Deformable Segmentation using Sparse Shape Representation

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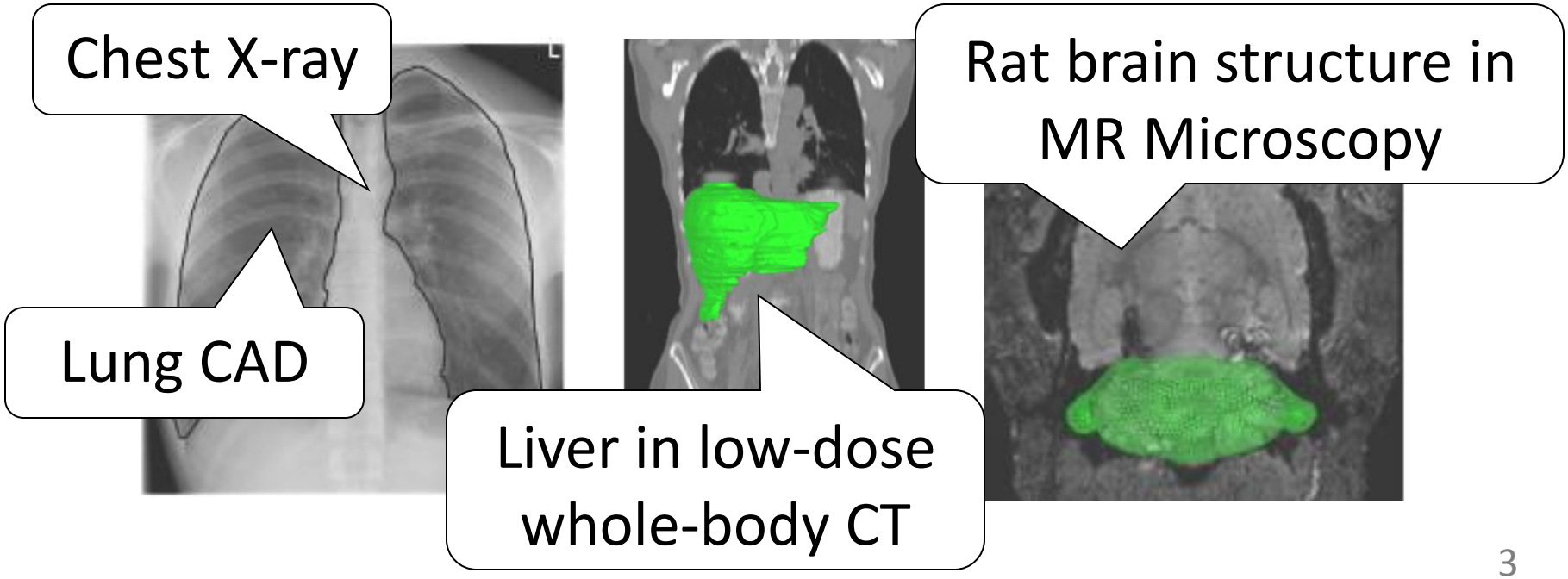
Outline

- Introduction
- Our methods
  - Segmentation framework
  - Sparse shape representation
- Applications
  - 2D lung localization in X-ray
  - 3D liver segmentation in whole body PET-CT
  - 3D rat brain structure segmentation
- Conclusions

Introduction

Motivations

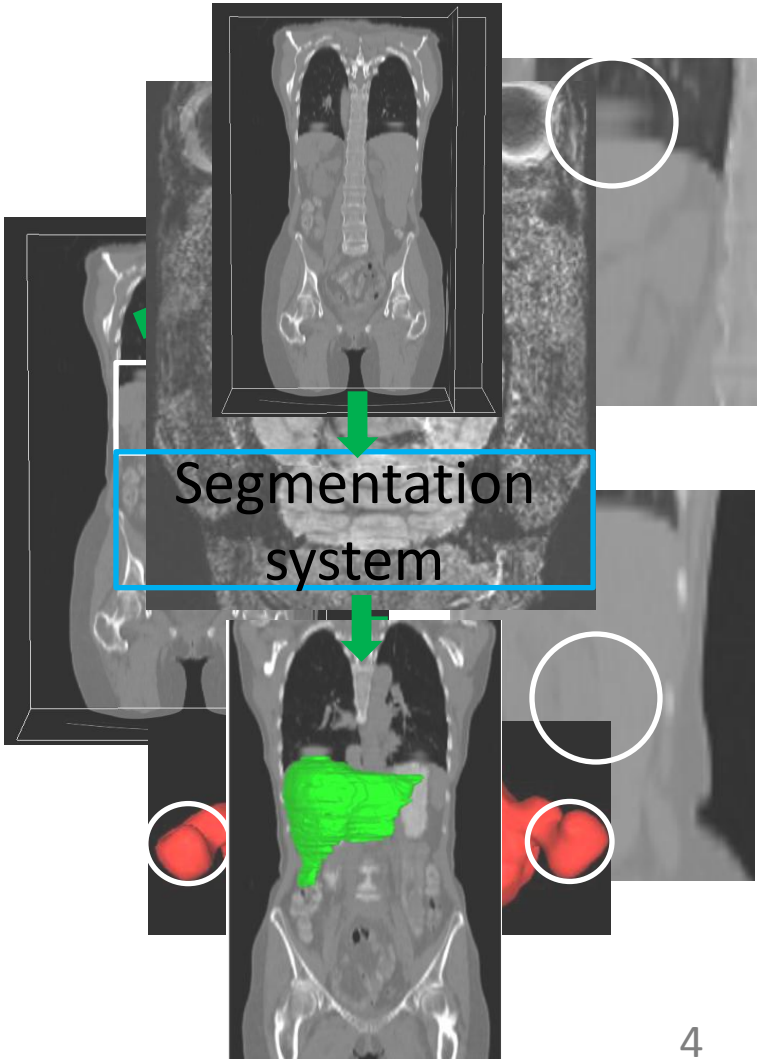
- Segmentation (i.e., finding 2D/3D ROI) is a fundamental problem in medical image analysis.
- We use deformable models and shape prior. Shape representation is based on landmarks.



Introduction

Challenges – deformable segmentation

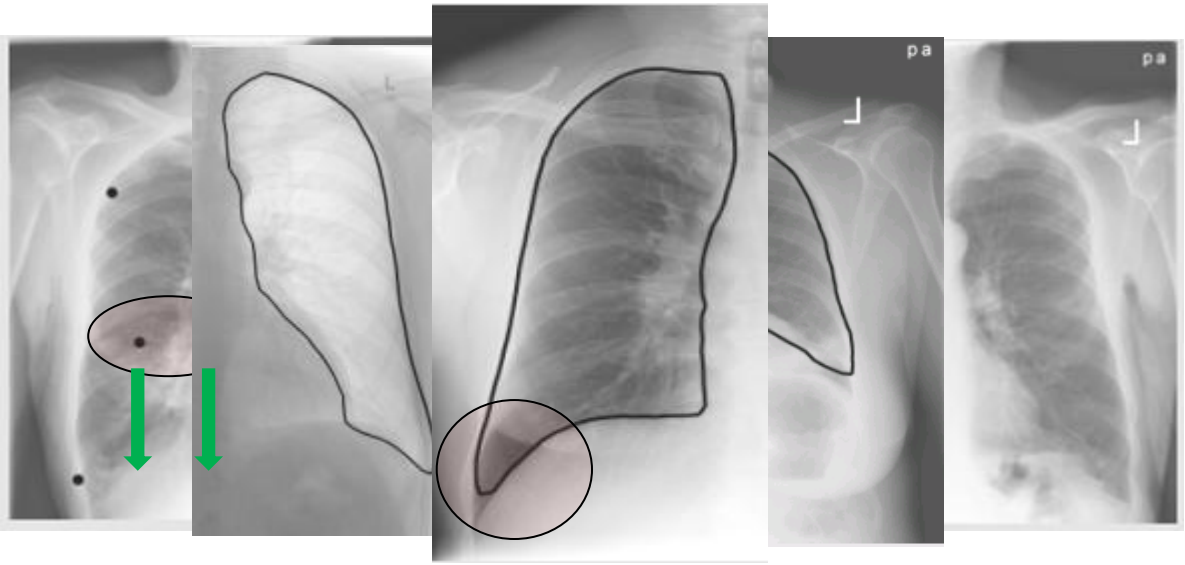
- Good segmentation system:
  - Automatic, accuracy, efficiency, robustness.
  - Handle weak or misleading appearance cues from image information.
  - Discover or preserve complex shape details.



