1

ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT
Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

Statistical Shape Models for Medical Image Analysis

Tobias Heimann

Medical and Biological Informatics
German Cancer Research Center, t.heimann@dkfz.de

With contributions from:

Martin Styner – Medical Image Display and Analysis Group, University of North Carolina
Marleen de Bruijne – Image Group, IT University of Copenhagen
Tim Cootes – Imaging Science and Biomedical Engineering, University of Manchester

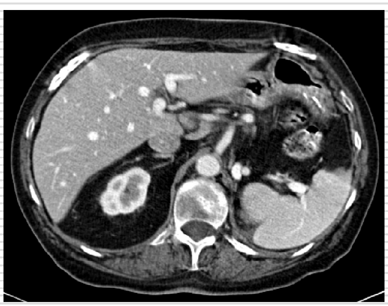
International Summer School **Advances in Medical Imaging**, Aghios Nikolaos, Crete, Greece, 24-29 April 2006 1

2

ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT
Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

Motivation

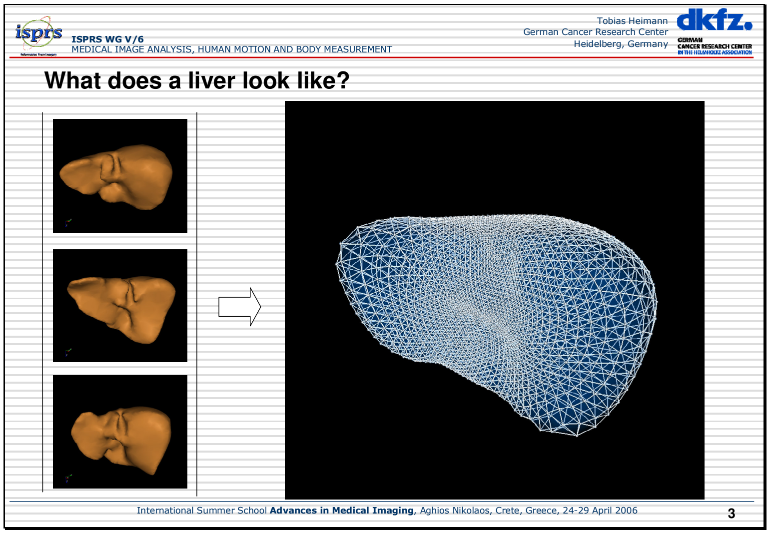
Classical Problem in Segmentation:
Insufficient contrast, noise and artifacts lead to incomplete information



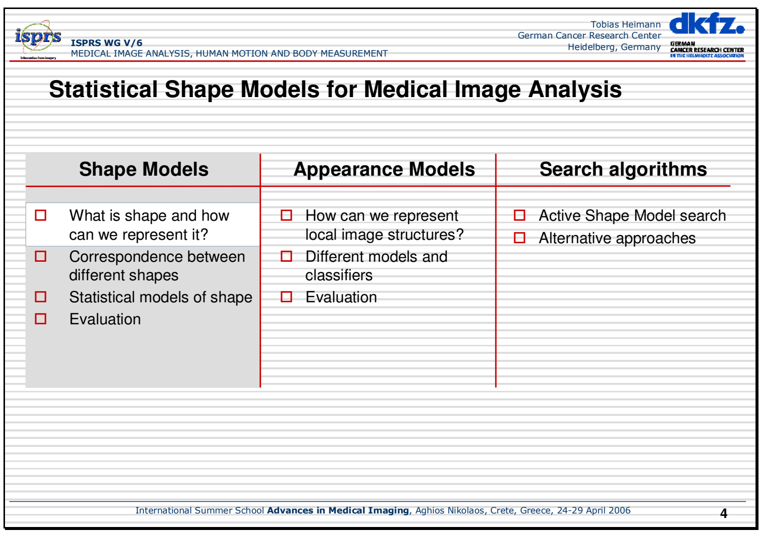
Complex Segmentation tasks can only be solved using specific domain knowledge

International Summer School **Advances in Medical Imaging**, Aghios Nikolaos, Crete, Greece, 24-29 April 2006 2

3


ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT
Tobias Heimann
German Cancer Research Center
Heidelberg, Germany
What does a liver look like?
International Summer School Advances in Medical Imaging, Aghios Nikolaos, Crete, Greece, 24-29 April 2006
3

4


ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT
Tobias Heimann
German Cancer Research Center
Heidelberg, Germany
Statistical Shape Models for Medical Image Analysis
Shape Models
What is shape and how can we represent it?
Correspondence between different shapes
Statistical models of shape
Evaluation
Appearance Models
How can we represent local image structures?
Different models and classifiers
Evaluation
Search algorithms
Active Shape Model search
Alternative approaches
International Summer School Advances in Medical Imaging, Aghios Nikolaos, Crete, Greece, 24-29 April 2006
4

5

ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT

Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

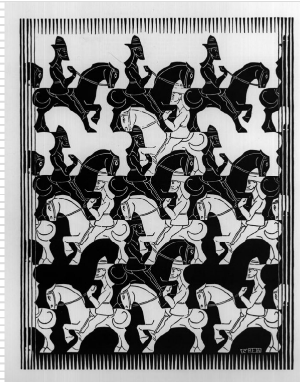
A priori knowledge about shape

*Whence and what art thou,
execrable shape?*

- John Milton (1667), Paradise Lost II, 681

Definition of Shape:

Invariant against similarity transformations (translation, rotation, scaling)



6

ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT

Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

Shape representation

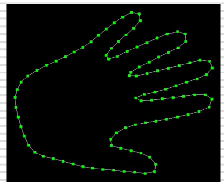
How to store shape information in computers?

