A Statistical Aspect of Imaging Analytics Based Computer-Aided Diagnosis

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Next decade will be very exciting for AI in computer vision and machine intelligence

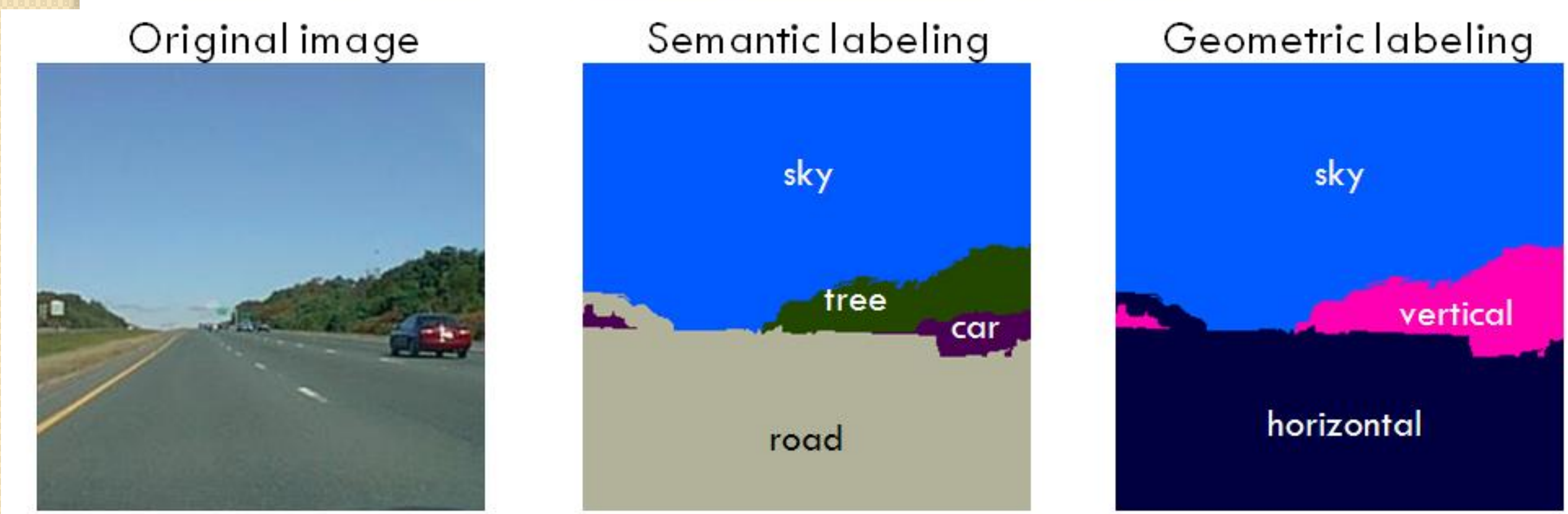
- http://www.youtube.com/watch?v=cdgQpa1pUUE
- **Self-Driving Car Test: Steve Mahan**

- http://www.youtube.com/watch?v=lK2PkSr5n3E
- **At Google I/O: New gadgets, Google glasses**

- **Best paper award on Kinect Human Pose Estimation using Single Depth Images of CVPR 2011**

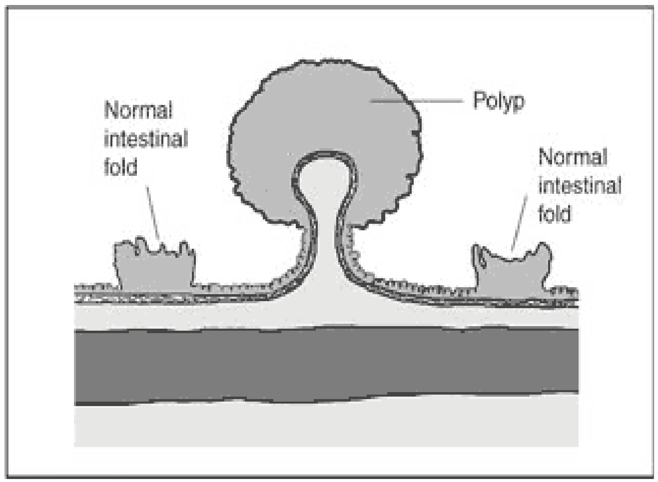
- …so what we do? Reliability and performance can make a difference

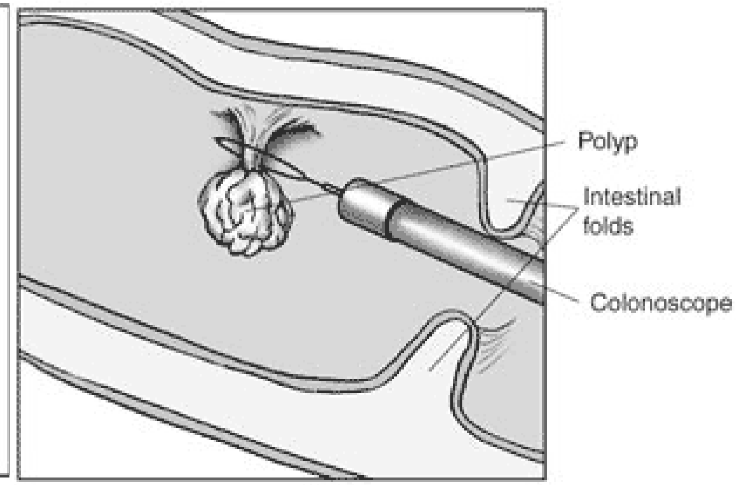
Image Segmentation is Semantic (thus supervised learning is needed)?



Medical Image Computing in Computer-Aided Diagnosis: A Statistical Approach

- What's a polyp (in textbook)?





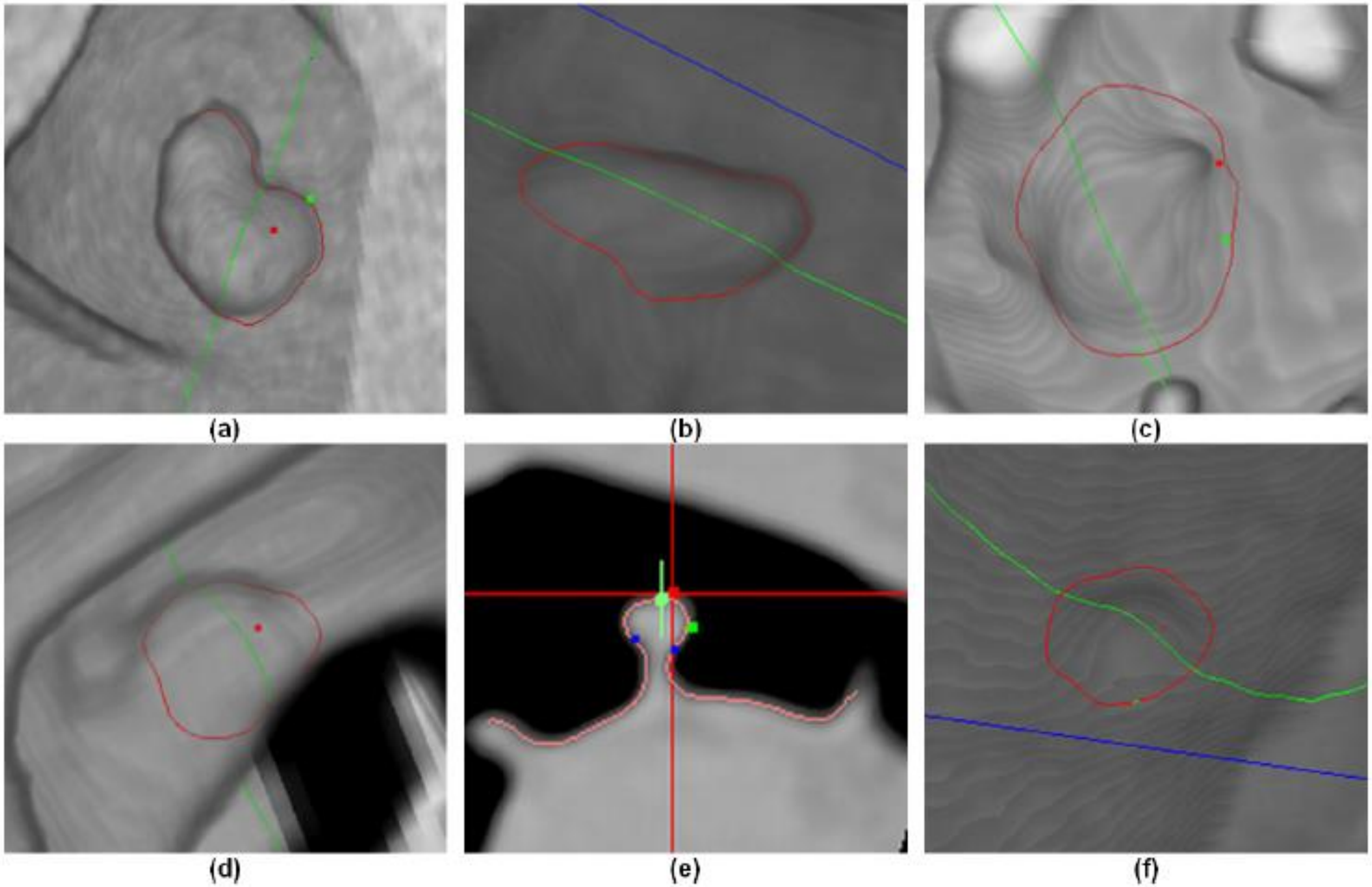
- What's CAD, or CADx?
  - A (hopefully) useful tool assisting Radiologists to have better performance in finding cancer lesions (significantly higher sensitivity with manageable cost)
  - **Human-in-the-loop**: Only radiologists have the legal right and responsibility for clinical reports. There is no notation that lesion is found by human or machine

CT Colonography

Outlines

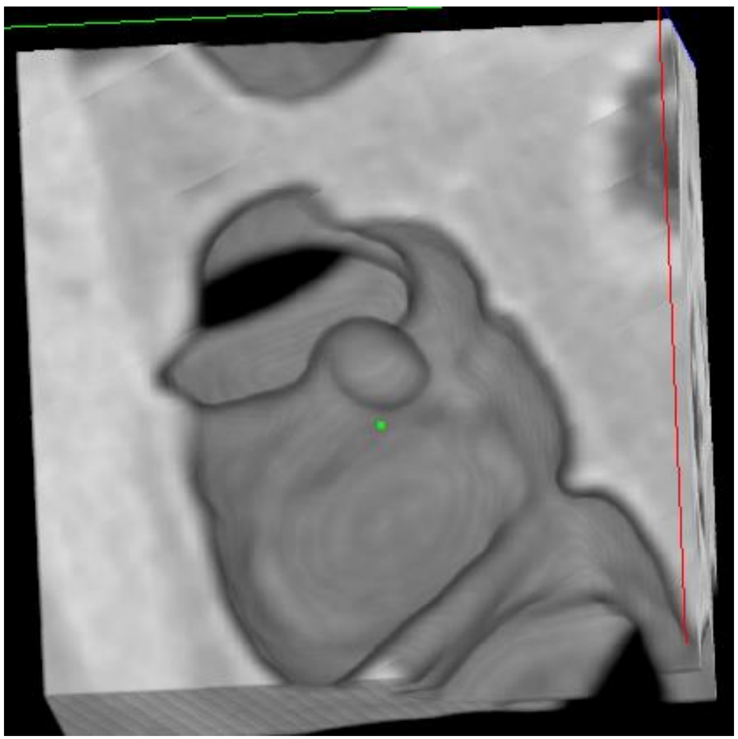
- Colon CAD:
  - Polyp segmentation [CVPR 08]; from polyp segmentation features [CVPR 11] to segmentation-less features for unified detection [NIPS 12, submitted]
  - False Positive Reduction: Ileo-Cecal Valve detection & removal [ECCV 08; MCV 10; RSNA 07]; colon segmentation [MICCAI 09]; CTC Ecleansing on Weakly Tagging Cases
- CAD Diagnosis Support:
  - GGN segmentation & detection [MICCAI 09]; Lung Nodule Context Learning [CVPR 10]; Metric Learning based Polyp Prone-supine matching; Sparse Classification [MICCAI 11]; Coarse-to-fine Classification [CIKM 12]
- Others (full-body image parsing):
  - Vertebra segmentation & identification [MICCAI 10]; Hierarchical curvature structure parsing: with application on coronary artery tree modeling [ICCV 09]; flexible structure parsing and segmentation based labeling …

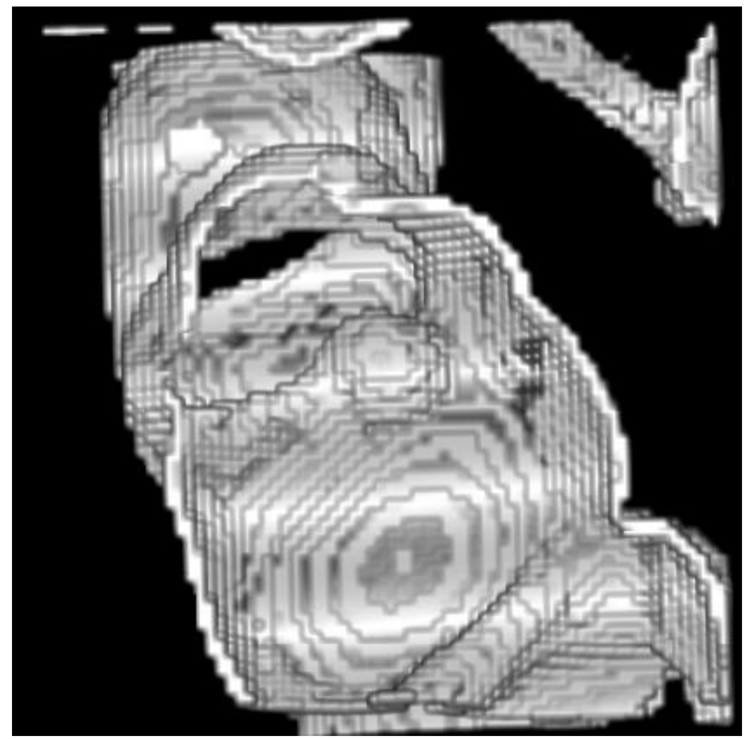
Multistage Probabilistic Polyp Segmentation (CVPR'08)



Diagnosis purpose: helping radiologist to decide whether finding is true; and cancer staging; can be shown in CTC visualization

0: CAD-input or manual input

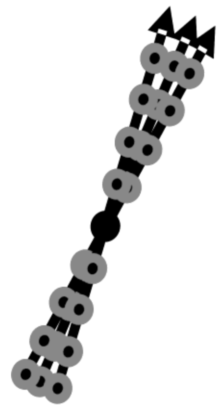




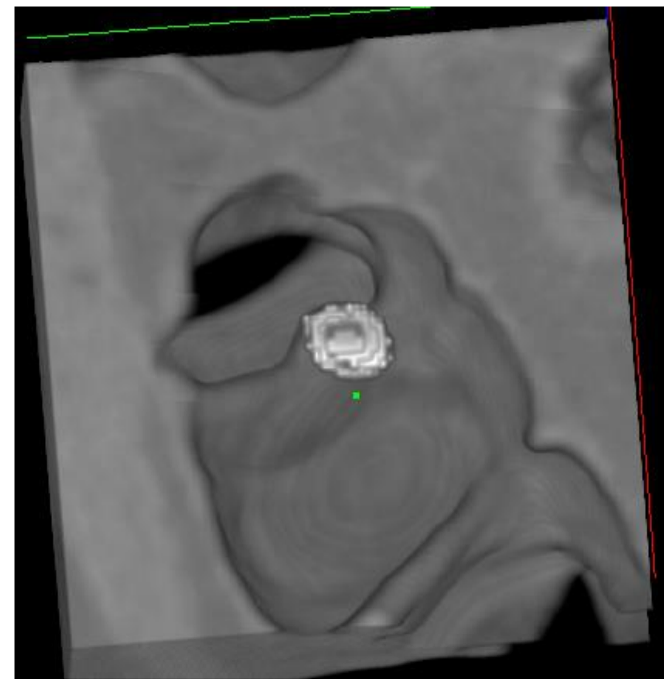
I: Polyp Tip Finding by Detection

1. 3D Point-detector (with probability output)
2. Grouping by Connected Component Analysis
3. Geometric centroid on surface

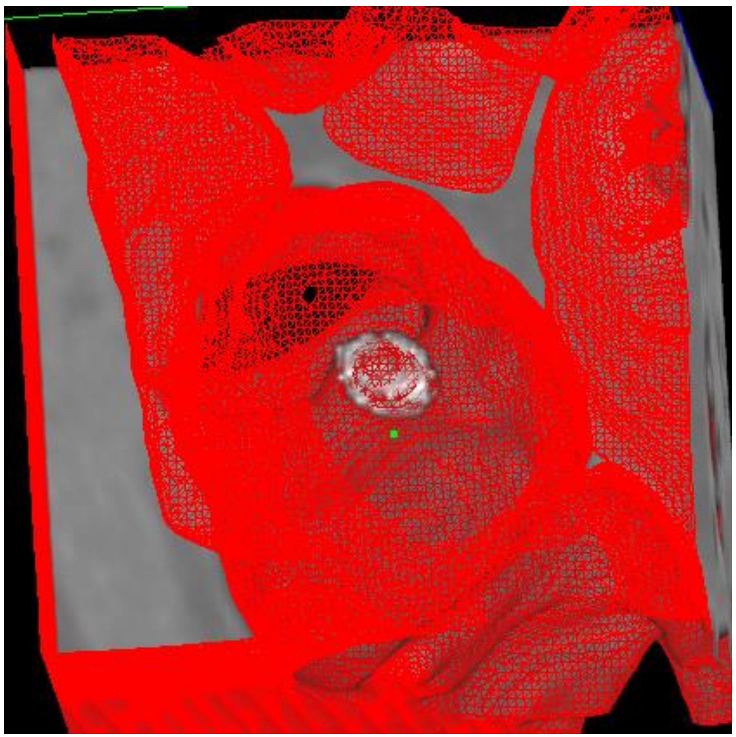
- Probabilistic spatial prior
- Learned using thousands of boosted low-level steerable image features in intensity, gradient, curvature … & their polynomial expansions in multiscale via PBT

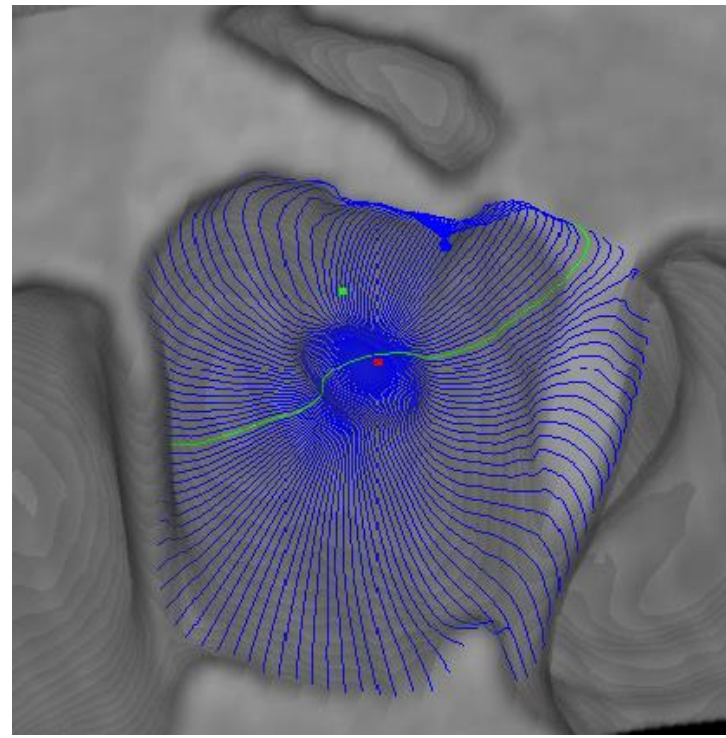


(a)

