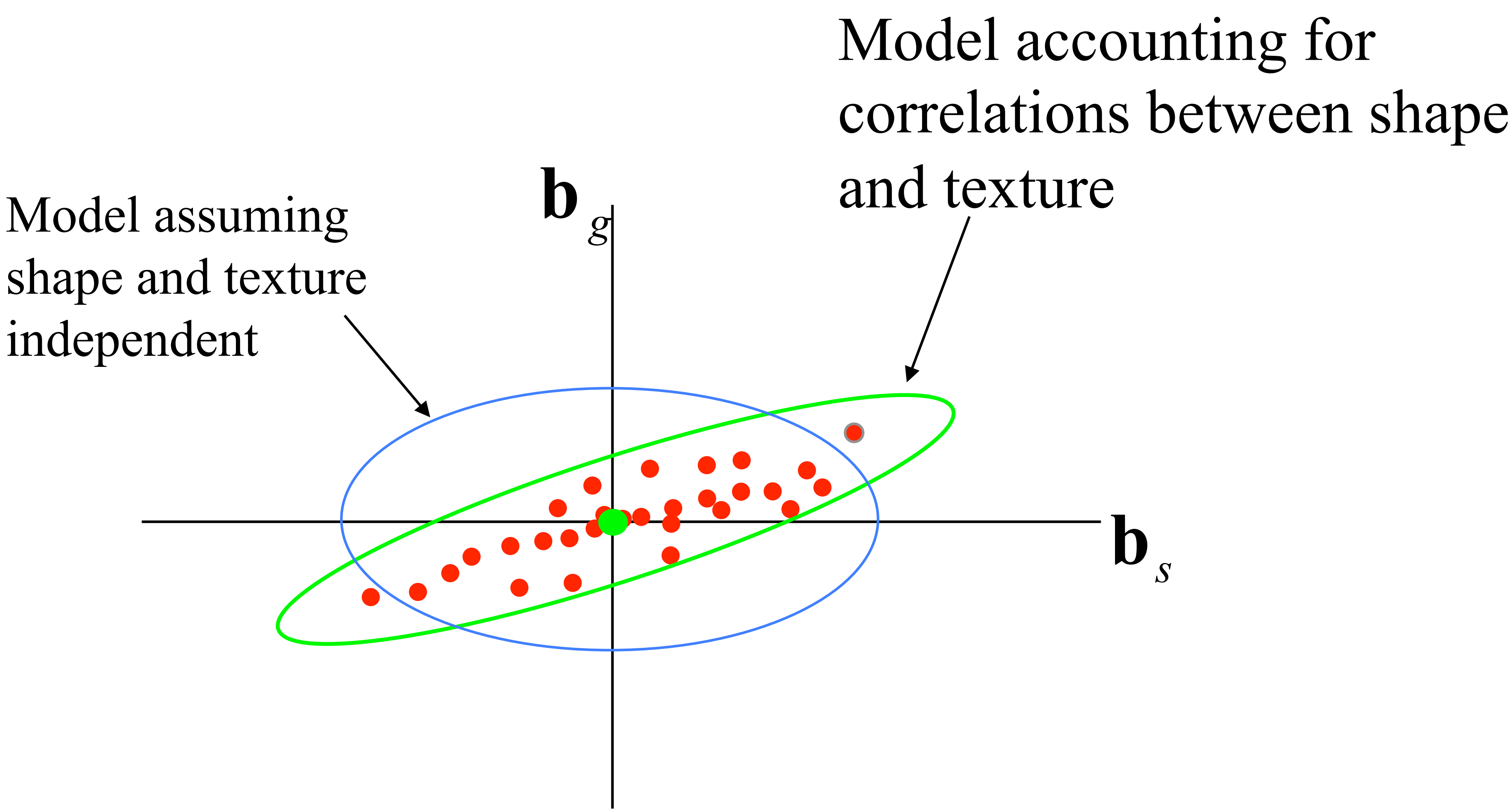
$$x \approx \bar{x} + Q_s c$$

$$g \approx \bar{g} + Q_g c$$

vary c

Brain MR, Cootes et. al. statistical shapes tutorial

Statistical Appearance Models: Correlation



Credit T. Cootes

Statistical Appearance Model: Combining both

- Shape and texture are modelled by $\mathbf{b_s}$ and $\mathbf{b_g}$.
- Appearance = Shape + texture.
- Both need to be combined into a single model:

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

- PCA is applied to these new vectors to obtain:

$$\mathbf{b} = \mathbf{P}_c \mathbf{c}$$

appearance parameters

Eigenvectors

Statistical Appearance Model: Combination

- Reformulating things:

$$\mathbf{x} = \bar{\mathbf{x}} + \mathbf{P}_s \mathbf{W}_s^{-1} \mathbf{P}_{cs} \mathbf{c} \quad , \quad \mathbf{g} = \bar{\mathbf{g}} + \mathbf{P}_g \mathbf{P}_{cg} \mathbf{c}$$

with

$$\mathbf{P}_c = \begin{pmatrix} \mathbf{P}_{cs} \\ \mathbf{P}_{cg} \end{pmatrix}$$

Simplifying

$$\begin{aligned} \mathbf{x} &= \bar{\mathbf{x}} + \mathbf{Q}_s \mathbf{c} \\ \mathbf{g} &= \bar{\mathbf{g}} + \mathbf{Q}_g \mathbf{c} \end{aligned}$$

$$\begin{aligned} \mathbf{Q}_s &= \mathbf{P}_s \mathbf{W}_s^{-1} \mathbf{P}_{cs} \\ \mathbf{Q}_g &= \mathbf{P}_g \mathbf{P}_{cg} \end{aligned}$$

Statistical Appearance Model: Model

$$
\begin{aligned}
\mathbf{x} &= \bar{\mathbf{x}} + \mathbf{Q}_s\mathbf{c} \\
\mathbf{g} &= \bar{\mathbf{g}} + \mathbf{Q}_g\mathbf{c}
\end{aligned}
$$

An image can be synthesised for a given **c** by generating a shape-free grey-level image from the vector **g** and warping it using the control points described by **x**.

