Towards robust and effective shape modeling: Sparse shape composition

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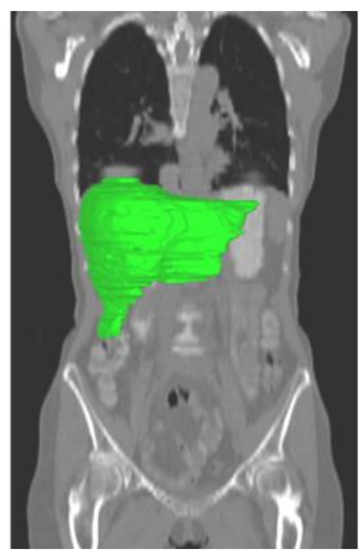
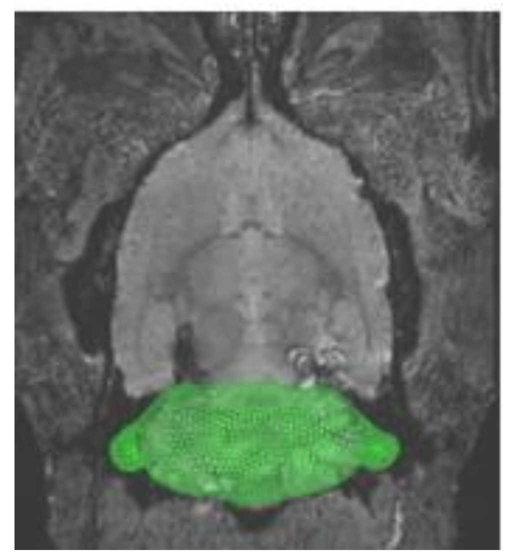
Introduction
Background

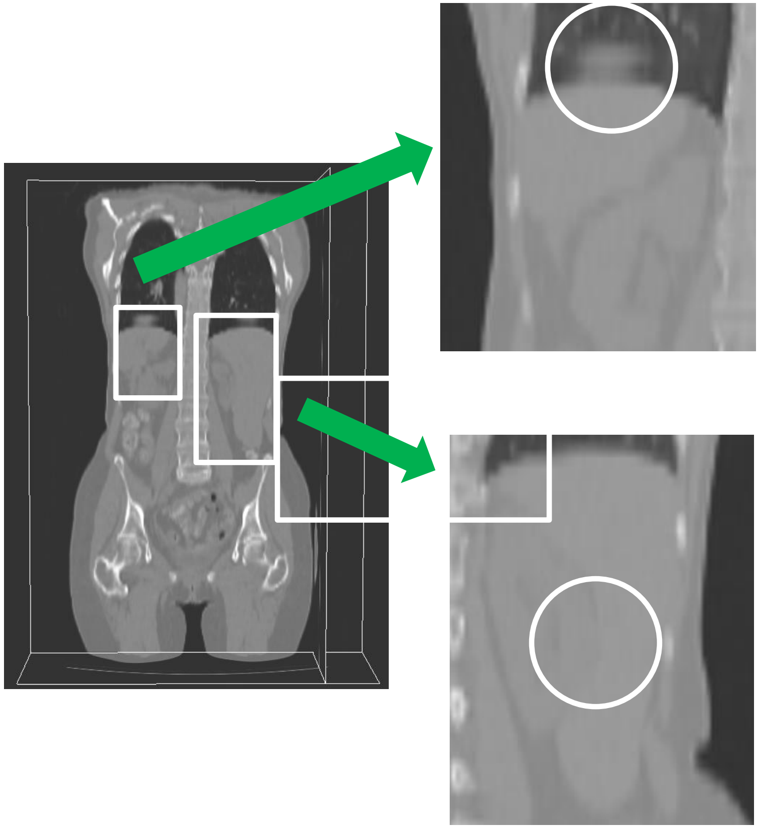
- Segmentation (finding 2D/3D region-of-interest) is a fundamental problem and bottleneck in many areas.
- We focus on learning-based deformable models with shape priors (2D contour or 3D mesh).

