Modelling Appearance

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Lessons learned

- ASM is relatively fast
- ASM too simplistic; not robust when new images are introduced
- May not converge to good solution
- Key insight: ASM does not incorporate all gray-level information in parameters

Combined Appearance Models

- Combine shape and gray-level variation in single statistical appearance model
- Goals:
  - Model has better representational power
  - Model inherits appearance models benefits
  - Model has comparable performance

How to generate a AAM

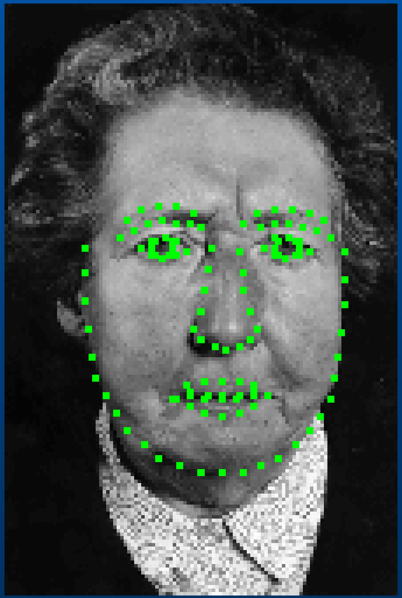
- Label training set with landmark points representing positions of key features
- Represent these landmarks as a vector x
- Perform PCA on these landmark vectors

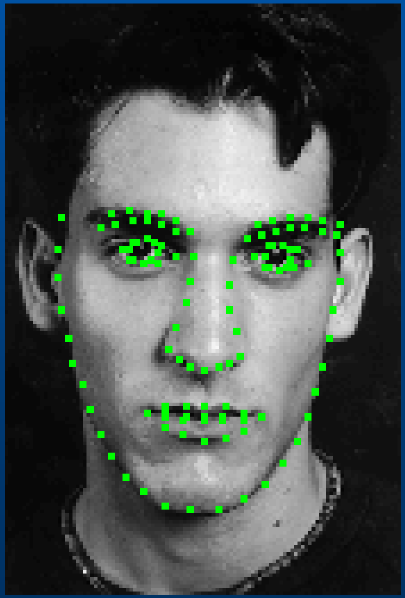
Appearance Models

- Statistical models of shape *and* texture
- Generative models
  - general
  - specific
  - compact (~100 params)