Another example

Shape variation

Texture variation

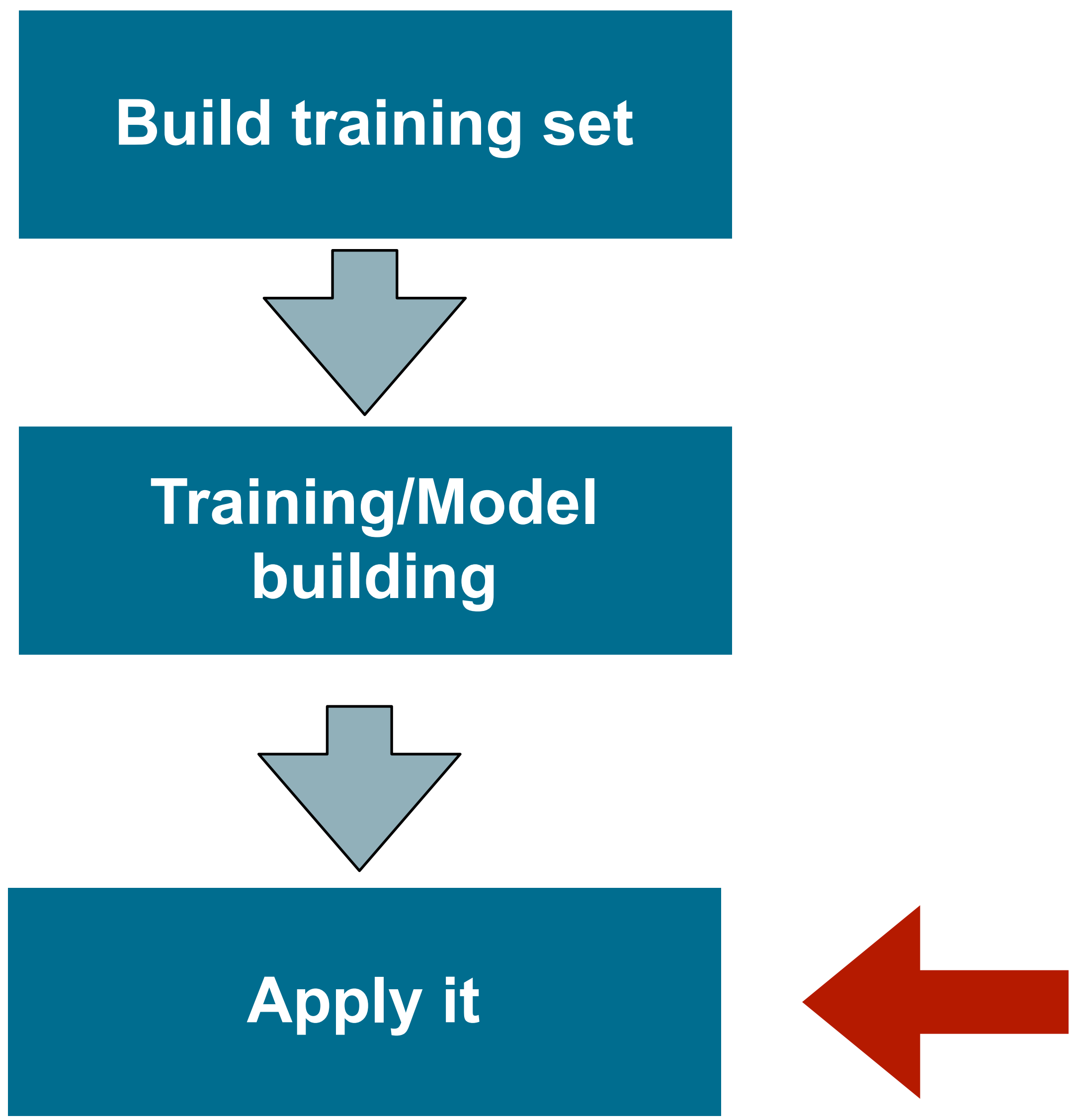
Appearance variation

Cootes & Taylor, 2004

Statistical Appearance Models: $\mathbf{W_s}$

- The elements of $\mathbf{b_s}$ and $\mathbf{b_g}$ have different units: distance and intensity.
- The role of $\mathbf{W}_s$ is to commensurate both elements
- What effect does it have in $\mathbf{b_s}$ to vary $\mathbf{b_g}$ and viceversa, measured through RMS change per unit change.
- In practice, it has been shown that algorithms are relatively insensitive to the choice of $\mathbf{W}_s$.

In Summary



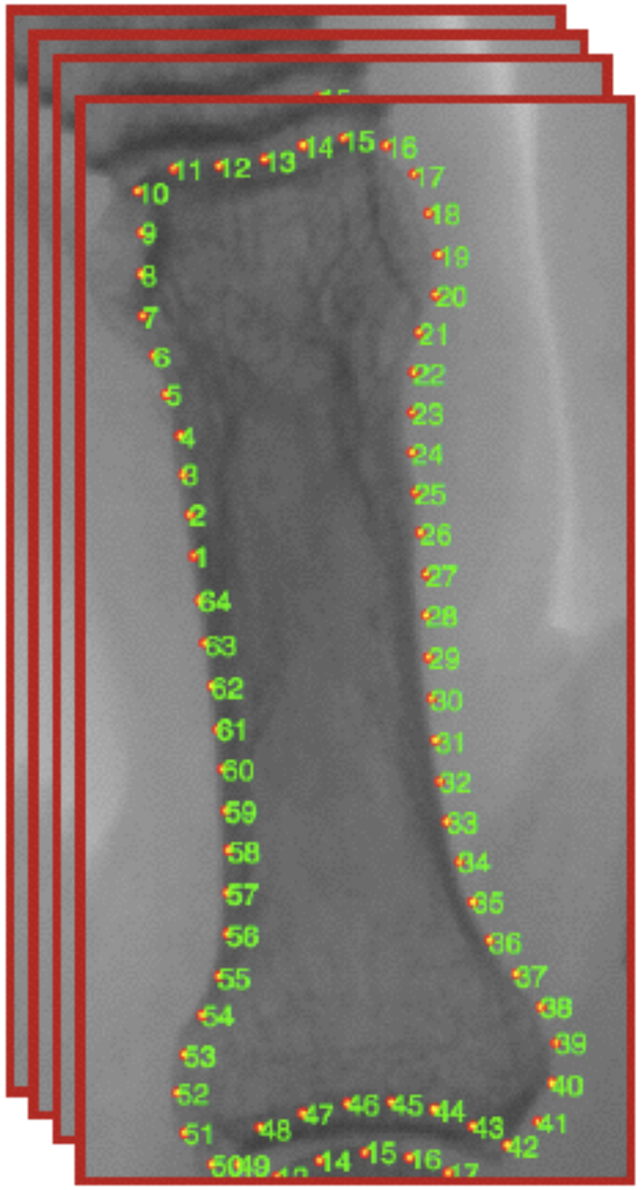
Now we need to match the model to an image

Outline

- Motivation
- Statistical Shape Models
- Statistical Appearance Models
- **Active Shape Models**
- Active Appearance Models
- New approaches
- Summary

Active Shape Models

- A set of training examples (images)
- A set of landmarks, that are present on all images
- Build a statistical model of shape variation (PCA)
- Build a statistical model of the local texture (PCA)
- Use the model for the search in a new image



Credit G. Langs

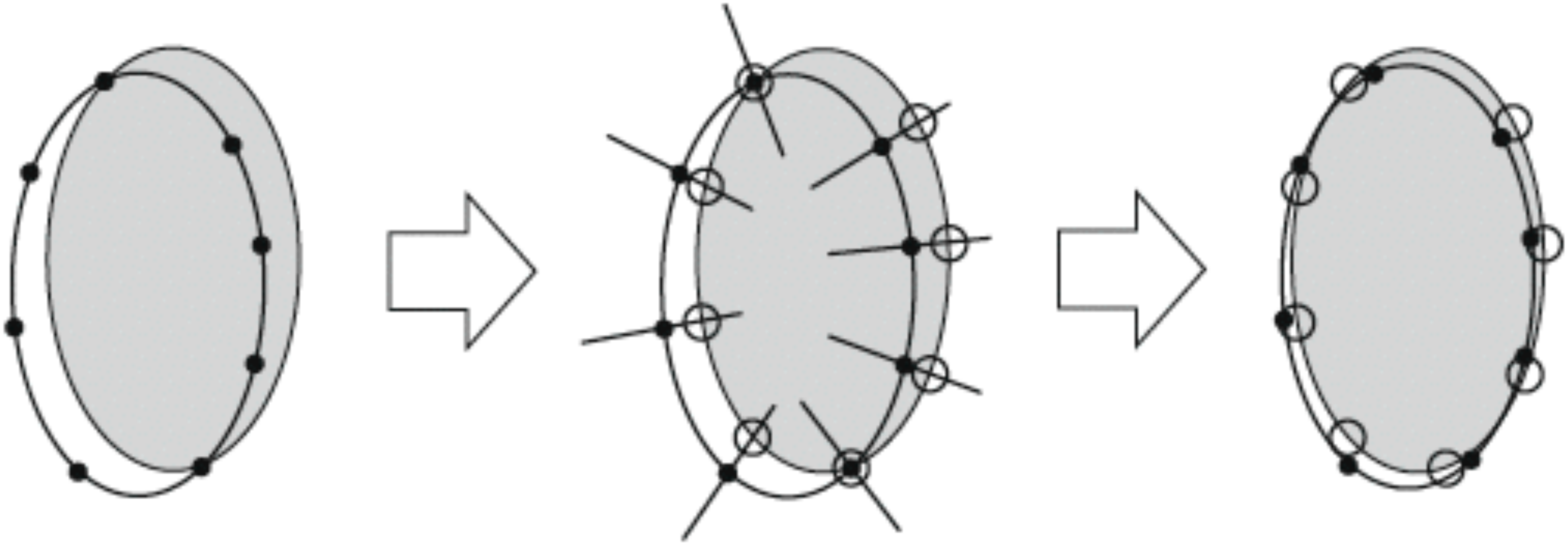
Active Shape Models (ASM)

- We have a statistical shape model (no appearance)
- How do we use it to infer the content of a new image?
- Active Shape Models - Iterative local search algorithm that seeks to match a model to an image.

Cootes, T.F., Taylor, C.J., Cooper, D., Graham, J., 1992. Training models of shape from sets of examples. In: Proc. British Machine Vision Conference. Springer.