Introduction

Background

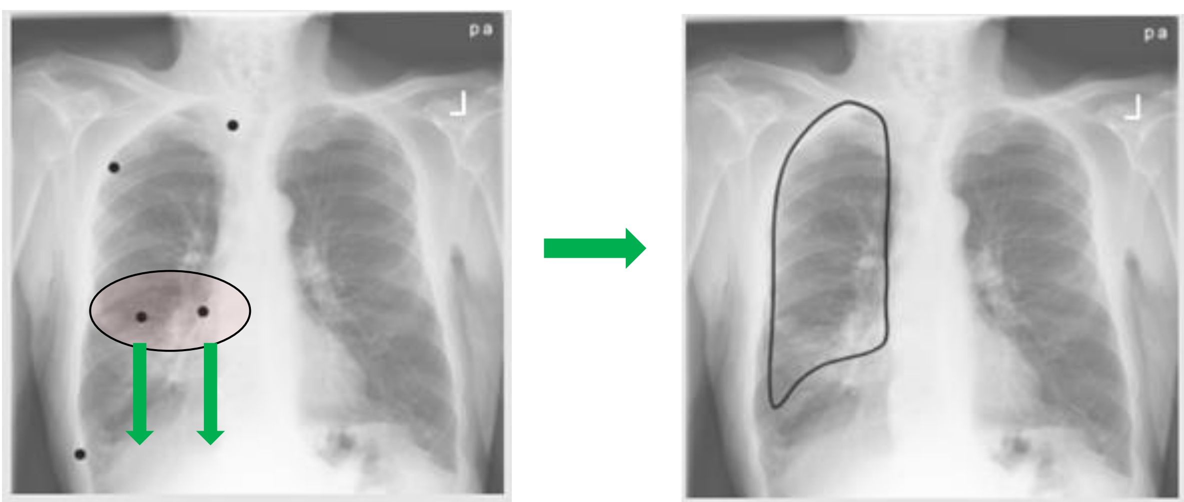
- End-to-end, automatic, accurate, efficient.
- **<u>Robustness</u>**
  - Handle weak or misleading appearance cues.
  - Handle diseased cases (e.g., with tumor/cancer).
  - Leverage **<u>shape priors</u>** to improve the robustness (Active Shape Model, T. Cootes, CVIU'95; 3D ASM for cardiac segmentation, Y. Zheng, TMI'08)



Introduction

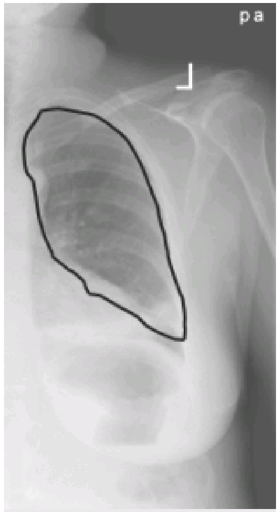
Research Void

- Limitations of existing shape prior methods:
  - Assume Gaussian errors → Sensitive to outliers



Introduction
Research Void

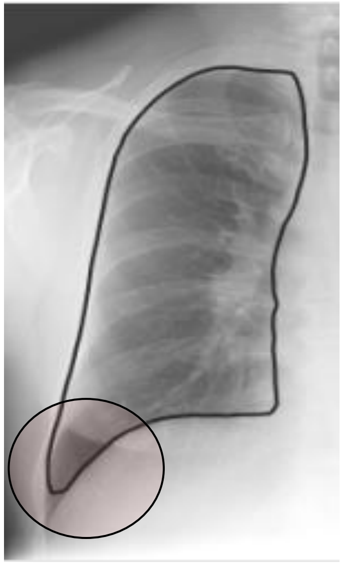
- Limitations of existing shape prior methods:
  - Assume Gaussian errors → Sensitive to outliers
  - Assume unimodal distribution of shapes → Cannot handle large shape variations, e.g., multimodal



Introduction

Research Void

- Limitations of existing shape prior methods:
  - Assume Gaussian errors → Sensitive to outliers
  - Assume unimodal distribution of shapes → Cannot handle large shape variations, e.g., multimodal
  - Only keep major variation → Lose local shape detail



Introduction

Research Void

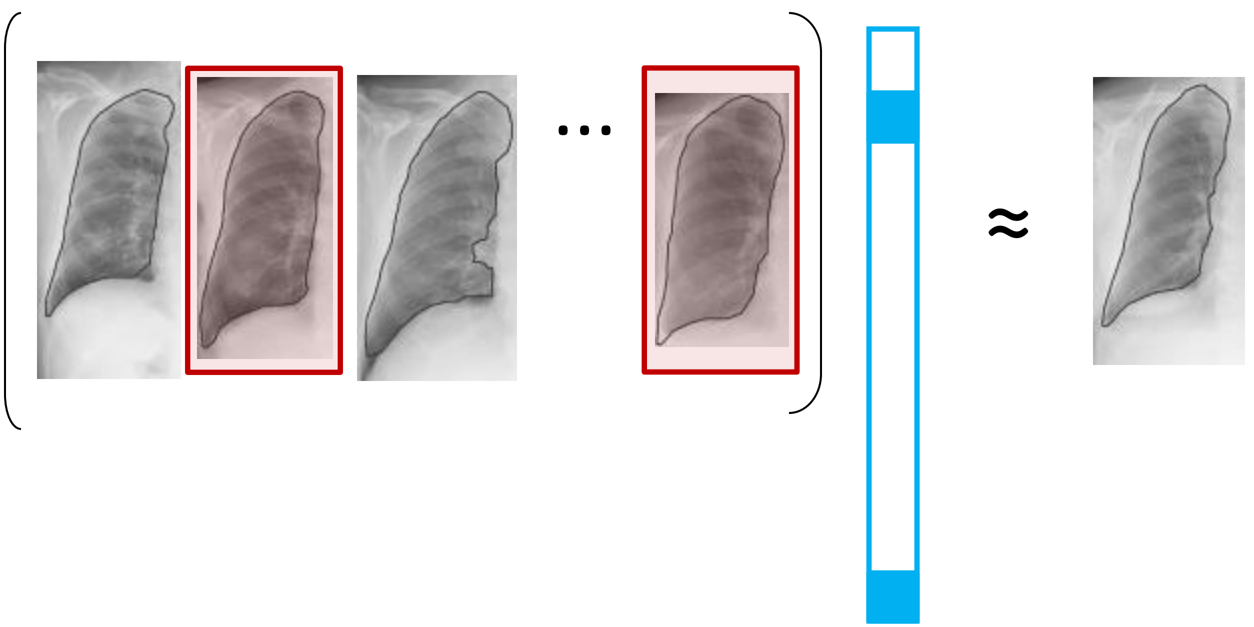
Need to solve all three challenges simultaneously in practice

