Knowledge driven segmentation of cardiovascular images

Boudewijn Lelieveldt, PhD
Division of Image Processing,
department of Radiology, Leiden University Medical Center

Introduction

- Introduction: why prior knowledge?
- Knowledge guided image processing
  - Model driven
  - Data driven
  - High level reasoning
- Future directions

Problem: amount of data

Rest Stress
Goal: automated segmentation

- Less work!!
- More objective
  - Less difference between observers
  - Less difference in repeated measurements
- More reproducible
  - Easier to compare with others
  - Easier to perform follow ups
  - Less patients in trial

Why knowledge?

- Robust segmentation only possible using knowledge about:
  - Anatomical shape + shape variation + motion
  - Spatial context of organs
  - Intensity and data characteristics
  - Behavior of your algorithms
- Modality independent:
  - Current applications:
    - Cardiac MR
    - Cardiac CT
    - LV Angiography
    - Echocardiography

Introduction: why knowledge?

- Robust segmentation only possible using knowledge about:
  - Anatomical shape + shape variation + motion
  - Spatial context of organs
  - Intensity and data characteristics
  - Behavior of your algorithms
- Modality independent:
  - Current applications:
    - Cardiac MR
    - Cardiac CT
    - LV Angiography
    - Echocardiography

General approach

- Tackle KGIP from three angles:
  - Model driven
    - Statistical shape models
      - Segmentation
      - Diagnosis
    - 3D thorax template
  - Data driven
    - Autonomous vehicle
  - High level reasoning
    - Multi-agent systems
    - Data fusion
General approach

- Tackle KGIP from three angles:
  - Model driven
    - Statistical shape models
      - Segmentation
      - 3D thorax template
  - Data driven
    - Autonomous vehicle
    - High level reasoning
      - Multi-agent systems
      - Data fusion

Active Shape Models

- Describe the shape of an organ in a population as
  - an average shape
  - a small number of characteristic shape variations

- DEMO

AAM Model Generation

Set of examples (N=20)  Average Shape  Average patch + eigenvariations
Appearance eigenvariations

Subsets: Male vs. female

Male (N=14)  Female (N=6)
Subsets: Ass. professors vs. others

- Ass. Professor (N=7)
- Non-ass. professor (N=14)

Active Appearance Models

- AAM’s can be used for contour tracing by:
  - initially positioning the model
  - fitting the model to the underlying image along ‘statistically plausible’ deformations

AAM Matching

- To match an AAM to an image requires:
  - a criterion function $e$
    - the RMS error of the ‘difference image’ between the model and the underlying image patch
  - a minimization procedure (Levenberg Marquardt / simplex)
  - derivatives of the criterion function with respect to all ‘optimizable’ parameters
    - can be estimated using multiple linear regression
    - examples of derivative images
2D + time modeling

- Modeling a heartbeat
  - Define point correspondence in 2D
  - Define “time-correspondence”
    - Divide interval between ED-ES-ED in fixed # steps
    - Interpolate in time (nearest neighbor)
**Echocardiography**

- Model initialization on average pose of training set
- Fully automated match for total sequence at once

Hans Bosch (TMI 2002)

**2D + time matching**

2D+time

van der Geest (JCMR 2004)
Multi-view analysis

- Why?
  - Different views of same organ are correlated
  - Different views are complementary

- Goal:
  - Exploit coherence and redundancy

Multi-view AAM: different geometries / phases

Multi-view AAM: Matching

- Minimize intensity error for all views:
  - shape and appearance are coupled
  - pose varies independently

Contour detection: multi-view AAM

Mehmet Uzumcu
Elco Oost
• Other applications: LV Angio

Elco Oost (FIMH 2005)

• Extension to 3D requires
  • Point correspondence
  • 3D procrustes alignment
  • 3D shape modeling
  • 3D matching mechanism

3D point correspondence
• Problem: no natural ordering in 3D
• Solutions:
  • Application specific manual (Mitchell, Stegman)
  • Through parameterization
    • Map to sphere
      – SPHARM (Brechbuhler)
      – MDL in 3D (Davies)
    • M-reps (Pizer group)
    • Object coordinate frame
  • Through registration
    • Deformable-mesh-to-binary-volume fitting (Kaus)
    • Non-rigid binary-binary registration (Frangi)

Application specific: manual
• Interpolate in through plane direction
• Fix orientation
• Radial sampling of each contour
• In cardiac MR case: problem: slice shift!
Point correspondence

- Non-rigid registration (Frangi, Rueckert)

Point correspondence

- 3D Mesh-to-binary registration (Kaus)
  - Represent one sample as triangle mesh
  - Rigidly align mesh to other samples
  - Non-rigid “snake-like” deformation, balancing an external with an internal energy
  - not restricted to spherical maps
  - non “optimal” parameterization

3D AAM Model Generation: MRI (Mitchell)
3D

4D AAM (Stegmann)

c9285_opt_hires_c.avi

ASM Matching

- Updates on scanline can be generated by
  - Edge detector
  - Gray level model
  - Classifier

ASM: Matching

- Vector $y$ = candidate points
- Vector $x = \bar{x} + \Phi b$ = current model state
- Align $y$ to current shape in model frame
- Scale $y$ with $1/\langle y \cdot \bar{x} \rangle$
- Update model parameters to match $y$
  
  \[ b = \Phi^T (y - \bar{x}) \]
- Apply constraints on $b$
  - Per parameter: $|b_i| \leq 3 \sqrt{\lambda_i}$
  - Mahalanobis distance: $\left( \sum_{i=1}^{3} \frac{b_i^2}{\lambda_i} \right) \leq M_t$
- Repeat until convergence
ASM: matching