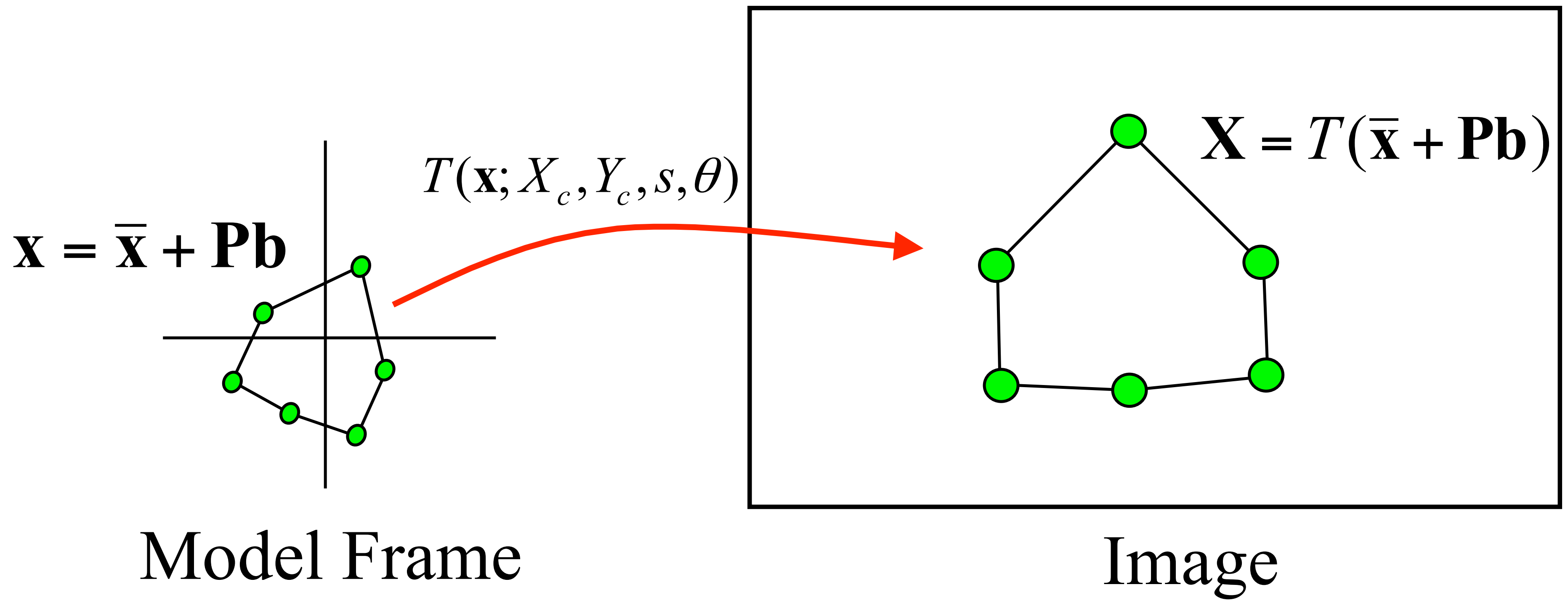
Cootes, T.F., Taylor, C.J., 1995. Combining point distribution models with shape models based on finite-element analysis. Image Vis. Comput. 13 (5), 403–409.

ASM: An overview



ASM: Placing the model in the image

- The model points are in the model coordinate frame.
- A transformation is required to place them in the image.



Credit T. Cootes

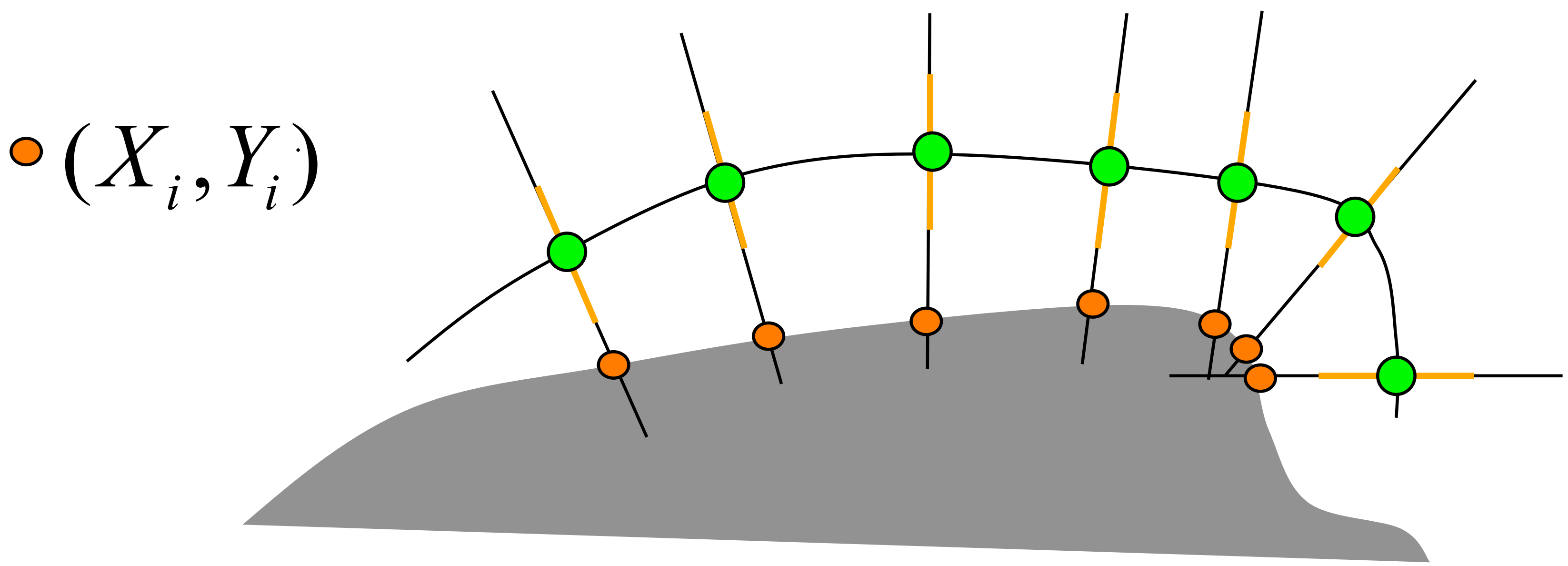
ASM: Initialisation

- User interaction
- Image processing
- Learning from the image

If the initialisation is not good, the subsequent stage is likely to fail

ASM: Search strategy

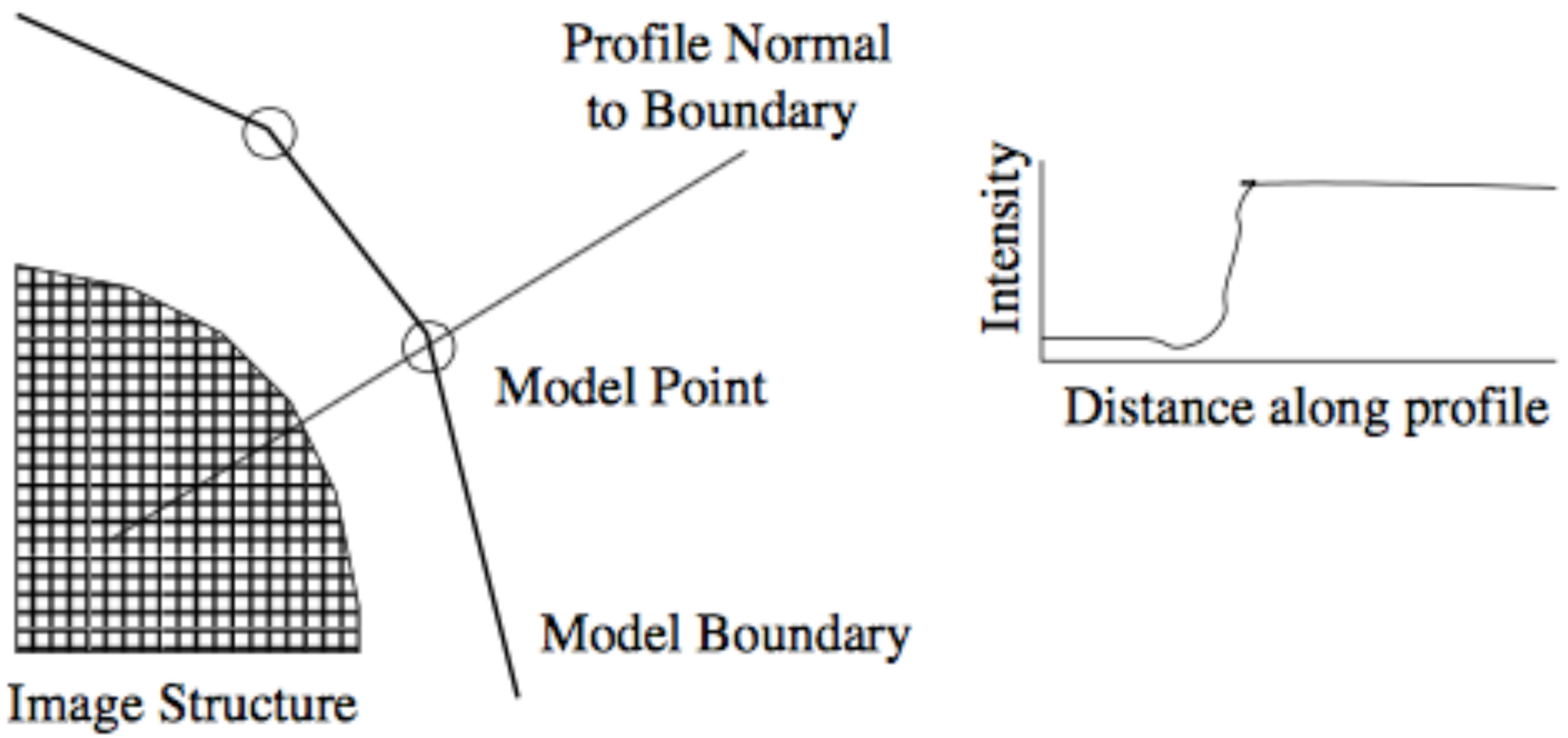
- Initialize near the target.
- Search along profiles to find the best match X'.
- Update parameters to match X'.