- Handling gross errors or outliers.
  - RANSAC + ASM [M. Rogers, ECCV'02]
  - Robust Point Matching [J. Nahed, MICCAI'06]
- Handling multimodal distribution of shapes.
  - Mixture of Gaussians [T. F. Cootes, IVC'97]
  - Manifold learning for shape prior [Etyngier, ICCV'07]
  - Patient-specific shape [Y. Zhu, TMI'10]
- Preserving local shape details.
  - Sparse PCA [K. Sjostrand, TMI'07]
  - Hierarchical ASM [D. Shen, TMI'03]

Methods

Shape prior using sparse shape representation

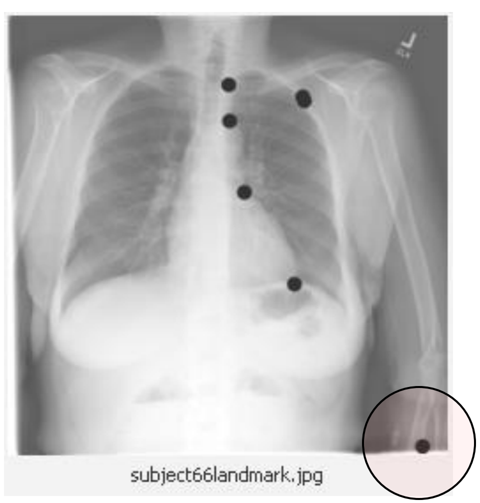
- Our method is based on two observations:
  - An input shape can be approximately represented by a sparse linear combination of training shapes.



Methods

Shape prior using sparse shape representation

- 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.