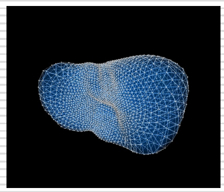
Explicit representation	Implicit representation
☐ Point Distribution Models	☐ Isocontours on scalar functions
☐ Fourier descriptors	
☐ Spherical Harmonics	
☐ Medial representation	

7

Point distribution models (PDMs)

- Cloud of points on object contour/surface
- Very versatile, arbitrary topology
- Simple to store as list of coordinates
- Connectivity not required, but useful for practical application
- Often named „landmarks“

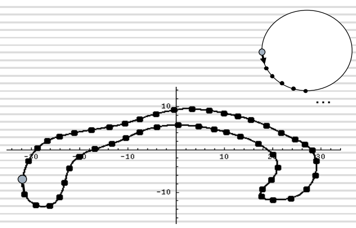




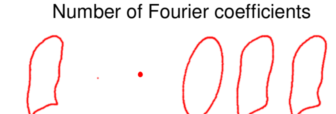
8

Fourier descriptors

- View closed 2D contour as complex periodic function
- Parameterization over arc-length (0..2π)
- Calculate coefficients with standard Fourier transform
- Number of coefficients determines accuracy of representation
- Inherent correspondence and alignment between shapes



Number of Fourier coefficients



Martin Steyner, UNC

9

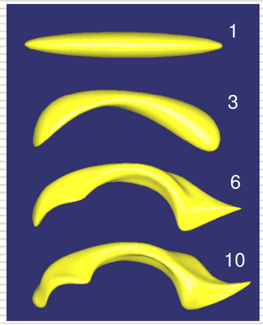
ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT
Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

Spherical Harmonics (SPHARM)

- 3D version of Fourier synthesis
- Only for models with spherical topology
- Shape as addition of several basis functions
- Hierarchical description (coarse to fine)
- Inherent correspondence and alignment between shapes

$$\begin{matrix} x \\ y \\ z \end{matrix} \longrightarrow \boldsymbol{r}(\theta,\phi) = \begin{pmatrix} x(\theta,\phi) \\ y(\theta,\phi) \\ z(\theta,\phi) \end{pmatrix}$$

$$\boldsymbol{r}(\theta,\phi) = \sum_{k=0}^{K} \sum_{m=-k}^{k} \boldsymbol{c}_k^m Y_k^m(\theta,\phi)$$

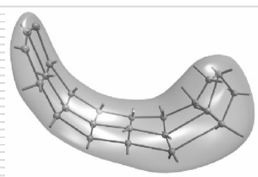


Martin Steyner, UNC

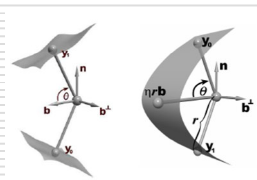
10

ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT
Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

Medial Representation (M-Reps)



- Based on skeleton of shape
- Defined by a chain or grid of atoms with specific position and radius
- Two corner points per atom to compute boundary efficiently
- Different combination of atoms linked in multi-scale fashion
- Easy to interpret shape changes
- Generative model (to avoid skeletonization problems)



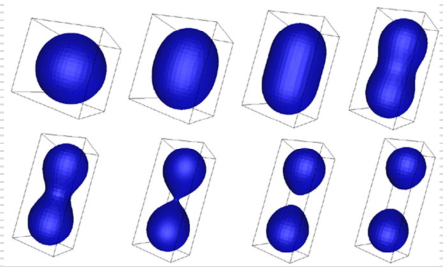
Medical Image Display & Analysis Group, UNC

11

Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

Implicit Representations

- Isocontour on a scalar function (distance function)
- Can model topology changes
- No explicit correspondences



Images by Paul Bourke

12

Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

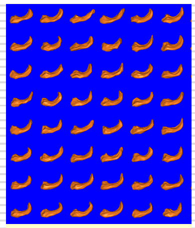
Statistical Shape Models for Medical Image Analysis

Shape Models	Appearance Models	Search algorithms
What is shape and how can we represent it?	How can we represent local image structures?	Active Shape Model search
Correspondence between different shapes	Different models and classifiers	Alternative approaches
Statistical models of shape	Evaluation	
Evaluation		

13

The correspondence problem

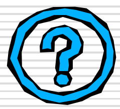
Landmarks on all training shapes have to correspond!



Martin Steyner, UNC

What is "good correspondence"?