Building an Appearance Model

- Labelled training images
  - landmarks represent correspondences





Building an Appearance Model

- For each example

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

Warp to mean shape

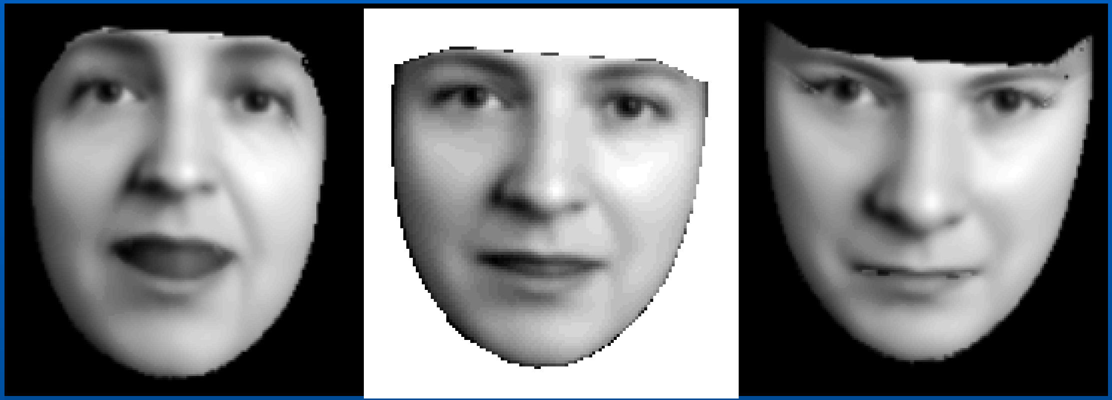
Raster Scan

Texture: $\mathbf{g}$

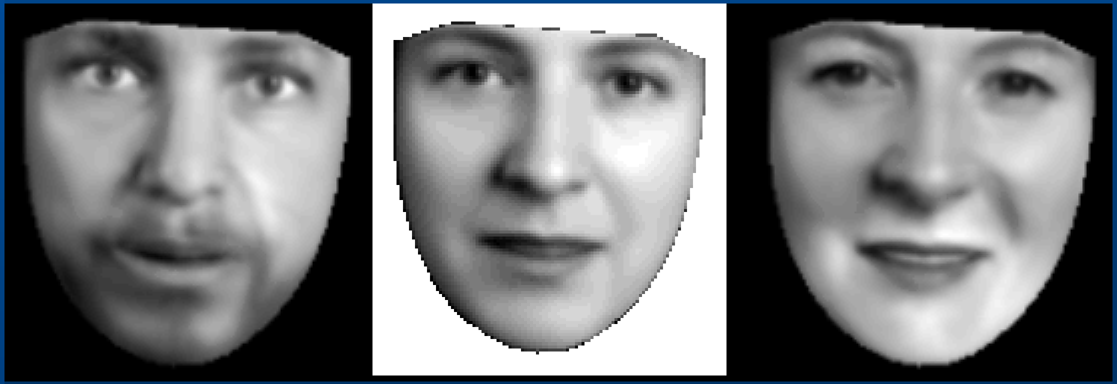
Building an Appearance Model

- Principal component analysis
  - shape model: $\mathbf{x} = \bar{\mathbf{x}} + \mathbf{P}_s \mathbf{b}_s$
  - texture model: $\mathbf{g} = \bar{\mathbf{g}} + \mathbf{P}_g \mathbf{b}_g$
- Columns of $\mathbf{P}_r$ form shape and texture bases
- Parameters $\mathbf{b}_r$ control modes of variation

Shape and Texture Modes



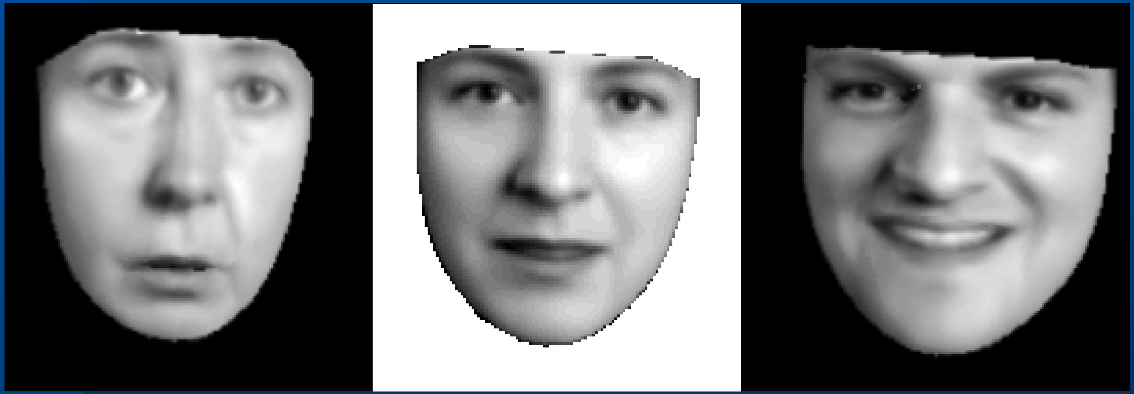
Shape variation (texture fixed)



Texture variation (shape fixed)

Combined Appearance Model

- Shape and texture may be correlated
  - PCA of $\begin{pmatrix} \mathbf{b}_s \\ \mathbf{b}_g \end{pmatrix} \Rightarrow \begin{pmatrix} \mathbf{x} \\ \mathbf{g} \end{pmatrix} = \begin{pmatrix} \overline{\mathbf{x}} \\ \overline{\mathbf{g}} \end{pmatrix} + \begin{pmatrix} \mathbf{Q}_\mathbf{x} \\ \mathbf{Q}_\mathbf{g} \end{pmatrix} \mathbf{c}$