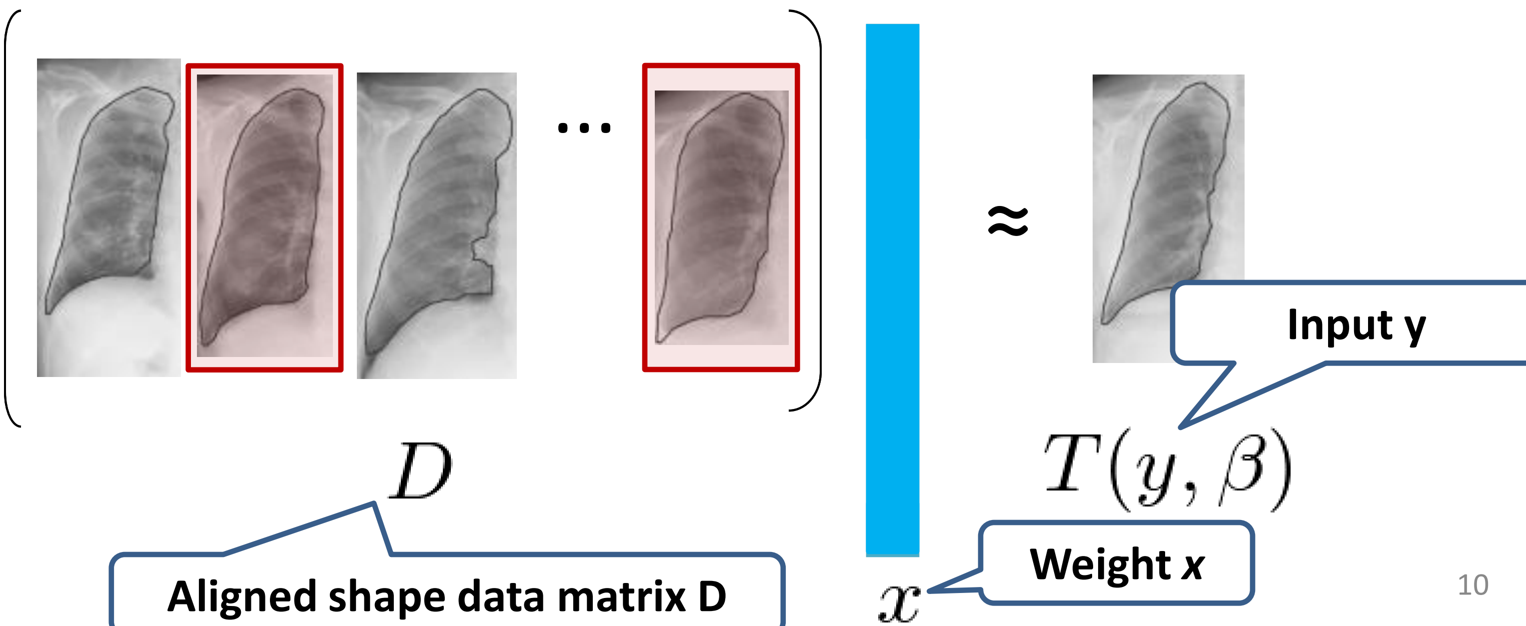
subject66landmark.jpg

subject20landmark.jpg

Methods

Shape prior using sparse shape representation

- Formulation:
  - $Min_{\{x,\beta\}} \|T(y,\beta) - Dx\|_2$

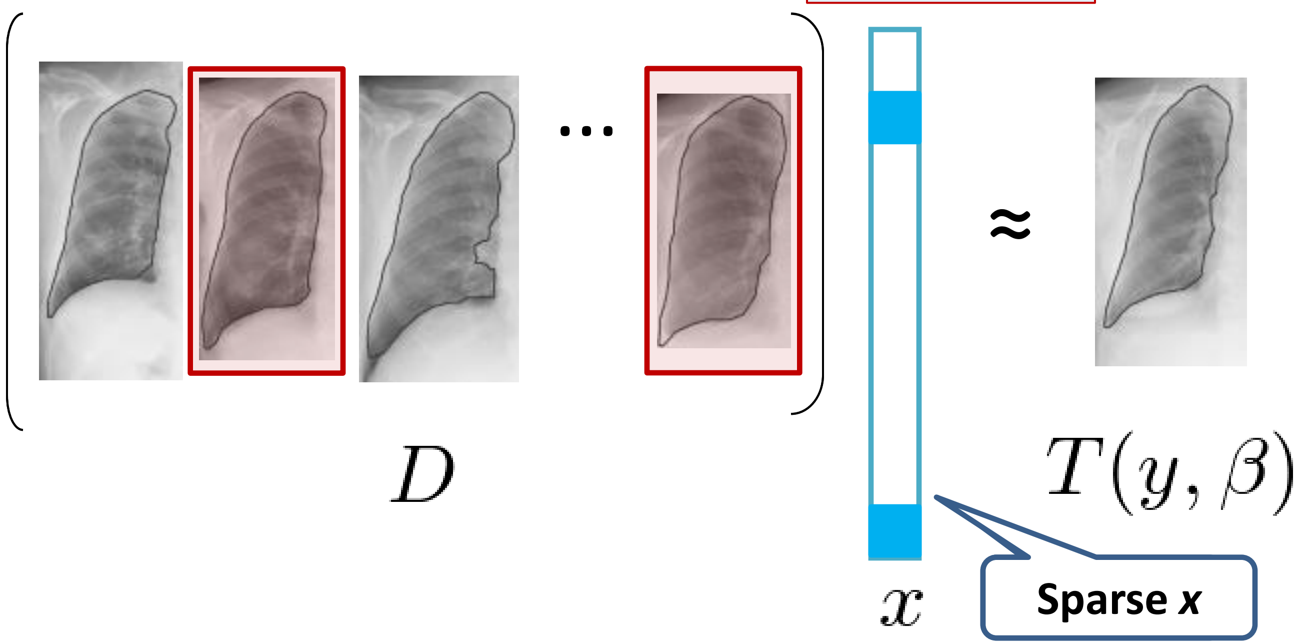


Methods

Shape prior using sparse shape representation

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

Number of nonzero elements



Methods

Shape prior using sparse shape representation

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

subject66landmark.jpg

subject20landmark.jpg

Methods

Shape prior using sparse shape representation

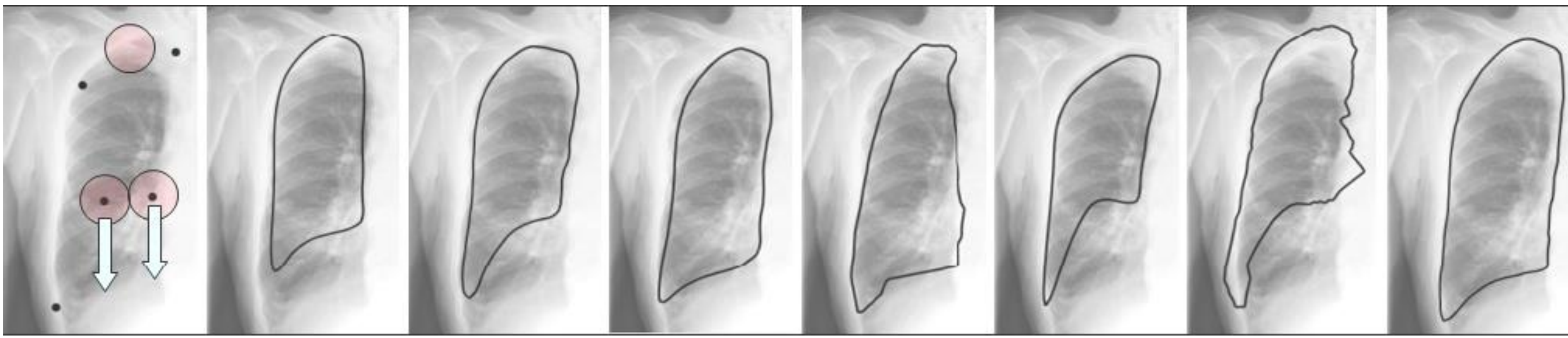
- Why it works?
  - <u>Robust</u>: Explicitly modeling "e" with L0 norm constraint. Thus it can detect gross (sparse) errors, i.e., non-Gaussian
  - <u>General</u>: No assumption of any parametric distribution model (e.g., a unimodal distribution assumption in ASM). Thus it can model large shape variations.
  - <u>Lossless</u>: It uses all training shapes. Thus it is able to recover detail information even if the detail is not statistically significant in training data.

