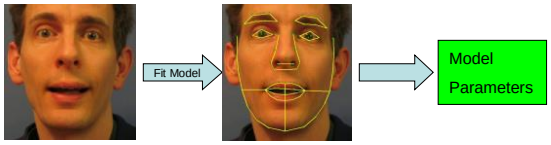
Image Segmentation using Statistical Shape Models

Prof Tim Cootes
Centre for Imaging Sciences
The University of Manchester

Aim of Research

Extract useful information from images
- often using statistical models
- 'explain' the image

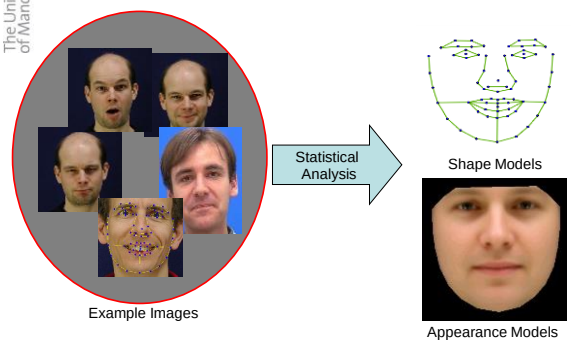


Model encodes information about object appearance and variability

Why is it difficult?

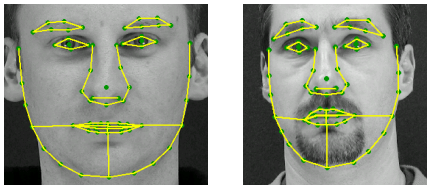
- Wide variation in shape and appearance

Model Building



Building Shape Models

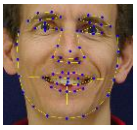
- Require labelled training images
  – landmarks represent correspondences

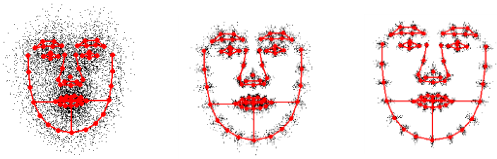


$$\mathbf{x} = (x_1, \cdots, x_n, y_1, \cdots, y_n)^T$$

Aligning Shapes

- Generalised Procrustes Analysis
  – Align each shape to the mean





Unaligned | Align with translation | Align with similarity

Building Shape Models

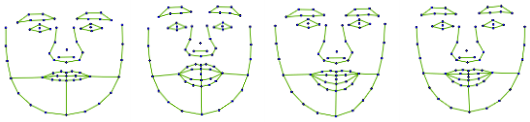
- Given aligned shapes, $\{\mathbf{x}_i\}$
- Apply PCA
  - Compute mean and eigenvectors of covar.

$$\mathbf{x} = \bar{\mathbf{x}} + b_1\mathbf{p}_1 + b_2\mathbf{p}_2 + b_3\mathbf{p}_3 + \cdots$$

- **P** – First *t* eigenvectors of covar. matrix
- **b** – Shape model parameters

Face Model Modes

- 100 people, 4 images each



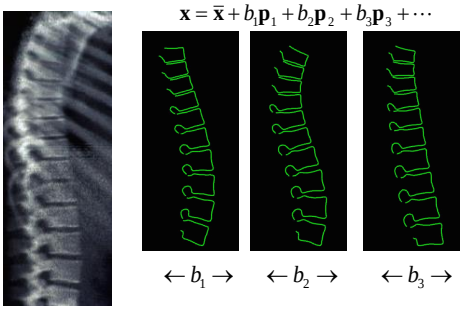
Varying b_1 Varying b_2 Varying b_3 Varying b_4

$$\mathbf{x} = \bar{\mathbf{x}} + b_1\mathbf{p}_1 + b_2\mathbf{p}_2 + b_3\mathbf{p}_3 + \cdots$$

Spine Shape Model

Martin Roberts, Judith Adams

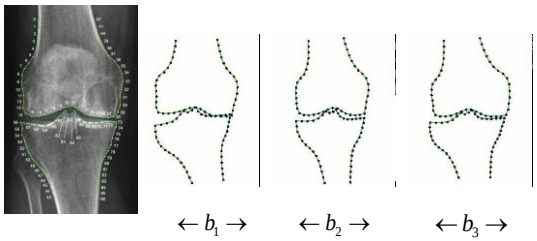
$$\mathbf{x} = \bar{\mathbf{x}} + b_1\mathbf{p}_1 + b_2\mathbf{p}_2 + b_3\mathbf{p}_3 + \cdots$$