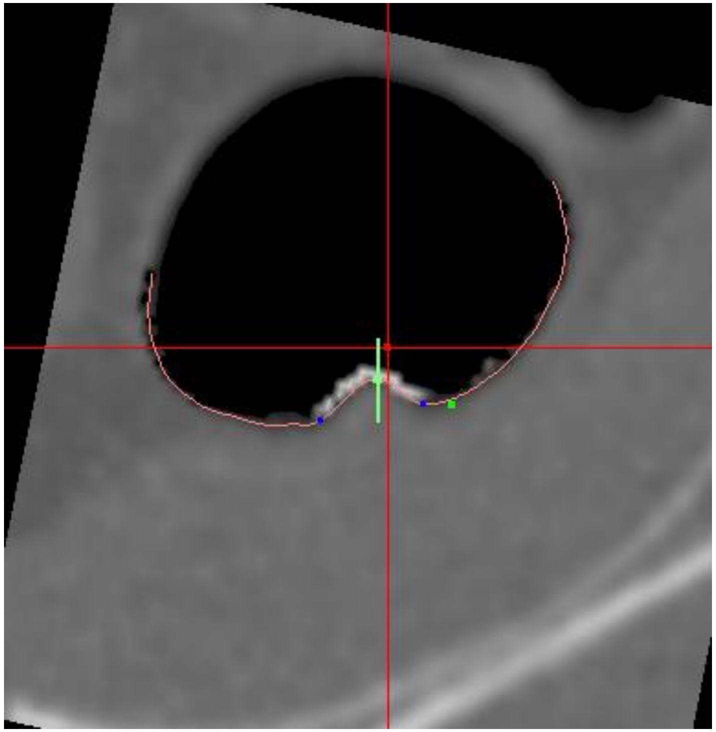


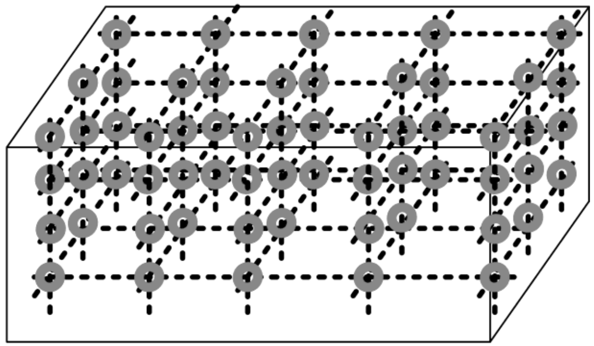
1.5: Marching-cubes & Polar-coordinates





II: Polyp Interior-Exterior Detection

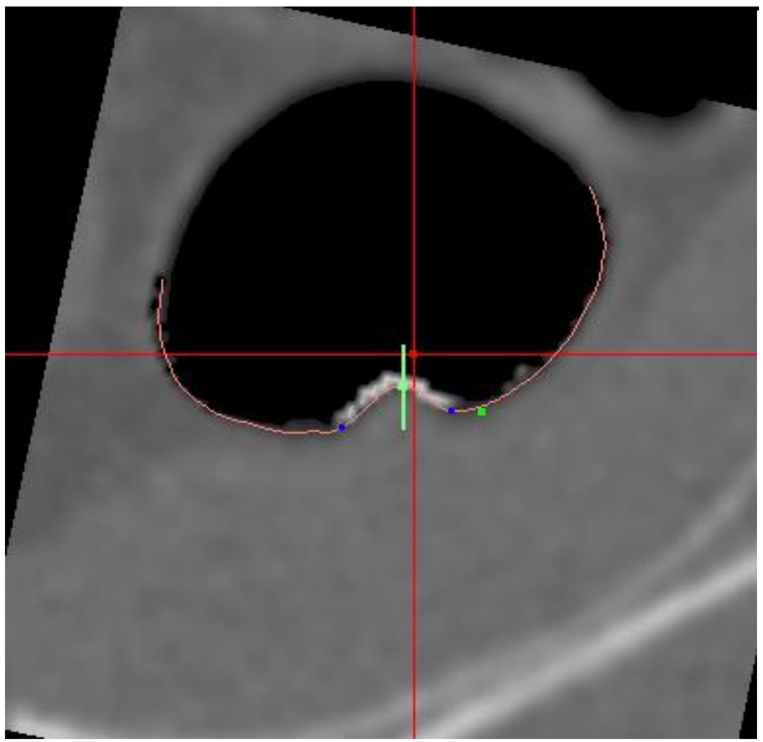


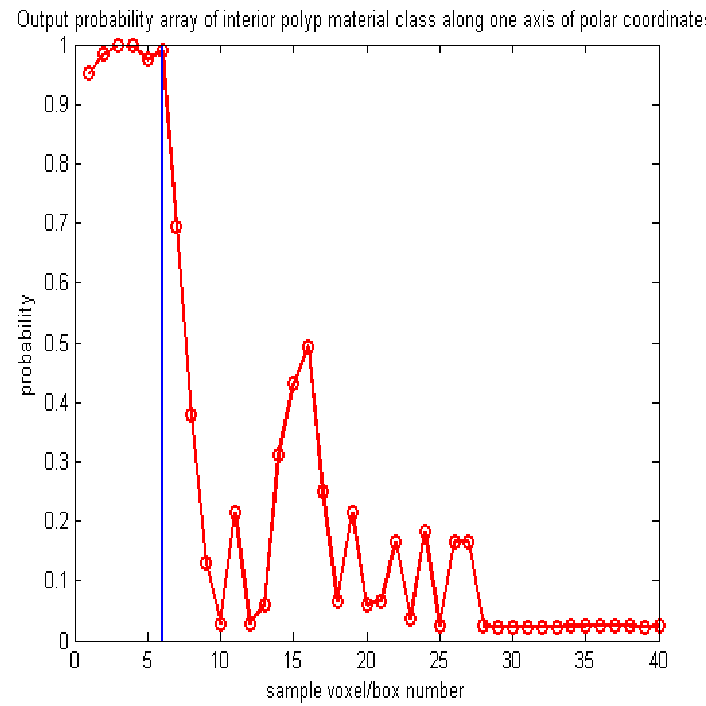


(b)

- Multiscale 7X7X7 sampling patterns with tens of thousands image features, 81 features for each grid

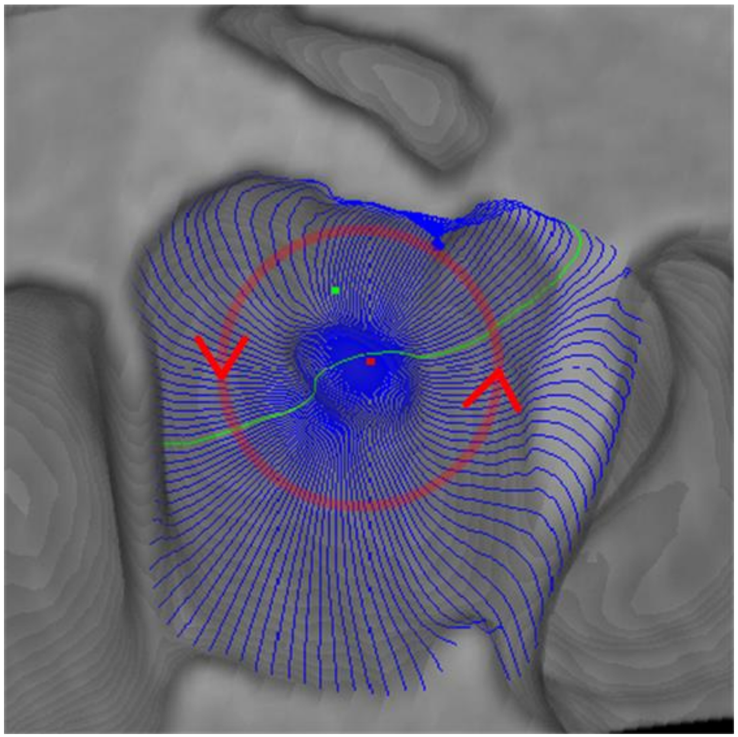
III: Boundary Classification via Robust Curve Parsing (Bi-partitioning by Stacked Learning), or regression?

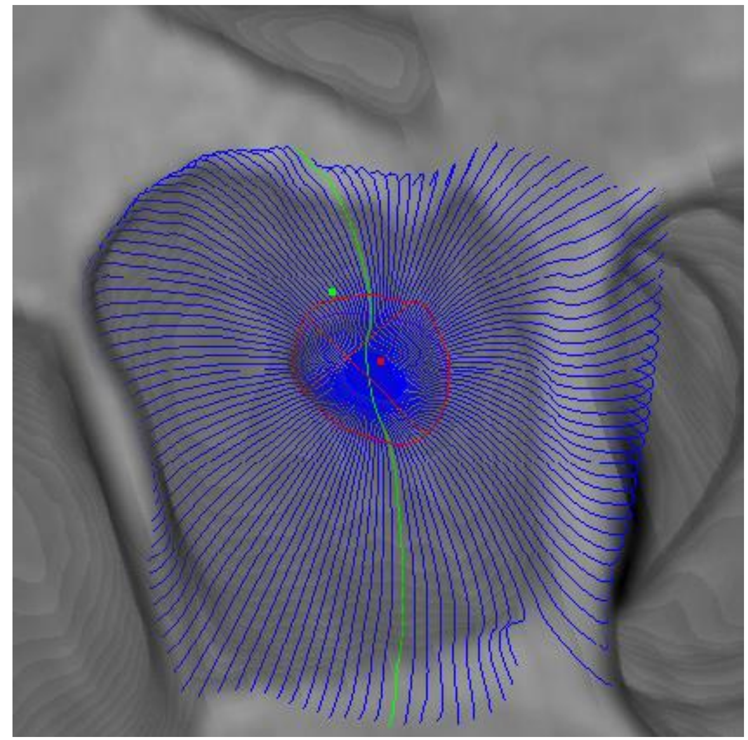




- 440 curve parsing features for boosting which captures full-range interactions for more complex statistical patterns

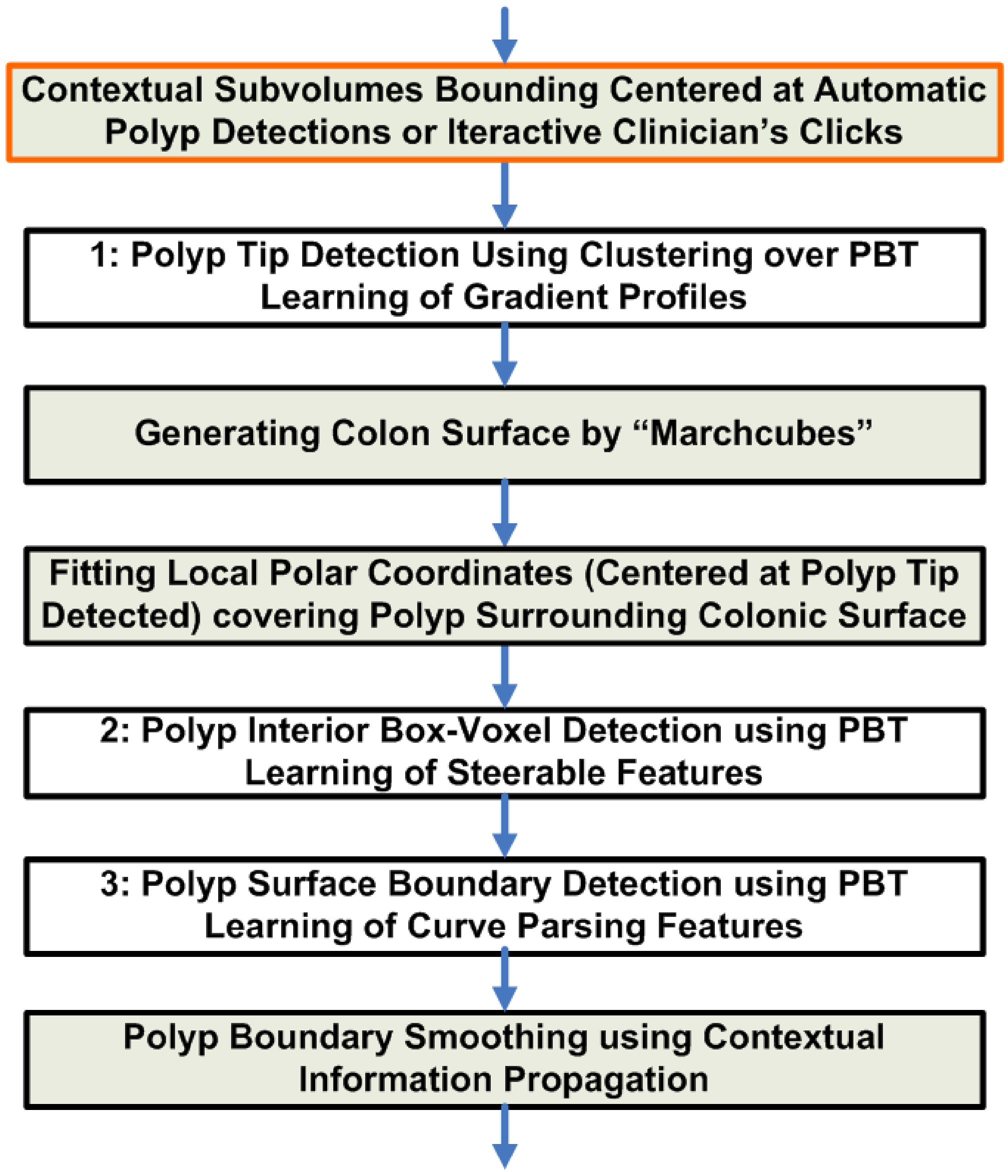
IV: Compositional Model & Multistage Learning (stacked generality)





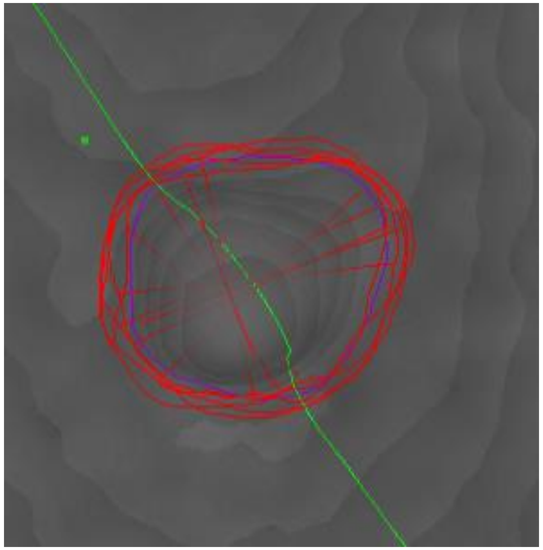
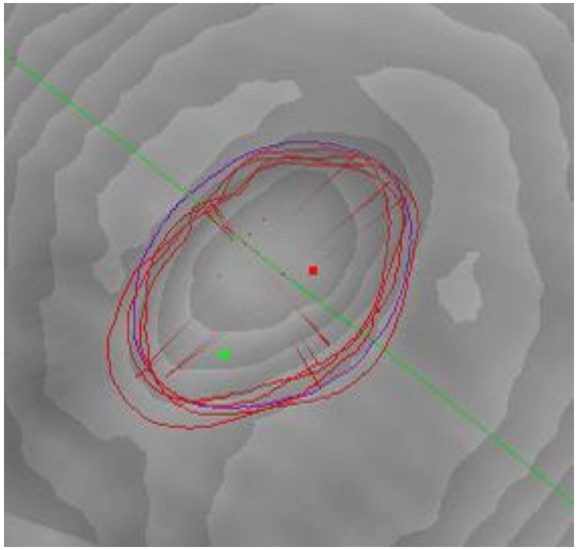
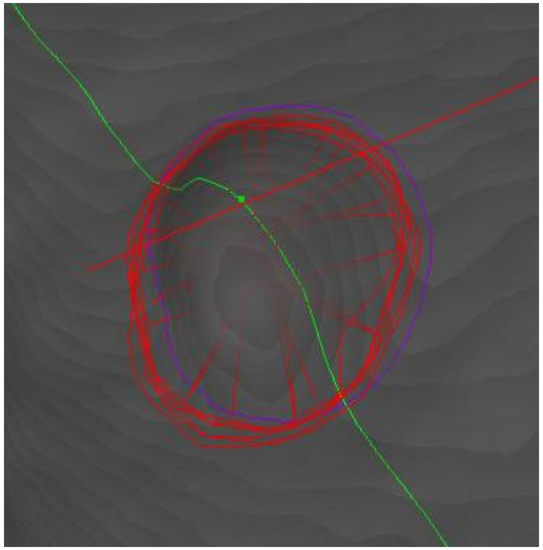
- Smoothness: Gaussian, Viterbi-like Dynamic Programming, Loopy Belief-Propagation

Polyp Segmentation Flow-chart



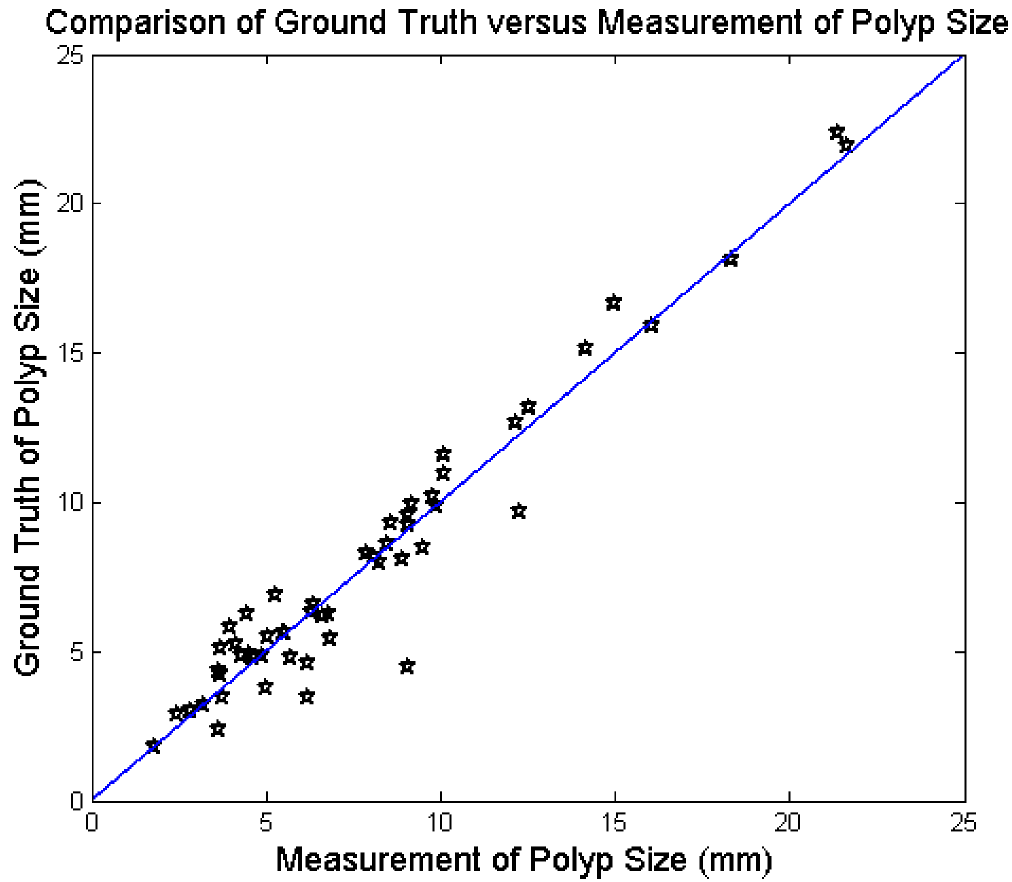
The Power of Compositional Model

- Break-down: The Dual of low-dimensional training & more training samples (Trainability)
- Assembling: new polyp instances can be assembled from different basis curves (lower-dimensional feature/primitive sharing for Generality)

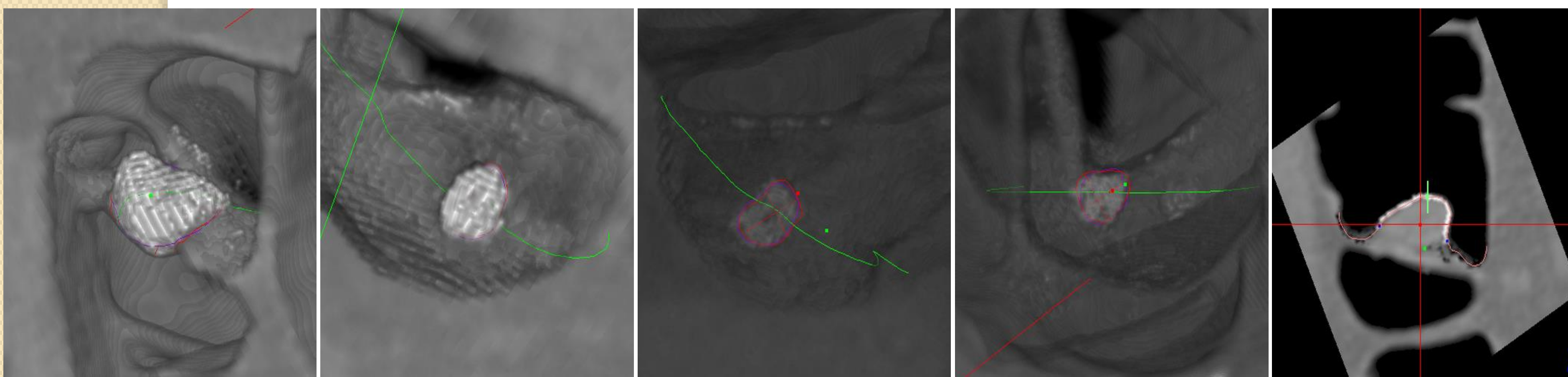
- Surface Representation Versus a Pencil of Curves Representation

Generality & Accuracy (of Supervised Segmentation)



- Testing-in-the-wild: **The most accurate polyp segmentation method based on large scale unseen data validation: ~2.22mm average error versus 2.54mm error from the regressed polyp size measurements [CVPR'11], trained using all polyp detection features (400+), in unseen tagged-prep datasets (358 polyps >= 3mm).**

Probabilistic Polyp Segmentation Features for Detection & Size Regression (CVPR'11)



Flowchart or Workflow (stratified or interleaved?)