Introduction

Challenges – shape prior modeling

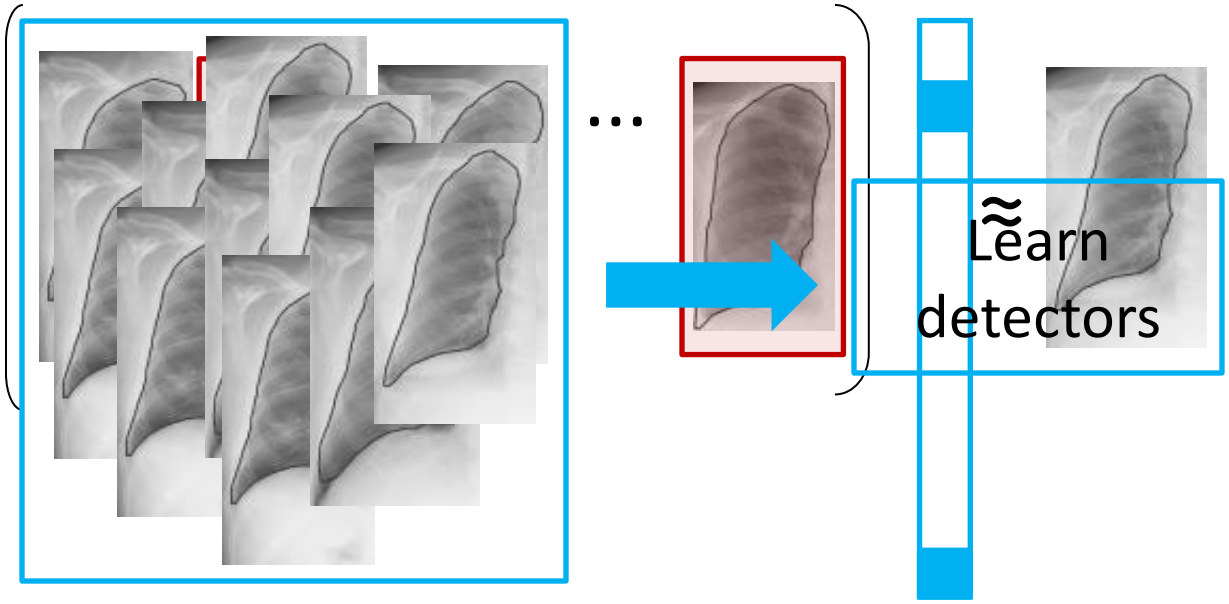
- Good shape prior method:
  - Handle gross errors of the input data.
  - Model complex shape variations.
  - Preserve local shape details.



Methods

Our solutions

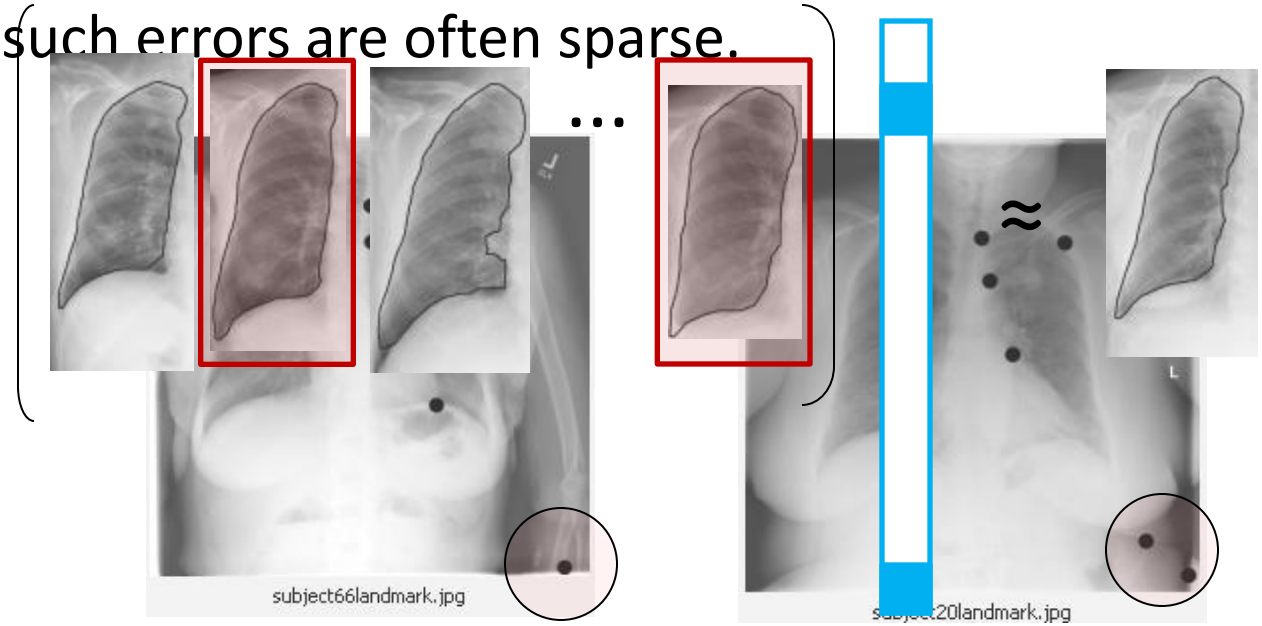
- Learning based deformable segmentation.
- Sophisticated shape prior algorithm.
  - Sparse shape composition.



Methods

Shape prior using sparse shape composition

- Our method is based on two observations:
  - An input shape can be approximately represented by a sparse linear combination of training shapes.
  - The given shape information may contain gross errors, but such errors are often sparse.



Methods

Shape prior using sparse shape composition

- Formulation:
  - $Min_{\{x,\beta\}} \|T(y,\beta) - Dx\|_2$
- Sparse linear combination:
  - $Min_{\{x,\beta\}} \|T(y,\beta) - Dx\|_2, s.t. \|x\|_0 < k_1$

Number of nonzero elements

D

Aligned data matrix D

x

Weight *x*

$T(y,\beta)$

Global transformation operator

Methods

Shape prior using sparse shape composition

- Non-Gaussian errors:
  - $Min_{\{x,e,\beta\}} \|T(y,\beta) - Dx - e\|_2, s.t. \|x\|_0 < k_1, \|e\|_0 < k_2$

Methods

Shape prior using sparse shape composition

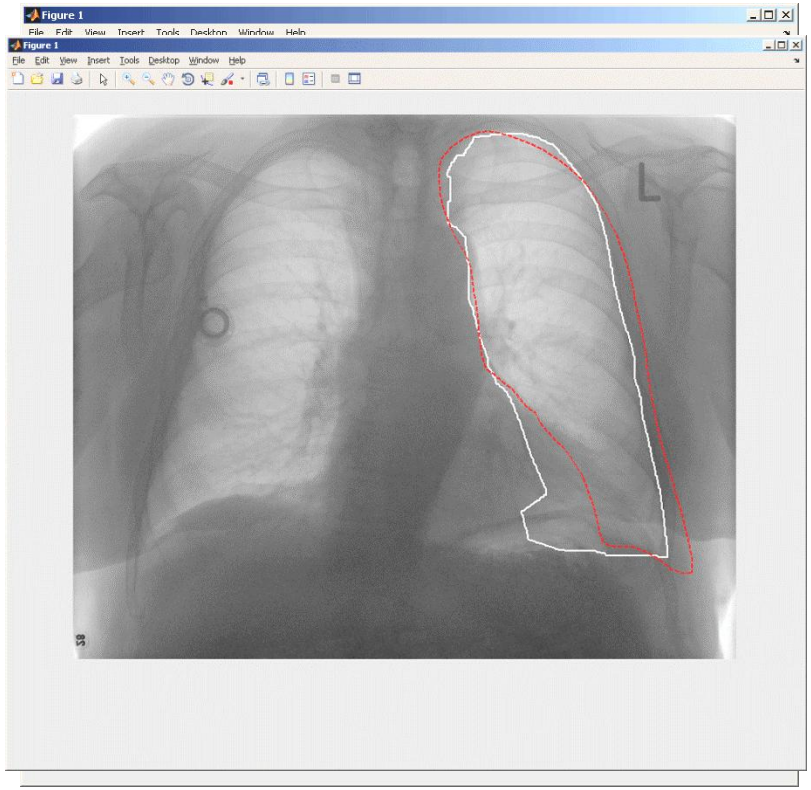
- Why it works?
  - Robust: Explicitly modeling “e” with L0 norm constraint. Thus it can detect gross (sparse) errors.
  - General: No assumption of a parametric distribution model (e.g., a unimodal distribution assumption in ASM). Thus it can model complex shape statistics.
  - Lossless: It uses all training shapes. Thus it is able to recover detail information even if the detail is not statistically significant in training data.

Zhang, Metaxas, et.al.: MedIA’11

Applications – Part I

2D lung localization in X-ray

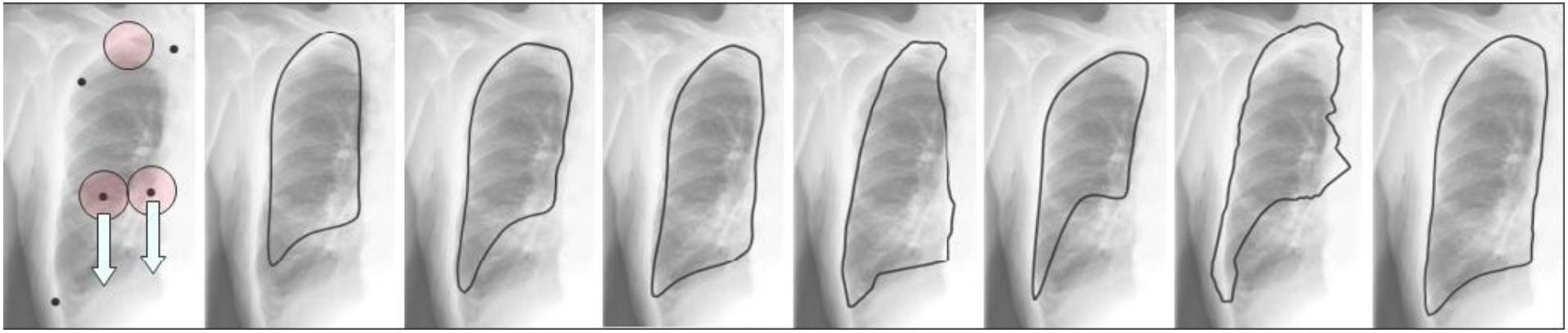
- Setting:
  - Manually select landmarks for training purpose.
  - 200 training and 167 testing.
  - To locate the lung, detect landmarks, then predict a shape to fit them.
  - Sensitivity (P), Specificity (Q), Dice Similarity Coefficient.