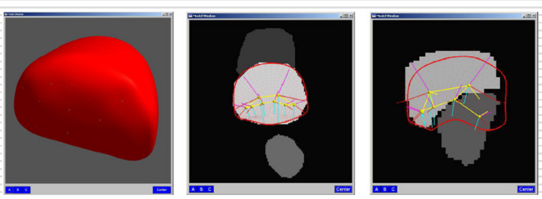
- Opinion of experts
- Points with same curvature
- Physical model (FEM)
- Good performance of shape model



14

Correspondence for M-Reps

- Template shape is fitted to all training samples
- Boot-strapping approach to refine model
- Correspondence defined by position of atoms
- Can the model be fitted adequately?
- Are the correspondences optimal for the model?

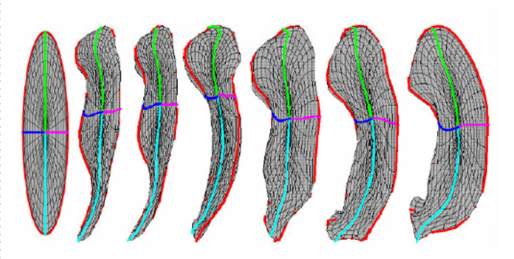


Medical Image Display & Analysis Group, UNC

15

Correspondence for SPHARM

- Alignment based on first order ellipsoid
- Point correspondences following the individual parameterizations r(θ, φ)



Martin Steyner, UNC

16

Correspondence for PDMs

Occam‘s Razor: The simplest model ist the best one!

- MDL = Minimum Description Length
- Simplest Model has minimum stochastic complexity
- Based on information theory
- Cost function ~ Sum of logarithmic variances

17

Correspondence by optimization

Spread landmarks equally on surface

⇓

- Create shape model
- Calculate MDL cost function
- Change landmark distribution

⇓

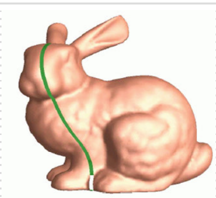
Until cost function converges at minimum

18

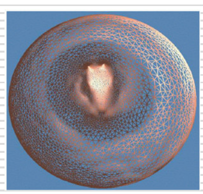
Spreading landmarks on surfaces…

Distribution in 3D difficult, since only a fraction of all points are valid

„Flattening“ of surface to be able to work with a compact 2D-parameter space



⇔

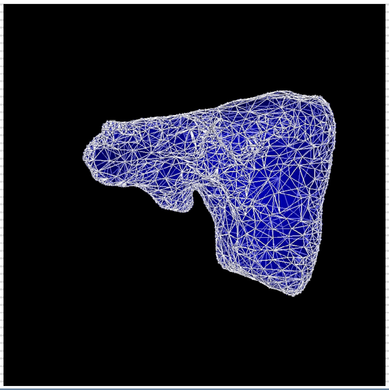


Images by X. Gu and Y. Wang

19

Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

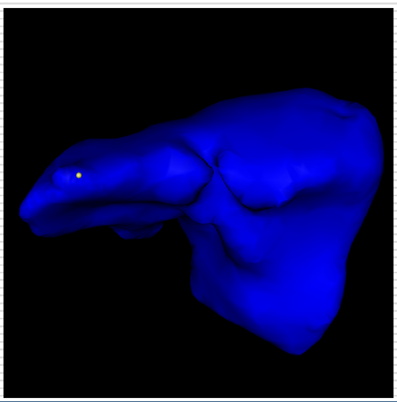
Creation of a parameterization



20

Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

Mapping from parameterization to mesh



21

Correspondence by optimization

Spread landmarks equally on surface

⇩

- Create shape model
- Calculate MDL cost function
- Change landmark distribution

⇩

Until cost function converges at minimum

22

Modifying landmark positions

Possibilities:

1. Change spherical landmarks for each shape (keep parameterizations)
2. Change parameterizations for each shape (keep spherical landmarks)

Consider:

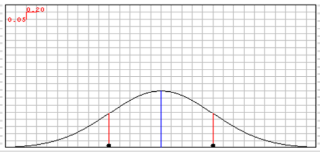
- Problem of overlapping triangles (one-to-one-constraint) against problem of crossing landmarks
- Parameterization can only be modified for certain regions, not for specific landmarks
- One global set of landmarks can be used to control landmark density

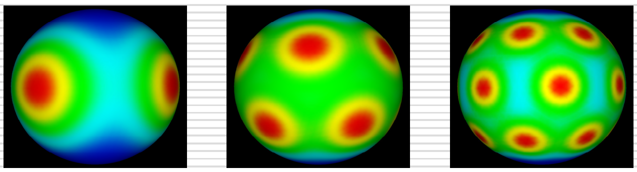
23

Re-parameterization

Gauss-kernel-approach:

- In a strictly local region points on the parameterization are moved in a specific direction
- Smooth transitions by using Gaussian envelope function