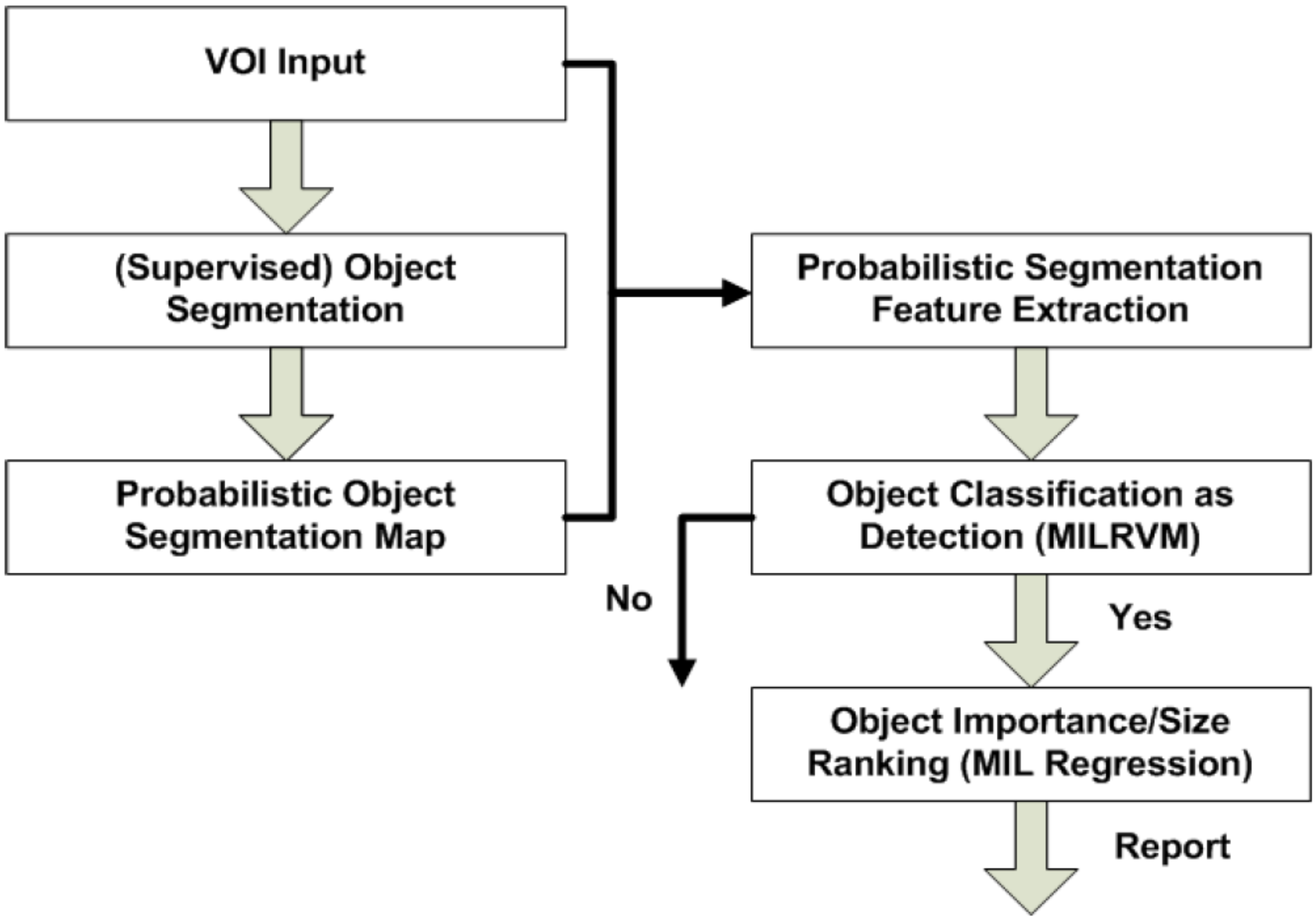


Figure 1. Flow-chart of the staged object/polyp segmentation, classification/detection, and size/importance regression process.

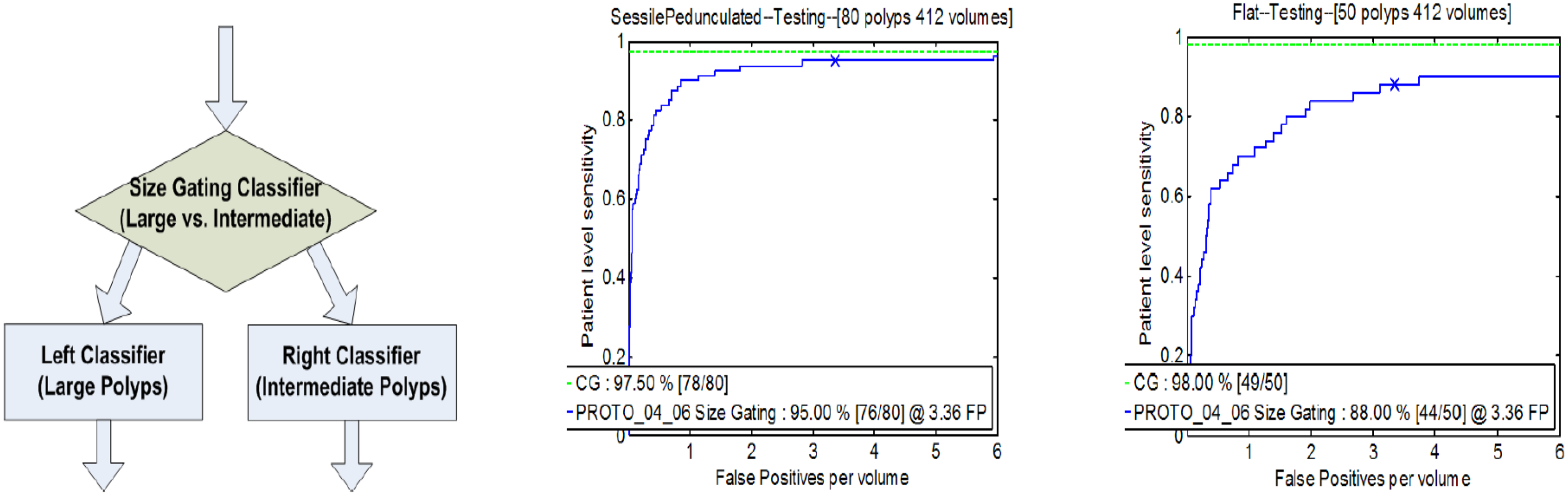
Probabilistic Polyp Segmentation Features for Detection (CVPR'11)

What exactly PSM features are:

1) Statistics of polyp dimensions and class-specific probabilities, their polynomial expansions [to fit linear classification]
2) Multi-resolution object-class polyp boundary smoothness [Gestalt Perception Law, most discriminative!!]
3) Spatially banded class probability and area statistics [multi-resolution shape context [Belongie'01], related to [Yao'09]]
4) 3D Ellipsoid Shape Descriptor [shapeness]
5) Multiscale Intensity Histogram Features [extendable to 3D rotation-invariant HOG, effective to tagged stool versus stool coated polyp]
6) …

**Proposing sensible image features is an open and probably more heuristic "art" in studying related subjects. By augmenting the class-conditional prob-maps with intensity images, there are more work to be done … General computer vision has a lot of work … auto-tuning, auto-learning, transformation-invariance build-in; http://www.vlfeat.org/; …

Results

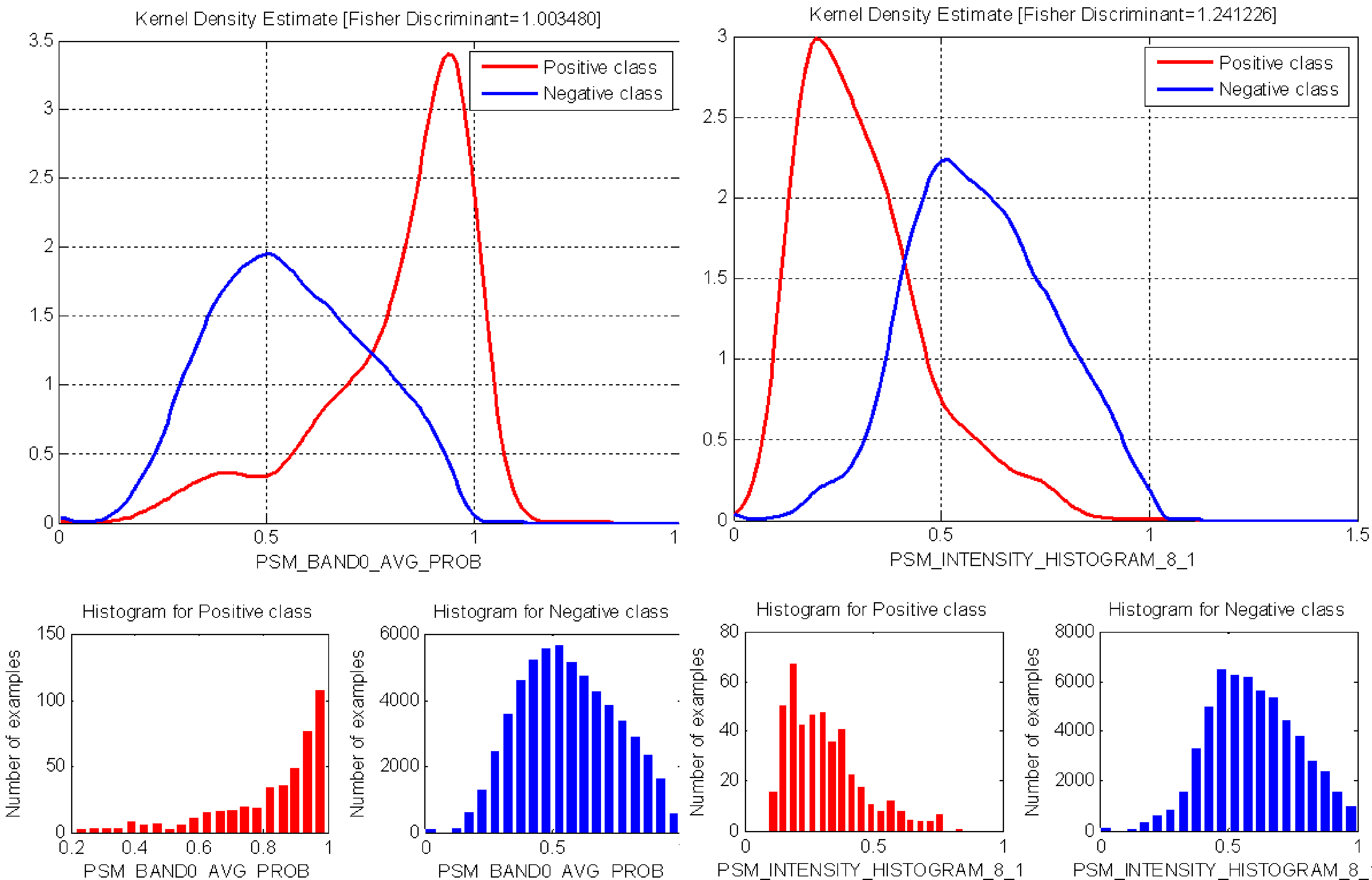


(a) Soft-gating Classifier (b) Sessile-Pedunculated Polyp Detection FROC (C) Flat Polyp Detection FROC

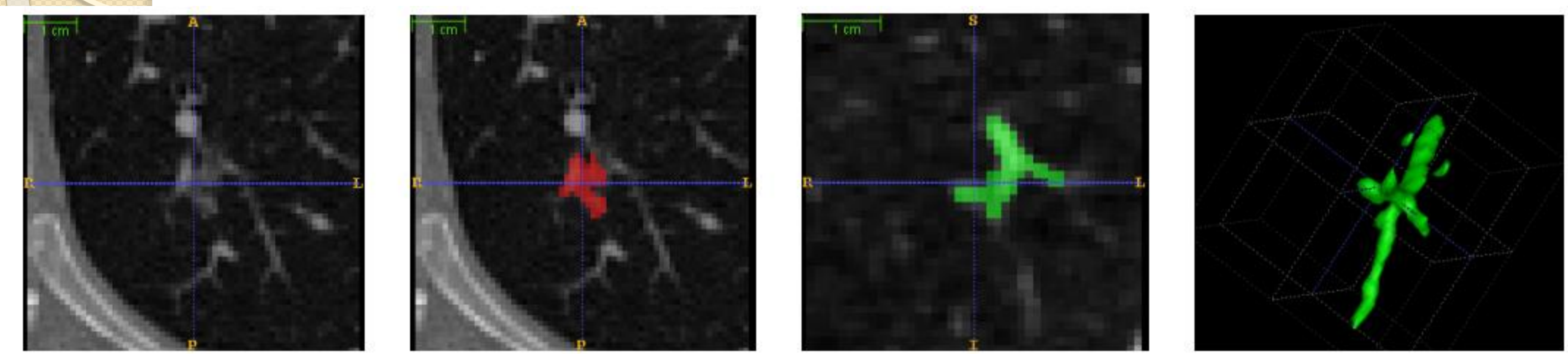
Figure 4. Size-based soft-gating classification framework (a) and FROC curves of polyp detection using size-gating classification tree with PSM features incorporated, on two polyp subcategories of 80 (142 in volume-level) Sessile-Pedunculated (b) and 50 (89 in volume-level) flat polyps (c). Green dot lines are the CG sensitivity upper bound and FROC curves are shown in Blue.

- The best FROC results reported in literature by then. By injecting PSM features into the branch node and leaf nodes building, the sensitivity system levels increase 7~8%, at similar FP rates per patient. 95% sensitivity for SP polyps, and 88% for flat polyps @ 3.36FP/vol.
- The art of hierarchical probabilistic discriminative (PHD) learning.

Power of Inductive Information/Feature Fusion



Segmentation-less features & extension to Lung CAD (nodule versus vessel, NIPS 2012, submitted)



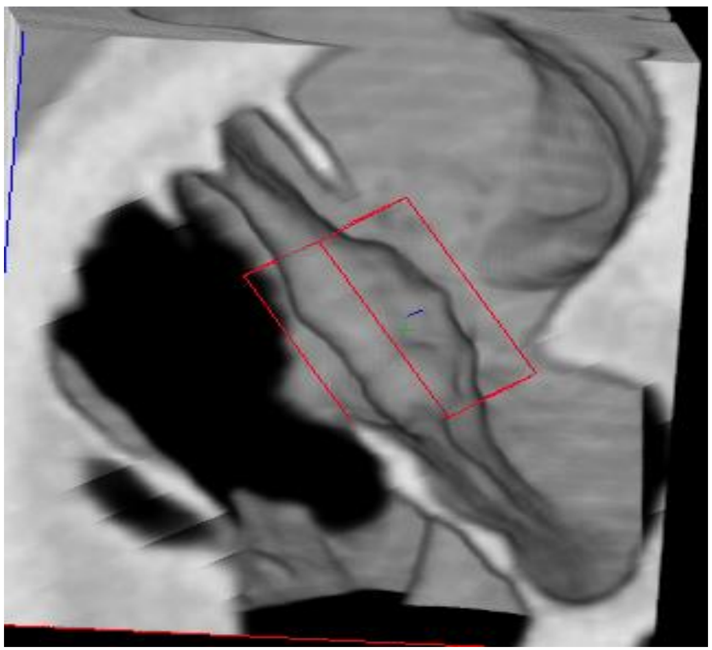
- Generic probabilistic voxel labeling & thresholding
- Simplified, Summarizing response features in joint space
- Almost effective as PSM features in detection performance, not size estimation
- Curvature is important for polyps, but not significant for nodules (a joint appearance model for solid, partial-solid and GGN)
- Tunable to make weak class work better, e.g., GGN, partial-solid, flats, small lesions by balancing and twisting the empirical distributions of training

Discussion & Thoughts

Geometric or Probabilistic Process? A variety of drastically different techniques have been proposed for lesion detection feature computation. However, most previous work [4, 7, 11, 18–20, 31, 32, 35–37] focus on *extracting low-level, directly observable surface geometry and volumetric intensity features*: as geometric descriptors (mostly curvature based) to describe the degree of satisfying the sphericity polyp shape assumption [11, 20, 37], segmentation or geometric protrusion based polyp occupancy measurements [32], fuzzy clustering and deformable model [35], and intensity features (as mean, median, maximum, minimum, etc.) [31] or Hessian statistics [23] for polyp detection. [4, 7, 18, 19, 36] all address nodule shape morphology modeling versus other structures. In our work, geometry and intensity information are first encoded into the voxel labeling process through PBT learning. Then translation and rotation invariant visual features are computed summarizing the joint distribution of intensity and learned lesion-class probability.

Data-driven Learning: Probabilistic approach of modeling the shape differences between polyps and other colonic surface structures is exploited [17]. Similarly, [19] discuss its counterpart in nodule detection. However, these method strongly depends on the validity and generality of the restricted, parametric prior assumptions from medical literature which often does not reflect well the image noise and appearance variations in real hospital scale datasets. Their predefined models are also difficult to be tuned from a data-driven perspective. Consequently, they report significantly inferior performance results on very limited datasets of 36 volumes and 24 polyps [17] and 50 volumes with 60 solitary solid nodules [19]. Our feature computation is learned from a large radiologist annotated image database in both colon and lung CAD. Compared with our work, [17, 19] fail to capture the complex, high-dimensional and multi-modal underlying feature distributions that a common CAD system deals with a large screening patient population, cross races and demographies.

False Positive Reduction: What's Ileo-cecal Valve?

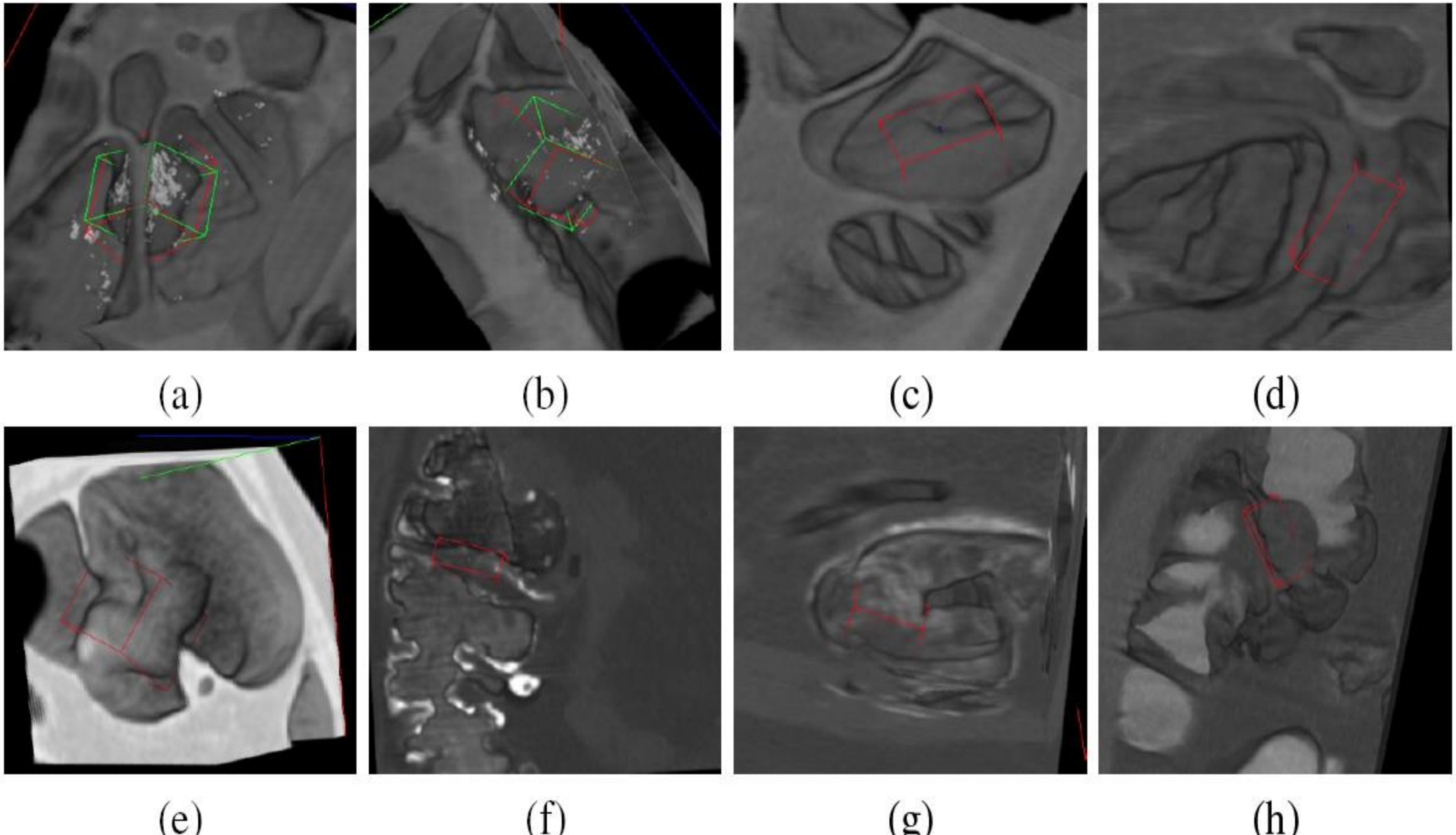


- Ileo-Cecal Valve can present with bumpy, polyp-like sub-structures
- Importance: a CAD system can mistakenly detect those bumps – resulting in polyp false-positives (FPs), up to 15~20% (really hard ones!!)