Applications – Part I

2D lung localization in X-ray

- Handling gross errors



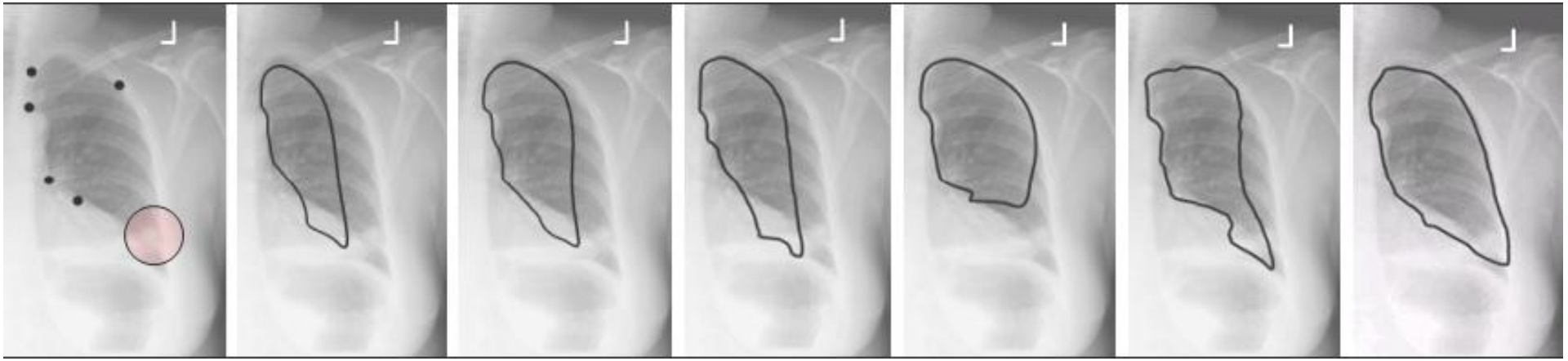
Detection	PA	ASM	RASM	NN	TPS	Sparse1	Sparse2
P%	62	66	81	81	[illegible]	6[illegible]	[illegible]7
Q%	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
DSC%							

Procru | Activ | Robus | Wit | Proposed method

Applications – Part I

2D lung localization in X-ray

- Multimodal distribution

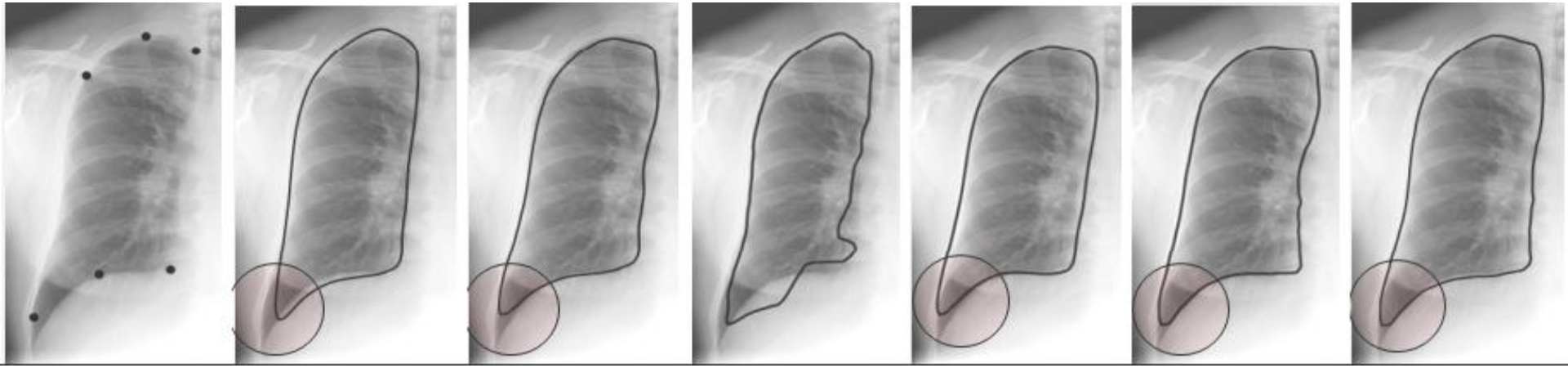


Detection	PA	ASM/RASM	NN	TPS	Sparse1	Sparse2
P%	50	61	63	75	73	**92**
Q%	99	99	98	99	99	**99**
DSC%	64	72	73	79	79	**91**

Applications – Part I

2D lung localization in X-ray

- Recover local detail information

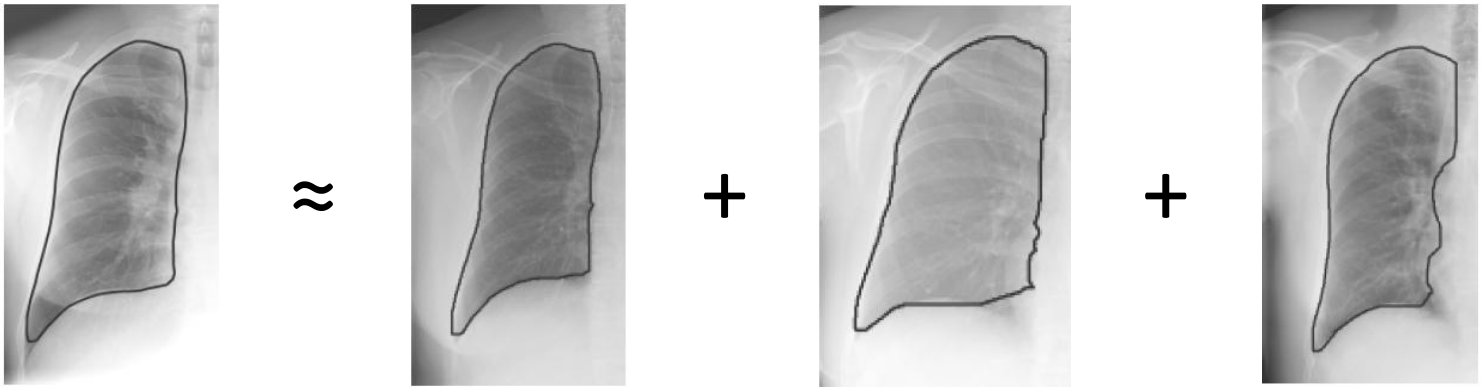


Detection	PA	ASM/RASM	NN	TPS	Sparse1	Sparse2
P%	93	93	87	97	97	**98**
Q%	99	99	99	98	99	**99**
DSC%	94	95	90	94	96	**96**

Applications – Part I

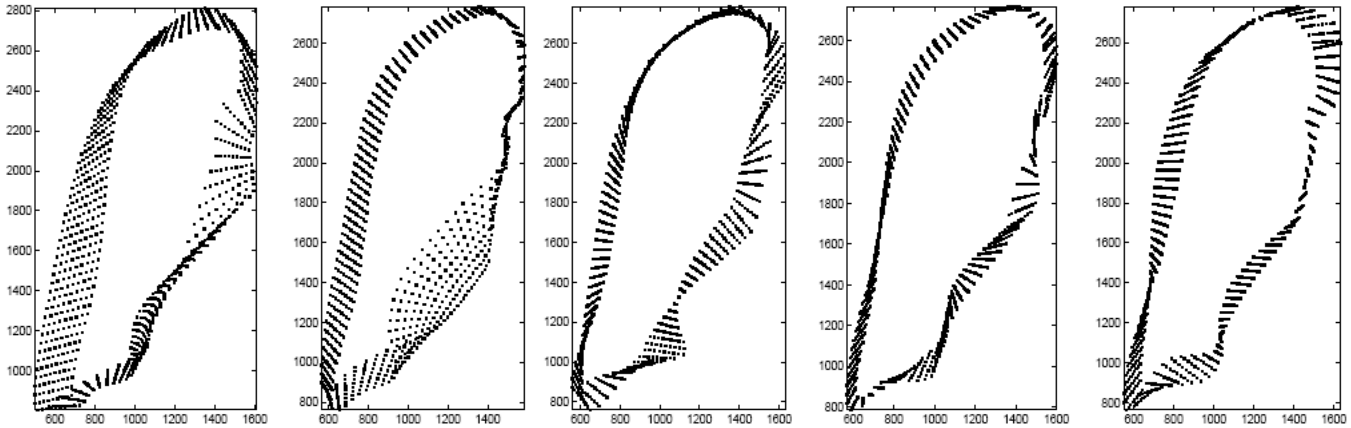
2D lung localization in X-ray

- Sparse shape components



≈ 0.5760 + 0.2156 + 0.0982

- ASM modes:



(a) 1st mode (b) 2nd mode (c) 3rd mode (d) 4th mode (e) 5th mode

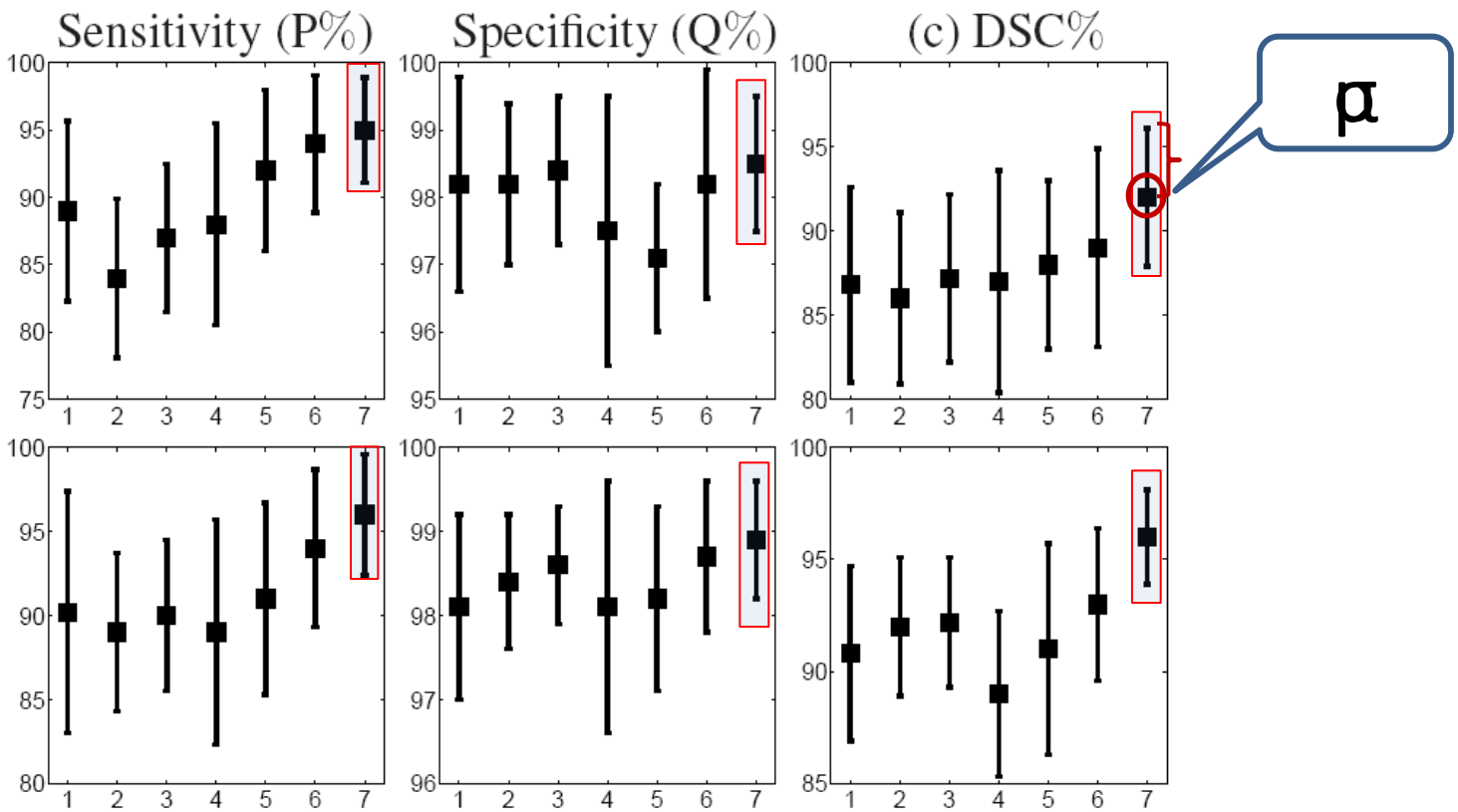
Applications – Part I

2D lung localization in X-ray

- Mean values (μ) and standard deviations (σ).

Left lung

Right lung

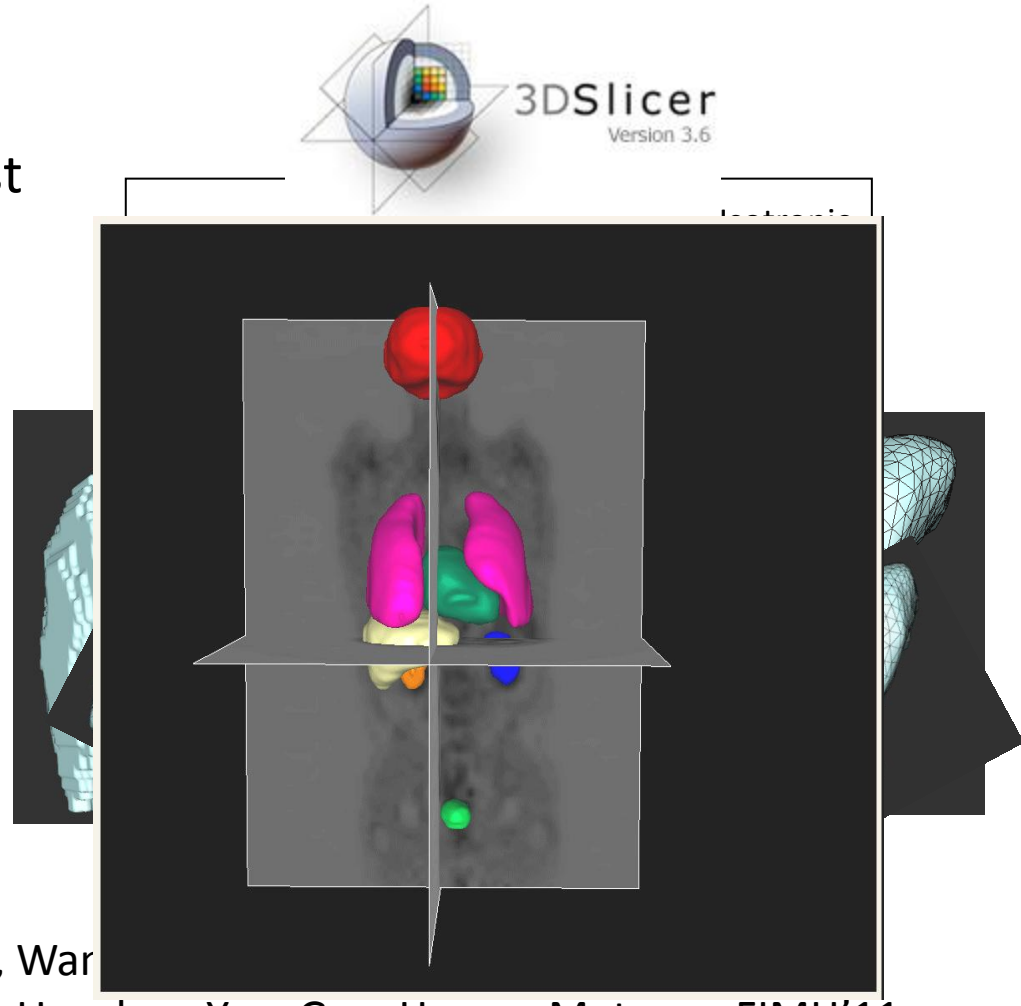


1)PA, 2)ASM, 3)RASM, 4)NN, 5)TPS, 6)Sparse1, 7)Sparse2

Applications – Part II

3D liver segmentation in low-dose CT

- Setting
  - 3D low-dose CT, low contrast and fuzzy boundaries. 40 training and 27 testing.
  - Use 3D Slicer to segment ground truth.
  - Geometry processing (decimation, smoothing, isotropic remeshing).
  - Use shape registration to guarantee one-to-one correspondence.