Applications – Part I

2D lung localization in X-ray

(Lung computer-aided diagnosis system, Siemens)

- Handling gross errors

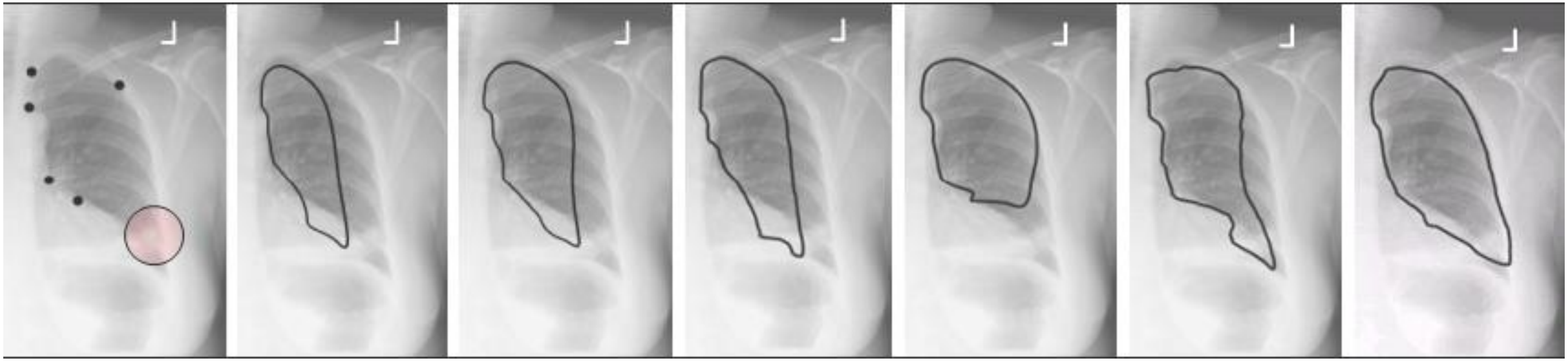


Detection	PA	ASM	RASM	NN	TPS	Sparse1	Sparse2
Sensitivity	62	66	81	81	59	63	**87**
Specificity	99	99	99	99	99	98	**99**
Dice SC	76	78	88	87	74	71	**91**

Applications – Part I

2D lung localization in X-ray

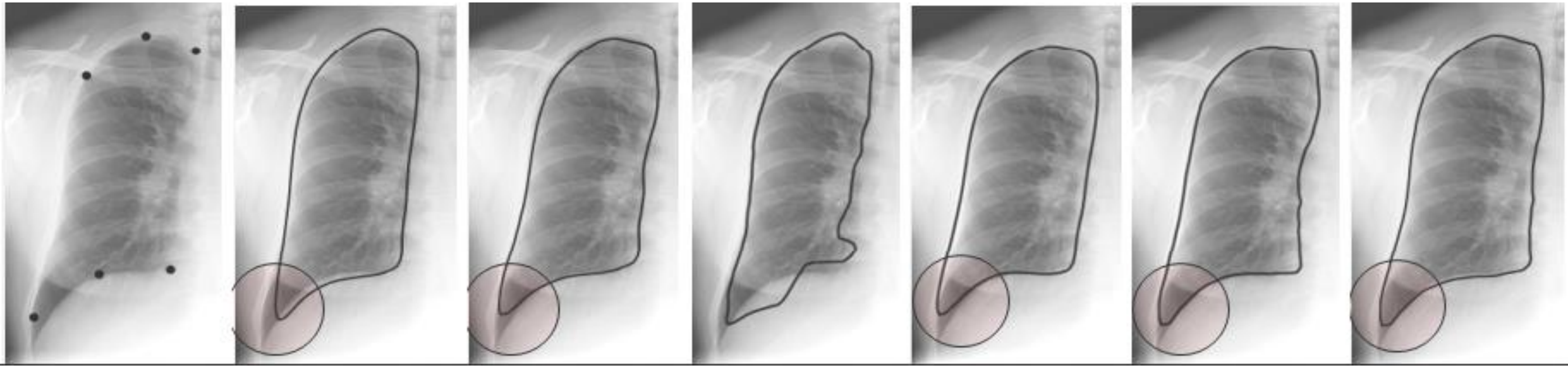
- Multimodal shape distribution



Detection	PA	ASM/RASM	NN	TPS	Sparse1	Sparse2
Sensitivity	50	61	63	75	73	**92**
Specificity	99	99	98	99	99	**99**
Dice SC	64	72	73	79	79	**91**