- Previous approach: Summers et al. 2004, *Radiology* – technique not fully automatic;
- Recent approach: Ye & Slabaugh: Concavity analysis for reduction of ileo-cecal valve false positives in CTC, ISBI 2011.

- Detect "Forest of trees", object detection scale!

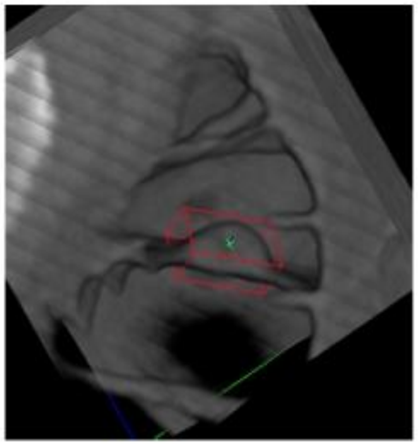
Ileo-cecal Valve Detection (ECCV'08)

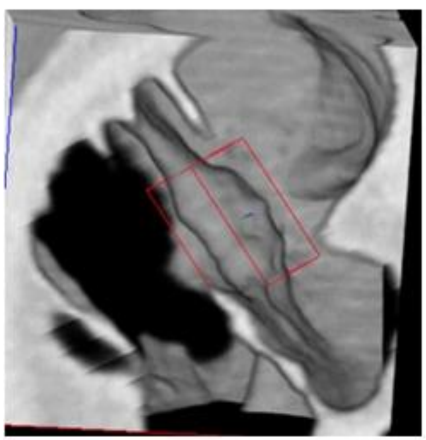


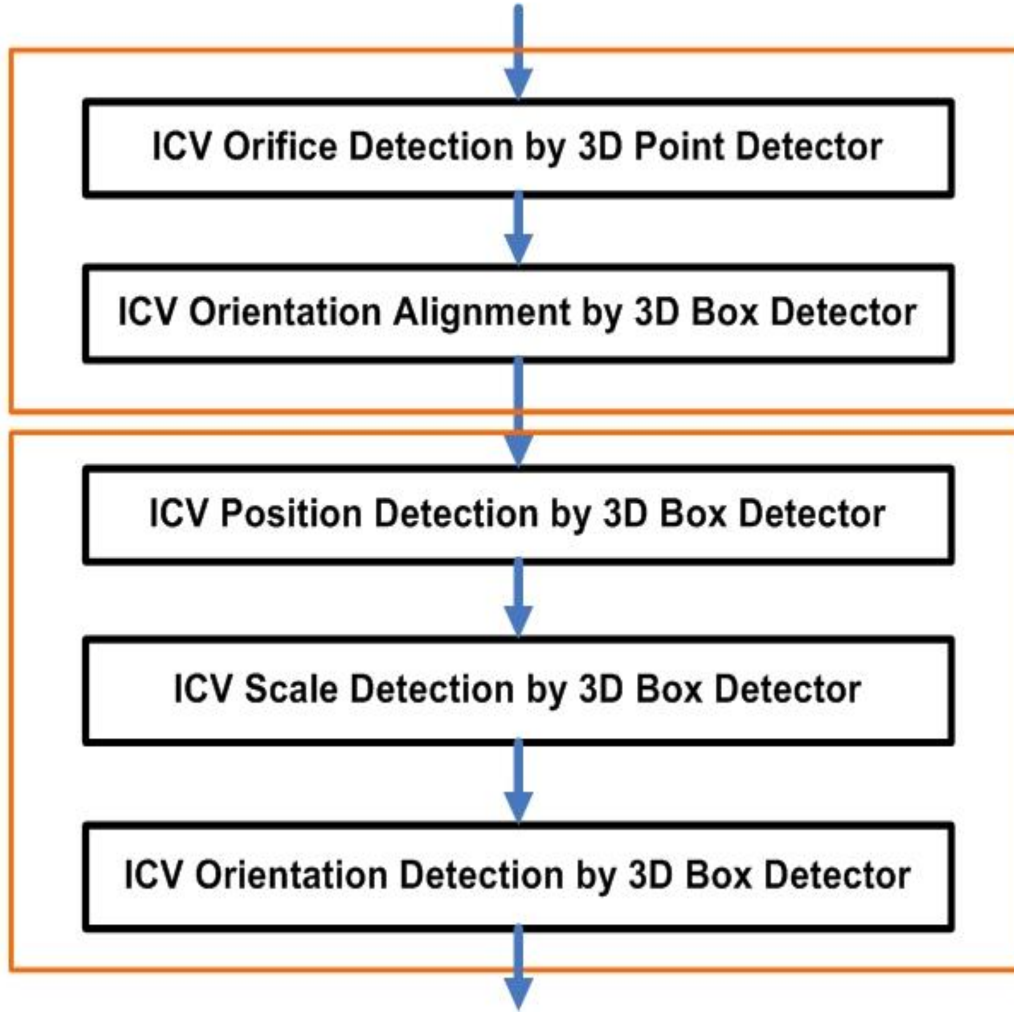
(a) (b) (c) (d) (e) (f) (g) (h)

Quantitative Evaluation: 90~92% detection rate for unseen data (trained on clean; validated on clean and tagged) under PASCAL Detection Standard.

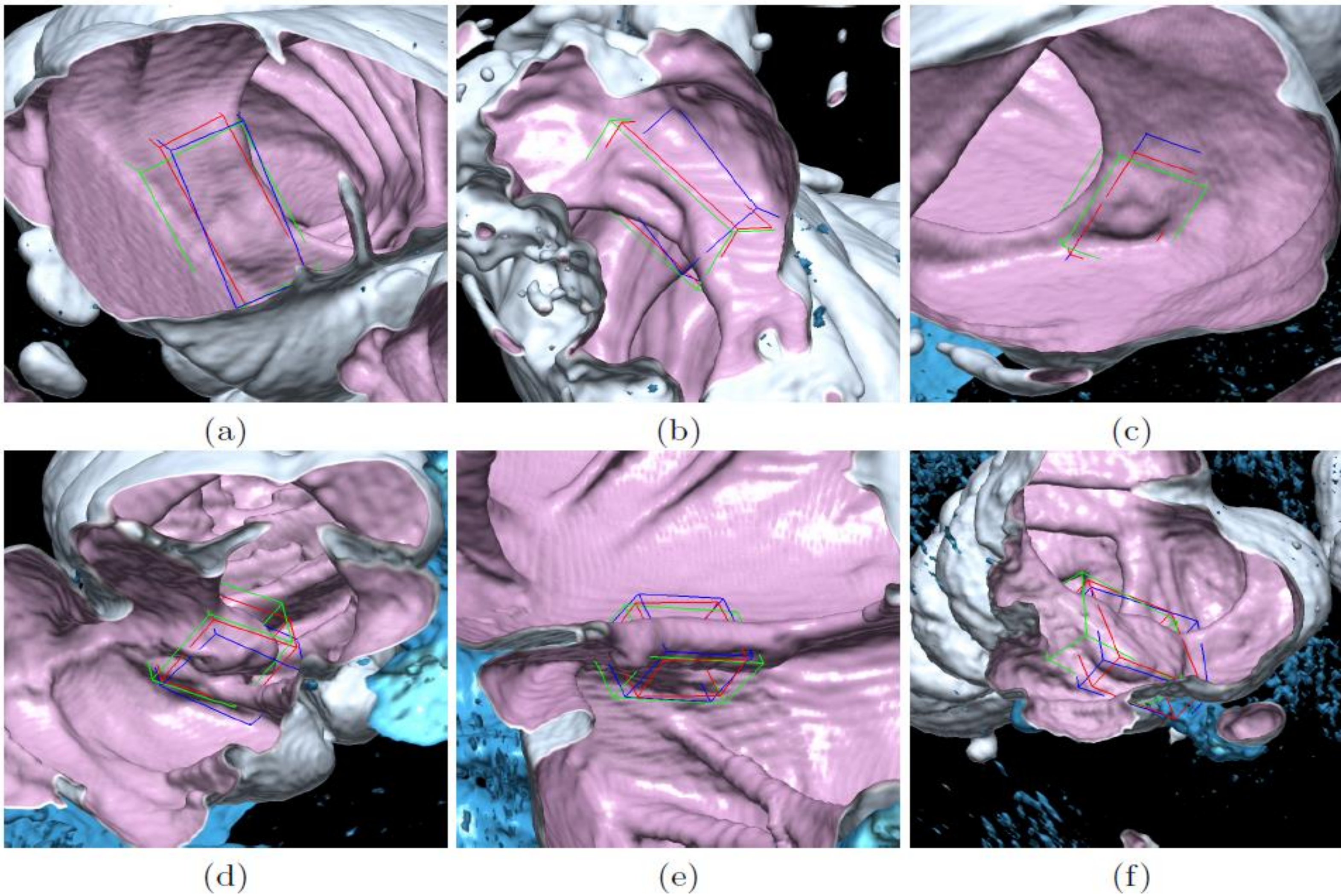
System Flowchart: Prior Learning & Incremental Parameter Learning (Marginal Space Learning in full 3D for highly deformable objects under possible severe tagging artifacts)



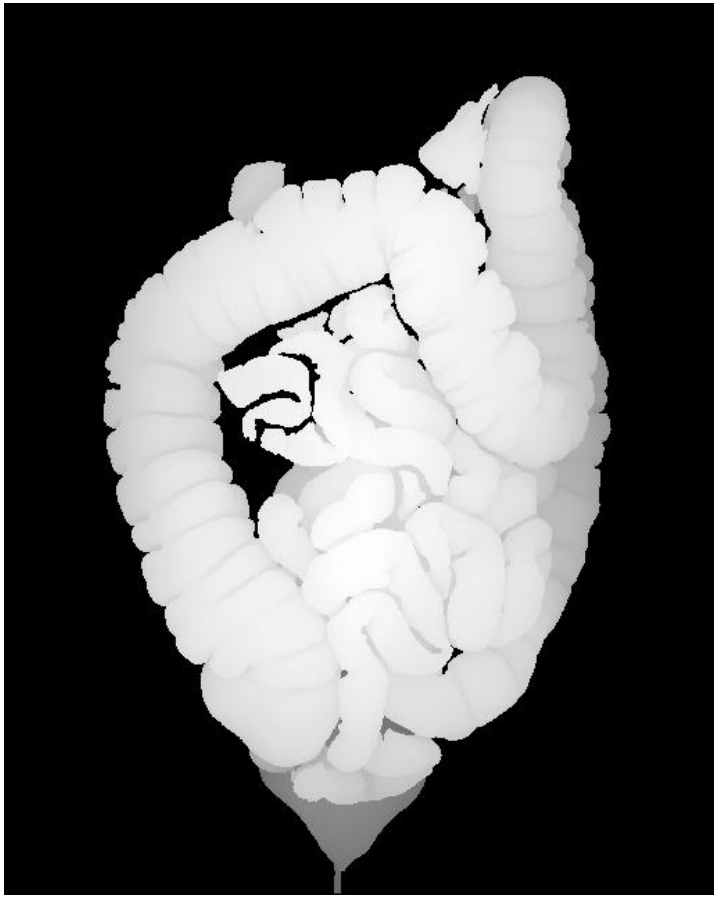




Extension: MICCAI-MCV 2010 (90% CAD detection performance gain on FP reduction with 1% extra effort on multi-component parsing)



Extra-colonic Removal, or Supervised Colon Segmentation (MICCAI'09)



Good value for CTC visualization as well!

Daisy-Chaining & Adaptive Confidence Level

Results

- Colon Fragment "Classification + Tracing" (supervised learning formulation, apart from heuristic topological reasoning in literature)
- Colon Segmentation Evaluation:
  - Our ECR module enables to remove > 90% or higher extra-colonic volumes (mm^3), at the detection rate of 99.5%, for training or testing datasets respectively.
  - Better accuracy than previous work on (>5 times) larger dataset.
- Impacts on CAD False Positive Reduction:
  - It results in sensitivity of 77/89 = 86.5% (Extra-Colonic FPs) and specificity as (147−3)/147 = 98%, which conforms the same system detection rate at significantly lower FP rates (~45% low using as post-filter).
  - "Simple geometry feature + statistical modeling (rank-1 SVM)" generalizes well to clean-prep and tagging-prep datasets.
  - Find an error in radiologist's annotation!

A New Algorithm Paradigm for Weakly Tagging Ecleansing

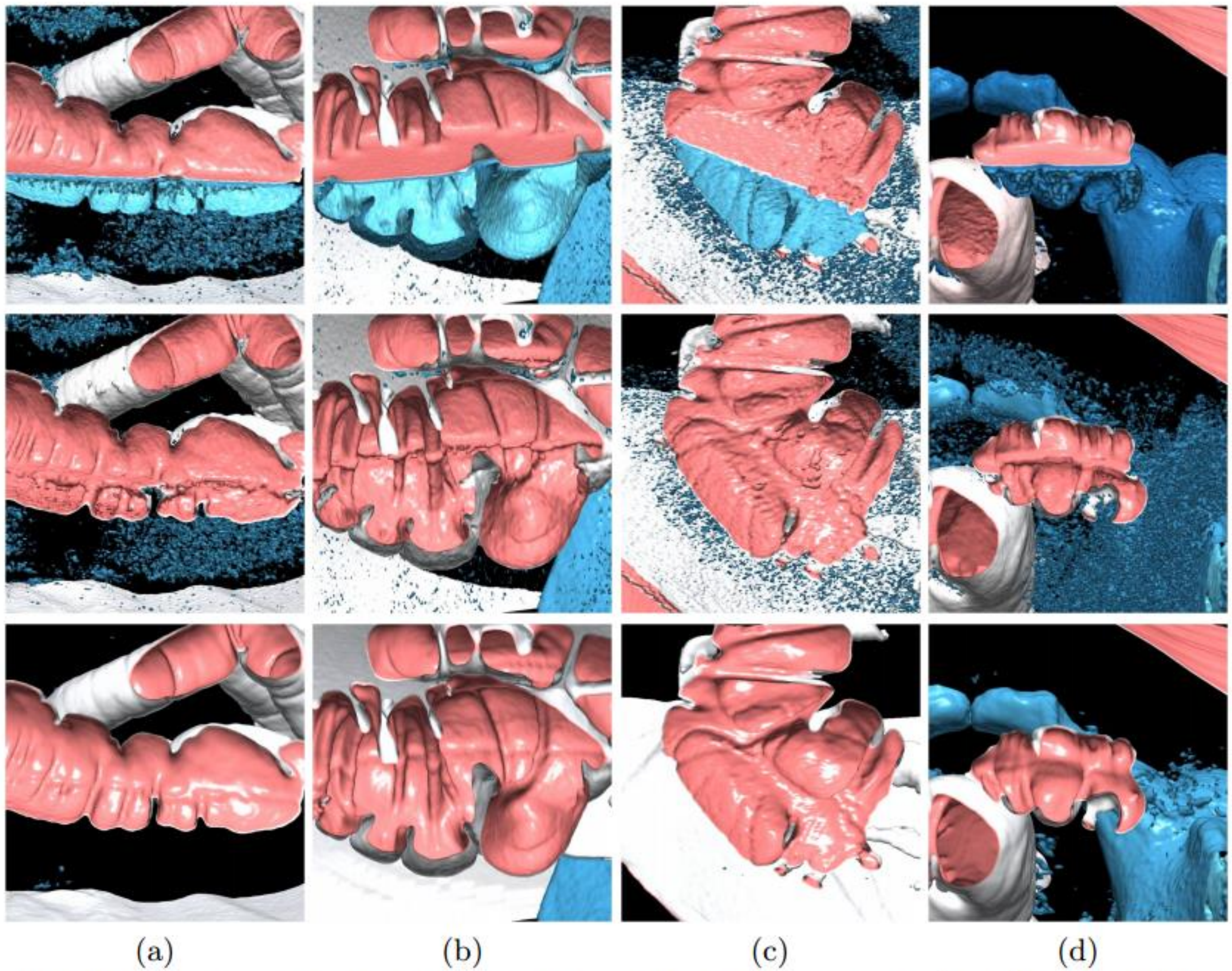


Fig. 2. *Examples of E-cleansing results: original volume rendering (***Top***), generated by an implementation of GMM-EM method [7] (***Middle***) and our method (***Bottom***).*

Outlines

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  - Polyp segmentation [CVPR 08]; from polyp segmentation features [CVPR 11] to segmentation-less features for unified detection [NIPS 12, submitted]
  - False Positive Reduction: Ileo-Cecal Valve detection & removal [ECCV 08; MCV 10; RSNA 07]; colon segmentation [MICCAI 09]; CTC Ecleansing on Weakly Tagging Cases
- CAD Diagnosis Support:
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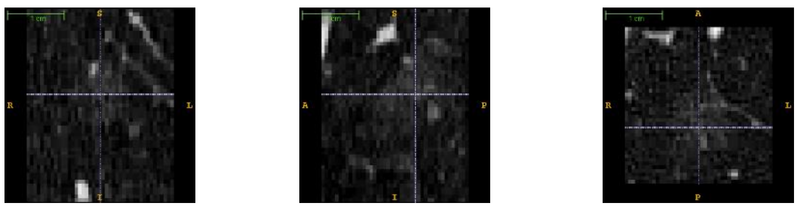
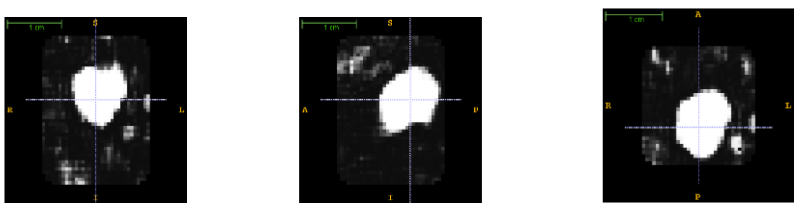
- Others:
  - Vertebra segmentation & identification [MICCAI 10]; Hierarchical curvature structure parsing: with application on coronary artery tree modeling [ICCV 09]; flexible structure parsing and segmentation based labeling …

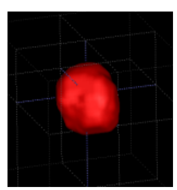
Ground-glass Lung Nodule Segmentation & Detection (MICCAI'09) iterated auto-context



