Lessons from Cardiac Ultrasound Image Analysis

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Cardiac vs. Tongue Image Processing

- Both organs are essentially muscle.
- The boundary of interest in both is a muscle-fluid boundary.
- Cardiac video sequence: order of 10 frames, 1 frame/sec, gated.
- Geometric parameters used in everyday diagnosis (cardiac).
- Automation desirable because of clinical setting (cardiac).
- Computational resources are not hard to come by (cardiac).
Cardiac Ultrasound Image Analysis

- Image analysis in cardiac images:
  - Segmentation (Endo- and Epicardium).
  - Motion Analysis.
  - Strain Analysis.

- Ultrasound segmentation research:
  - Edge Detectors (early 80s). Connected boundaries, local algorithms.
  - “Snake” + Template warping algorithms (late 80s - early 90s).
    Mildly-disconnected boundaries, local algorithms.
  - Probabilistic (Bayesian) level-set algorithms (90s-00s). Ultrasound physics, region-based, non-local algorithms.
Overview

- Cardiac Anatomy
- Ultrasound physics and image formation.
- Ultrasound Segmentation.
- Challenges.
Cardiac Anatomy

Thoracic Cavity

Myocardium

Fibers (Schematic)

Fibers (Sample)
Cardiac Ultrasound Image

How do we understand image content?
Ultrasound Image Formation (1d)

1-10 Mhz.

~1-0.1m.m.

Transducer

Random Phase “speckle”

Specular reflection

Ampl.

Time
Ultrasound Image Formation (Anisotropy)

Ultrasound Image Formation (2d)

Artifacts:

1. Contrast inhomogeneity and data drop-out.
2. Spurious signal from side lobes.
Cardiac Ultrasound Image

Anatomy

Image
First-order Ultrasound Statistics

Mean and stdev. are proportional

Summary of Ultrasound Image Statistics

- Images contain specular reflection and speckle.
  - Specularity due to acoustic impedance change.
  - Speckle due to scattering.
- Speckle inhomogeneity due to fiber-like structures.
- Side-lobe and total internal reflection.
Ultrasound Image Segmentation

- Exploit speckle statistics (mean, stdev. etc.)
  - Machine/operator independence
- Handle dropout and inhomogeneity
  - Model dropout and inhomogeneity
  - Model boundary shape (generic or organ specific)
- Contain the computational complexity
  - Non-local methods
  - Automatic segmentation
Ultrasound Image Analysis

- Ultrasound segmentation research:
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  - Probabilistic (Bayesian) level-set algorithms (90s-00s).
    Ultrasound physics, region-based, non-local algorithms.
Edge-based methods

Exploit difference in the local mean intensity
Roberts, Canny, Marr-Hildreth, Wavelet-based etc.
Edge-based methods (Example)
Snakes, Templates, Dynamic Programming


Image

Smoothed Image

Edge Image

Base template

Deformation along normals

Optimal deformation: Deformation passing over most edges
Snakes, Templates, Dynamic Programming (contd.)

- Computationally expensive.
  - Iterative solution

- Many methods (template $\times$ optimization)

<table>
<thead>
<tr>
<th>Template</th>
<th>Optimization</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed Manual</td>
<td>Grad. Desc.</td>
<td>Snake</td>
</tr>
<tr>
<td>Variable Manual</td>
<td>Dyn. Prog.</td>
<td>Live wire</td>
</tr>
<tr>
<td>Fixed template</td>
<td>Dyn. Prog.</td>
<td>Templ. deformation</td>
</tr>
</tbody>
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- Limitations
  - Difficult to bridge large gaps and inhomogeneities
  - Difficult to extend to 2d+time or 3d
  - Difficult to control deformation, model Multiple shapes, model complex images
  - Difficult to handle self-crossing
Snakes, Templates, Dynamic Programming (Example.)
Segmentation and Probability Theory
The New Approach

Key recent developments (90s-00s)

- Probability as the theoretical basis for segmentation (Mumford, Geman, Grenander, Chellappa, Jain etc.)
  - Replace ad-hoc objective functions with standard ones
  - Learn from real-world examples
  - Make all assumptions explicit

- Level sets for representing evolving curves (Tsitstiklis, Osher, Sethian, Vemuri etc.)
  - Self crossing is not a problem any more
  - Draws on mature numerical analysis for p.d.e.