Credit T. Cootes

ASM: Local search strategy

- A local match is required for each point



Cootes, 2004

- Strongest edge

- Statistical model of the profile

ASM: Global algorithm

- Search along profile.
- Update global transformation T, and parameters b to minimize:

$$|\mathbf{X} - T(\bar{\mathbf{x}} + \mathbf{Pb})|^2$$

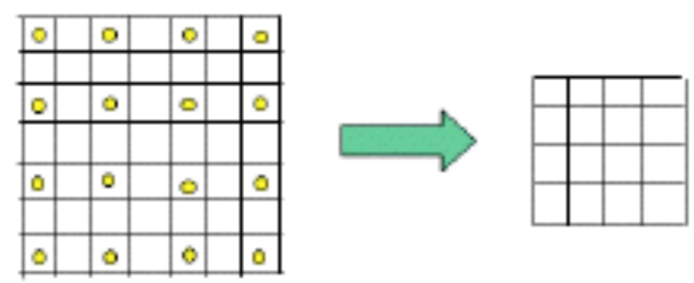
- Update parameters applying constraints (**b**).
- Repeat until convergence.

$$f(\mathbf{b}, X_c, Y_c, s, \theta) = |\mathbf{X} - T(\bar{\mathbf{x}} + \mathbf{Pb}; X_c, Y_c, s, \theta)|^2$$

ASM: Multi-resolution approach

- Improves efficiency

Multi-resolution framework



Each level half the size of the one below

Credit CAMPAR (Garching, Germany)

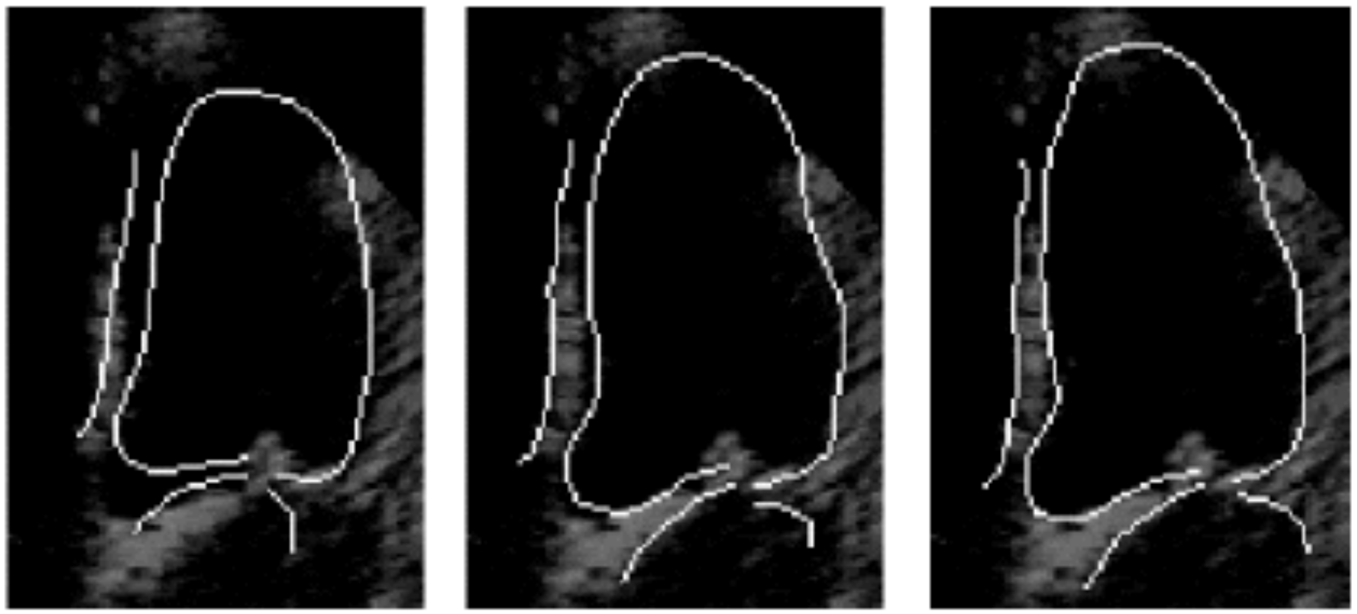
Original size

Level 2

Level 1

Level 0

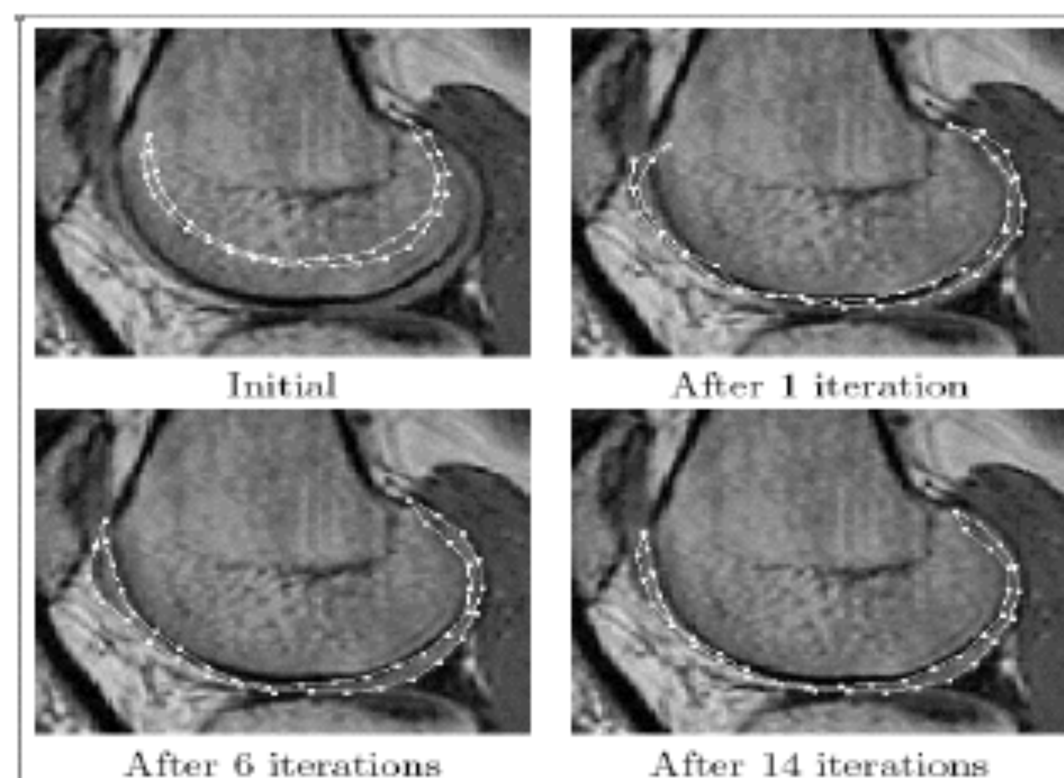
ASM: Examples



(a) Initial State (b) After 20 iterations (c) After 50 iterations

LV segmentation

Cartilage segmentation in MR



T. Cootes - Active shape tutorial

ASM: Examples

Initial | After 2 iterations | After 20 Iterations

ASM: Summary

- Advantages
  - Fast, simple and accurate
  - Efficient to extend to N-D
- Disadvantages
  - Local models are independent
  - Uses sparse information from the image

ASM: Summary

- Suitable for:
  - Well defined shapes
  - Cases where there is a good representative set of examples
  - It is possible to have a good first guess.