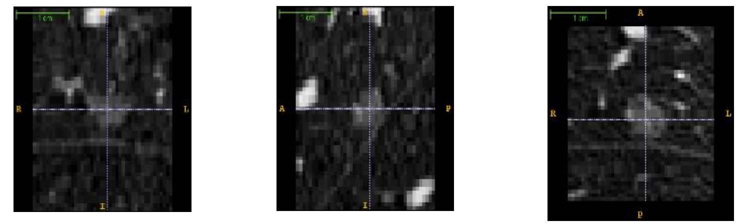
(a) Three Views of Original Image



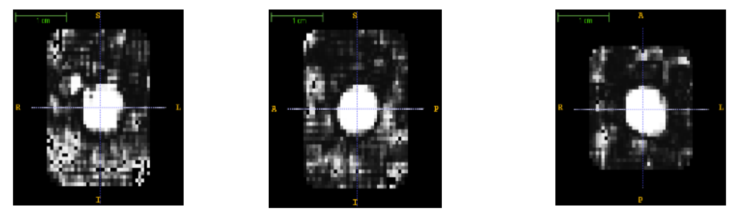
(b) Three Views of Probability Map



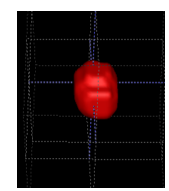
(c) Rendered of Segmented Result



(a) Three Views of Original Image



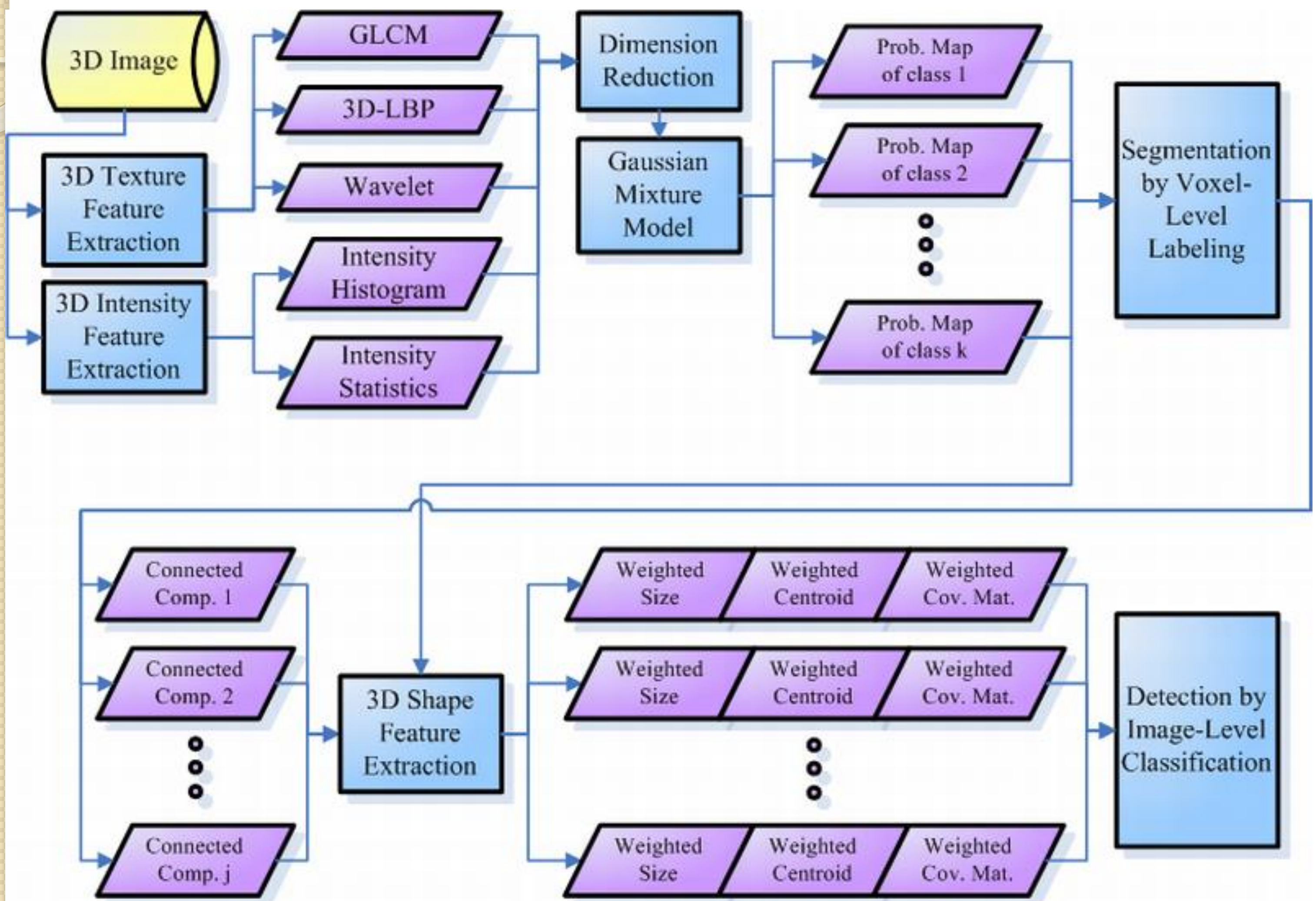
(b) Three Views of Probability Map



(c) Rendered of Segmented Result

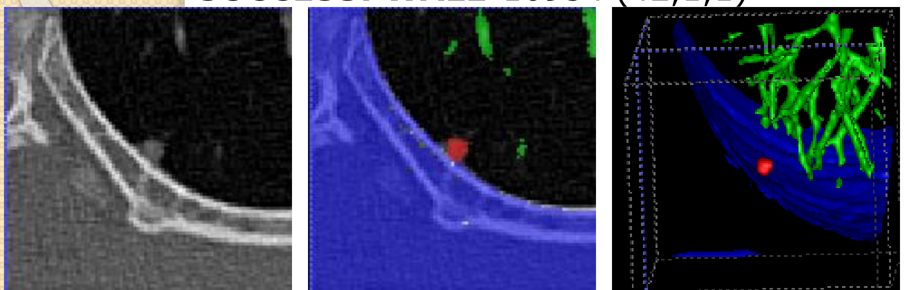
Partially inspired by "A Two Level Approach for Scene Recognition", Lu, Toyama & Hager, CVPR 2005.
Tu, Z.: Auto-context and its application to high-level vision tasks. In: IEEE Conf. CVPR, pp. 1–8 (2008)

System Flowchart

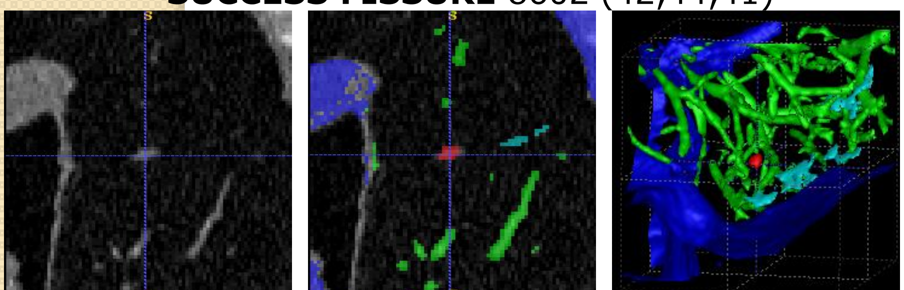


Nodule Attachment Attributes Classification (CVPR'10)

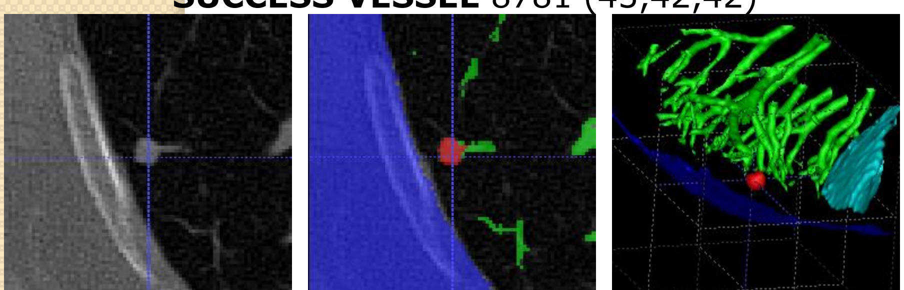
SUCCESS: WALL 16954 (42,1,1)



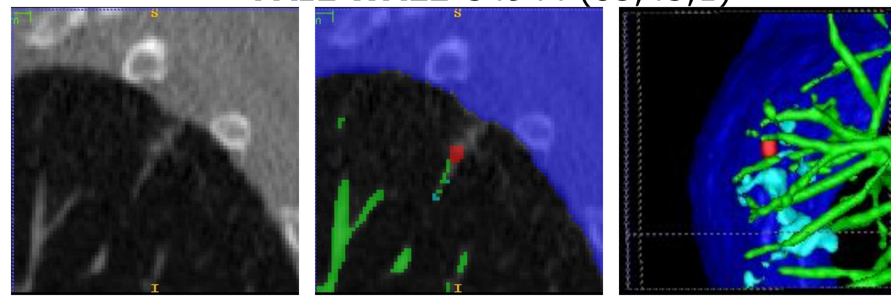
SUCCESS FISSURE 8602 (42,44,41)



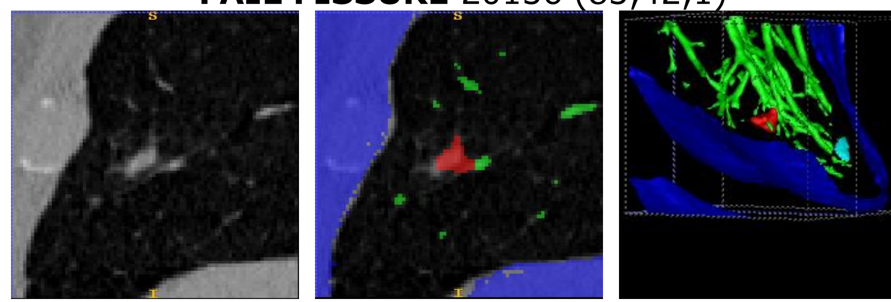
SUCCESS VESSEL 8781 (43,42,42)



FAIL WALL 34944 (83,43,1)



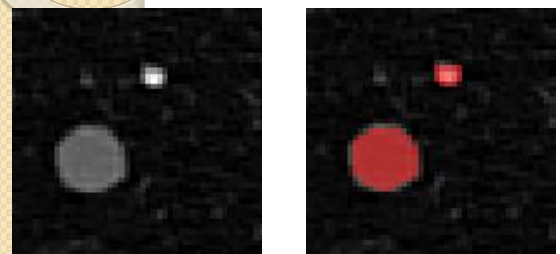
FAIL FISSURE 20136 (83,42,1)



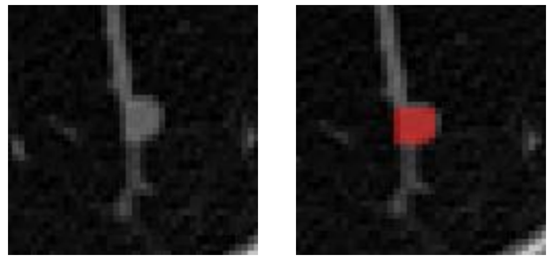
FAIL VESSEL 8721 (42,1,1)

Results on Nodule Segmentation from Graph-cut

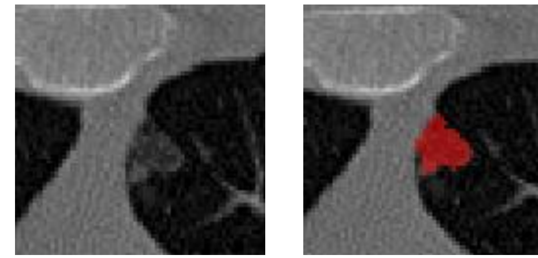
8442 (42 1 1)



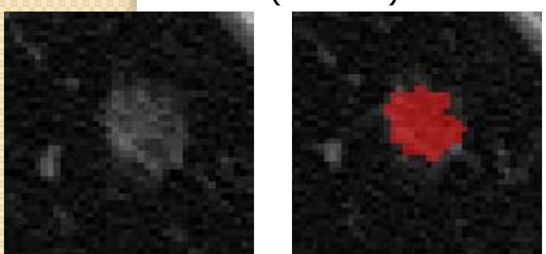
38223 (42 1 1)



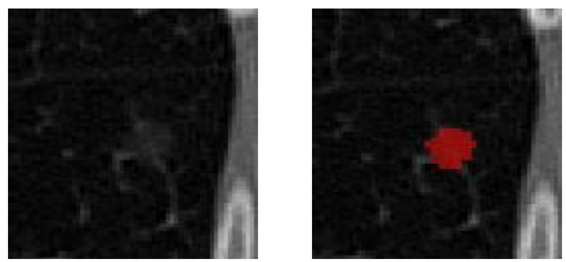
36991 (43 1 1)



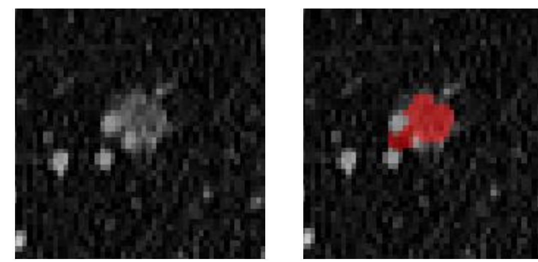
38099 (42 1 1)



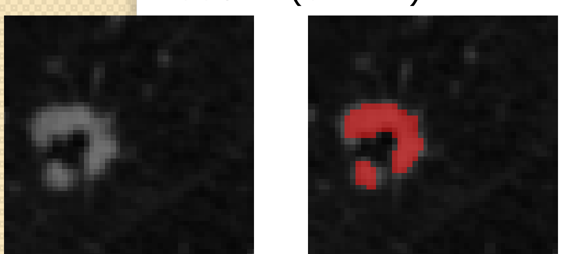
2848 (41 1 1)



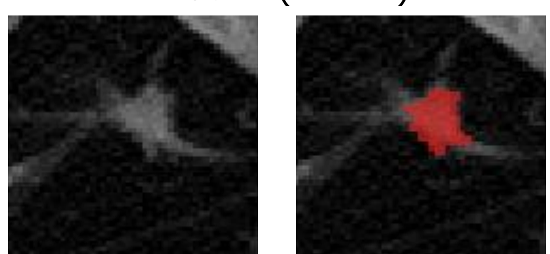
38287 (83 42 1)



35814 (39 1 1)



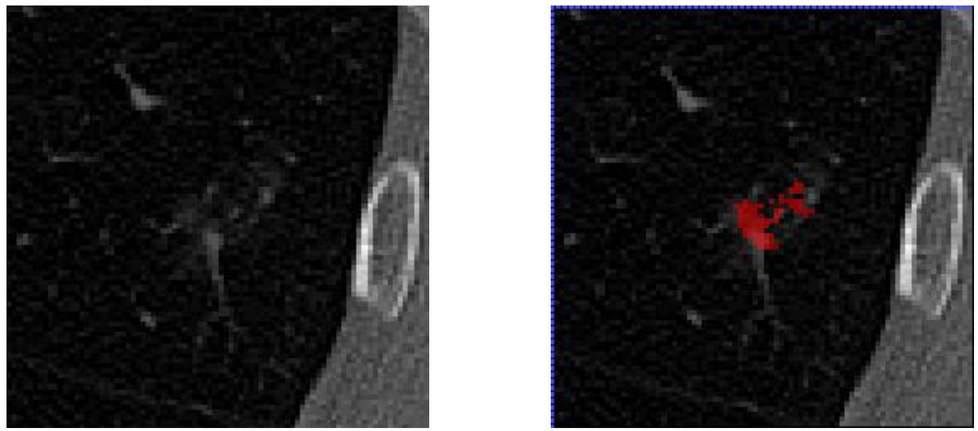
18671 (42 1 1)



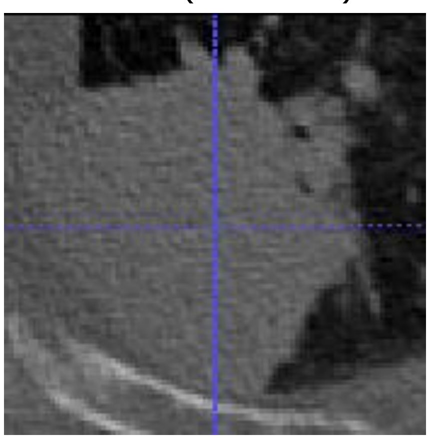
37057 (42 1 1)

Less acceptable or failed cases

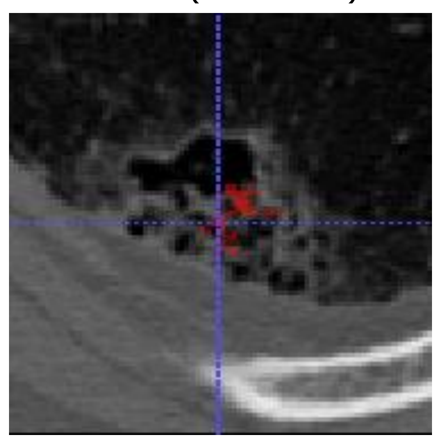
38235 (40 1 1)



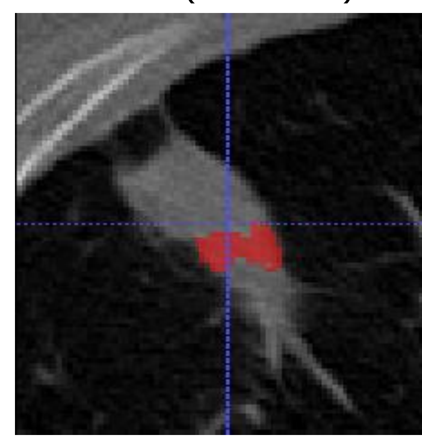
38455 (44 42 42)



38414 (42 42 42)

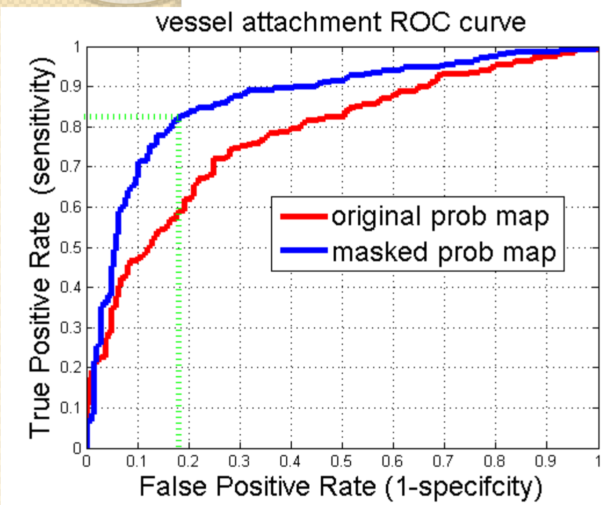


2568 (42 42 42)

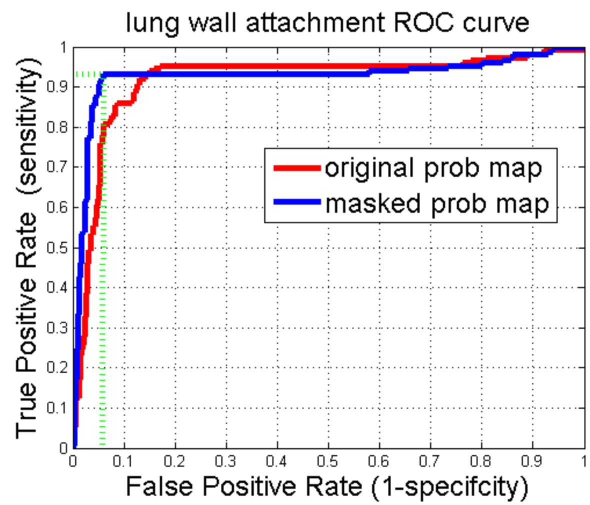


Experiment Results

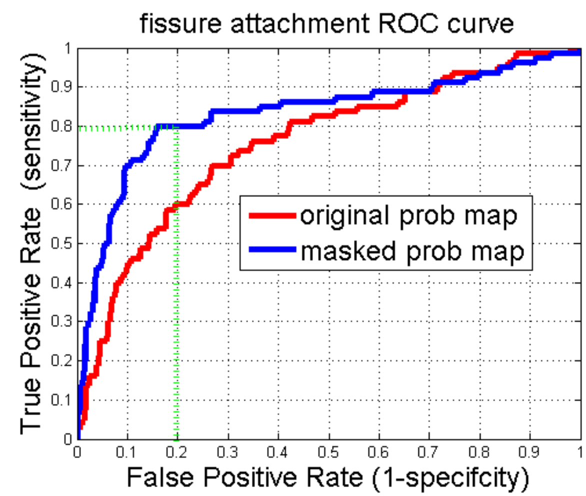
vessel connectivity



wall connectivity



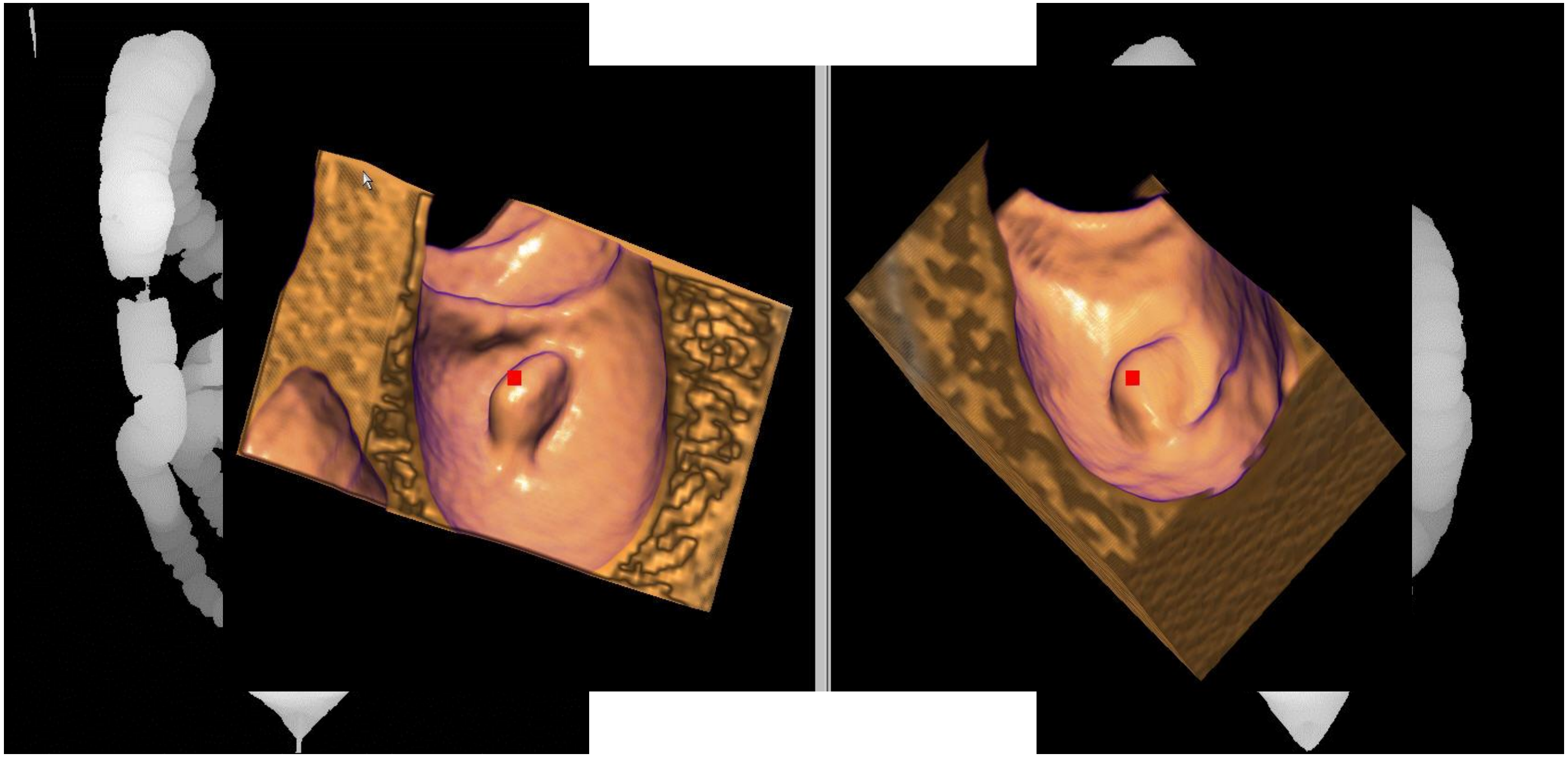
fissure connectivity



AUC	Vessel	Wall	Fissure
Original	0.7793	0.9184	0.7555
Masked	0.8676	0.9275	0.8318