Zhang, War

Zhang, Uzunbas, Yan, Gao, Huang, Metaxas, FIMH'11

Applications – Part II

3D liver segmentation in low-dose CT

Same landmarks + different shape priors

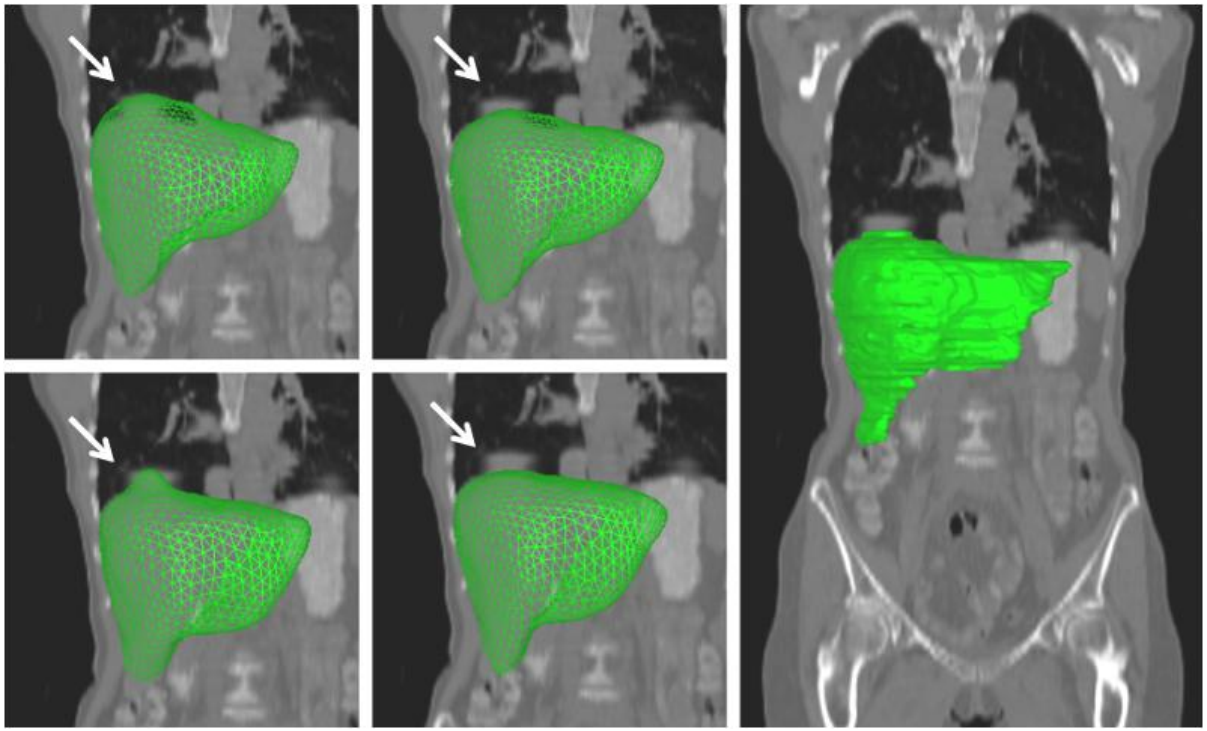
Procrustes analysis

Sparse shape

Ground truth

Initialization

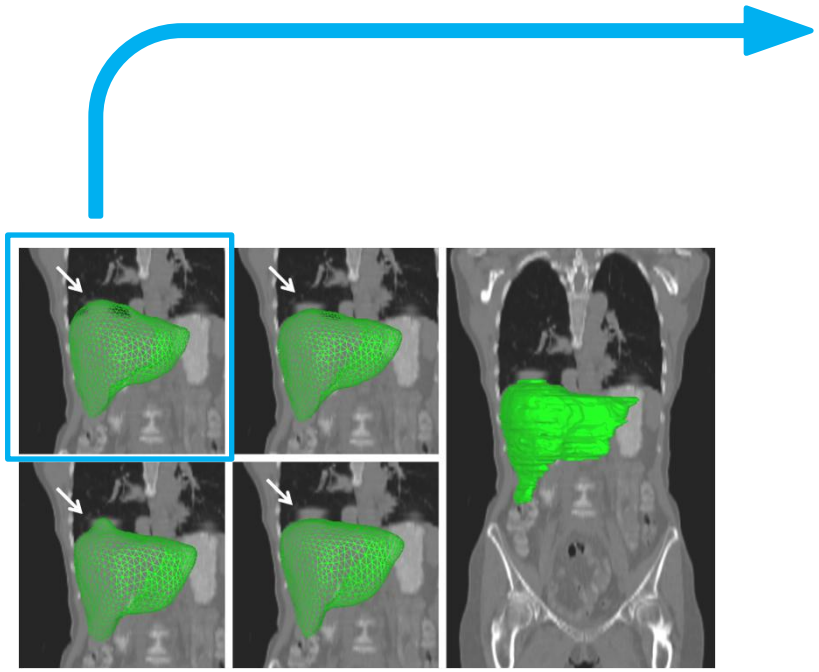
Deformation



Same deformation module

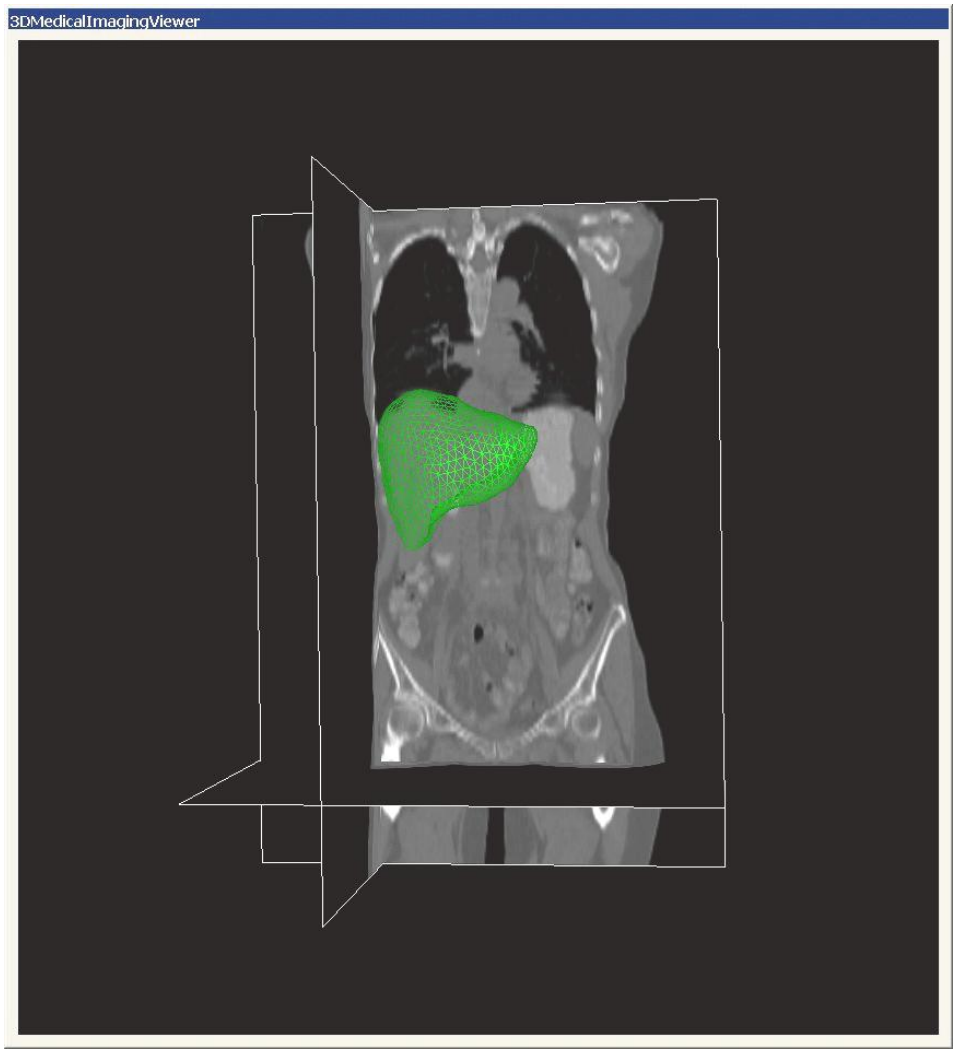
Applications – Part II

3D liver segmentation in low-dose CT



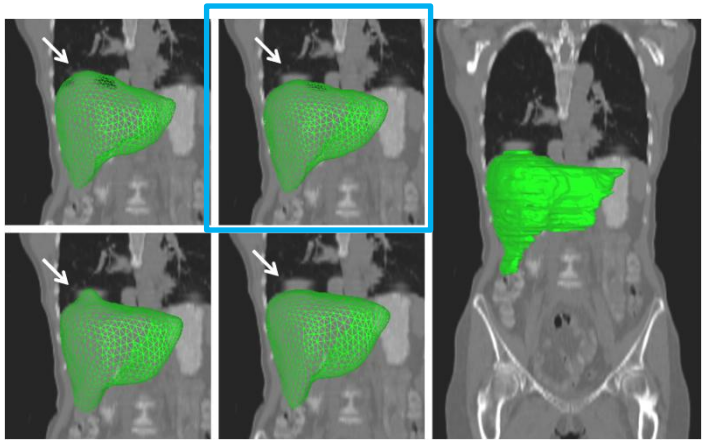
Procrustes analysis

Sparse shape