24

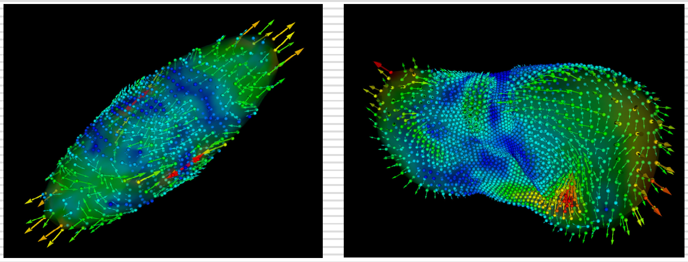
Determination of movement direction

Necessary steps:

1. Optimal direction for landmarks in 3D
   - MDL-Gradients
2. Best possible direction for landmarks on mesh surface
   - Projection
3. Best direction for points on parameterization
   - Spherical coordinates
4. Best direction for Gaussian kernel

25

Examples for MDL gradient fields



26

Correspondence by optimization

Spread landmarks equally on surface

⇩

- Create shape model
- Calculate MDL cost function
- Change landmark distribution

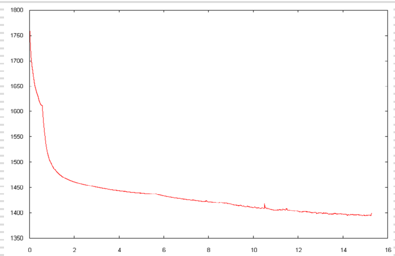
⇩

Until cost function converges at minimum

27

The optimization process

- Align all shapes at the beginning (optimize rotation)
- Use fixed step size
- Reduce kernel size in the course of optimization
- Terminate when cost function does not decrease anymore



28

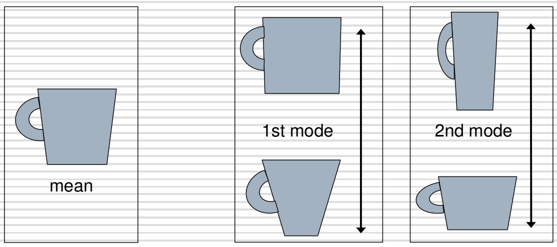
Statistical Shape Models for Medical Image Analysis

Shape Models	Appearance Models	Search algorithms
What is shape and how can we represent it?	How can we represent local image structures?	Active Shape Model search
Correspondence between different shapes	Different models and classifiers	Alternative approaches
Statistical models of shape	Evaluation	
Evaluation		

29

Shape modeling

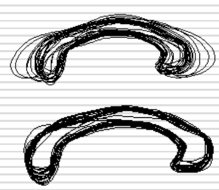
- Statistical analysis of a set of training shapes yields mean shape and several axes of variance
- „Shape learning“
- All statistics need common reference frame



30

Alignment of training shapes

- Using Moments
  - Match centers of gravity
  - Match principal axis of variance
- Using SPHARM
  - Match centers of gravity
  - Match first order ellipsoid
- Procrustes transform
  - Minimizes Sum-of-squares error between two point sets
  - Returns optimal rigid or similarity transform
  - Generalized version aligns an arbitrary number of shapes to unknown mean

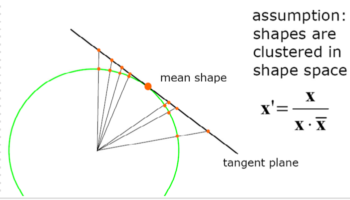


Martin Steyner, UNC

31

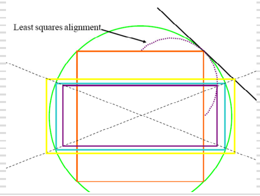
Scaling during alignment

- If shapes are translated to origin and normalized to unit size, they lie on a unit hypersphere
- Statistics should be computed on the surface of the sphere, non-Euclidean metric
- Approximate by ordinary statistics in tangent space



assumption: shapes are clustered in shape space

$$\mathbf{x}' = \frac{\mathbf{x}}{\mathbf{x} \cdot \bar{\mathbf{x}}}$$



Marleen de Bruijne, ITU

32

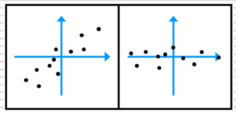
Capturing variances

1. Store each training sample as a (n*d)-dimensional vector
2. Build a landmark configuration matrix **L** from columns of all training samples
3. Calculate the mean landmark positions and build matrix **M** with all columns set to the mean
4. Calculate the covariance matrix: $\mathbf{\Sigma} = 1/(n-1)\,(\mathbf{L}-\mathbf{M})\,(\mathbf{L}-\mathbf{M})^T$
5. Perform a principal component analysis (PCA) on the covariance matrix **Σ**

$$\begin{vmatrix} X_1 \\ X_2 \\ \ldots \\ X_N \\ Y_1 \\ \ldots \\ Y_N \\ Z_1 \\ \ldots \\ Z_N \end{vmatrix}$$

33

The statistical shape model



- PCA aligns a dataset along the axes of maximum variance
- Result from PCA:
  (n_s-1) modes of variation with a displacement vector and a variance each (eigenvector and eigenvalue)
- Each training sample can be described by a linear combination of the mean and the displacement vectors:

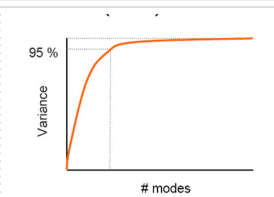
$$\mathbf{x}_i = \bar{\mathbf{x}} + \sum_{m=1}^{n_s-1} y_i^m \mathbf{p}^m$$

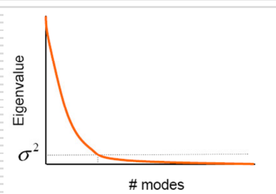
- Modes with low standard deviation can be neglected to reduce the number of parameters

34

How to chose the number of parameters?