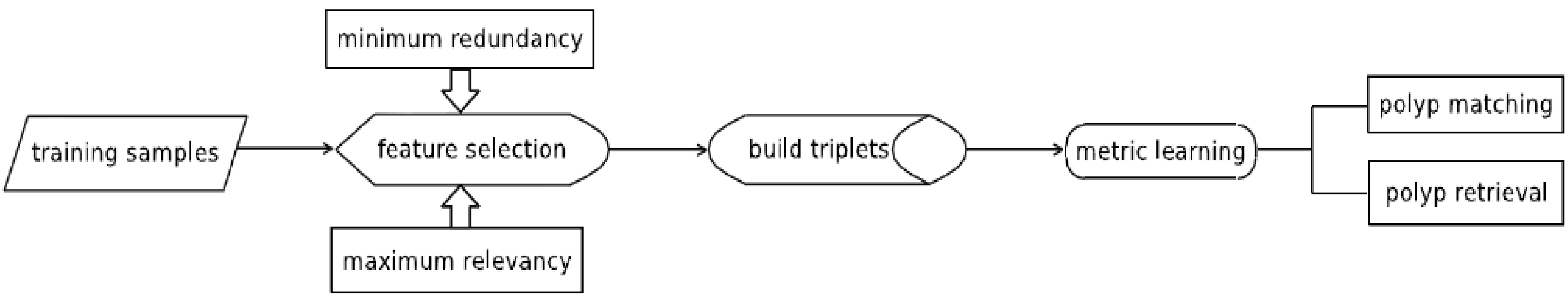
* RVM, 10-fold cross validation

Metric Learning Approach for Prone-Supine Polyp Matching using Local Features (MICCAI'11)



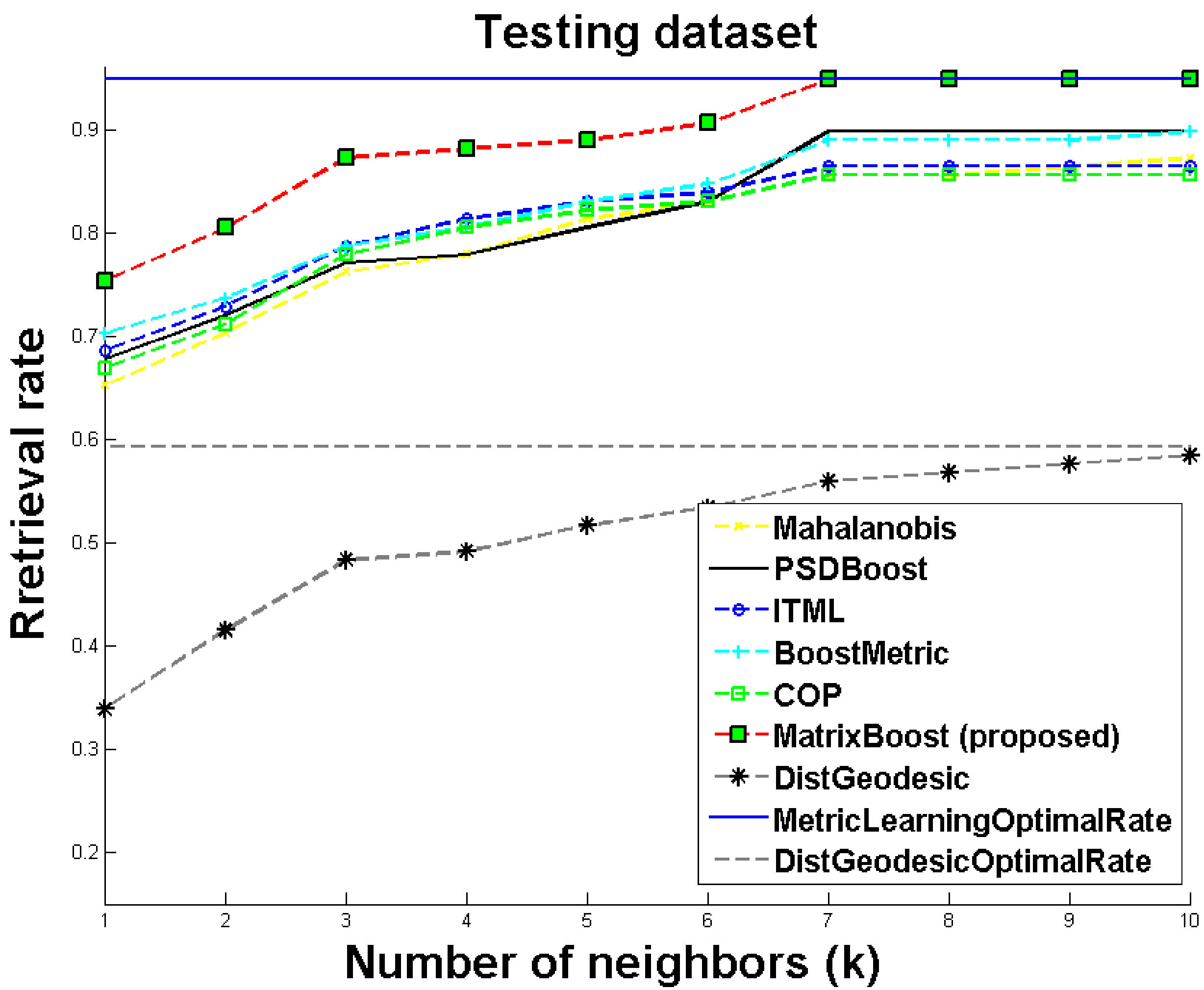
Counter-intuitive thinking can be important, even critical!

Flow Chart for Training (testing is just a Mahalanobis distance computing and ranking!)

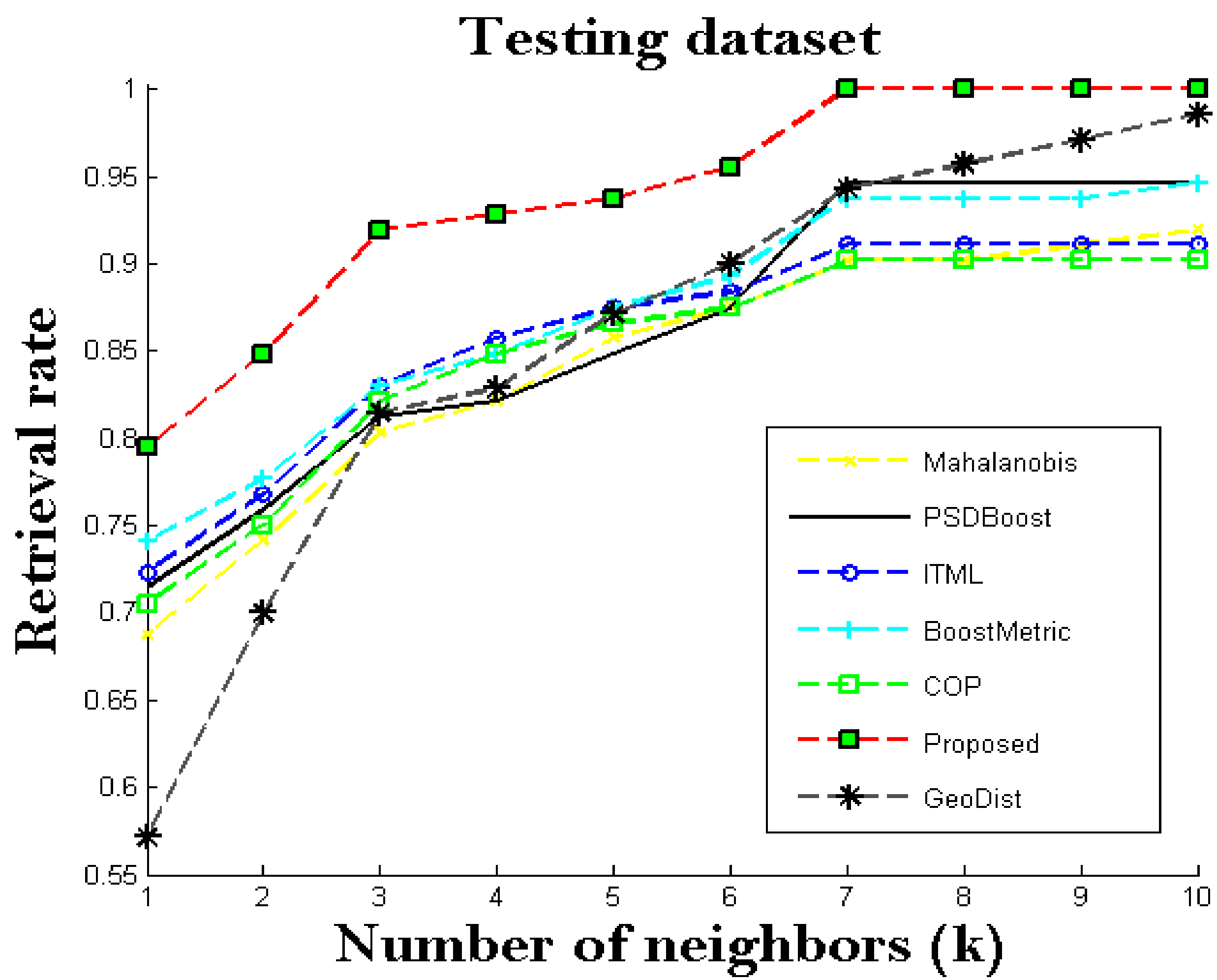


- **Important influence** on the current CTC clinical workflow: our technology is an enabler to **make polyp matching more feasible without global colon geometry computing**. Only local CAD features are utilized for training (which is sufficient), and no extra computational overhead, fully automatic and with tremendous improvement on robustness (via learning cross data population).
- Polyp matching becomes feasible for ***collapsed CTC cases (>= 50%)*** where traditional ways do not apply…

Polyp Matching as a Retrieval Problem (Testing)



Normalized Retrieval Rate (Testing)

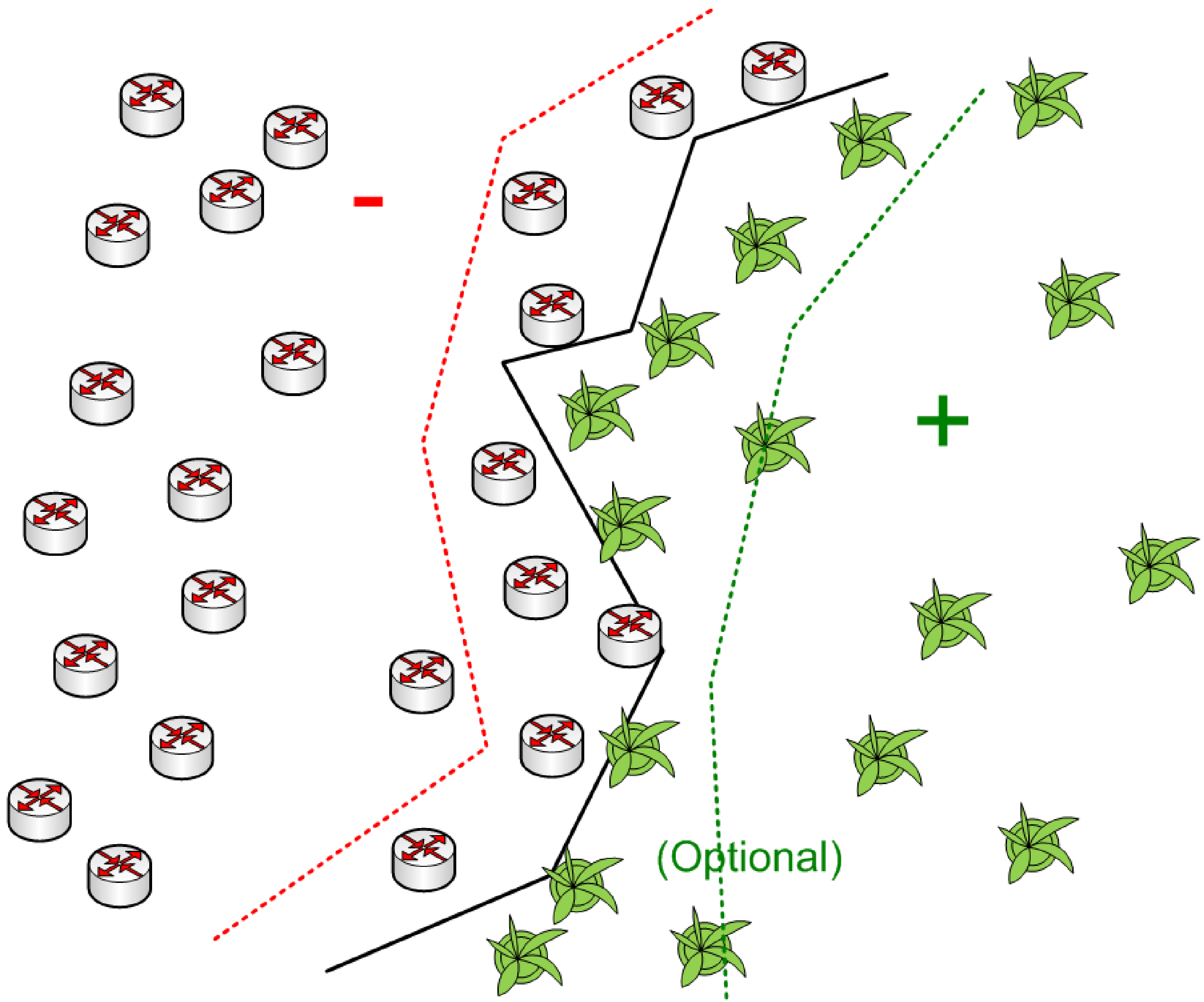


Coarse-to-Fine Classification: What's the STORY? [MICCAI 2011, CIKM 2011]

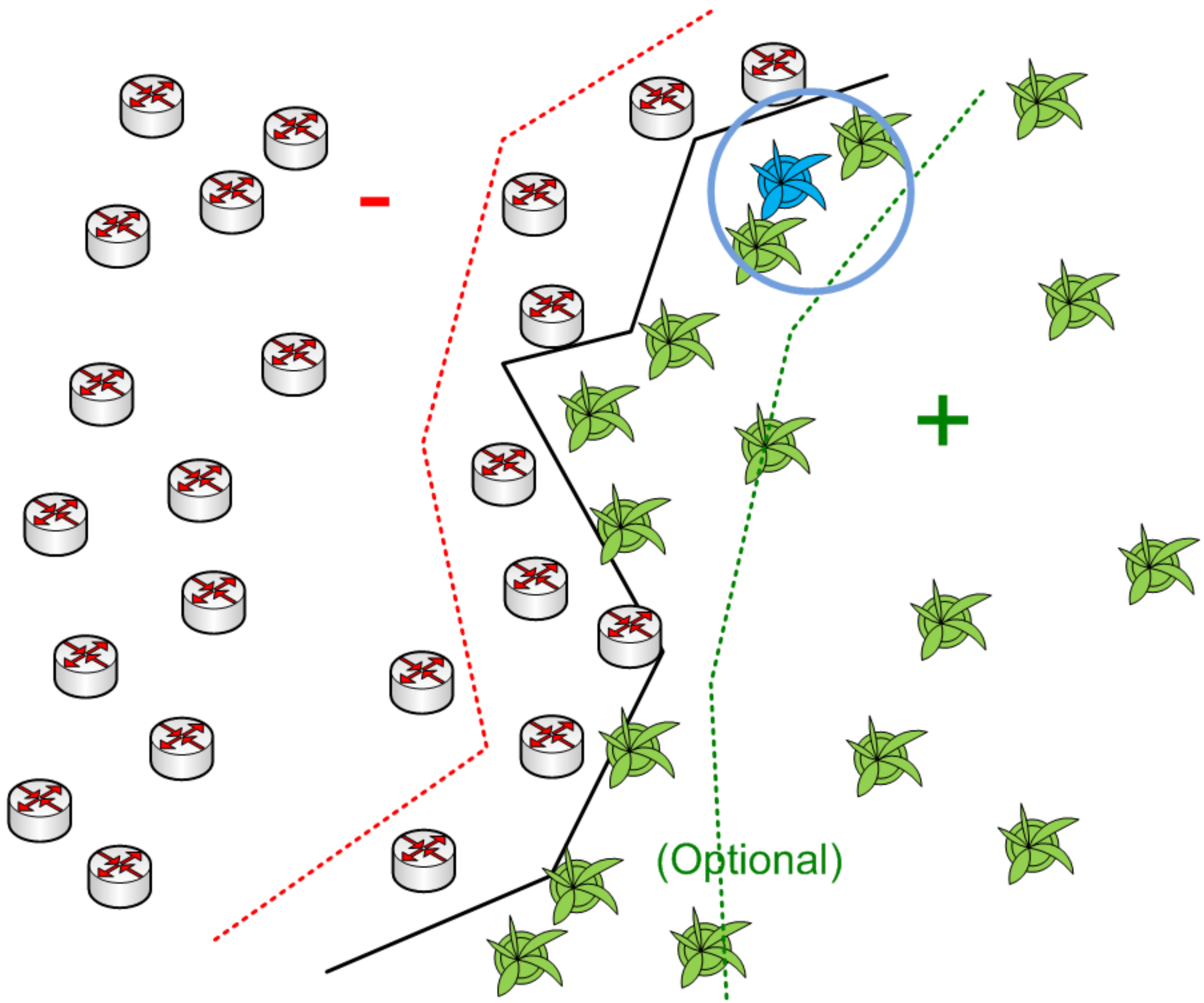
- **Three Requirements:**
  - High sensitivity (recall) is a must-to-have feature to make CAD meaningful.
  - It is equivalently important to archive sensibly low false positive rate per case (e.g., 2~5, or lower).
  - **Decision Support:** an ideal setup is to make the system capable of storing and retrieving similar or counterpart lesions when available. → Nonparametric (fine-level) Methods!
- **Two Challenges (where and how to apply NP methods):**
  - There are dominating numbers of false positives initially;
  - NN and TM are very sensitive to the feature space or subspace where matching distance or (dis-)similarity metrics are computed (or generally, distance metric learning).

  - Note: Natural extensions to multiclass problem may be ideal by NP methods, which may be useful for polyp/nodule/lesion categorization!

Illustrative Example



"The paper is well-written and therefore easily accessible. It did unfortunately shoot down an idea I'd had recently by pointing out that something similar is already out there :) The motivation for the problem setting and the choices for the different steps is clear and sensible."



Coarse-to-Fine Classification

- **Coarse-Level**
  - RVMMIL to get classifier score; according to the classification score to select only those passed a threshold testing for the next step (samples close to classification boundary, or positives + negatives hard to dismiss); *this step can be done by other type of parametric classifiers or even nonparametric ones*. Very high sensitivity and high false positive rate!!
- **Fine-Level**
  - Refine the feature set using MRMR;+ Extract the intrinsic feature space using dimension reduction, (CIKM 2011)
  - Finally perform various (parametric, or non-parametric, e.g., *k*NN, template matching) classification methods in the intrinsic feature subspace.
  - Or, Learn data-driven dictionaries as templates by solving SPARSITY Coding problem (MICCAI 2011)

❖ Features for Learning are heterogeneous, statistically strong middle-level features which are already aggregated from 10~20 low-level image parsing processes and suitable for more sophisticated feature selection & learning. For learning thousands of low-level images on millions of training samples, boosting!