Varying appearance vector **c**

Colour Appearance Model

c_1

c_2

c_3

AAM Properties

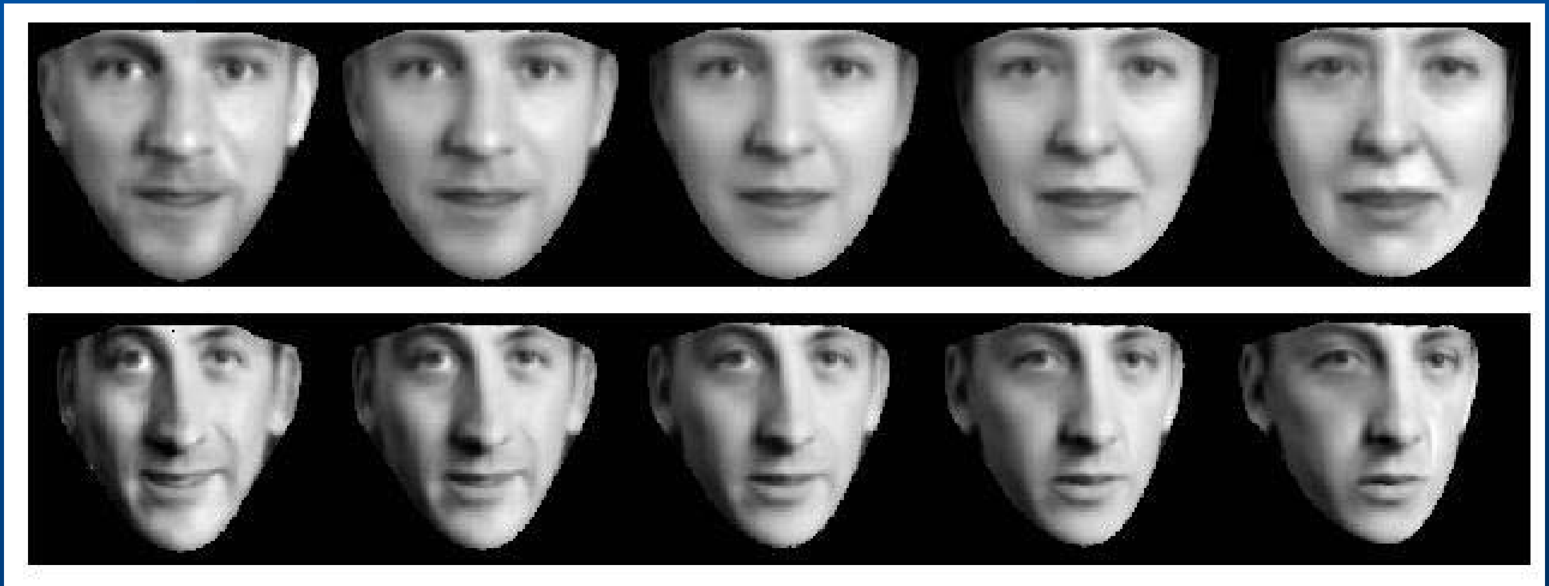
- Combines shape and gray-level variations in one model
  - No need for separate models
- Compared to separate models, in general, needs fewer parameters
- Uses all available information

AAM Properties (cont.)

- Inherits appearance model benefits
  - Able to represent any face within bounds of the training set
  - Robust interpretation
- Model parameters characterize facial features

AAM Properties (cont.)

- Obtain parameters for inter and intra class variation (identity and residual parameters) – “explains” face



AAM Properties (cont.)