$\leftarrow b_1 \rightarrow$ $\leftarrow b_2 \rightarrow$ $\leftarrow b_3 \rightarrow$

Knee shape model

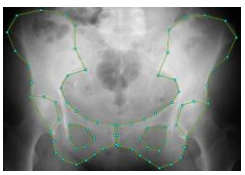
Xenios Milidonis & ARCOGEN

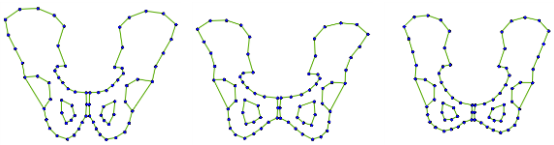


$\leftarrow b_1 \rightarrow$ $\leftarrow b_2 \rightarrow$ $\leftarrow b_3 \rightarrow$

Shape Model of the Pelvis

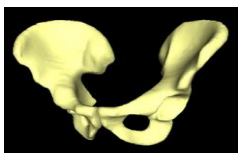
Raja Ebsim

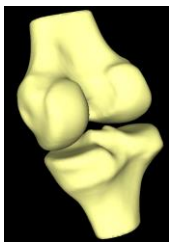




$\leftarrow b_1 \rightarrow$ $\leftarrow b_2 \rightarrow$ $\leftarrow b_3 \rightarrow$

3D Models

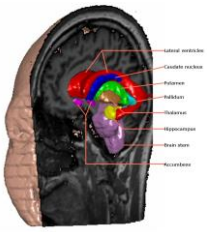


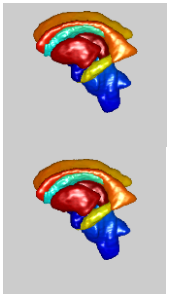


Generated by Imorphics Ltd

Brain Structures

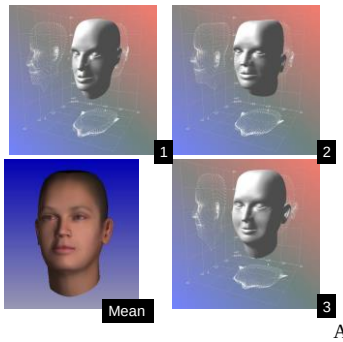
Kola Babalola





3D Face Model

Trained on approx. 1000 people



Angela Caunce

Appearance Models

- Model both shape and texture
- Use all image information

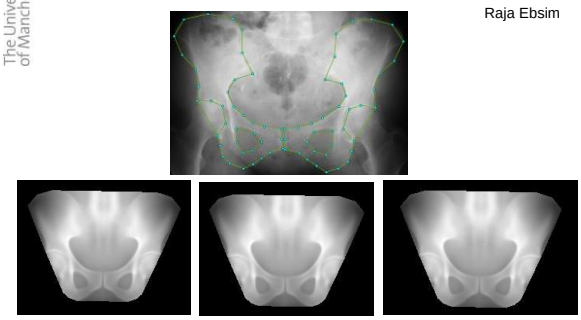
Global Face Model

- 400 images from 100 different people

Note: Mixes ID, expression, head pose etc

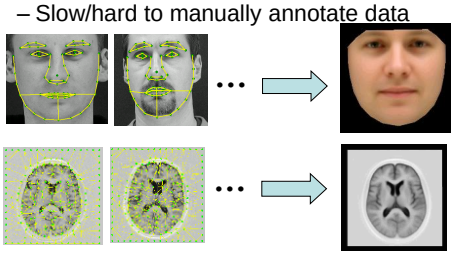
Appearance Model of Pelvis

Raja Ebsim



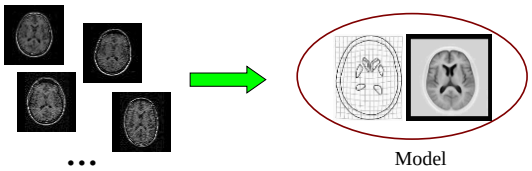
Automatic Annotation

- Accurate correspondences required to build shape/appearance models
  - Slow/hard to manually annotate data