Coarse-to-fine Cascade Classification (C3)

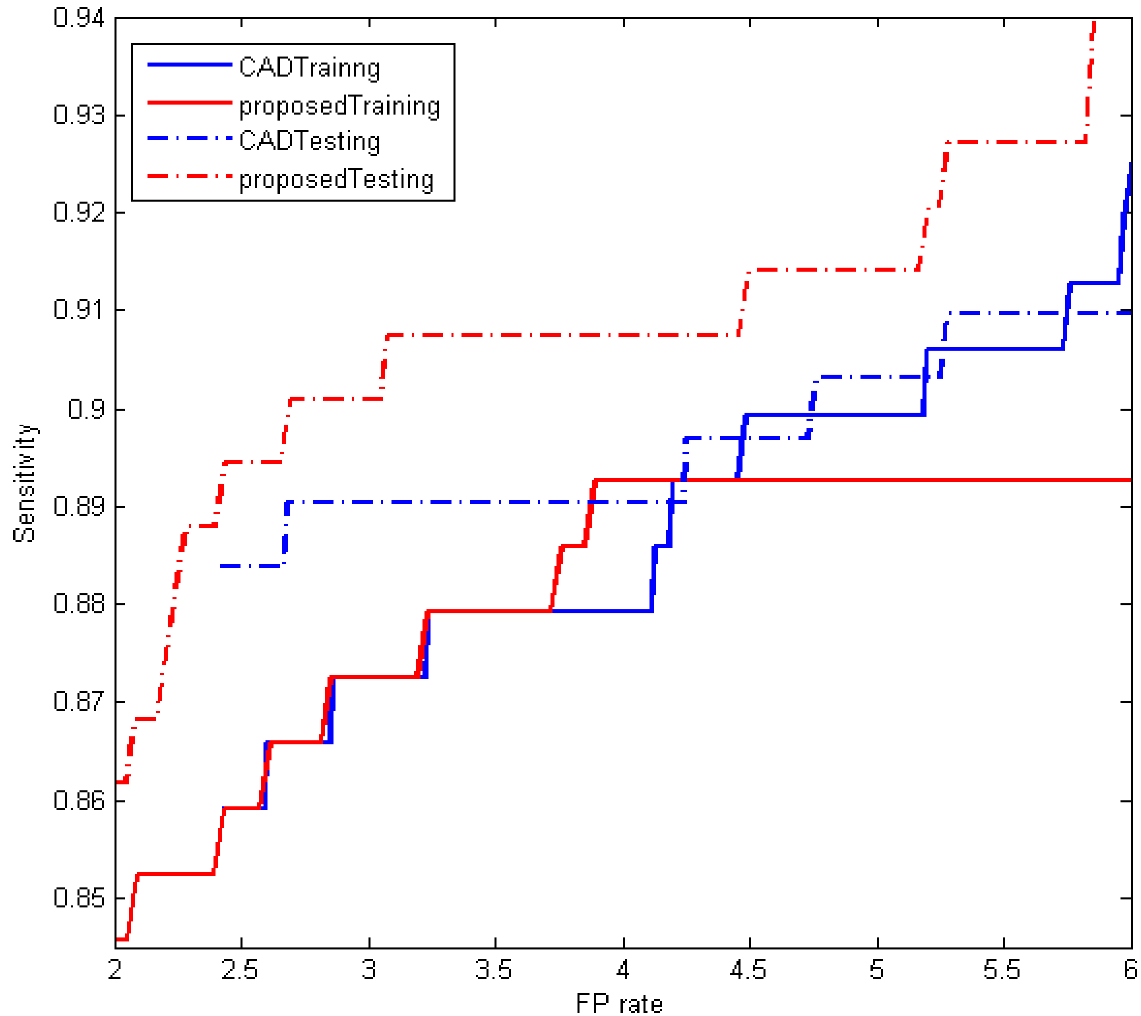
- For validation, the testing results demonstrate that our CTF method can increase the sensitivity of RVMMIL by 2.58% (from 0.8903 to 0.9161) at the per-patient FP rate = 4, or reduce the FP rate by 1.754 (from 5.338 to 3.584) when sensitivity is 0.9097, which are statistically significant improvements for colorectal cancer detection. (polyps >= 3mm)

$\boxed{\text{Samples}} \rightarrow \boxed{\text{Sample pruning}} \rightarrow \boxed{\text{Feature selection}}$

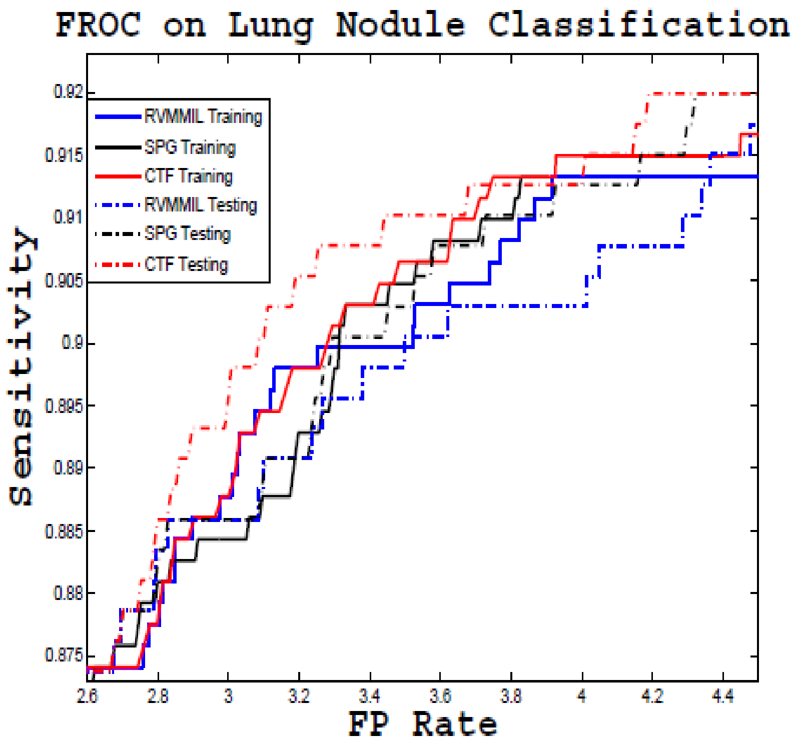
$\rightarrow \boxed{\text{Class regularized graph embedding}}$

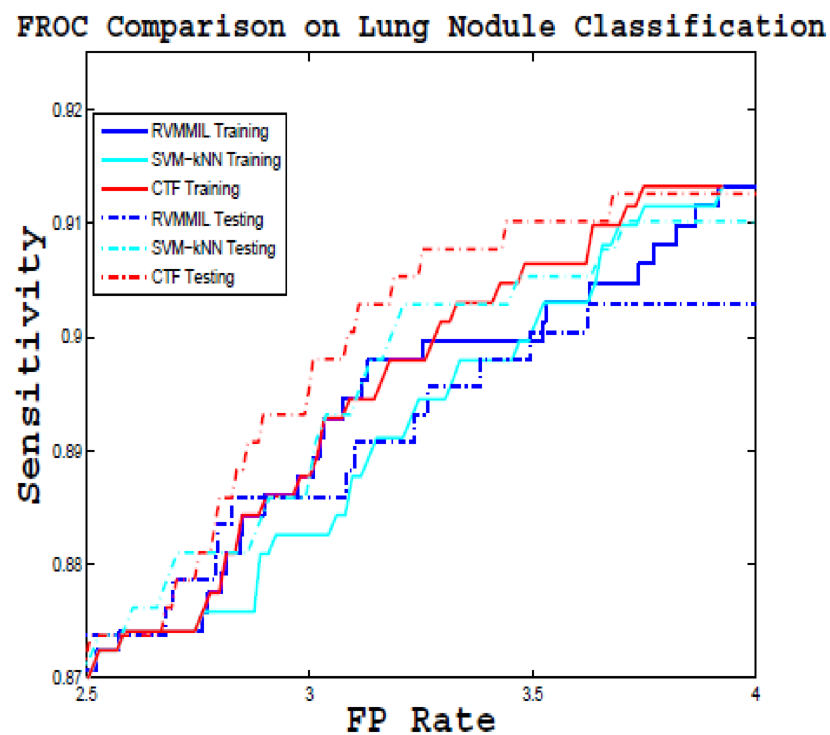
$\rightarrow \boxed{k\text{NN/Template matching}}$

Results: Colon Polyp Classification (close-up)



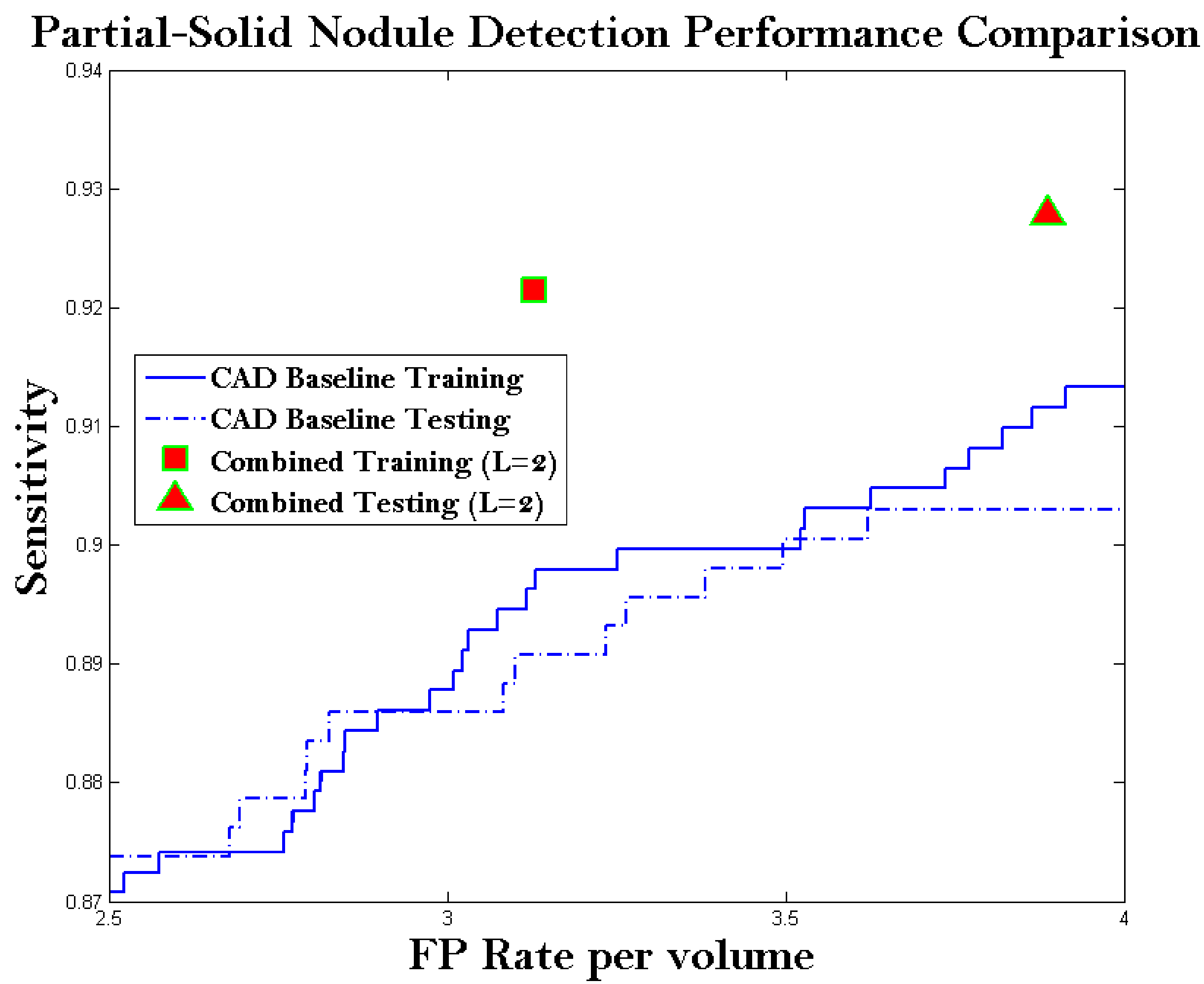
Discussion on Stratified Approach versus Joint Sparse Optimization and SVM-KNN





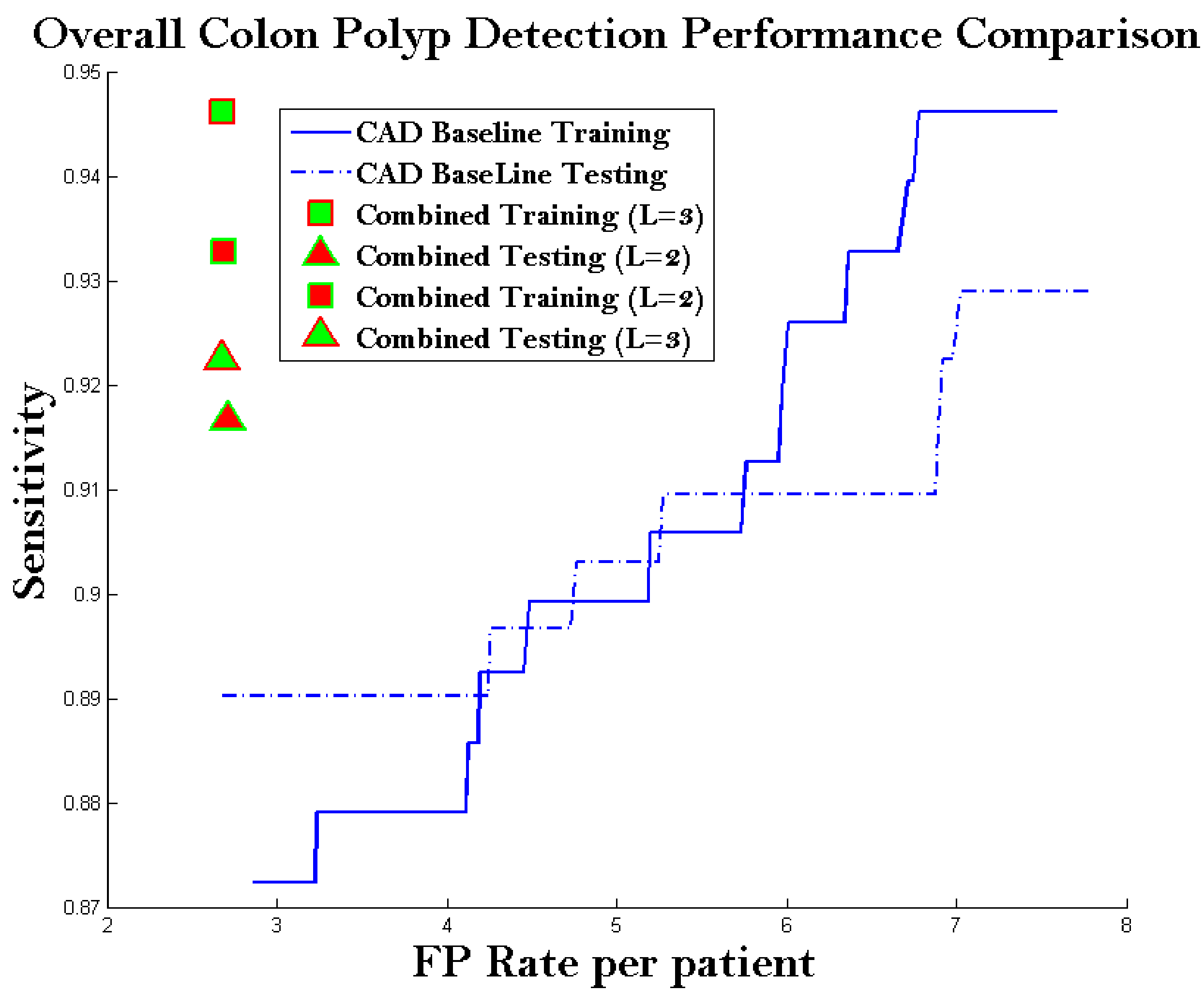
- D. Cai, X. He, and J. Han. Sparse Projections over Graph. *Proceedings AAAI Conference on Artificial Intelligence*, pages 610-615, 2008.
- H. Zhang, A. Berg, J. Malik, SVM-KNN: Discriminative Nearest Neighbor Classification for Visual Recognition, IEEE CVPR, 2006.

Importance of Having a new Idea (sparse coding based Classification)…



- Sparse Classification for Computer Aided Diagnosis Using Learned Dictionaries, **MICCAI'2011**

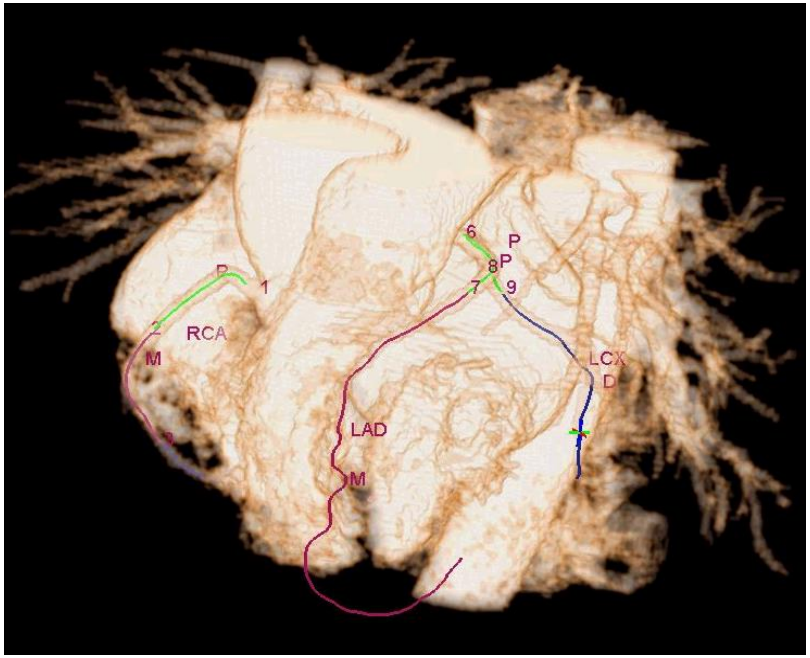
Generalizable to Colon datasets …



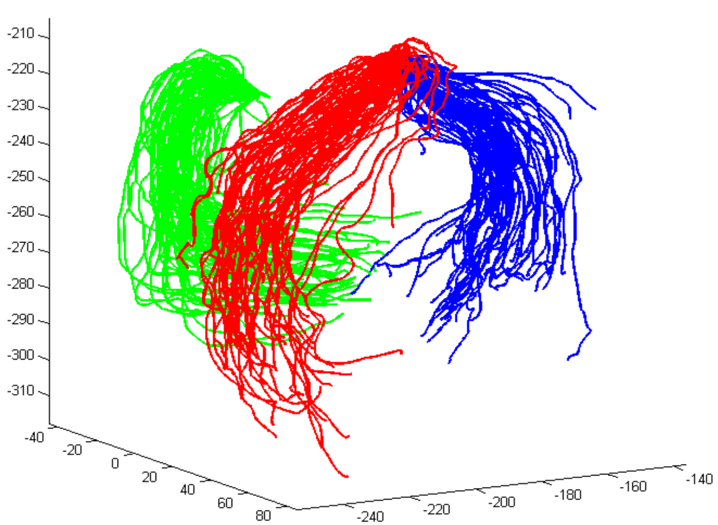
Outlines

- Colon CAD:
  - Polyp segmentation [CVPR 08]; from polyp segmentation features [CVPR 11] to segmentation-less features for unified detection [NIPS 12, submitted]
  - False Positive Reduction: Ileo-Cecal Valve detection & removal [ECCV 08; MCV 10; RSNA 07]; colon segmentation [MICCAI 09]; CTC Ecleansing on Weakly Tagging Cases
- CAD Diagnosis Support:
  - GGN segmentation & detection [MICCAI 09]; Lung Nodule Context Learning [CVPR 10]; Metric Learning based Polyp Prone-supine matching; Sparse Classification [MICCAI 11]; Coarse-to-fine Classification [CIKM 12]
- Others:
  - Vertebra segmentation & identification [MICCAI 10]; Hierarchical curvature structure parsing: with application on coronary artery tree modeling [ICCV 09]; flexible structure parsing and segmentation based labeling …

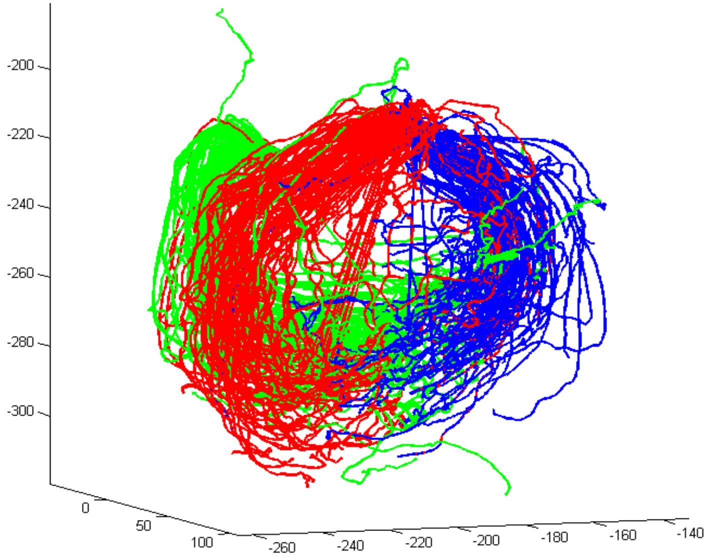
Hierarchical Vessel Structure Parsing (ICCV'09)