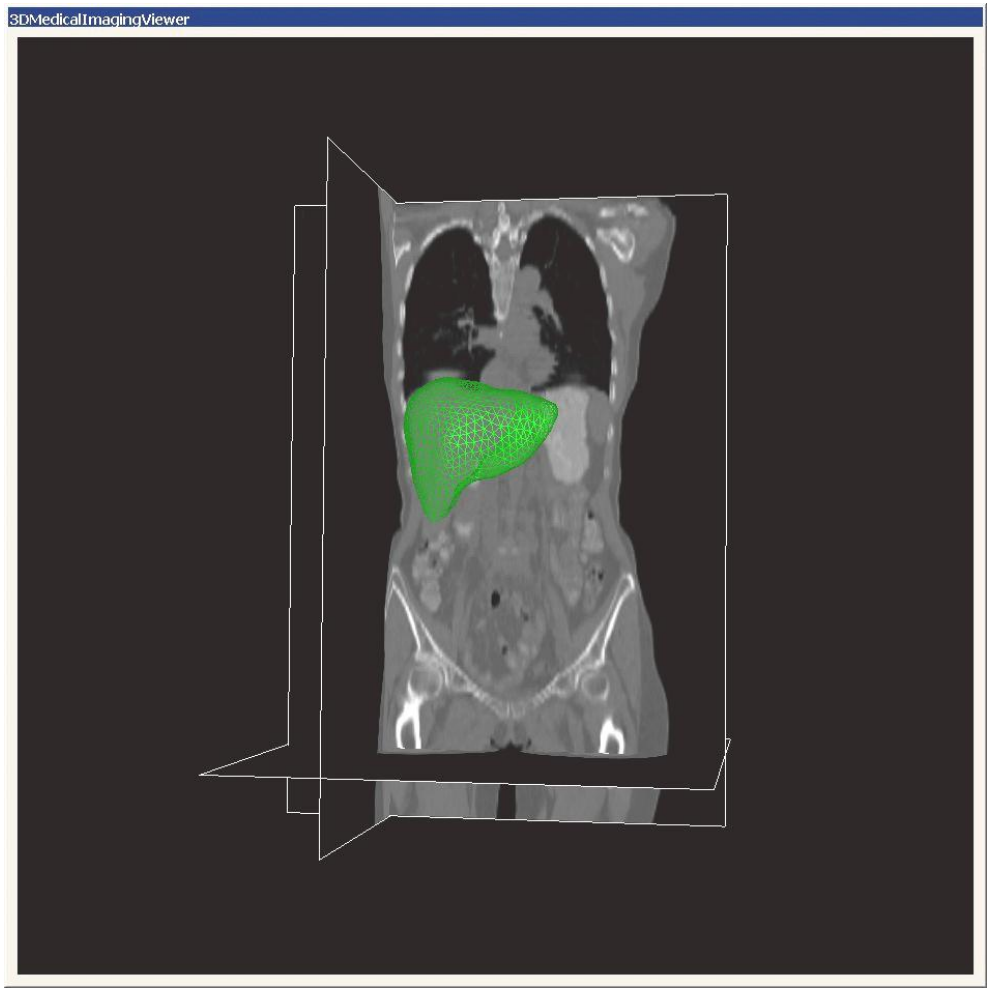
Applications – Part II

3D liver segmentation in low-dose CT



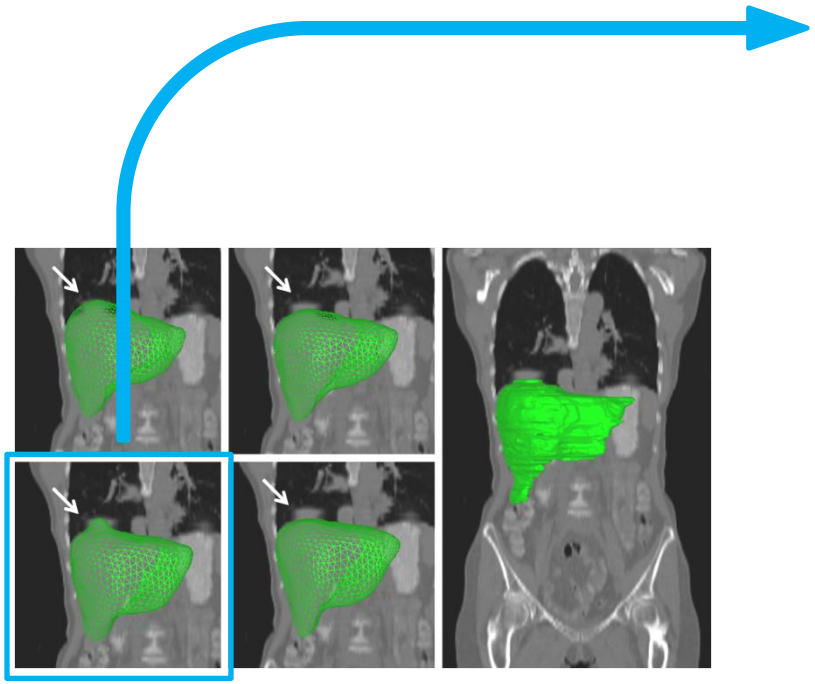
Procrustes analysis

Sparse shape



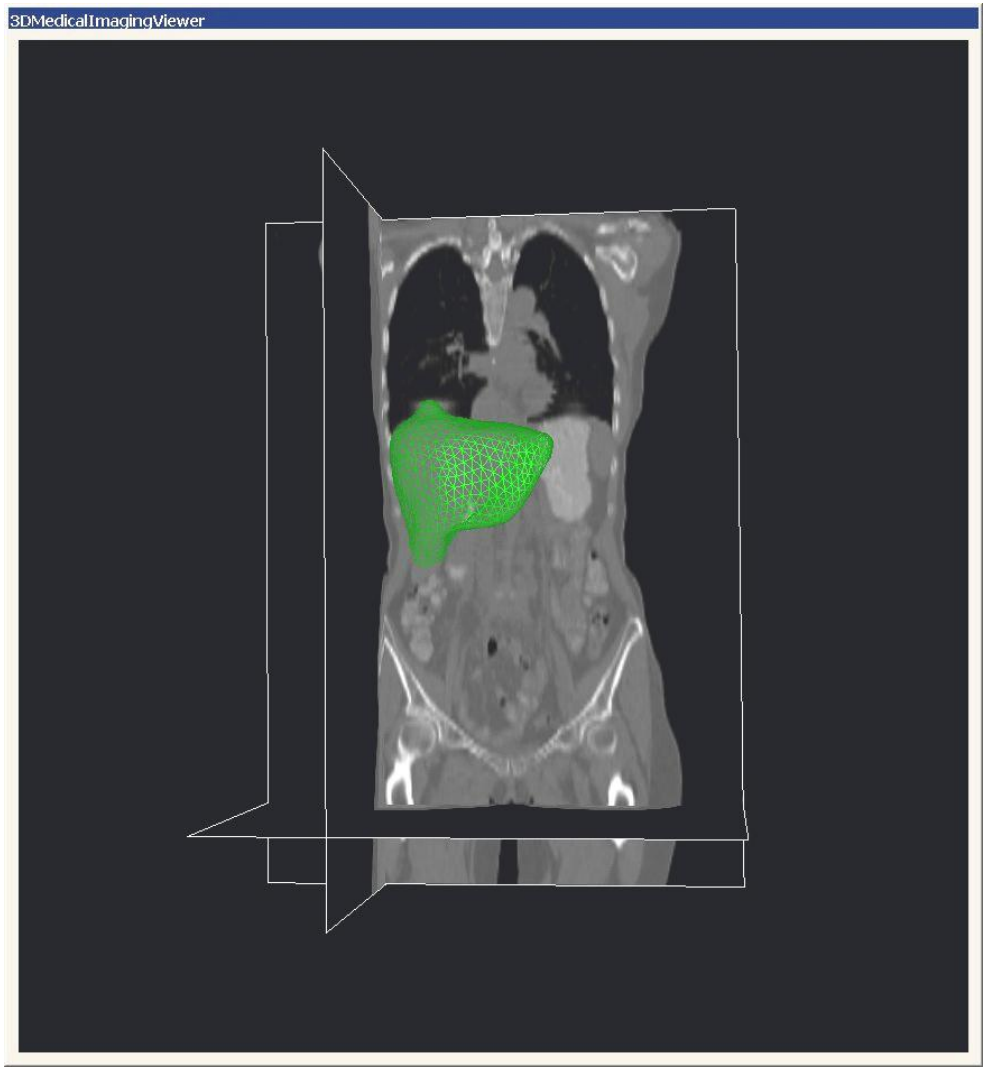
Applications – Part II

3D liver segmentation in low-dose CT



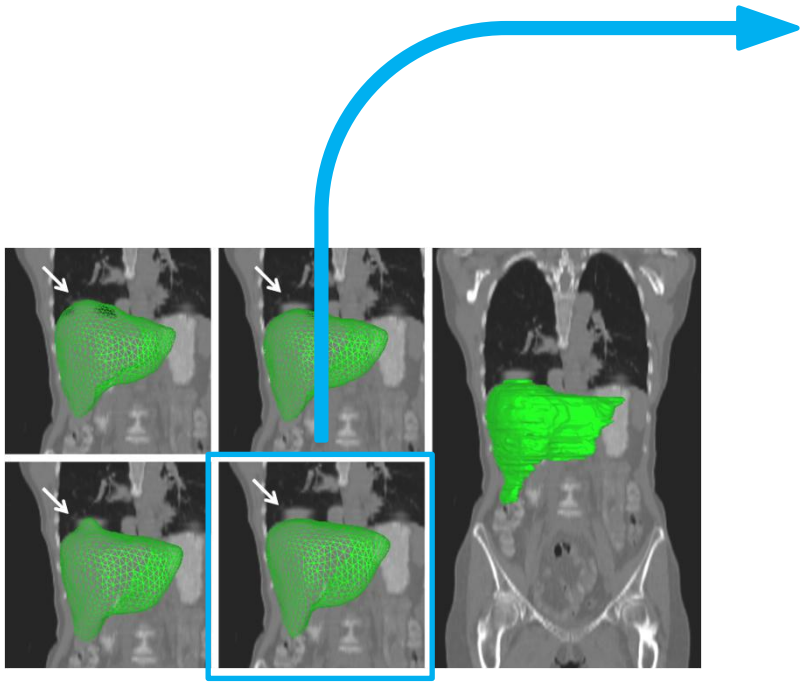
Procrustes analysis

Sparse shape



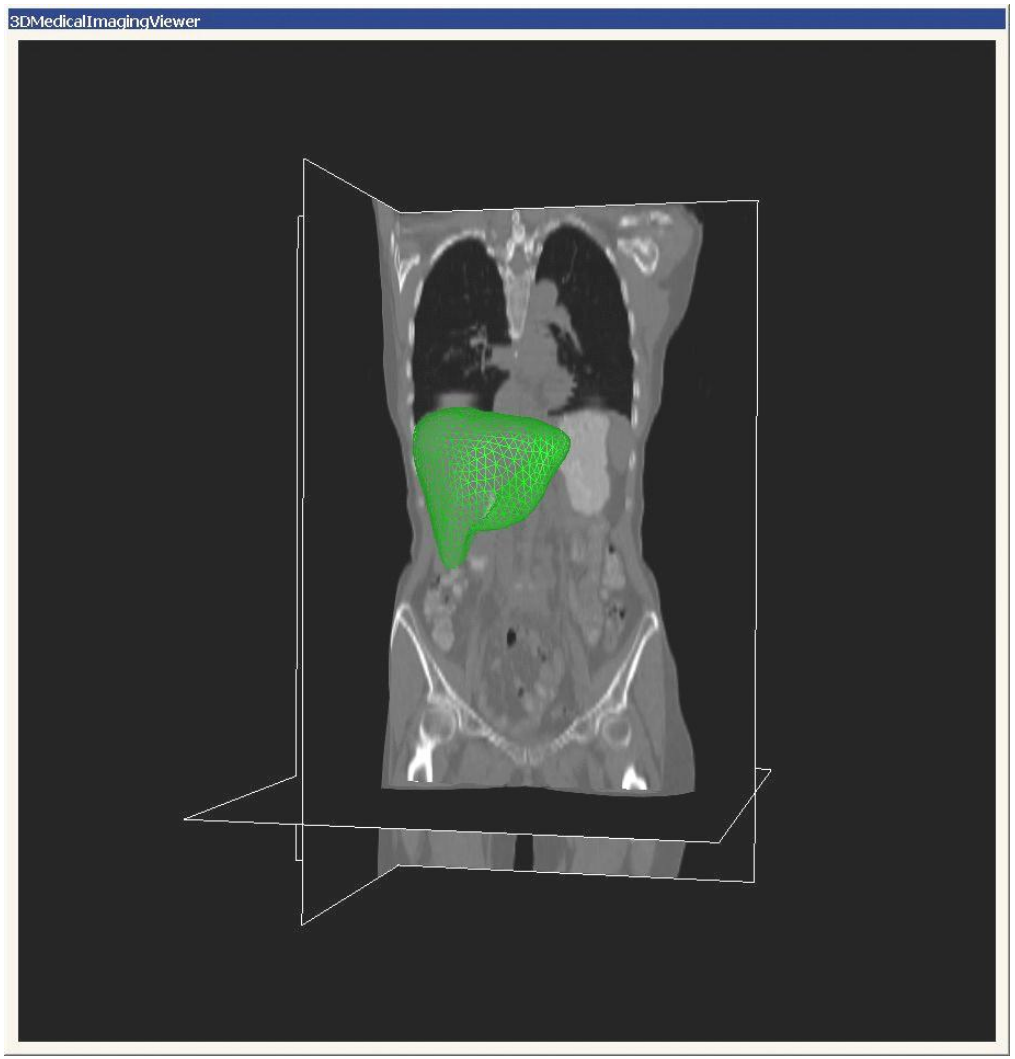
Applications – Part II

3D liver segmentation in low-dose CT



Procrustes analysis

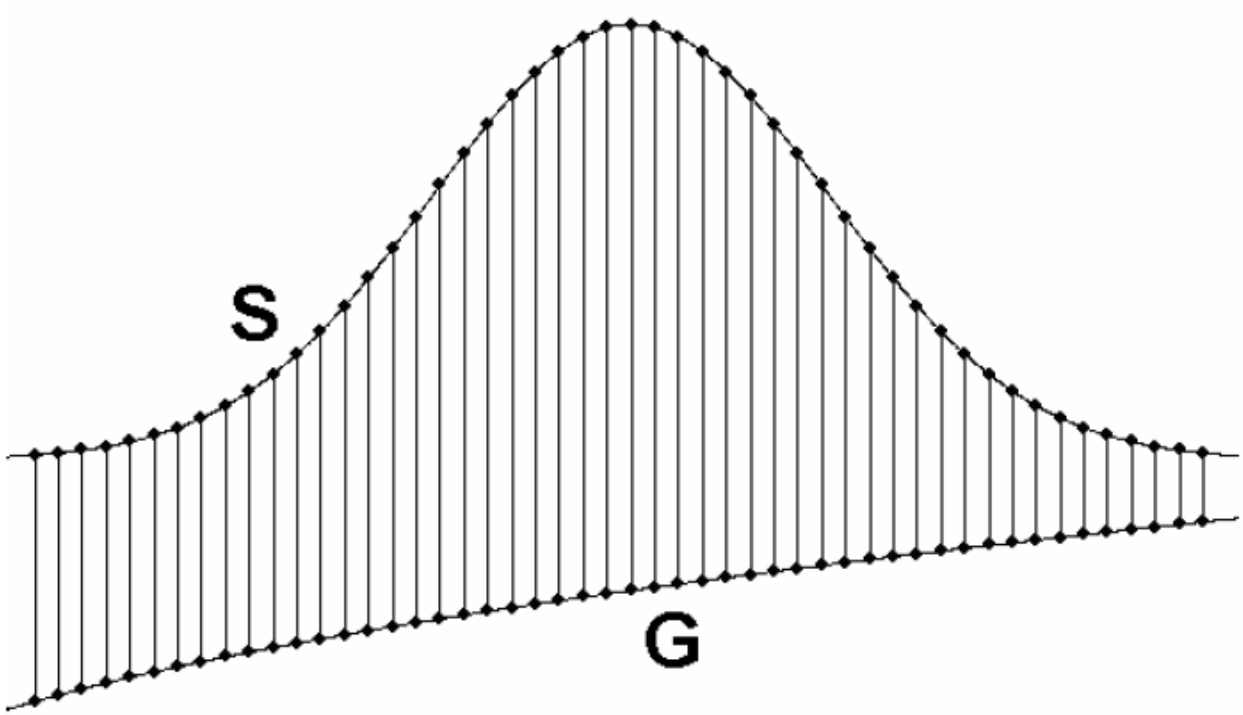
Sparse shape



Applications – Part II