- Chose threshold on variance to be explained by the model (e.g. 95%), rest is assumed to be noise
- Chose noise level (e.g. 1%) and consider all modes smaller than this level as noise
- Cross-validation, maximize log(P(test shapes | model))



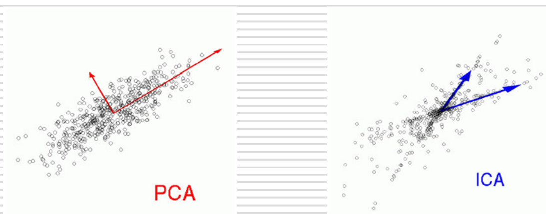


Marleen de Bruijne, ITU

35

Alternative decompositions: ICA

- Independent Component Analysis for blind source separation (Cocktail party problem)
- Shape instance is a mixture of deformation components
- PCA finds uncorrelated directions (2nd order statistics), ICA independent directions (higher order)



Marleen de Bruijne, ITU

36

Statistical Shape Models for Medical Image Analysis

Shape Models	Appearance Models	Search algorithms
What is shape and how can we represent it?	How can we represent local image structures?	Active Shape Model search
Correspondence between different shapes	Different models and classifiers	Alternative approaches
Statistical models of shape	Evaluation	
Evaluation		

37

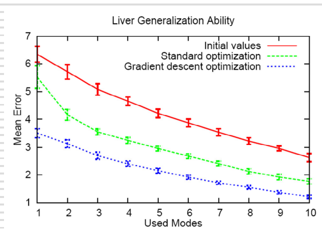
Evaluation of shape models

- Anatomically sensible correspondences
  - Not objective
  - Not necessarily the best model
- Compactness
  - „Low variances = good model“ is only an assumption, not proven
- Generalization ability
  - How well can the model represent new shapes?
- Specificity
  - Does the model only produce valid shapes?

38

Generalization ability

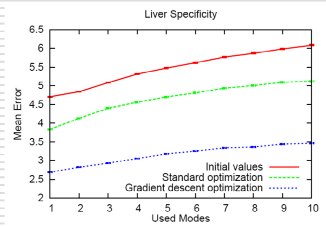
- Leave-one-out cross validation:
  - Build model from (n-1) examples
  - Approximate missing sample and calculate average landmark distance
  - Average results and determine standard error
- Repeat for different number of modes used for approximation



39

Specificity

- Analyze model variations:
  - Generate high number (10,000) of random shapes
  - For every instance, search for „closest shape“ in training set (minimum average landmark distance)
  - Average results and and determine standard error
- Repeat for different number of modes

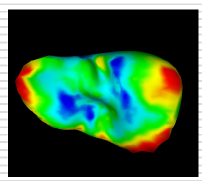


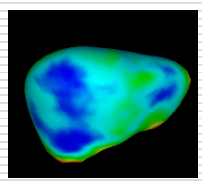
40

The Landmark Distribution Problem

For an objective comparison of different models:

- Variances underly strong local fluctuations
- Average distance to center changes with varying landmark distribution





Similar landmark distribution!

41

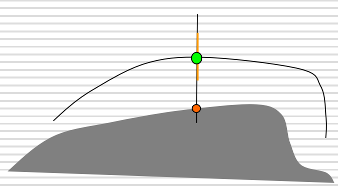
Statistical Shape Models for Medical Image Analysis

Shape Models	Appearance Models	Search algorithms
☐ What is shape and how can we represent it? ☐ Correspondence between different shapes ☐ Statistical models of shape ☐ Evaluation	☐ How can we represent local image structures? ☐ Different models and classifiers ☐ Evaluation	☐ Active Shape Model search ☐ Alternative approaches

42

Why do we need appearance models?

- ☐ Local appearance around landmarks needed to fit the model to new images
- ☐ Should describe the boundary

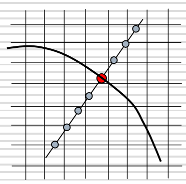


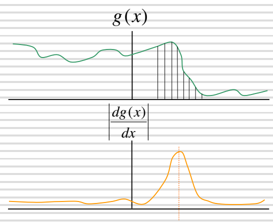
Tim Cootes, UM

43

Boundary description by strongest edge

- Sample a line perpendicular to model contour/surface (profile)
- Search for highest gradient magnitude
- Applied and proven in deformable models
- Easy to implement





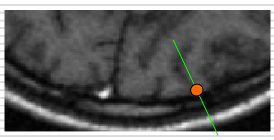
$$\frac{dg(x)}{dx} = 0.5(g(x+1) - g(x-1))$$

Tim Cootes, UM

44

The best solution?