- Useful for tracking and identification
  - Refer to: G.J.Edwards, C.J.Taylor, T.F.Cootes. "Learning to Identify and Track Faces in Image Sequences“. Int. Conf. on Face and Gesture Recognition, p. 260-265, 1998.
- Note: shape and gray-level variations are correlated

AAM Search

Model Parameters

- Features
- Identity
- Expression
- Pose
- Lighting

Practical Applications

Face Tracking

Original Tracking

Car Model

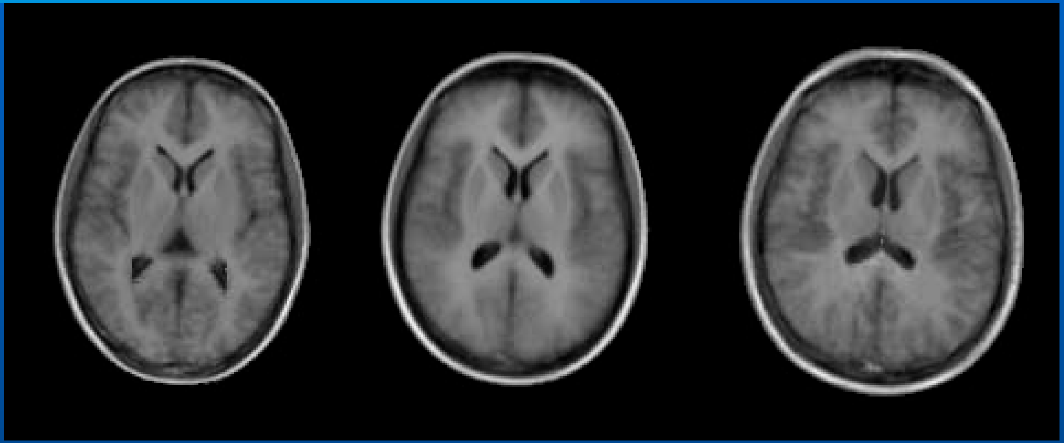
Main Mode of Variation

Original

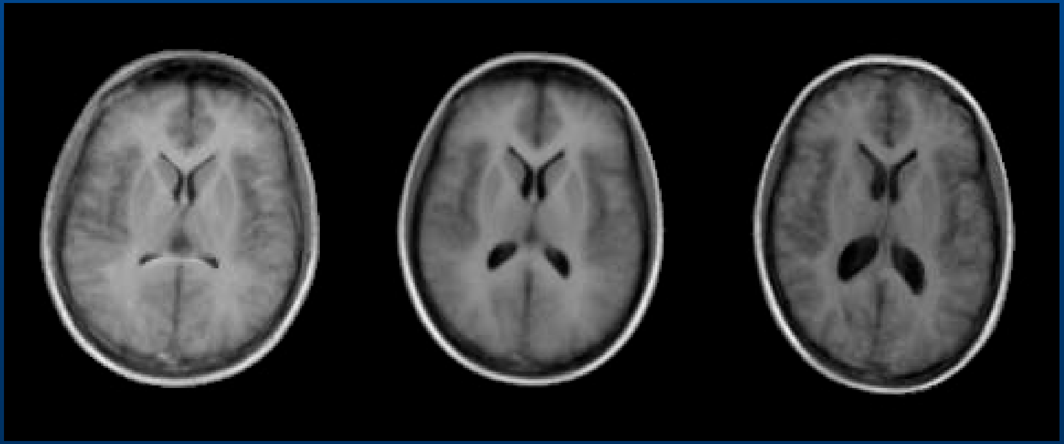
Search

MR Brain Slice

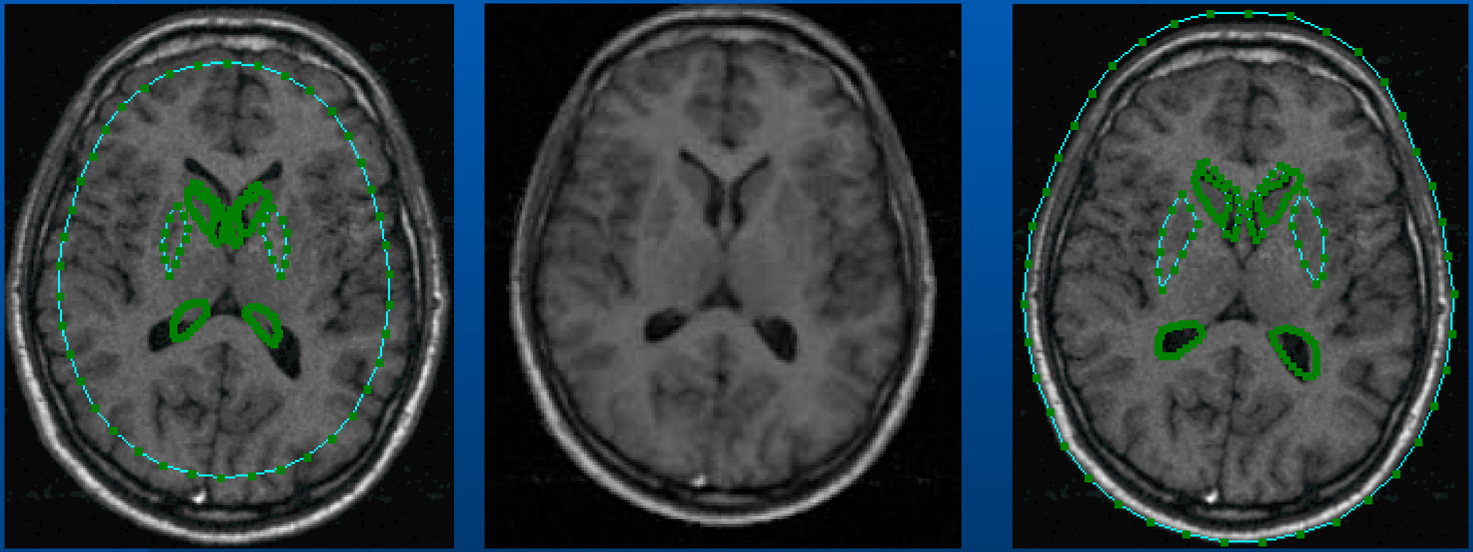
Combined Mode 1



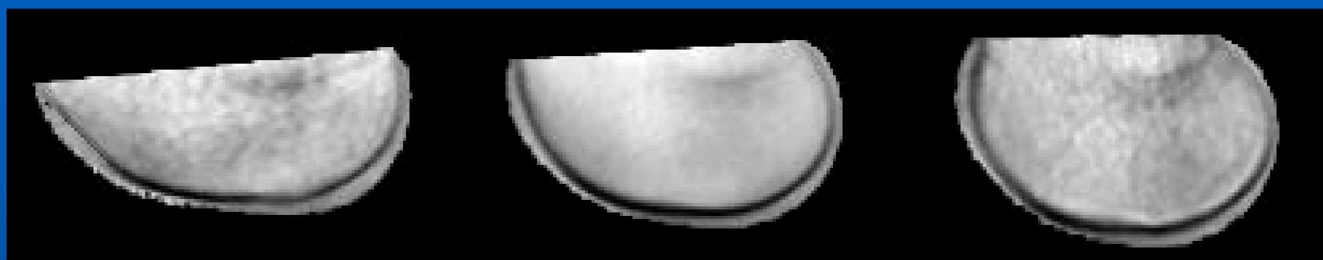
Combined Mode 2



MR Brain Slice - Search



MR Knee Cartilage



Summary

- Generic approach - *analysis by synthesis*
- Robust image interpretation
- Labelled structure
  - segmentation, measurement
- Recognition
  - parametric description
- Practical applications

Constrained AAMs

- Model results rely on starting approximation
- Want a method to improve influence from starting approximation
- Incorporate priors/user input on unseen image
  - MAP formulation

Constrained AAMs

- Assume:
  - Gray-scale errors are uniform gaussian with variance σ_r^2
  - Model parameters are gaussian with diagonal covariance $\mathbf{S}_p^2$
  - Prior estimates of some of the positions in the image along with covariances

Constrained AAMs (cont.)