3D liver segmentation in low-dose CT

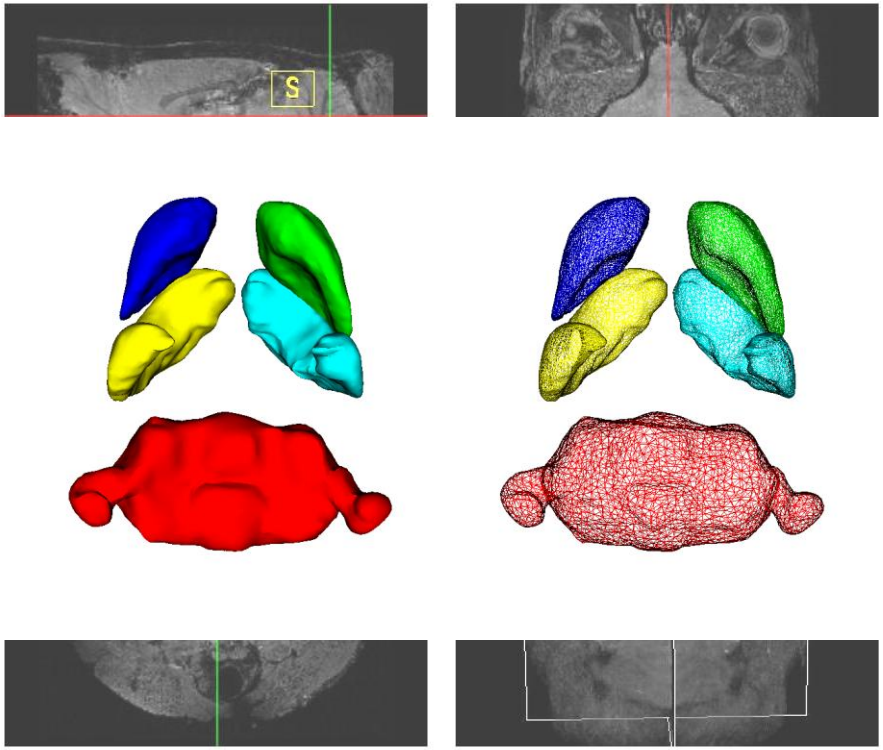
- Quantitative comparisons: surface distances.



Applications – Part III

3D rodent brain segmentation in MRM

- Setting
  - Rodents are often used as models of human disease.
  - 3D Magnetic resonance microscopy (MRM).
  - Create complex shape atlas of multiple structures using hierarchical shape priors.



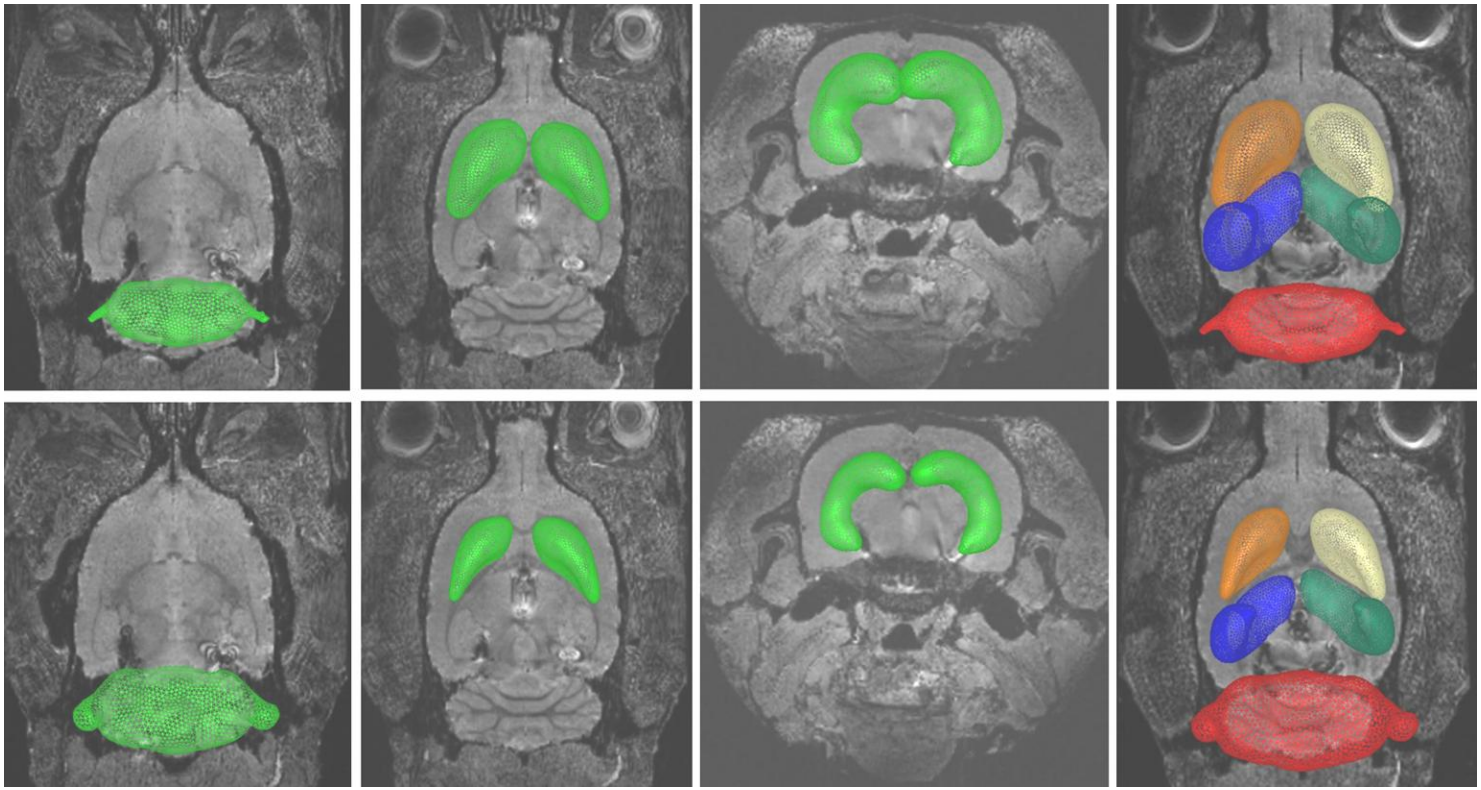
Applications – Part III

3D rodent brain segmentation in MRM

Cerebellum Striatum Hippocampus

Regular prior (smoothness)