- Sometimes true boundary position not on strongest edge…



- Use information from training data!
- Build statistical model of profiles:
  - Separate profile model for each landmark
  - Immediate gray values or their derivatives, possibly normalized
  - Sample profiles across boundary in all training images

Tim Cootes, UM

45

A statistical model of gray value profiles

- Analogous to shape model:

$$\mathbf{g}_i = (g_1, g_2, \ldots, g_k)^T$$

$$\overline{\mathbf{g}} = \frac{1}{N}\sum \mathbf{g}_i$$

$$\mathbf{\Sigma} = \frac{1}{N-1}\sum (\mathbf{g}_i - \overline{\mathbf{g}})(\mathbf{g}_i - \overline{\mathbf{g}})^T$$

$$p(\mathbf{g}_s) \propto \exp[-\tfrac{1}{2}(\mathbf{g}_s - \overline{\mathbf{g}})^T \mathbf{\Sigma}^{-1} (\mathbf{g}_s - \overline{\mathbf{g}})]$$

- Optimal position minimizes the Mahalanobis distance between the sampled profile g_s and the mean profile $\overline{g}$

Marleen de Bruijne, ITU

46

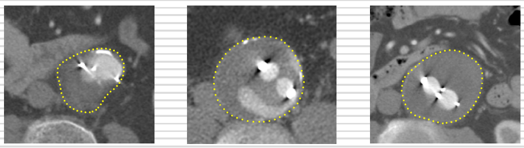
Statistical Shape Models for Medical Image Analysis

Shape Models	Appearance Models	Search algorithms
What is shape and how can we represent it?	How can we represent local image structures?	Active Shape Model search
Correspondence between different shapes	Different models and classifiers	Alternative approaches
Statistical models of shape	Evaluation	
Evaluation		

47

Problems with Gaussian appearance models

- Does not work well for low contrast objects with varying background (e.g. segmentation of abdominal aortic aneurysm)



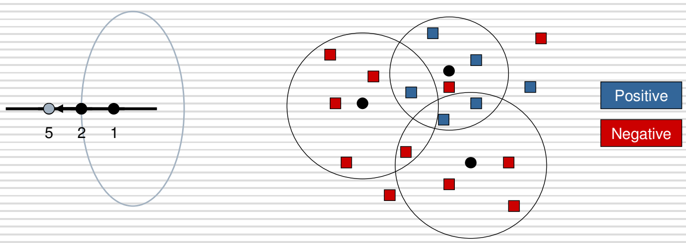
- Include negative examples („wrong positions")
- Estimate density non-parametrically

Marleen de Bruijne, ITU

48

A kNN-classifier for boundary description

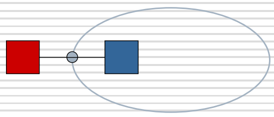
- Find k Nearest Neighbours to sampled profile
- Best position is the one with highest number of positive examples among neighbours



49

Region-based boundary detection

- Instead of explicit boundary modelling, learn to distiguish inside from outside object
- For each landmark in training data, sample appropriate regions of interest

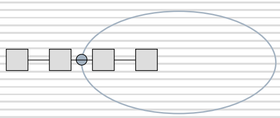


- Huge variety of potential features from classical pattern recognition (especially texture analysis)
- Use optimal feature selection for each landmark to acquire n best features

50

Finding the best fit with region-based classifiers

- Sample k regions of interest along the normal of each landmark



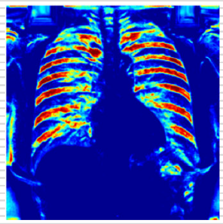
- Use favourite classifier to calculate probabilities g_i that ROI belongs to object
- Minimize cost function:

$$f(\mathrm{g}) = \sum_{i=-k}^{-1} g_i + \sum_{i=0}^{+k} (1 - g_i)$$

51

Using pixel classification

- Pre-calculate probability information for every pixel/voxel
- Use these values during model-search
- Can improve performance for complex search algorithms



Marleen de Bruijne, ITU

52

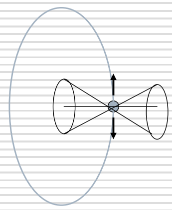
Statistical Shape Models for Medical Image Analysis

Shape Models	Appearance Models	Search algorithms
What is shape and how can we represent it?	How can we represent local image structures?	Active Shape Model search
Correspondence between different shapes	Different models and classifiers	Alternative approaches
Statistical models of shape	Evaluation	
Evaluation		

53

Evaluation of appearance models

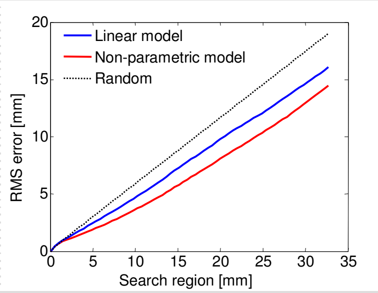
- Independent from search algorithm
- Test models on training data
- Which displacement from the boundary gives the best fit?
  ⇨ Ideally zero.
- For better significance:
  - Randomize position on surface
  - Randomize normal vector