- New optimization techniques
  - Escape from local minima (Zabeh, Tagare etc.)
  - Graph cuts
Likelihood of Segmentation

- Find the most probable segmentation. This is the best segmentation possible (given the model for $p(\text{Curve} \mid \text{Image})$).
**Approach I: Generative (Bayesian)**

- **Bayes Theorem:** \( p(C \mid I) \propto p(I \mid C)p(C) \).
- **Translation:** \( \frac{p(I \mid c)}{p(C)} \) Generative model Shape prior
The Bayesian Approach

Pros:

• Models the entire image (region-based rather than edge-based)
• The segmentation is optimal (minimum variance) if the generative model is correct
• No ad-hoc techniques
• Canonical introduction of prior shape information (can be weak)

Cons:

• Can get trapped in spurious local maxima
• Spatially in-homogenous generative models are cumbersome
  • Many extra parameters
  • Optimization is difficult
The Bayesian Approach (Examples)

- Successful segmentation
  - Homogenous myocardium (Movie)
  - Inhomogenous myocardium (Movie)
- Leakage

The Discriminative Approach

- Use a training set (learn spatial inhomogeneity)
- Penalized logistic field
- Learn only what is needed for segmentation
The Discriminative Approach (contd.)

Validation

Mean Distance: 1.38 pixels.

Prof. E. Madsen, Univ. Wisc.

Collaboration between Yale University, University of Florida, and University of Wisconsin
Why is this hard?

High-dimensional spaces are very non-intuitive
Optimization is difficult

• \( \frac{V_{sphere}}{V_{cube}} \to 0 \).
• Distance to nearest neighbor \( \to \) Distance to farthest neighbor.
• Most of the volume of the sphere is concentrated near the surface.
• All diagonals of the unit cube are almost perpendicular to the sides.

All of these phenomenon are apparent between \( \text{dim}=10 \) & 20

• Many local maxima to get trapped in.
But there is hope!

Most image classes have low intrinsic dimension

• Low dimensional support for image and the segmentation class:
  - PCA, ICA, Manifold Learning (Isomap etc.), Kernel-based approaches etc.

• Low dimensional approximation to the probability distribution:
  - Gaussian models, Mixture models, Markov random fields, Logistic models etc.
Shape-based Motion Analysis
Analysis of Correspondence


**Point Motion from Shape Change**

Khalil's comments:

- Shape change in the tongue during speech production is accompanied by the motion of fleshpoints on it. A major question is how analysis using fleshpoints relates to analysis using shape change.

- Several methods for tongue motion detection track the motion of these points.

- One area where success in cardiac imaging could inform tongue imaging is the estimation of point motion from contour change.

- If this can be done, these the two levels of analysis of tongue motion can be related to each other.
Final Comments

- Probabilistic approach gives principled solutions
- Generative approach works with simple models (no training)
- Discriminatory approach works with training sets
- Shape tracking is a proxy for motion of the endocardium

Further work:
- Extend discriminatory approach to large heterogenous training sets
- Towards true drag and drop segmentation (speed)
- Dynamic shape analysis (shape grammar?)
- Shape motion vs. physical motion
Acknowledgements

Yale:

- Students: Zhong Tao, Xiaoning Qian, James Beaty
- Post-docs: Yong Yue
- Faculty: Al Sinusas, Rob McNamara, Leslie Scoutt

Univ. of Florida:

- Faculty: David Groisser, Yunmei Chen, Murali Rao

Univ. Wisconsin:

- Faculty: Ernest Madsen

Supported by grant R01 HL077810 from NHLBI (NIH).