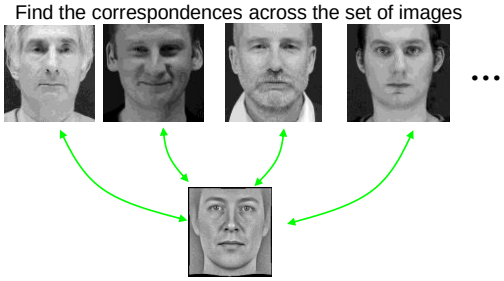
Goal: Fully Automatic System

- Build models from unlabelled images



Approach

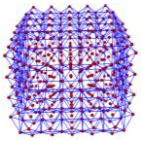
Find the correspondences across the set of images

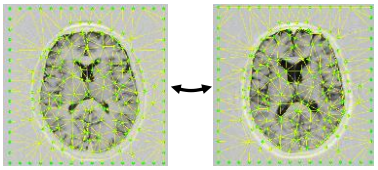


Construct model in an 'average' reference frame

Representation of Deformation

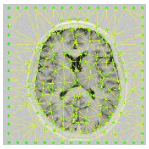
- Use piece-wise linear warp field
  - Triangular/Tetrahedral mesh
  - Simple, compact, efficient
  - Trivially invertible





Groupwise Algorithm

- Initialisation: Affine registration
- Generate control points
- Repeat
  - Build model from current data
  - For each image
    - Optimise positions of control points
- Until happy/dead/conference deadline etc



Registering Faces

- 293 individuals from XM2VTS
- Evolution of robust estimate of mean:

Example Modes

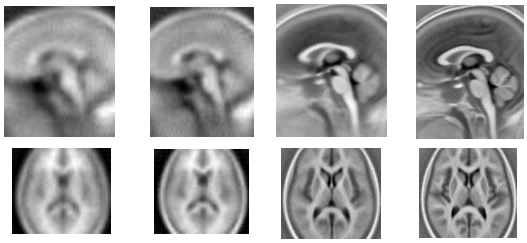
Varying appearance model parameters

(Note shadowing caused by glasses)

Modes of model built from images without glasses:

3D Registration

- Registering 270 3D MR Brain Images
- Evolution of the model mean:



Initialisation

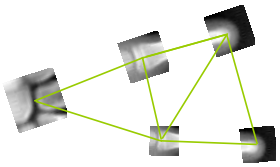
- Affine registration not always sufficient

Mean after affine registration

- Problem:
  - Many similar structures, so many local minima

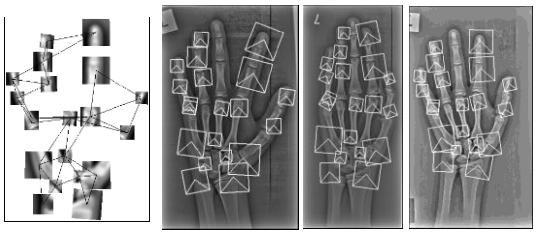
Improved Initialisation

- Parts+Geometry models can efficiently consider many candidates
- Automatically construct parts+geometry model to initialise dense registration



Pei Zhang

Results of Parts+Geometry Matching



Model

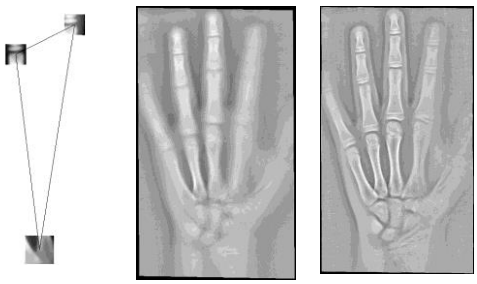
Matches on three images

Pei Zhang

Automatic Model building

- Challenge is to select good set of parts
- Use Genetic Algorithm style optimisation:
  - Create set of different models
    - Each a random selection of parts
  - Repeat
    - Evaluate each model
    - Discard worst 50%
    - Combine good examples to form new set
  - Until happy