- Not suitable for:
  - Objects with widely varying shapes.
  - Problems involving a large number of small things

Outline

- Motivation
- Statistical Shape Models
- Statistical Appearance Models
- Active Shape Models
- **Active Appearance Models**
- New approaches
- Summary

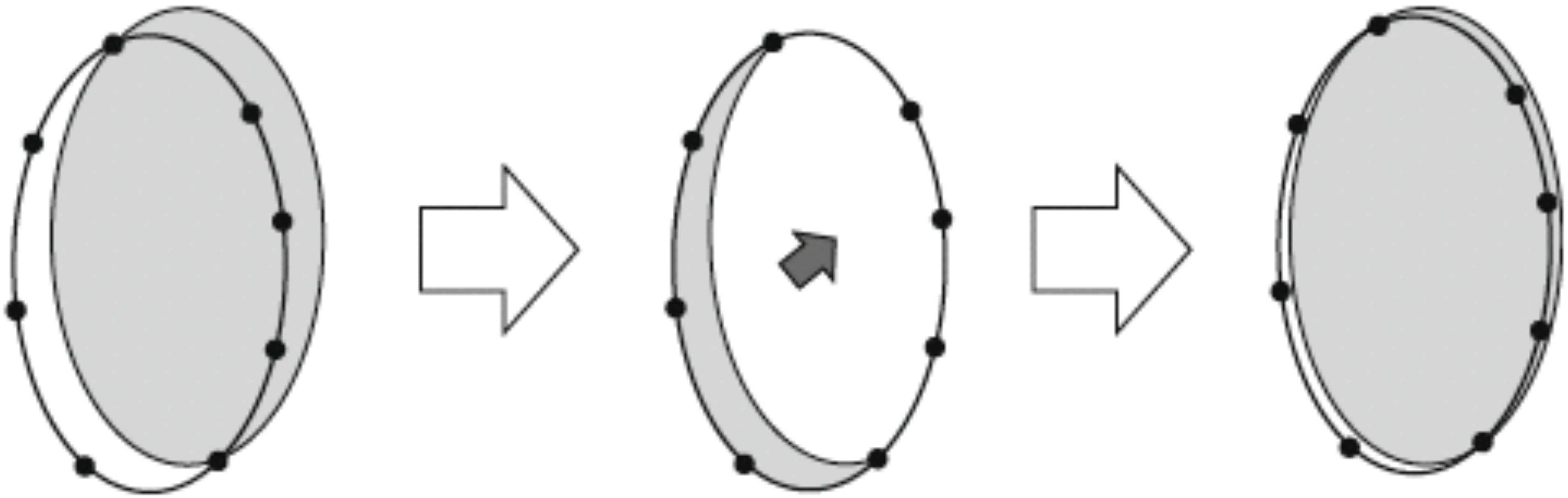
Active Appearance Models (AAM)

- Now we have a appearance shape model
- How do we use it to infer the content of a new image?
- Active Appereance Models - Iterative search algorithm that seeks to match a model to an image.

Cootes, T.F., Edwards, G.J., Taylor, C.J., 1998. Active appearance models. In: H. Burkhardt, B. Neumann (Eds.), Proc. ECCV, vol. 2.

Cootes, T.F., Edwards, G.J., Taylor, C.J., 1998. A comparative evaluation of active appearance model algorithms. In: Lewis, P., Nixon, M. (Eds.), Proc. British Machine Vision Conference, vol. 2. BMVA Press, Southampton, UK.

AAM: An overview



AAM: Search

- High dimensional problem

- To simplify it, a constant relationship between the texture model residuals **r(p)** and parameter updates **dp** is assumed:

$$\mathbf{r}(\mathbf{p}) = \mathbf{g}_{img} - \mathbf{g}_{model}$$

$$\mathbf{dp} = -R\mathbf{r}(\mathbf{p})$$

p: parameters of the model

Obtained from training

AAM: The algorithm

<u>Basic algorithm</u>:

I. Initial estimate $I_m(p)$

II. Start at coarse resolution

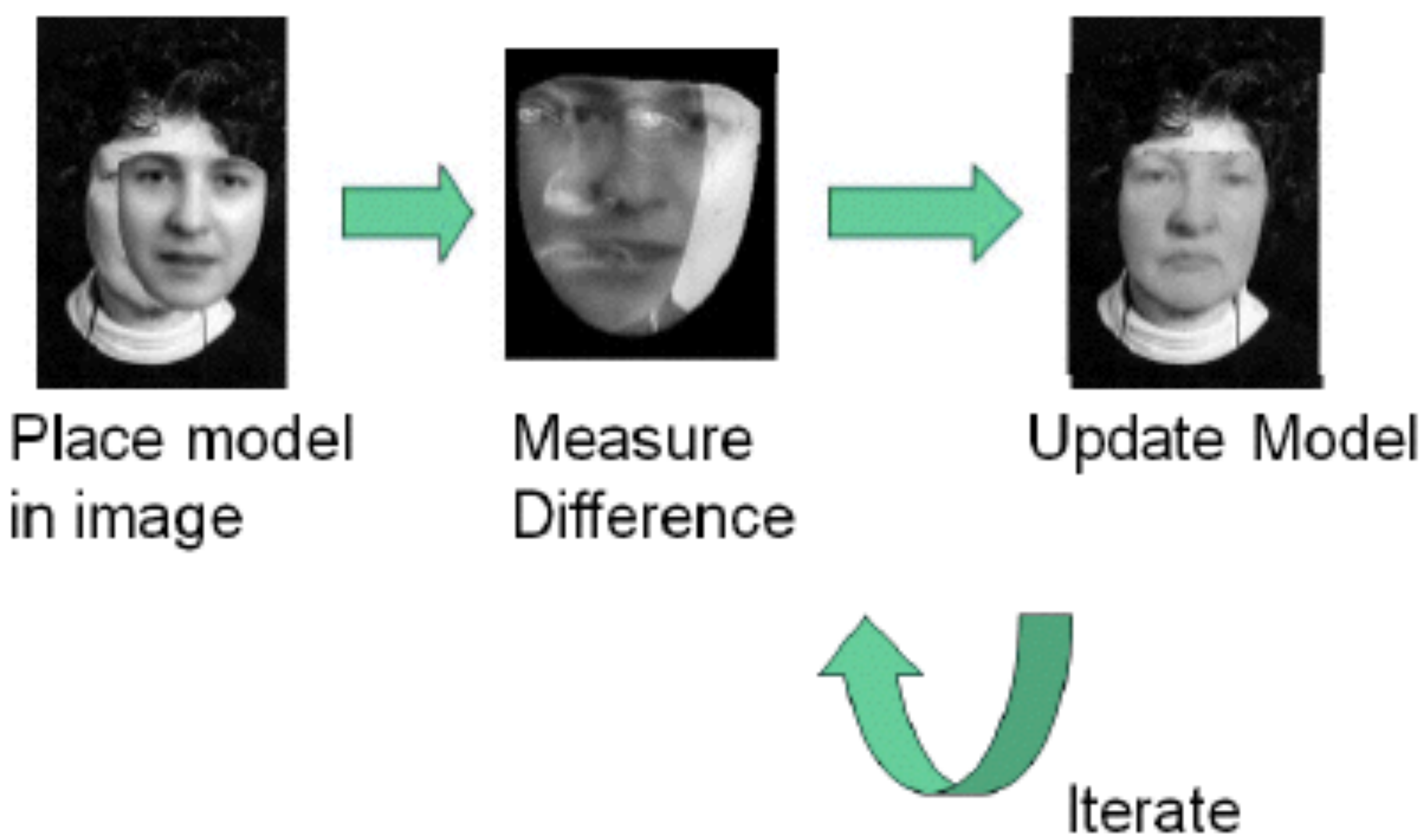
III. At each resolution

- Measure residual error, $r(p)$
- predict correction

$$\delta p = Rr$$

- repeat to convergence

$$p \Rightarrow p - \delta p$$

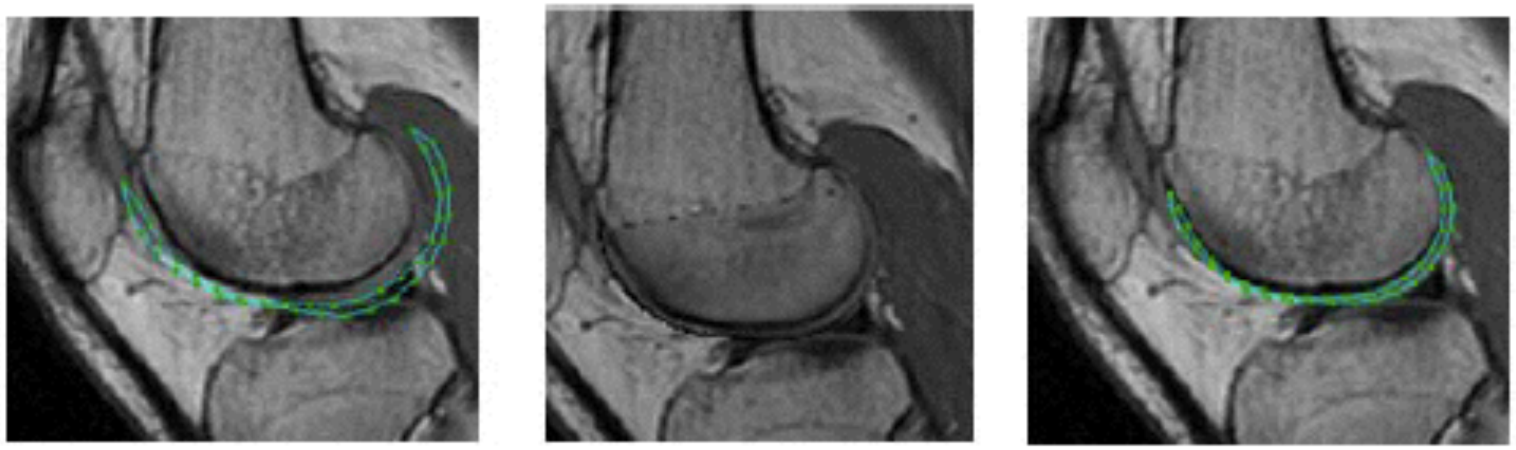


AAM: Examples

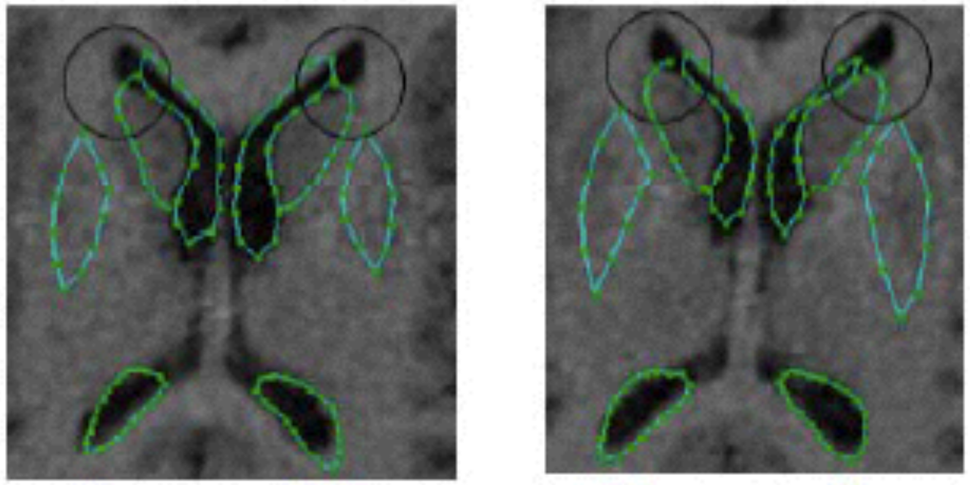
Initial 2 its 8 its 14 its 20 its converged

AAM: An Example

MR of a knee



MR of Brain
Poor initialization can lead to failure



Cootes et. al. Active Appearance Models tutorial

AAM: Summary

- Advantages
  - Introduces the concept of texture
  - Can be extended to further dimensions
- Disadvantages
  - Requires correspondences that are hard to achieve (model building).
  - Relies on human knowledge.
  - Requires a very good initialization.
  - Multidimensional models can become too large.

Differences between ASM and AAM

- ASM only uses localised models of the image texture.

- ASM does the searching along profiles, AAM samples the image at the current position

- ASM minimises points between model and image, AAM minimises the difference between the synthesised model and the target image.

Outline

- Motivation
- Statistical Shape Models
- Statistical Appearance Models
- Active Shape Models
- Active Appearance Models
- **New approaches**
- Summary

New Approaches

- SSM, ASM and AAM are at the base of statistical models.
- For an “up-to-date” review on existing methods:

Medical Image Analysis 13 (2009) 543–563

Contents lists available at ScienceDirect

Medical Image Analysis

journal homepage: www.elsevier.com/locate/media

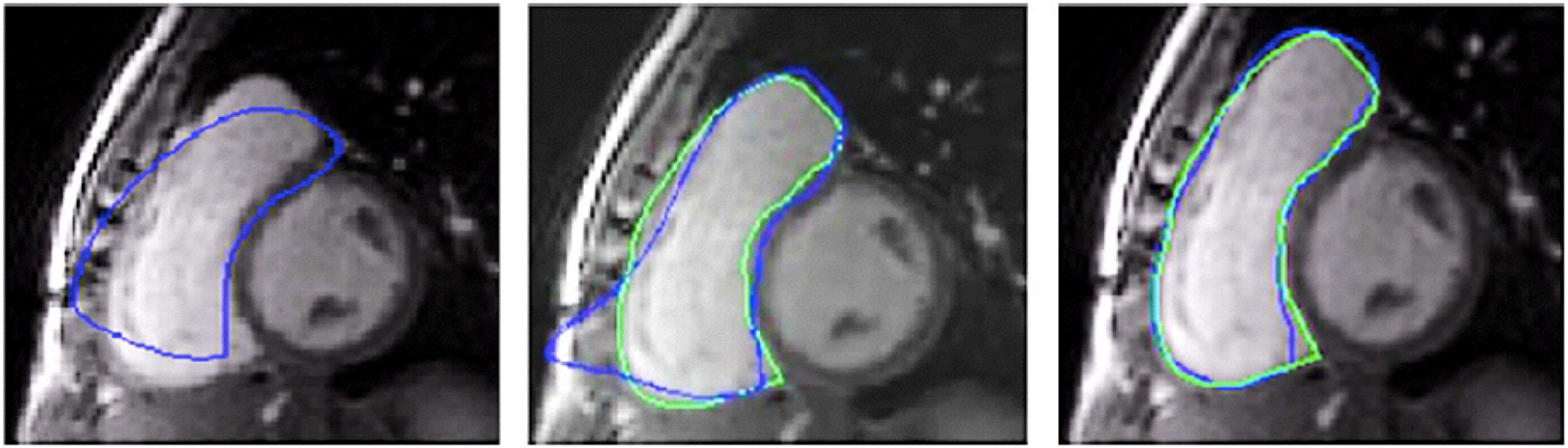
ELSEVIER

Statistical shape models for 3D medical image segmentation: A review

Tobias Heimann *, Hans-Peter Meinzer

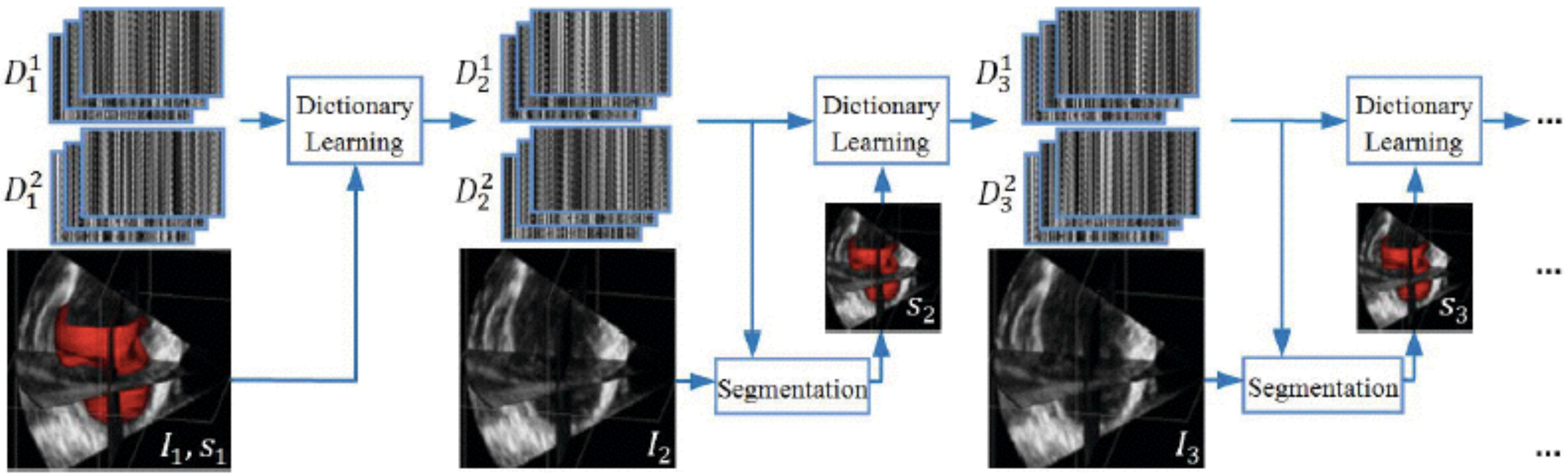
Div. of Medical and Biological Informatics, German Cancer Research Center, Im Neuenheimer Feld 280, D-69120 Heidelberg, Germany