Applications – Part I
2D lung localization in X-ray

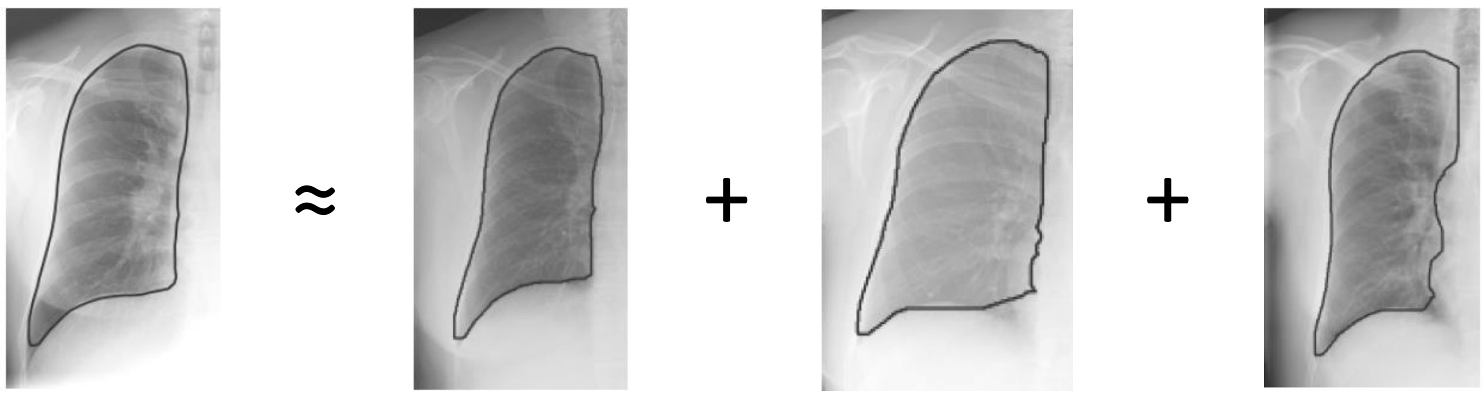
- Recover local detail information



Detection	PA	ASM/RASM	NN	TPS	Sparse1	Sparse2
Sensitivity	93	93	87	97	97	**98**
Specificity	99	99	99	98	99	**99**
Dice SC	94	95	90	94	96	**96**

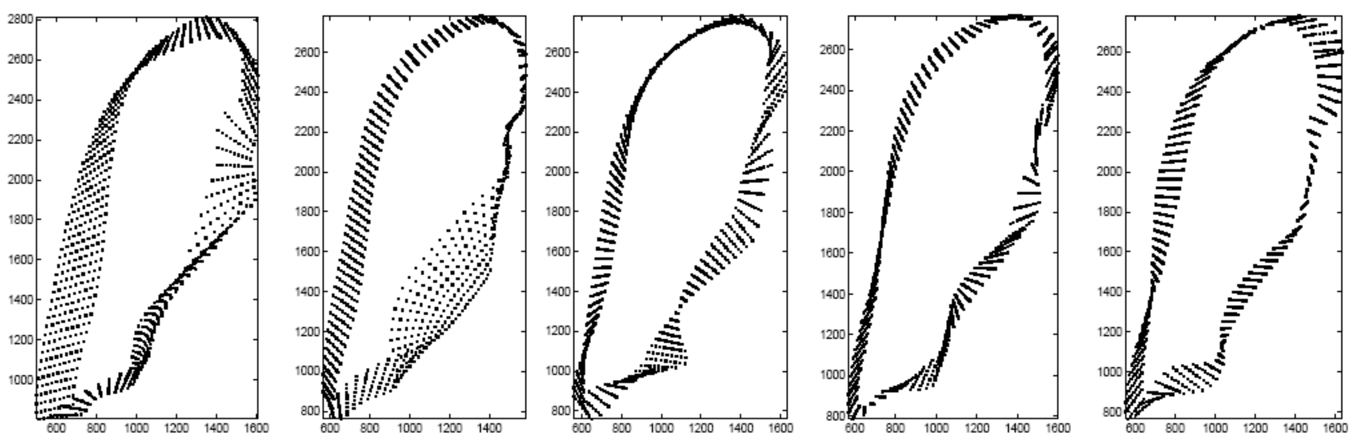
Applications – Part I
2D lung localization in X-ray

- Sparse shape components



0.5760 0.2156 0.0982

- ASM modes:

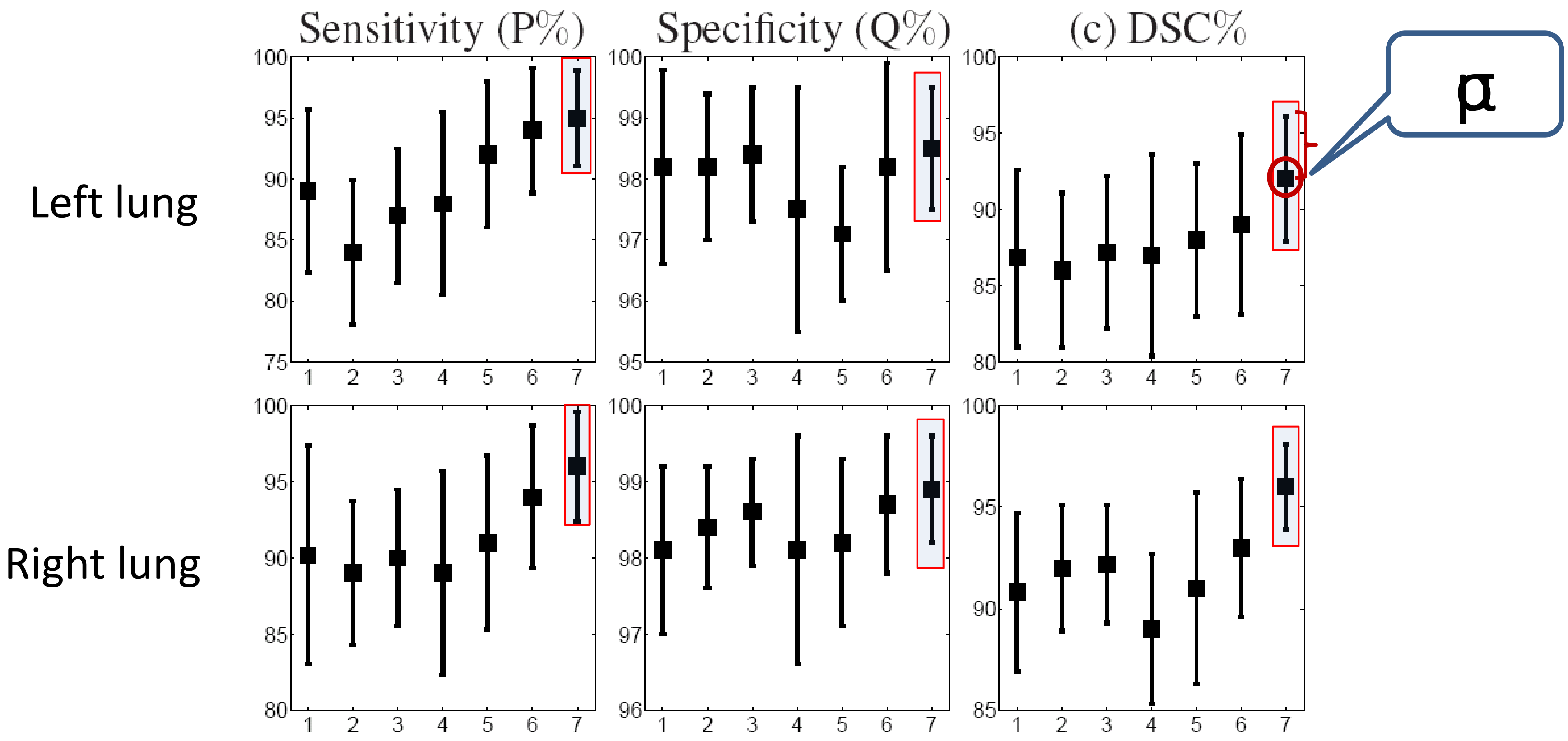


(a) 1st mode (b) 2nd mode (c) 3rd mode (d) 4th mode (e) 5th mode

Applications – Part I

2D lung localization in X-ray

- Mean values and standard deviations. ~1,000 cases.