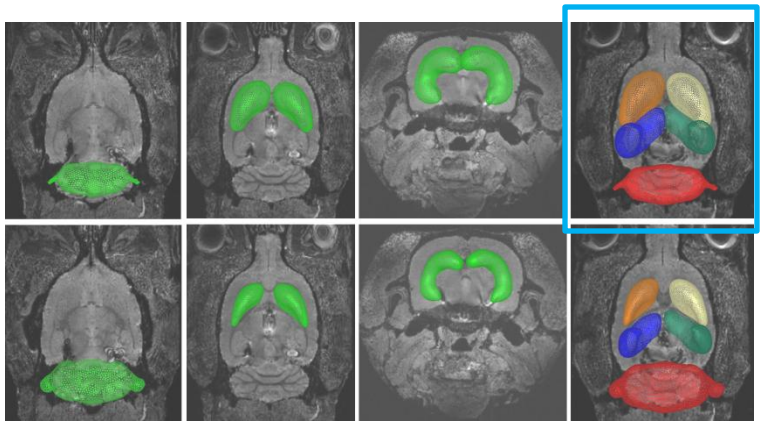
Hierarchical shape prior



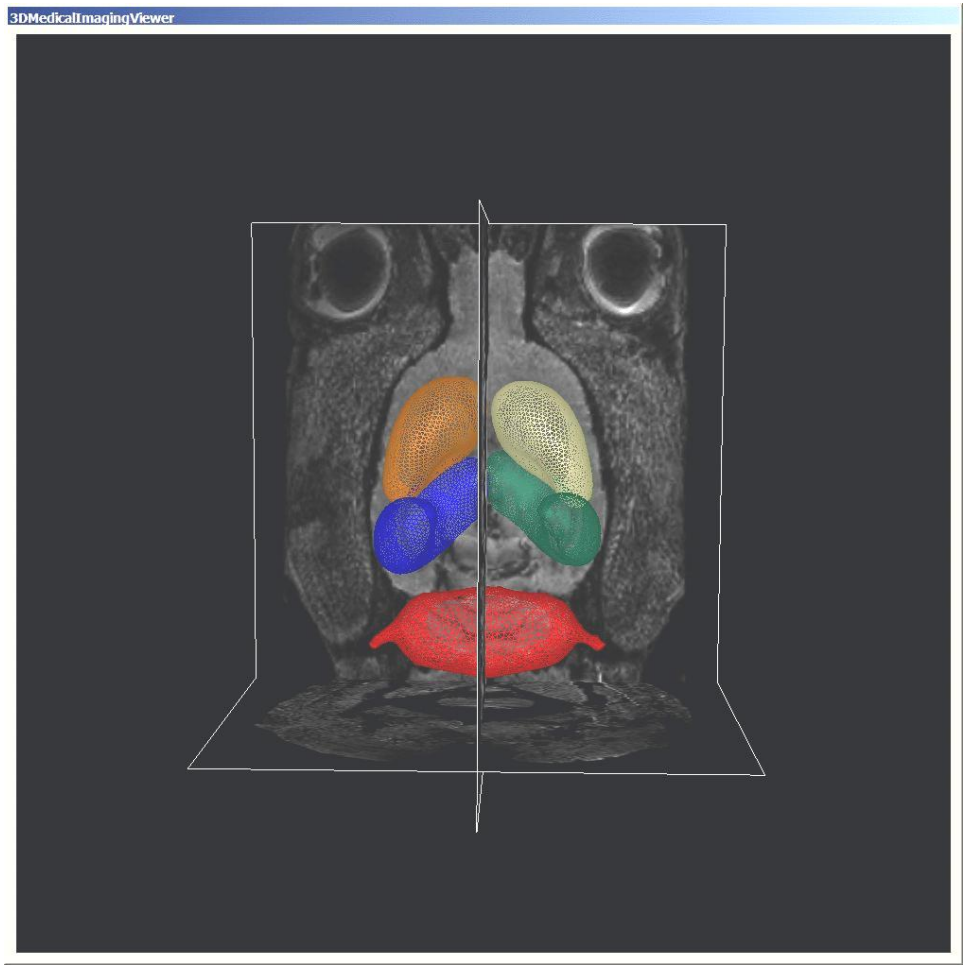
Applications – Part III

3D rodent brain segmentation in MRM

Regular prior (smoothness)



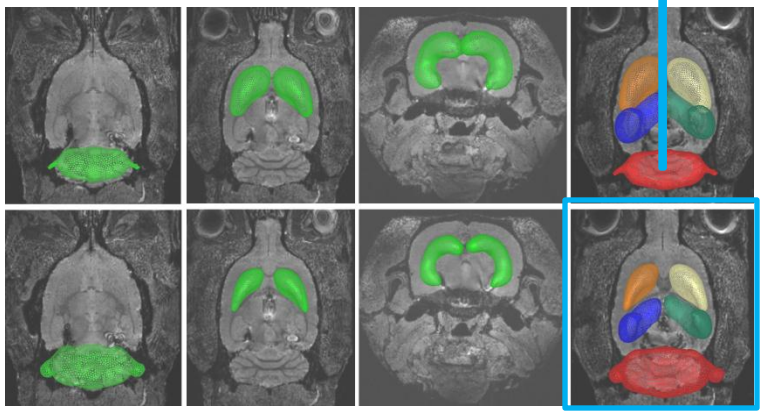
Hierarchical shape prior



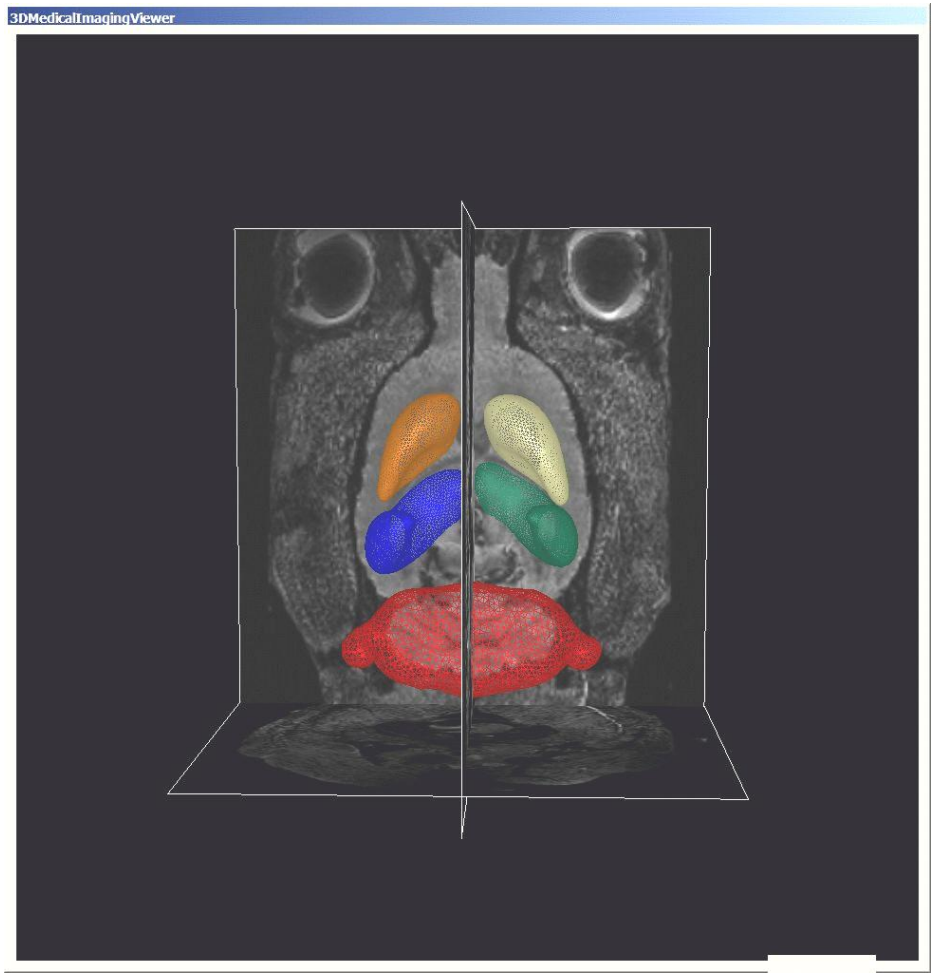
Applications – Part III

3D rodent brain segmentation in MRM

Regular prior (smoothness)



Hierarchical shape prior



Applications – Part III

3D rodent brain segmentation in MRM

- Quantitative comparisons: surface distances, relative error of volume magnitude

Structures	Methods	Distance	Volume
Cerebellum	Smoothness prior	4.35±2.17	0.22±0.12
	Independent prior	1.74±1.18	0.05±0.02
	Hierarchical prior	**1.70±1.13**	**0.04±0.02**
Striatum	Smoothness prior	3.79±2.05	0.51±0.19
	Independent prior	2.93±1.81	0.19±0.06
	Hierarchical prior	**1.37±1.09**	**0.07±0.03**
Hippocampus	Smoothness prior	3.82±2.14	0.53±0.18
	Independent prior	2.69±1.83	0.17±0.05
	Hierarchical prior	**1.22±1.05**	**0.06±0.02**

Thanks!

Questions and comments