New Approaches



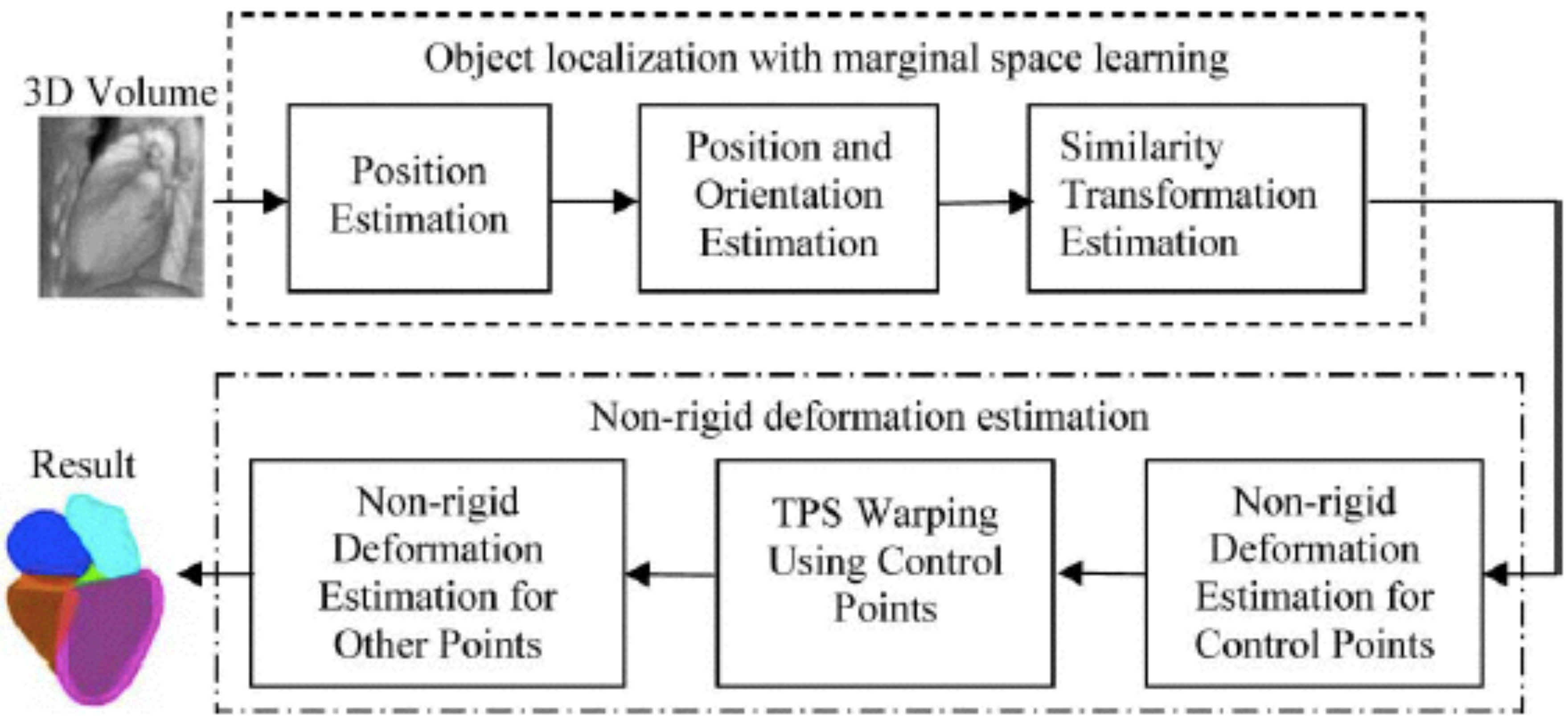
ElBaz et al , MICCAI 2012 - 2D PCA to account for time variations

New approaches: Use of machine learning



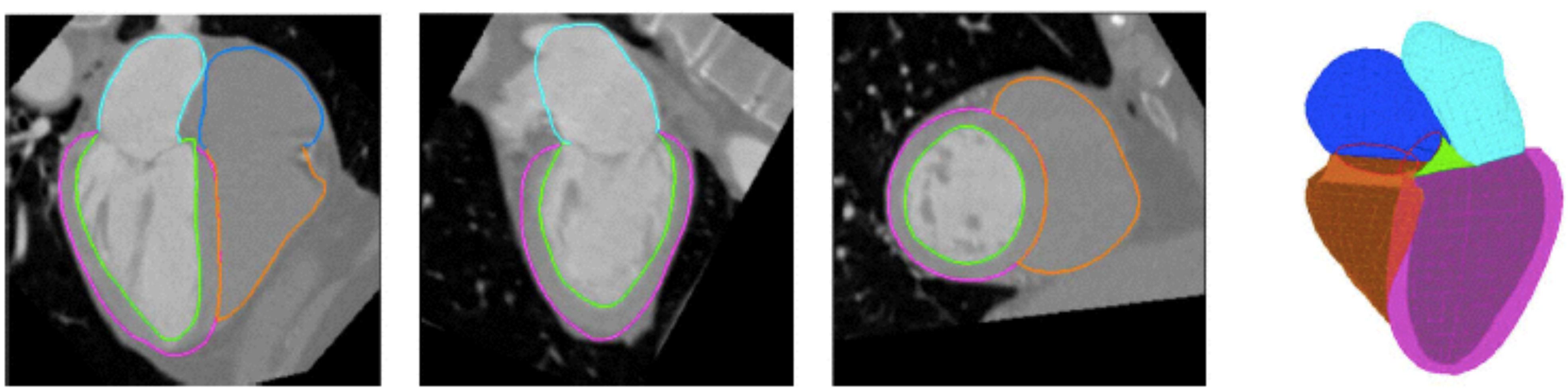
DAM - Dynamic appearance model (Huang et al. MICCAI 2012)