54

Sum of squares error analysis

- Calculate RMS error for varying search regions

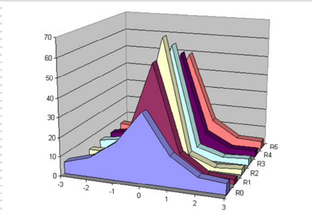


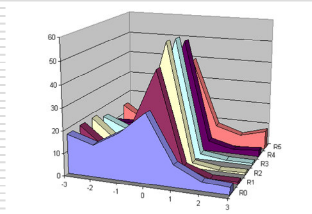
Marleen de Bruijne, ITU

55

Histogram analysis

- Use fixed search region and display distribution of displacements
- Allows detection of skew problems





56

Statistical Shape Models for Medical Image Analysis

Shape Models	Appearance Models	Search algorithms
What is shape and how can we represent it?	How can we represent local image structures?	Active Shape Model search
Correspondence between different shapes	Different models and classifiers	Alternative approaches
Statistical models of shape	Evaluation	
Evaluation		

57

Active Shape Model search

- Iterative approach with local landmark search
- Initialize model and repeat:
  - Find optimal displacements for each landmark independently
  - Retain shape and find best matching pose **T**
  - Fix **T** and find best matching shape parameters
  - Update landmarks

58

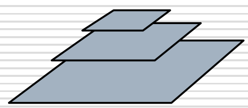
Optimizing shape parameters

- Simple matrix multiplication: $\mathbf{b} = \mathbf{P}^T (T^{-1}(\mathbf{X}) - \bar{\mathbf{x}})$
- Variations should be limited!
- Hard constraints
  - Restrict each mode independently: $|b_i| \leq 3\sqrt{\lambda_i}$
  - Restrict variation of complete shape: $\left(\sum_{i=1}^{t} \frac{b_i^2}{\lambda_i} \right) \leq M_t$
- Soft constraints
  - Penalize large $|b_i|$

59

Extension: multi-resolution search

- Train models at each level of pyramid
  - Gaussian pyramid with step size 2
  - Use same points but different local models
- Start search at coarse resolution
  - Refine at finer resolution
- Robust behaviour even for large initial deviations



Tim Cootes, UM

60

Extension: landmark weighting

- Weight landmarks in pose and shape optimization
- Different weighting schemes:
  - Size of displacement
  - Goodness of fit for the appearance model
  - Reliability of the appearance model
- More robust against outliers

61

ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT

Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

Active Shape Models

- Pros:
  - Fast
  - Works well on images with consistent shape and appearance
  - Extension to higher dimensions straightforward
- Cons:
  - Requires good initialization
  - Sparse use of image information
  - Linear model
  - PDM allows for self-intersections and other illegal shapes

Marleen de Bruijne, ITU

International Summer School **Advances in Medical Imaging**, Aghios Nikolaos, Crete, Greece, 24-29 April 2006 61

62

ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT

Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

Statistical Shape Models for Medical Image Analysis

Shape Models	Appearance Models	Search algorithms
What is shape and how can we represent it?	How can we represent local image structures?	Active Shape Model search
Correspondence between different shapes	Different models and classifiers	Alternative approaches
Statistical models of shape	Evaluation	
Evaluation		

International Summer School **Advances in Medical Imaging**, Aghios Nikolaos, Crete, Greece, 24-29 April 2006 62

63

Deformable models

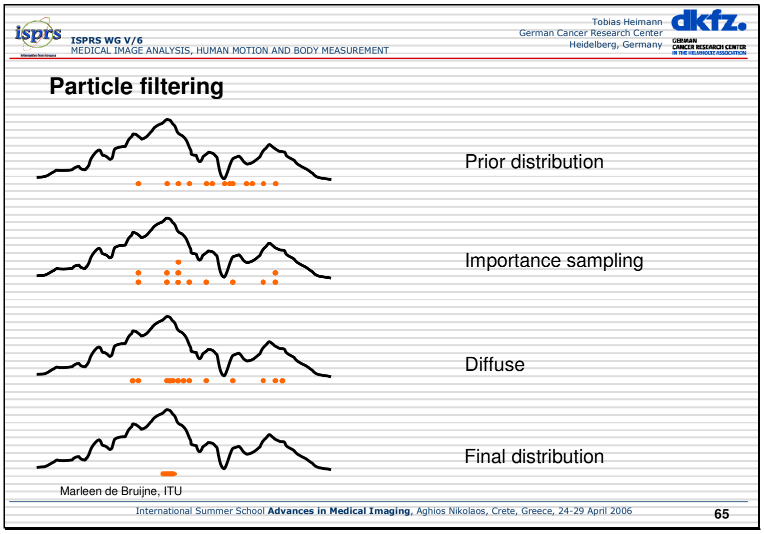
- In 2D also named „snakes“ or „live-wire“
- Find globally optimal solution by balancing two energies:
  - Internal energy: Shape constraints (stretching, bending)
  - External energy: Image forces (gradient, gray-value)
- Non-iterative solution using dynamic programming for 2D
- …but not for 3D