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

Applications – Part II

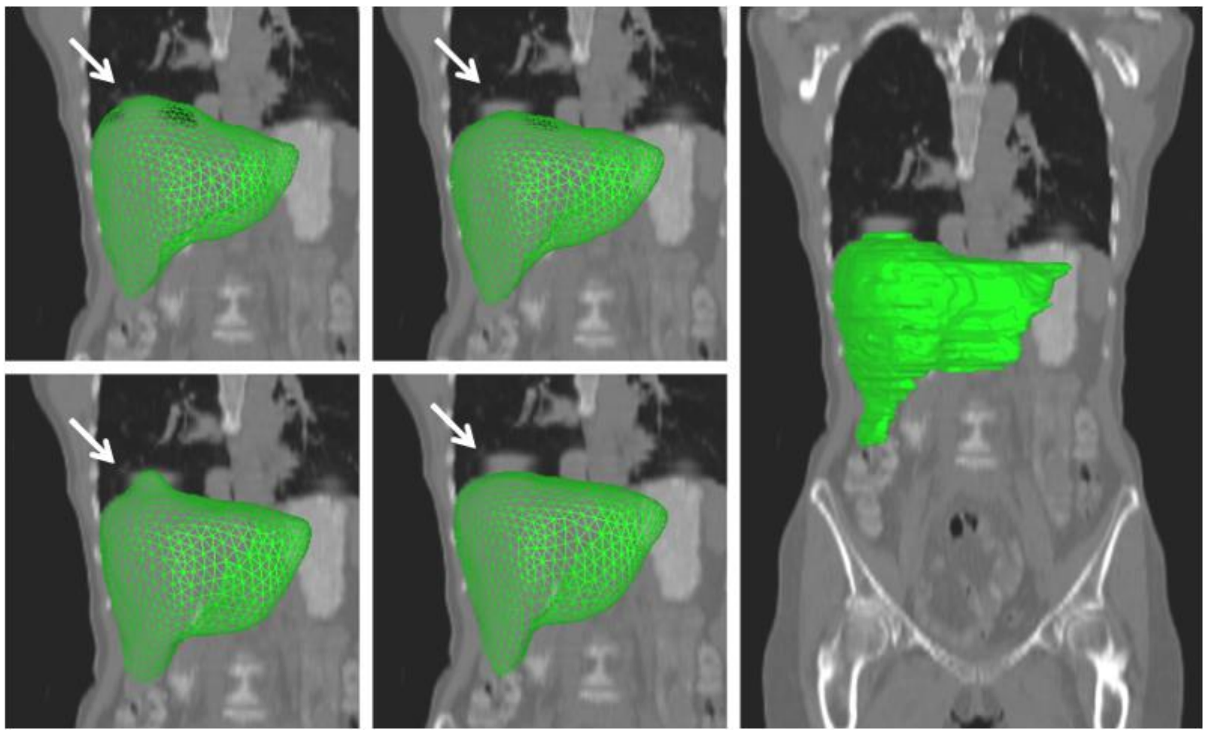
3D liver segmentation in low-dose CT

Same landmarks + different shape priors

Procrustes analysis | Sparse shape | Ground truth

Initialization

Deformation

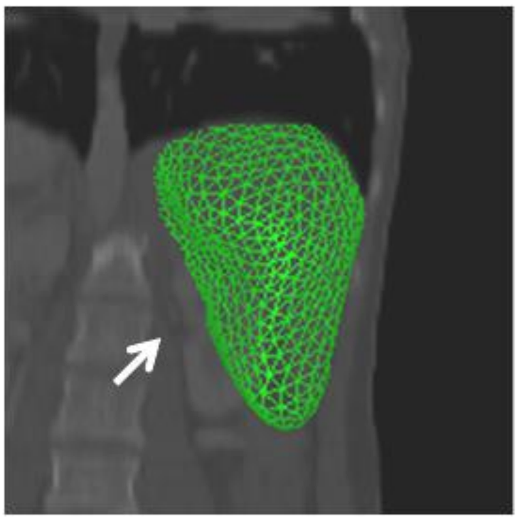


Same deformation module

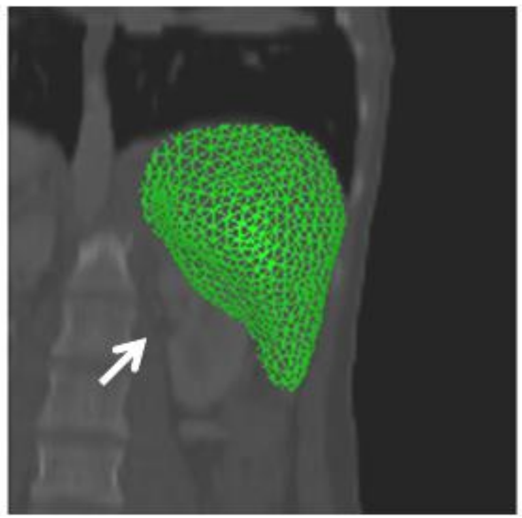
Applications – Part II

3D liver segmentation in low-dose CT

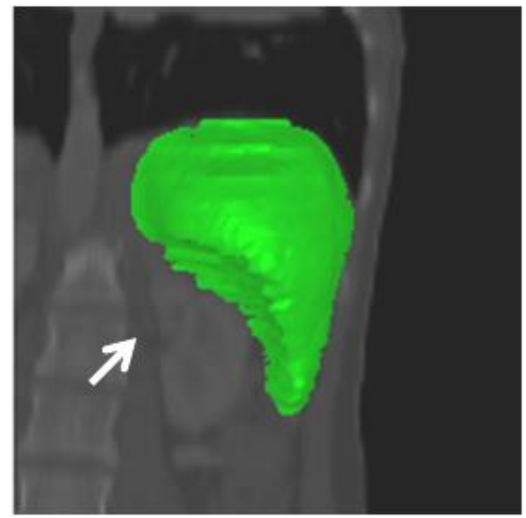
- Shape refinement during segmentation



ASM-type [Zhan’09]



Sparse shape



Ground truth

Summary of Robust Segmentation

- Robustly handle abnormal cases, such as diseased cases (liver tumor). Critical to healthcare applications such as computational diagnosis systems.
- Patent with Siemens. Used in several clinical applications. Key contribution for our awarded NSF-MRI grant ('12-'16).
- Relevant publications:
  - First author papers (**S. Zhang**, Y. Zhan, J. Huang, D. Metaxas):
    - MICCAI 2012 and 2011 (**MICCAI Young Scientist Award Finalist**)
    - CVPR 2011
    - Medical Image Analysis (Top 25 hottest articles in 2012)
  - Second author paper
    - Medical Physics 2013 (with my co-mentored student, G. Wang)
    - ISBI 2013, oral (with my co-mentored student, Z. Yan)

References

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