New approaches: Use of machine learning

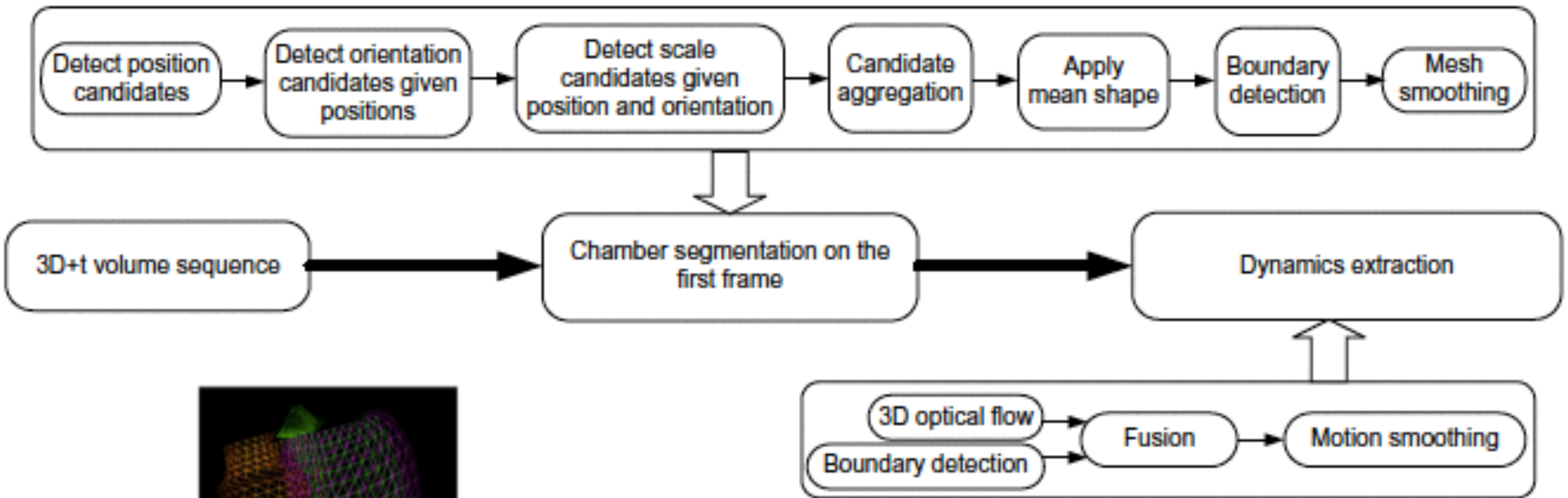


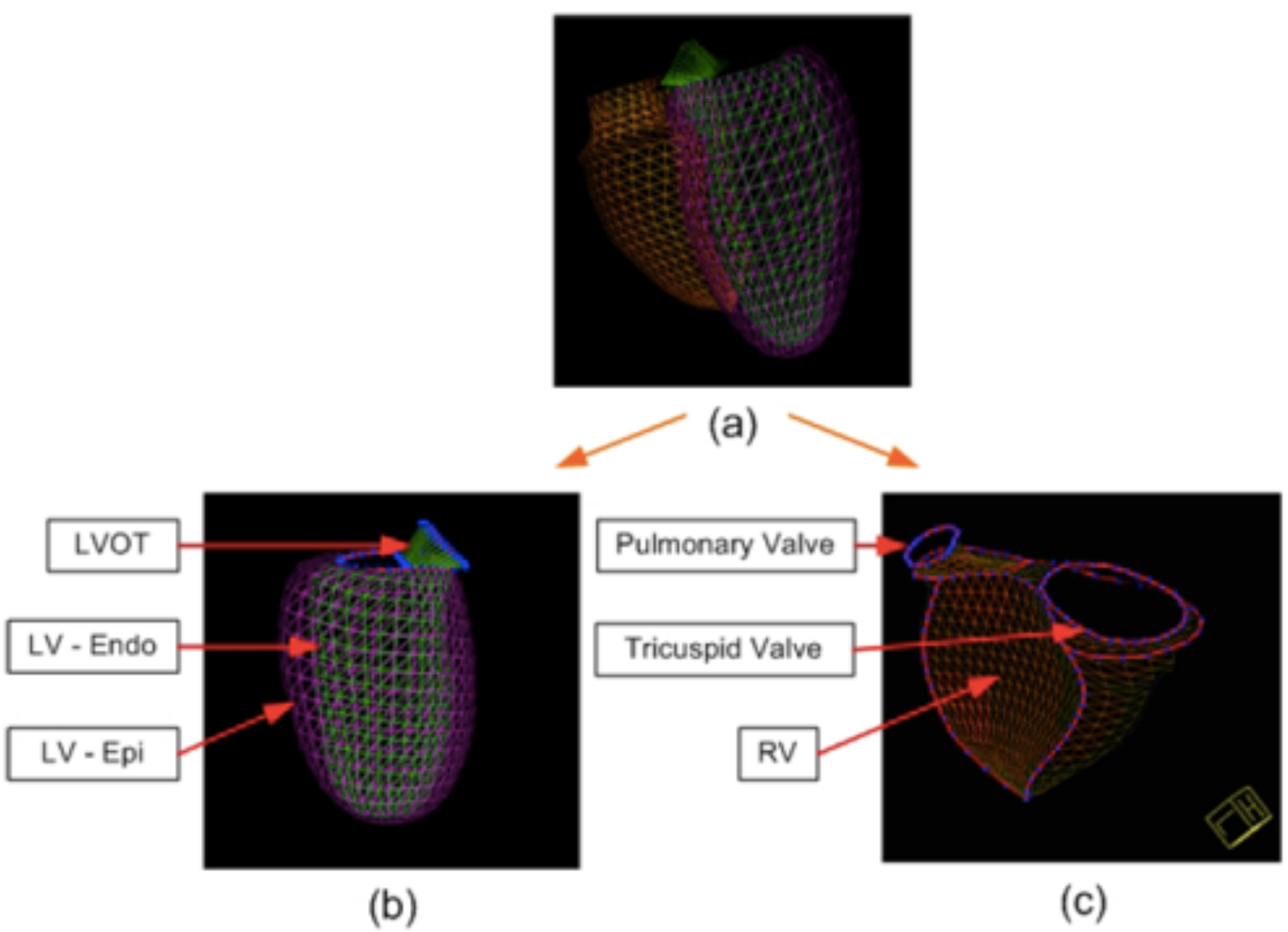
Zheng et al, TMI 2008

Marginal space learning to learn the transformation



New approaches: Use of machine learning





Lu et al, FIMH, 2011

Use of probabilistic boost trees to learn model parameters.

Outline

- Motivation
- Statistical Shape Models
- Statistical Appearance Models
- Active Shape Models
- Active Appearance Models
- New approaches
- **Summary**

Summary

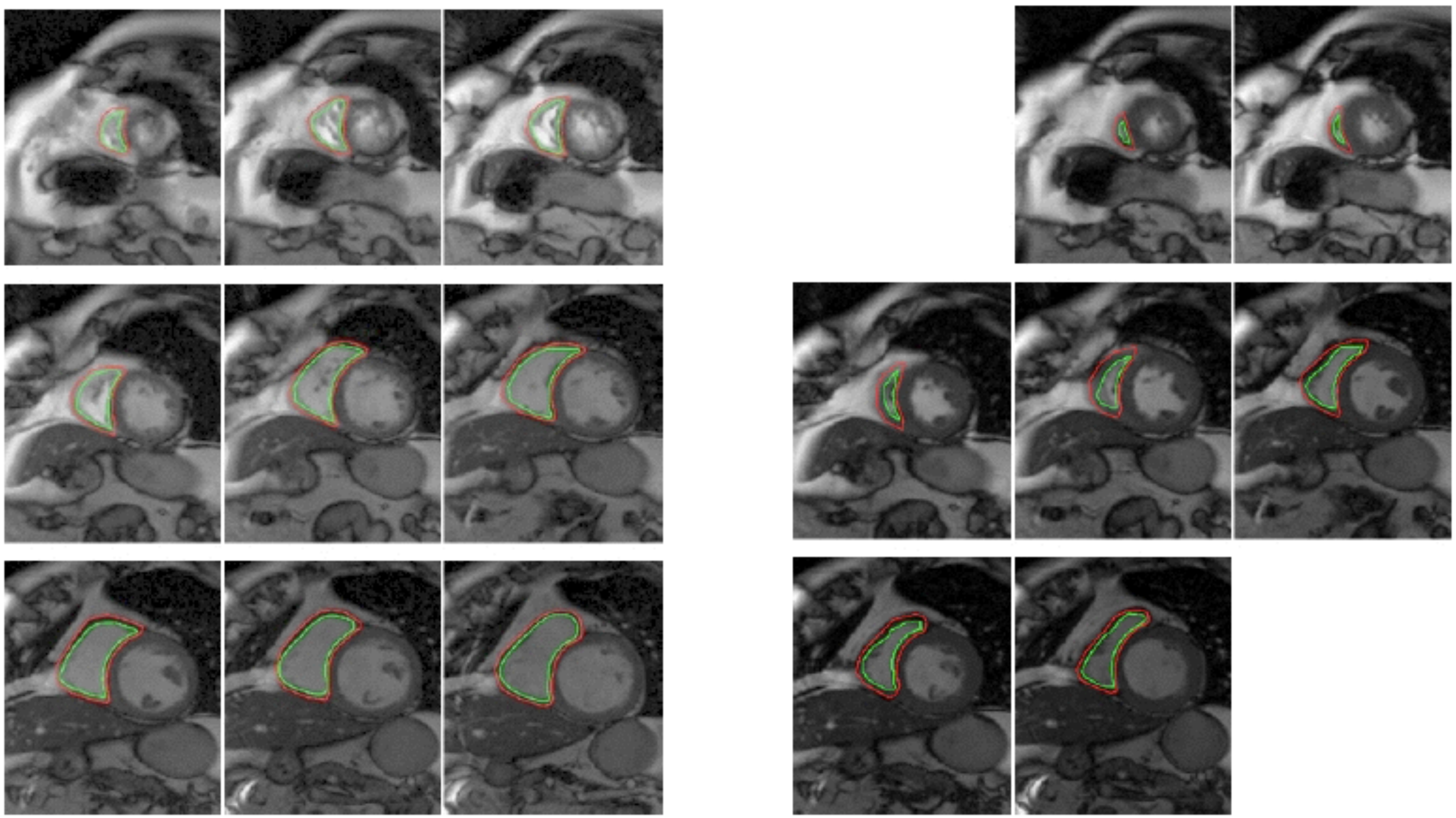
- It is possible to build models of shape change.
- Texture can be included within the model.
- ASM and AAM are the two most common methods to use SSM to infer information from images.
- Main applications:
  - Cardiac segmentation
  - Brain segmentation
  - Bone segmentation

Summary: Challenges

- Abnormal shape variations often characterise a disease.

What to do when variations are normal?

Summary: Challenges



(a) End diastole

(b) End systole

Petitjean et al, 2014 (submitted)

References

- T. Cootes and C.J Taylor, 2004. Statistical Models of Appearance for Computer Vision, Tutorial.
- Tim Cootes web page: http://personalpages.manchester.ac.uk/staff/timothy.f.cootes/
- T. Cootes et at, 2001. Statistical models of appearance for medical image analysis and computer vision. Proc SPIE Medical Imaging.
- T. Cootes et al. 1994. The use of active shape models for locating structures in medical images. Image vision and computing.

Questions?