64

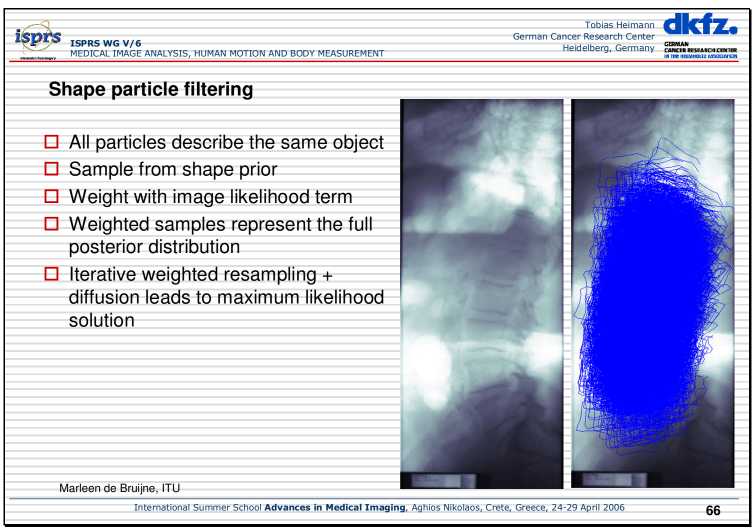
Combination with 3D shape model

- Use external energies from appearance model
  - Weight with distance to current position
  - Attract to plane, not to point (allow landmark to slide)
- Internal energy:
  - Sum of squared differences between edge lengths in deformable model and shape model
- Optimize pose with point registration method
- Optimize point positions + shape parameters using cunjugate gradient or similar

65


ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT
Tobias Heimann
German Cancer Research Center
Heidelberg, Germany
Particle filtering
Prior distribution
Importance sampling
Diffuse
Final distribution
Marleen de Bruijne, ITU
International Summer School Advances in Medical Imaging, Aghios Nikolaos, Crete, Greece, 24-29 April 2006
65

66


ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT
Tobias Heimann
German Cancer Research Center
Heidelberg, Germany
Shape particle filtering
All particles describe the same object
Sample from shape prior
Weight with image likelihood term
Weighted samples represent the full posterior distribution
Iterative weighted resampling + diffusion leads to maximum likelihood solution
Marleen de Bruijne, ITU
International Summer School Advances in Medical Imaging, Aghios Nikolaos, Crete, Greece, 24-29 April 2006
66

67

ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT

Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

References

- T.F. Cootes, C.J. Taylor, D.H. Cooper, J. Graham: Active shape models – their training and application. CVIU 61, pp. 38-59, 1995.
- G. Gerig, M. Styner , D. Weinberger, D. Jones , J. Lieberman: Shape Analysis of brain ventricles using SPHARM, Proc. MMBIA, pp. 171-178, 2001.
- S.M. Pizer, P.T. Fletcher, S. Joshi, A. Thall et al.: Deformable M-Reps for 3D medical image segmentation. IJCV 55 (2/3), pp. 85-106, 2003.
- R.H. Davies, C.J. Twining, T.F. Cootes, J.C. Wateron, C.J. Taylor: A minimum description length approach to statistical shape modelling. TMI 21, pp. 525-537, 2002.
- T. Heimann, I. Wolf, T. Williams, H.-P. Meinzer: 3D active shape models using gradient descent optimization of description length. Proc. IPMI, pp. 566-577, 2005.
- C.R. Goodall: Procrustes methods in the statistical analysis of shape. Journal of the Royal Statistical Society 53, pp. 285-339, 1991.
- T.F. Cootes, C.J. Taylor: Active shape model search using local grey-value models – a quantitative evaluation. Proc. BMVC, pp. 639-648, 1993.
- B. van Ginneken, A.F. Frangi, J.J. Staal, B.M. ter Haar Romeny, M.A. Viergever: A non-linear gray-level appearance model improves active shape model segmentation. IEEE workshop MMBIA, pp.205-212, 2001.

68

ISPRS WG V/6
MEDICAL IMAGE ANALYSIS, HUMAN MOTION AND BODY MEASUREMENT
Tobias Heimann
German Cancer Research Center
Heidelberg, Germany

References

- B. van Ginneken, A.F. Frangi, J.J. Staal, B.M. ter Haar Romeny, M.A. Viergever: Active shape models with optimal features. TMI 21, pp. 924-933, 2002.
- J. Weese, M. Kaus, C. Lorenz, S. Lobregt et al.: Shape constrained deformable models for 3D medical image segmentation. Proc. IPMI, pp. 380-387, 2001.
- M. de Bruijne, M. Nielsen: Shape particle filtering for image segmentation. Proc. MICCAI, pp. 168-175, 2004.