Best 3 part model

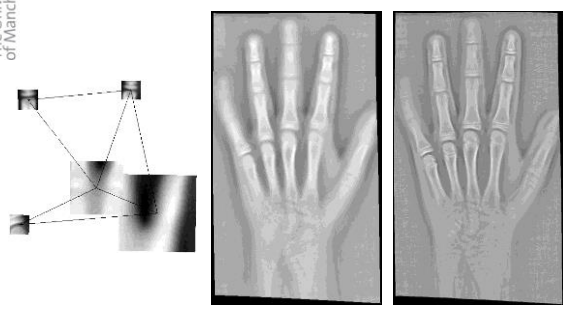


Model

Initial Mean

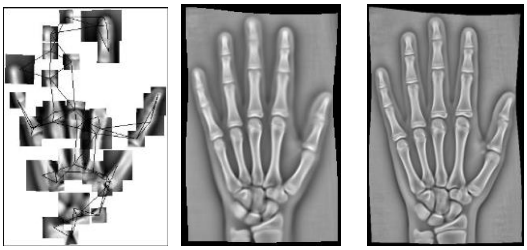
Mean after dense registration

Best 5 Part Model



Model | Initial Mean | Mean after dense registration

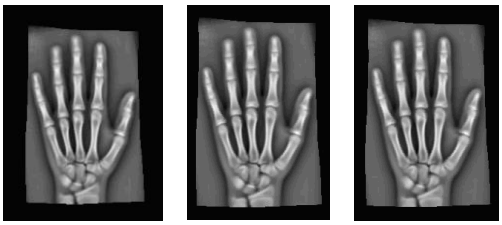
Best Model



P+G Model | Initial Mean | Mean after dense registration

Shape Models

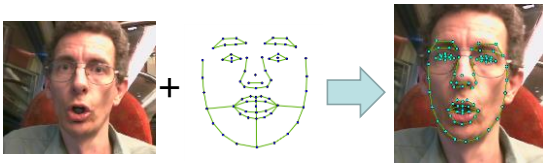
- Model from automatic registration



Pei Zhang

Image Interpretation

- Match model to new image
- Allows analysis of shape of object



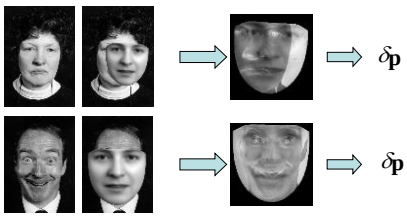
Matching Algorithms

Typical approach:

- Global search to find approx. position
- Local search:
  - Optimise pose/parameters of model
  - Maximise fit of model to image data

Model Matching using Regression

- Estimate parameter update from current image sample



Diff. in Ref Frame

Estimating updates

- Assume functional relationship

$$\delta\mathbf{p} = F(\mathbf{s})$$

s = normalised intensities, or residuals

- Learn function from displaced training examples

$$\{\delta\mathbf{p}_i\} \qquad \{\mathbf{s}_i = \mathbf{s}(\mathbf{p}_{true} + \delta\mathbf{p}_i)\}$$

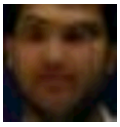
Random perturbations — Image samples

- Simplest approach: Linear Regression

$$\delta\mathbf{p} = \mathbf{R}\mathbf{s}$$

Active Appearance Model Algorithm

- Initial estimate $\mathbf{I}_m(\mathbf{p})$
- Start at coarse resolution
- At each resolution
  - Measure residual error, **r**(p)
  - predict correction $\delta\mathbf{p} = \mathbf{R}\mathbf{r}$
  - $\mathbf{p} \Rightarrow \mathbf{p} - \delta\mathbf{p}$
  - repeat to convergence



AAM Tracking

- Sequence of AAMs with increasing resolution
- Generic – trained on range of people
- Search each frame in a few ms

Mircea Ionita, Phil Tresadern

Non-linear Regression

- Boosted Haar features: $\delta p_j = \sum_{i=1}^{n} f_i(H_i(\mathbf{s}))$
- Random Forests: $\delta\mathbf{p} = \frac{1}{n}\sum_{i=1}^{n} T_i(H_i(\mathbf{s}))$
- Boosted Ferns
- …

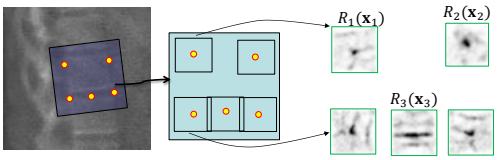
Boosted Sequences of Regressors

- Extension of multi-resolution approach
  - No iterations
- Supervised Descent Method [Xiong:CVPR2013]
  - Linear regression on non-linear features
- Explicit Shape Regression [Cao:CVPR12]
  - Boosted ferns/trees on pixel difference features