- Active Shape Models
  - Point distribution model with matching

Movies: Tim Cootes

3D ASM Matching: van Assen approach

- Solution to voxel anisotropy
  - Piecewise 2D matching: update 3D model state with 2D image info
  - Enables anisotropic data
  - Enables multiple orientations in data

Iterative matching algorithm

- Next iteration
- Align model to update points cloud, change b-vector
- Propagate updates
- Map results to mesh
- Place in data set
- Intersect with image planes
- Classify surrounding pixels, and detect edge positions

3D ASM on densely sampled data

Hans van Assen
Application to sparse data

Radial LA  Multi-view (2SA+2LA)  SA

Hans van Assen, MEDIA 2006

3D ASM on sparse data: LA / SA fusion

Hans van Assen

ASM versus AAM

- 3 key differences:
  - ASM only uses texture in small region around landmark, AAM complete patch
  - ASM searches around current positions, AAM only under current position
  - ASM minimizes distance to boundary, AAM intensity difference

ASM versus AAM (Cootes)

- General
  - ASM is faster
  - AAM possible with fewer landmarks
  - AAM has “interpretable” convergence criterion
    - automatic failure detection (Thodberg, Stegmann)
**Statistical model limitations**

- How to balance training set?
- How many samples necessary?
- Manual annotation of training samples
- Local refinement necessary
- Dimensionality vs nr training samples

**3D ASM matching: Kaus approach**

- Deformable model based on energy
  \[ E = E_{ext} + E_{int} \]
- Shape model is integrated in \( E_{ext} \)
  - Term for PDM for each single surface
  - Term for connections between surfaces term
  - General shape & connectivity constraint term
- Local intensity model in \( E_{ext} \)
  - Every scanline has different feature detector (3 classes)

**General approach**

- Tackle KGIP from three angles:
  - Model driven
    - Statistical shape models
    - Segmentation
    - Diagnosis
    - 3D thorax template
  - Data driven
    - Autonomous vehicle
  - High level reasoning
    - Multi-agent systems
    - Data fusion
Computer-aided diagnosis

- Construct a model of normal motion
- Classify and localize deviations from normal

Demo

Detection of Abnormal Contractility Patterns

Case 1:

Case 2:
Rest-stress comparison

Avan Suinesiaputra (IPMI 2005)

General approach

- Tackle KGIP from three angles:
  - Model driven
    - Statistical shape models
    - 3D thorax template
  - Data driven
    - Autonomous vehicle
    - Multi-agent systems
  - High level reasoning
    - Data fusion
\[ b(x, y, z) = 1 - \frac{1}{w} \left[ \frac{f(x, y, z) - c}{\|f(x, y, z)\|} \right] \]

Deformable thorax template

CMR scan planning

- Left lung
- Right lung
- Air
- Other
CMR scan planning

Scout views → Short-axis view

Deformable thorax template

Manual

Automatic

Characteristic of Cardiac Respiratory Motion

- Induced by changes in lung volumes
- Motion occurs in inferior and anterior direction. (truly 3D)
- Heart is adjacent to left lung
Data fusion between scout & perfusion scans

General approach

- Tackle KGI² from three angles:
  - Model driven
    - Statistical shape models
    - Segmentation
    - Diagnosis
    - 3D thorax template
  - Data driven
    - Autonomous vehicle
    - High level reasoning
    - Multi-agent systems
    - Data fusion

- Data from 3 infarct patients
  - Model fitted to fused feature points from scouts / perfusion scan
  - Lung volume correlated between manual contours and model lung
A Virtual Exploring Robot for Left Ventricle Contour Detection

Sensor system (Perception devices)

Range Sensors
- Navigation
- Contour Detection

Image Sensor (camera)
- Recognition
- Region Labeling

Endocardium Detection

Luca Ferrarini, Hans Olofsen, Faiza Behloul
Epicardium delineation

General approach

- Tackle KGIP from three angles:
  - Model driven
    - Statistical shape models
    - Diagnosis
    - 3D thorax template
  - Data driven
    - Autonomous vehicle
  - High level reasoning
    - Multi-agent systems
    - Data fusion

MA image processing
MA image processing: agent relations

Example: conflict resolution

Example: test-hypothesis

Example: segmentation results
General approach

- Tackle KGIP from three angles:
  - Model driven
    - Statistical shape models
    - Diagnosis
  - Data driven
    - Autonomous vehicle
  - High level reasoning
    - Multi-agent systems
    - Data fusion

Why Image (data) fusion?

- Redundancy
- Reduces uncertainty
- Complementary
- New features
  - Complete “view”

Data fusion: the challenge

PET / MRI Symbolic data fusion
(Behloul e.a., TMI 2001)
To summarize ....

- Tackle KGIP from three angles:
  - Model driven
    - statistical shape and template models for segmentation, diagnosis
  - Data driven
    - High level reasoning
    - coordinating multiple segmentation sources
    - fusion of complementary information

What's next?

- Integrating the three main directions
- Automatic “quality control”
- Computer aided diagnosis
- Data fusion for segmentation and analysis

Acknowledgements

Rob van der Geest
Avan Suinesiaputra
Hans van Assen
Hans Bosch
Faiza Behloul
Luca Ferrari
Maribel Adame
Elco Cost
Julien Miles
Steve Mitchell
Mehmet Uzumcu
Ernst Bovenkamp
Alejandro Frangi
Hans Reiber
Milan Sonka