- We get update equation:

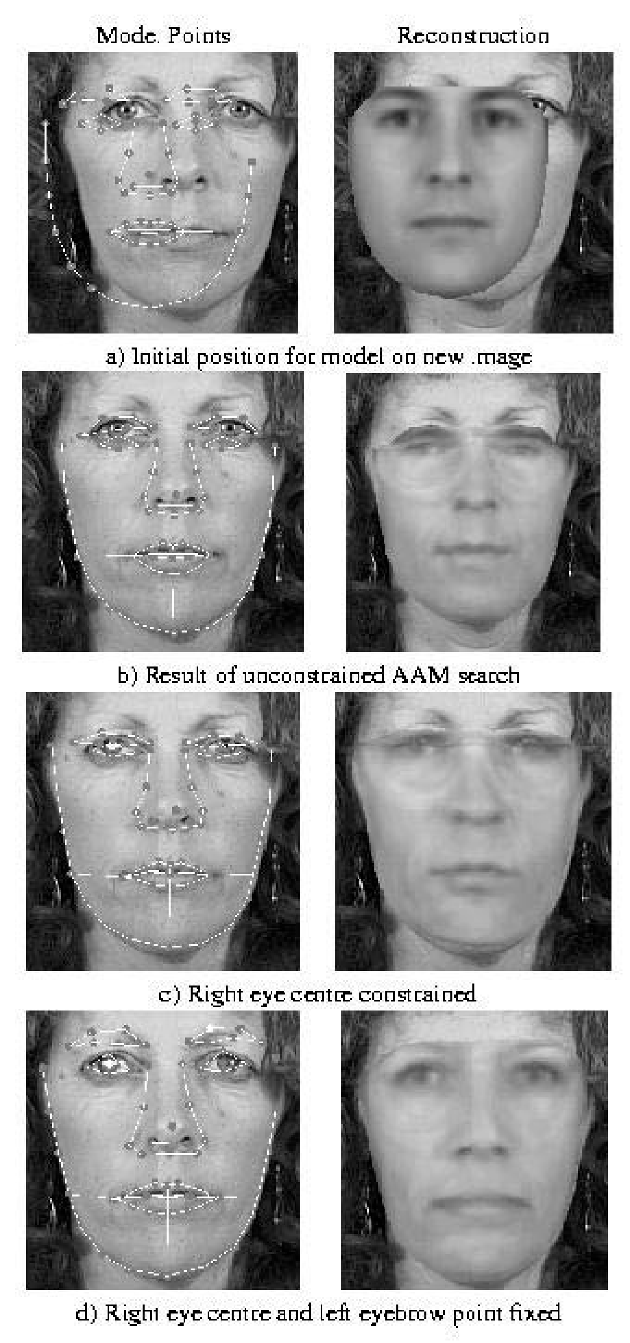
$$\mathbf{A}_1 \delta \mathbf{p} = -\mathbf{a}_1$$

where:

$$\begin{aligned}
\mathbf{A}_1 &= \left(\sigma_r^{-2} \frac{\partial \mathbf{r}}{\partial \mathbf{p}}^T \frac{\partial \mathbf{r}}{\partial \mathbf{p}} + \mathbf{S}_p^{-1} + \frac{\partial \mathbf{d}}{\partial \mathbf{p}}^T \mathbf{S}_X^{-1} \frac{\partial \mathbf{d}}{\partial \mathbf{p}} \right) \\
\mathbf{a}_1 &= \left(\sigma_r^{-2} \frac{\partial \mathbf{r}}{\partial \mathbf{p}}^T \mathbf{r}(\mathbf{p}) + \mathbf{S}_p^{-1} \mathbf{p} + \frac{\partial \mathbf{d}}{\partial \mathbf{p}}^T \mathbf{S}_X^{-1} \mathbf{d} \right)
\end{aligned}$$

Constrained AAMs

- Comparison of constrained and unconstrained AAM search



Conclusions

- Combined Appearance Models provide an effective means to separate identity and intra-class variation
  - Can be used for tracking and face classification
- Active Appearance Models enables us to effectively and efficiently update the model parameters

Conclusions (cont.)

- Approach dependent on starting approximation
- Cannot directly handle cases well outside of the training set (e.g. occlusions, extremely deformable objects)

End