Local Model Matching

- AAM and variants: Predict whole shape
  - Or parts of shape
- Alternative: Predict position of each point
  - Lower dimensional output space
  - Easier to train
  - Potential to be more robust

Local Model Matching



Find shape and pose parameters to optimise

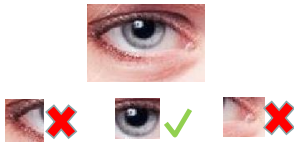
$$Q(\mathbf{b},\mathbf{t}) = \sum_{i=1}^{i=n} R_i(T_{\mathbf{t}}(\bar{\mathbf{x}}_i + \mathbf{P}_i\mathbf{b}))$$

Shape param.s Pose params

Classification vs Regression

Classification:

- Is this the point?



Classification vs Regression

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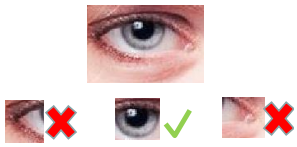
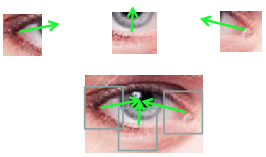


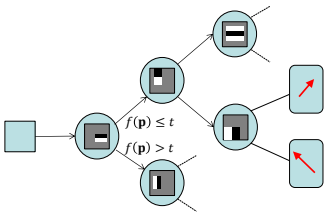
Regression:

- Where is the point?



Finding Points using Regression Voting

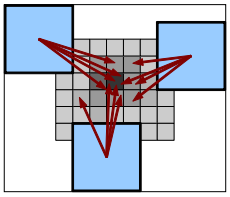
- Train "Random Forest" to predict offsets

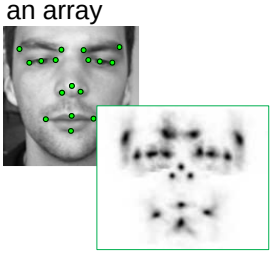


Each patch fed into each tree to predict offset and weight

Finding Points using Regression Voting

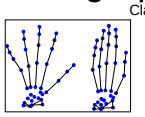
- Scan regressor across ROI
- Each patch produces 1 vote per tree
- Accumulate votes in an array



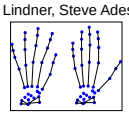


Hand Radiographs

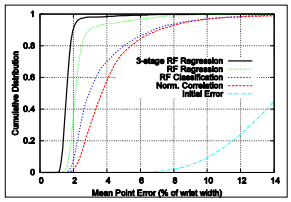
Claudia Lindner, Steve Adeshina



Varying b_1



Varying b_2



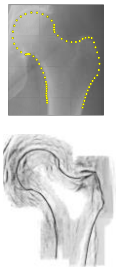
BoneFinder

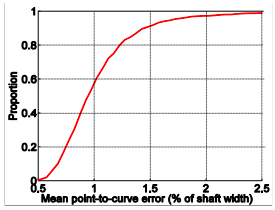
Running full automatic search...

Lindner et al., IEEE Transactions on Medical Imaging, 2013.

Fully automated femur detection

- Tested on 839 radiographs (ARCOGEN)



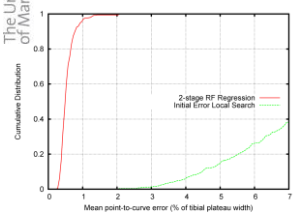


Error <0.9mm for 99% of cases

Claudia Lindner

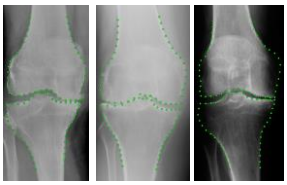
Knee Radiographs

Claudia Lindner, Xenios Milidonis



Fully automatic search results using AP knee radiographs.

Mean point-to-curve error:
< 1mm for 99% of 500 images

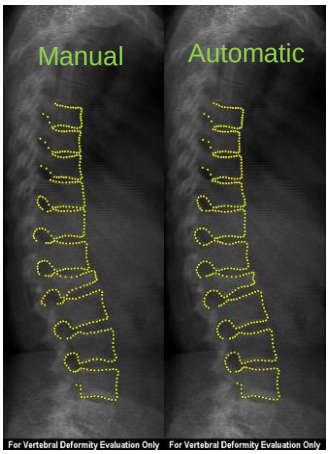


Median 95%ile 99%ile

Vertebral Fractures

Paul Bromiley, Judith Adams

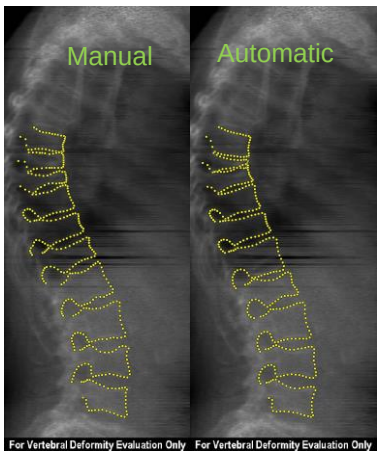
T7:	
T8:	
T9:	
T10:	
T11:	
T12:	
L1:	Grade 3
L2:	
L3:	
L4:	



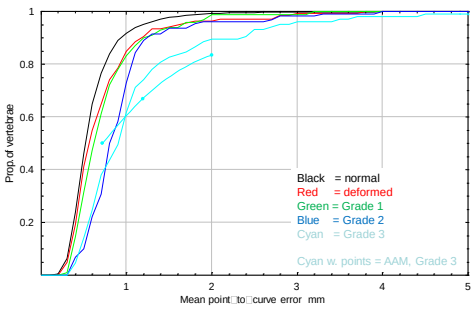
Vertebral Fractures

Paul Bromiley, Judith Adams

T7:	
T8:	Grade 3
T9:	Grade 3
T10:	
T11:	Grade 1
T12:	Grade 2
L1:	Grade 1
L2:	
L3:	Grade 1
L4:	Grade 1

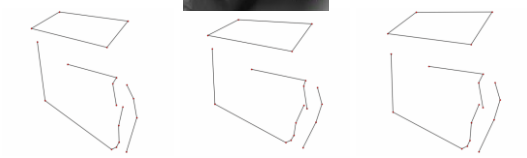


Performance vs. Classification



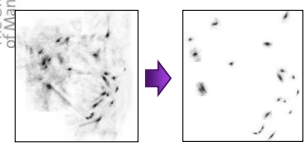
Landmarks on Cephalograms

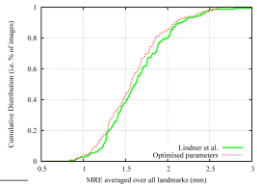
Claudia Lindner



Mode 1 Mode 2 Mode 3

ISBI Grand Challenge 2015

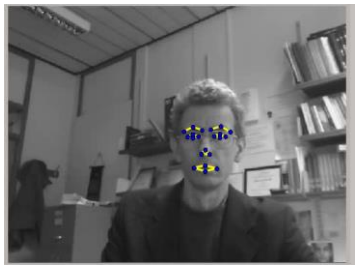




Landmark	MRE (mm)
AVERAGE	1.67 ± 1.65

Intra-observer variability		Inter-observer variability
Doctor1	Doctor2	Doctor1 vs Doctor2
1.73 ± 1.35	0.90 ± 0.89	1.38 ± 1.55

Facial Feature Tracking



Robust Facial Tracking

Conclusion

- Shape models powerful tools for image analysis
- Fast, robust, accurate matching algorithms now available

Tools available: www.bone-finder.com

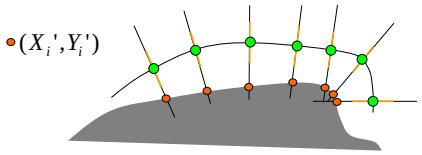
Shape modelling/ASM source code:
uomasm.sourceforge.net

Appearance modelling/AAM tools:
(See my website)

P.S. It works on faces too

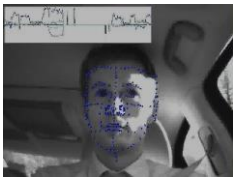
Active Shape Model

- Local optimisation
- Initialise near target
  - Search nearby for best match, **X**'
  - Update parameters to match to **X'**.



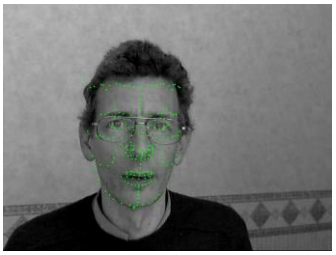
Matching 3D ASMs

- Search for each point independently
  - Local model depends on current pose
- Estimate shape param.s + projection



Angela Caunce

Face Tracking with a 3D Model



Angela Caunce