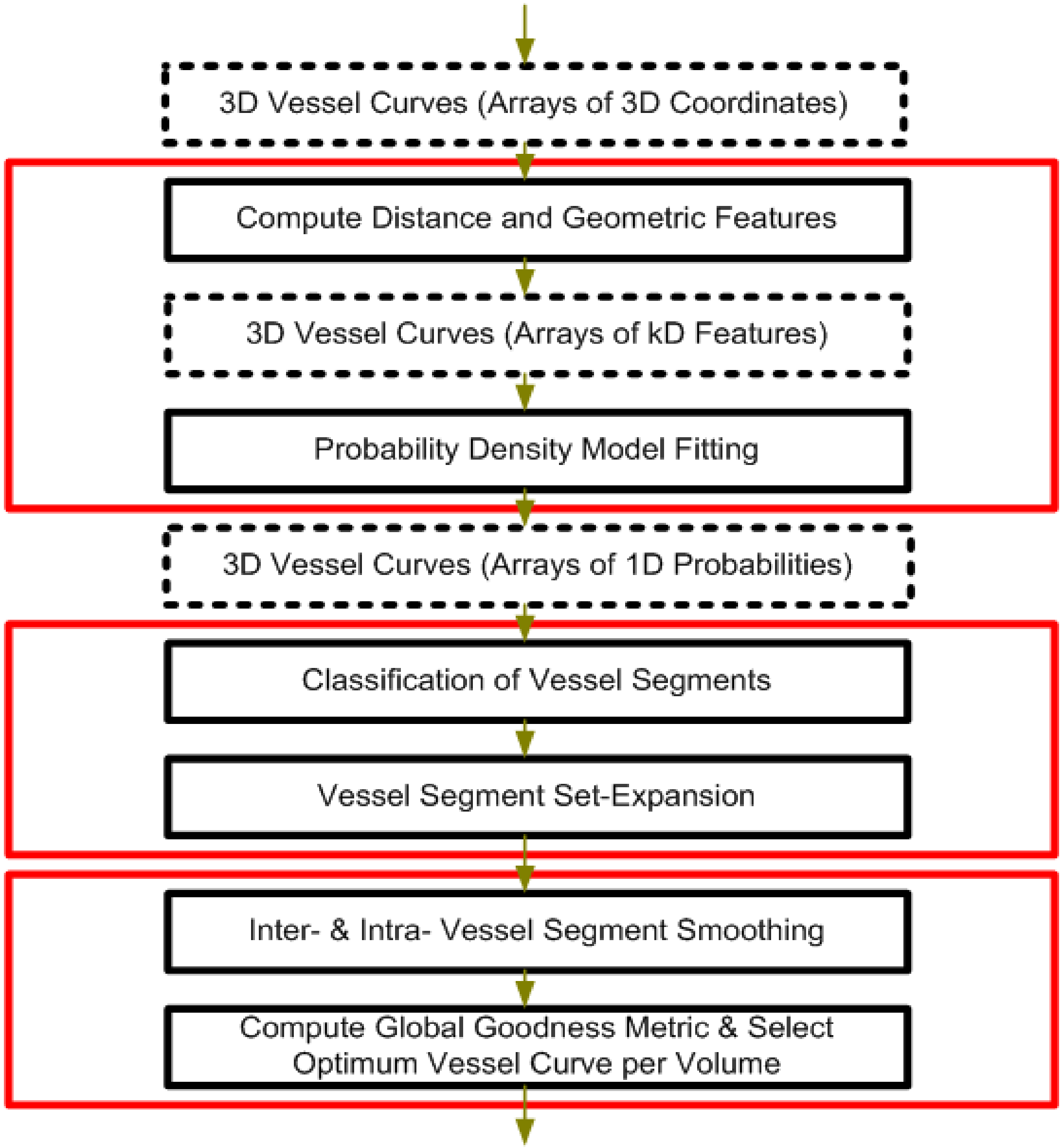
3D Plot of RCA, LAD and LCX Coronary Arteries from 82 Patients



3D Plot of RCA, LAD and LCX Vessel Segments (Detected) from 82 Patients



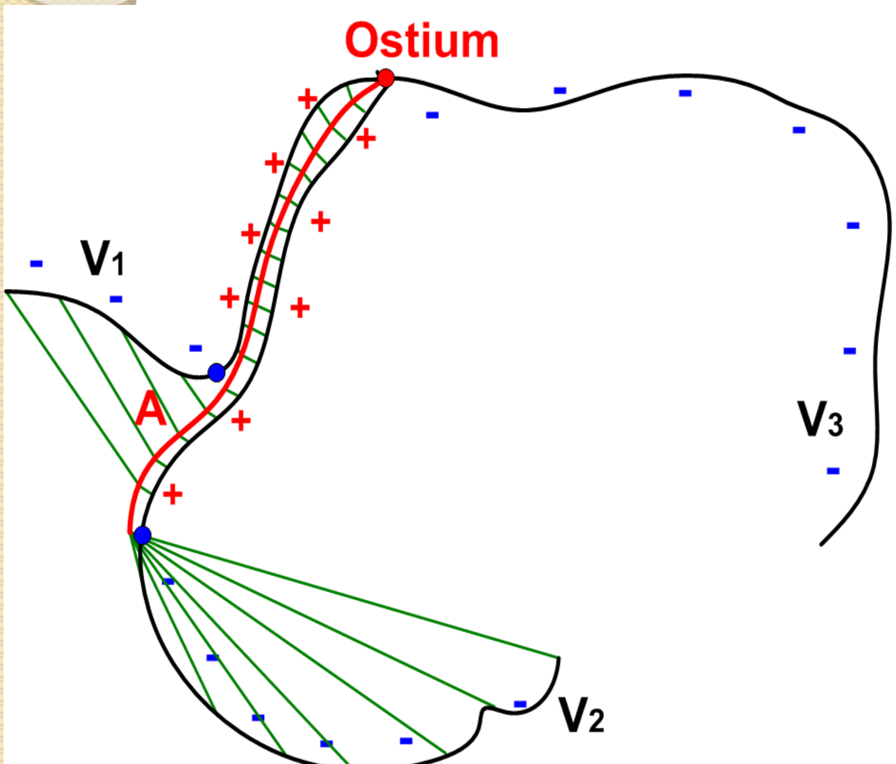
What I learned in class helps, and more!

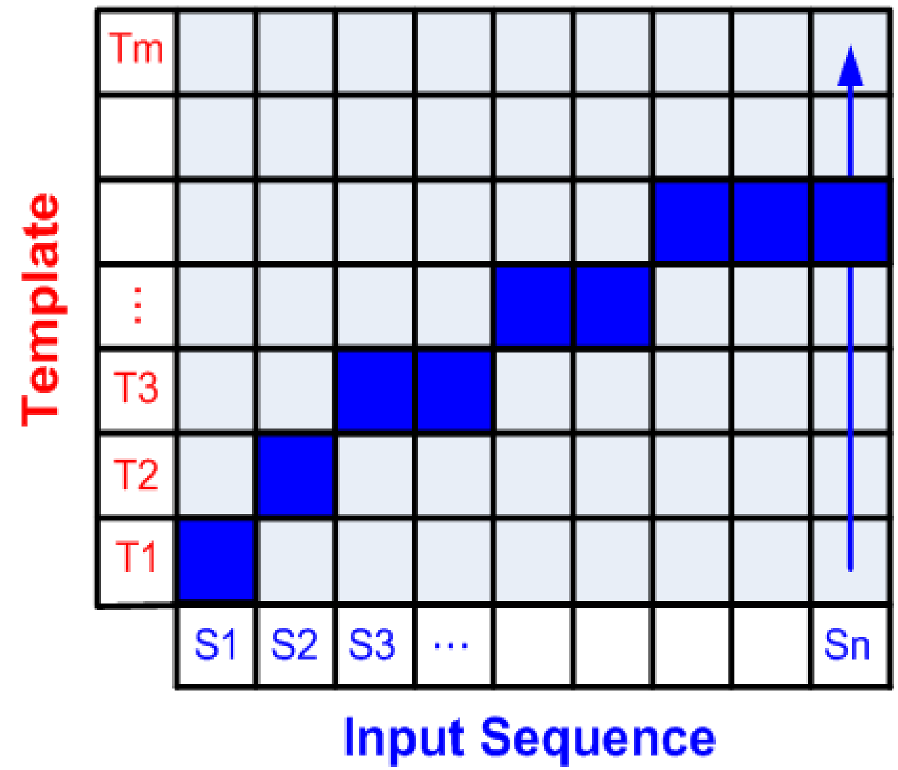


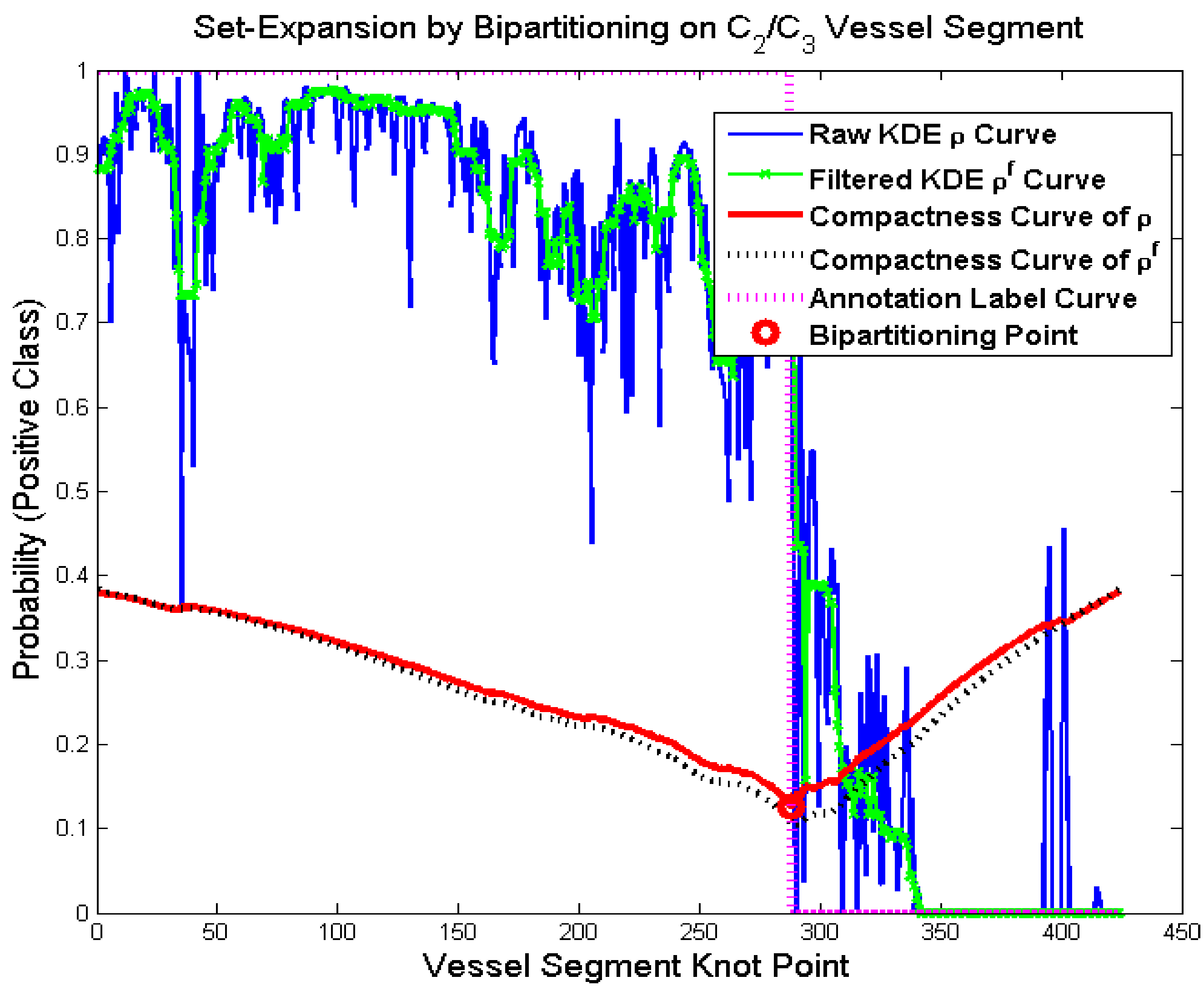
- D. Geman and B. Jedynak. An active testing model for tracking roads in satellite images. IEEE Trans. Pat. Anal. Mach. Intell., 18:1–14, 1996
- S. Konishi, A. Yuille, J. Coughlan, and S. Zhu. Statistical edge detection: Learning and evaluating edge cues. IEEE Trans. Pat. Anal. Mach. Intell., 25:57–74, 2003.
- **"on-off" likelihood ratio testing**; sequential testing, …CTF detection on **Geodesic distance-indexed local geometry features**!
- **Generative** models versus **Discriminative** models

Structure Alignment for Learning (Training)

- Annotated Curves versus Computer Extracted Curves

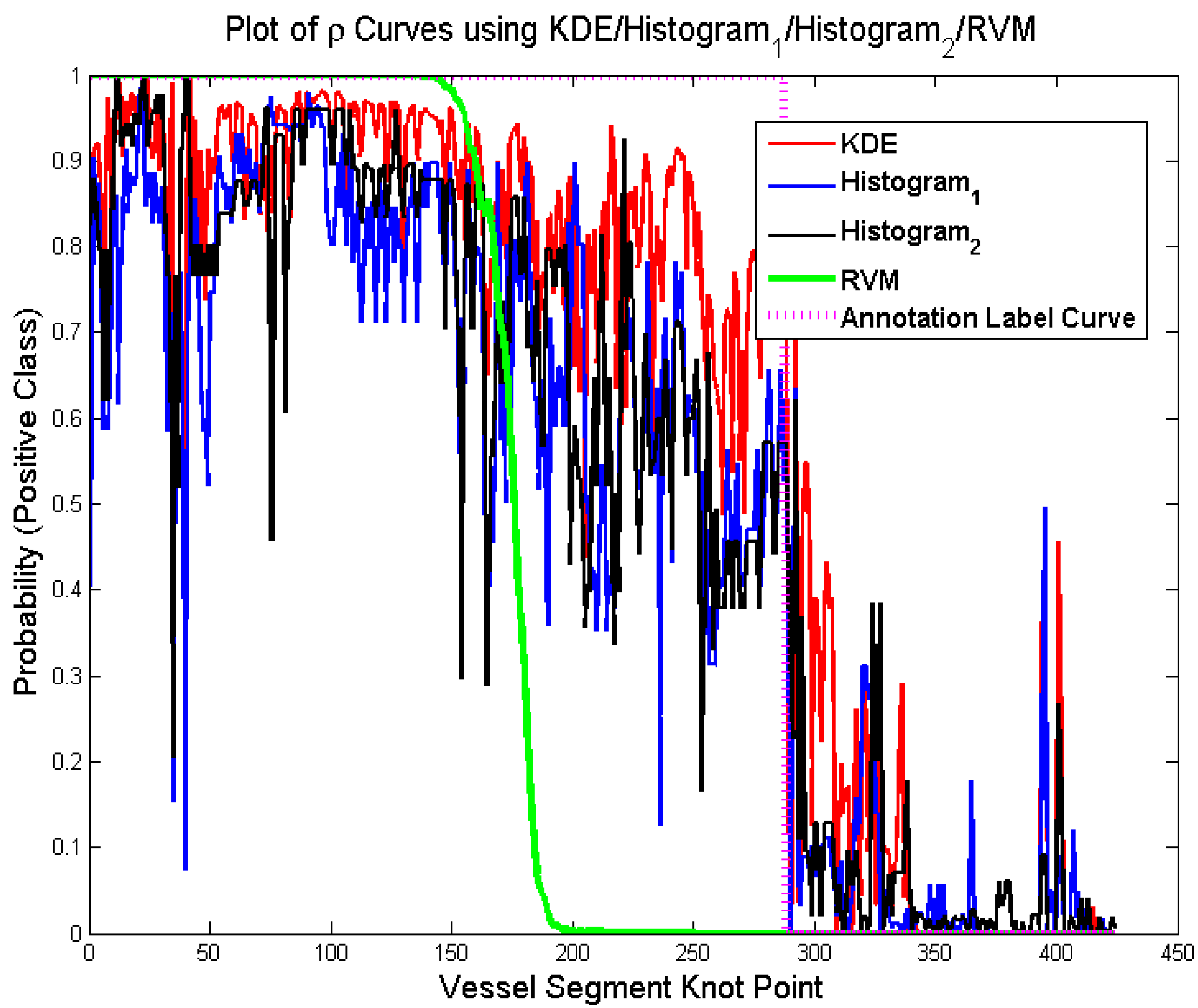




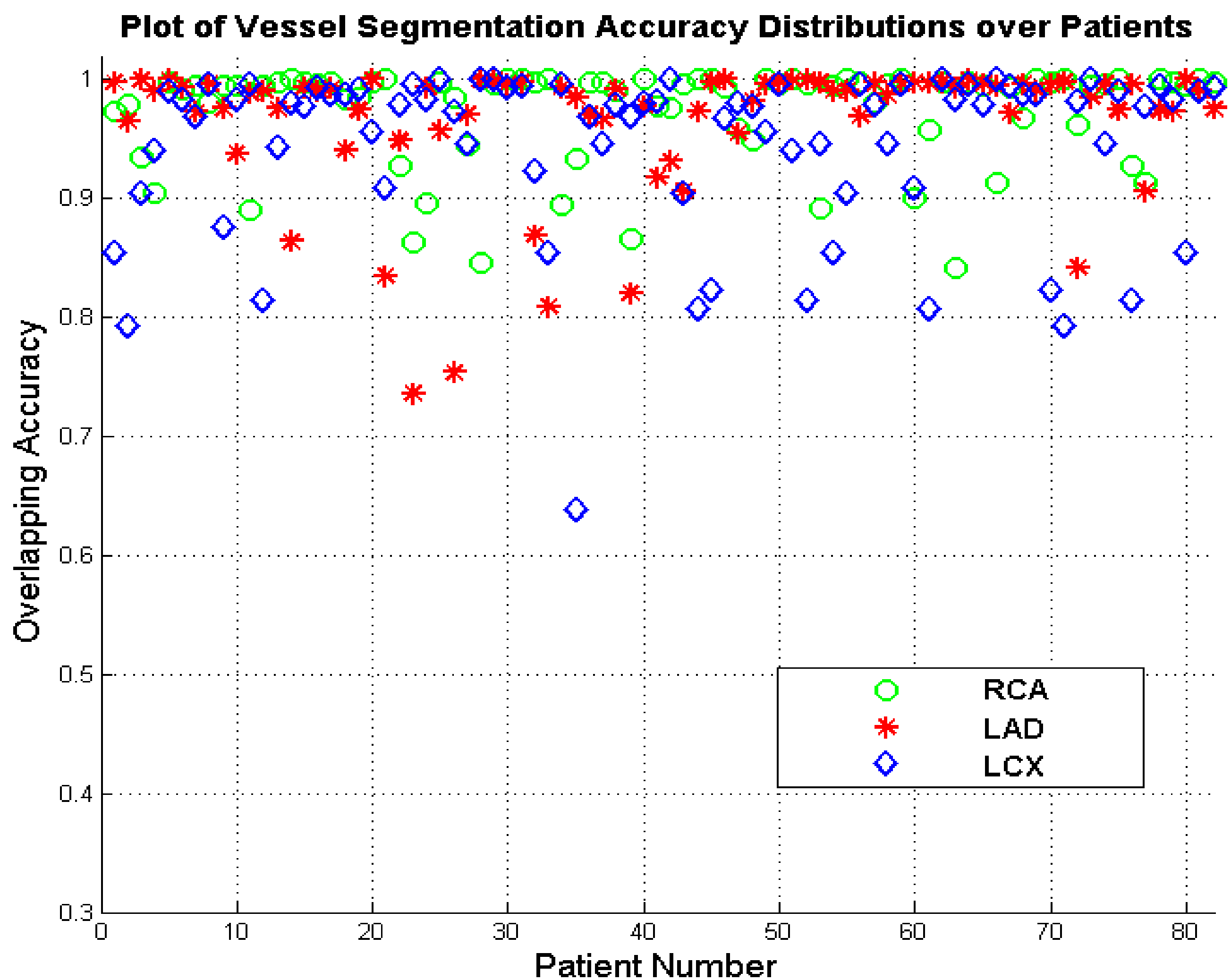


Set-Expansion by Bipartitioning on C2/C3 Vessel Segment
Raw KDE ρ Curve
Filtered KDE ρf Curve
Compactness Curve of ρ
Compactness Curve of ρf
Annotation Label Curve
Bipartitioning Point
Probability (Positive Class)
Vessel Segment Knot Point
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
50
100
150
200
250
300
350
400
450

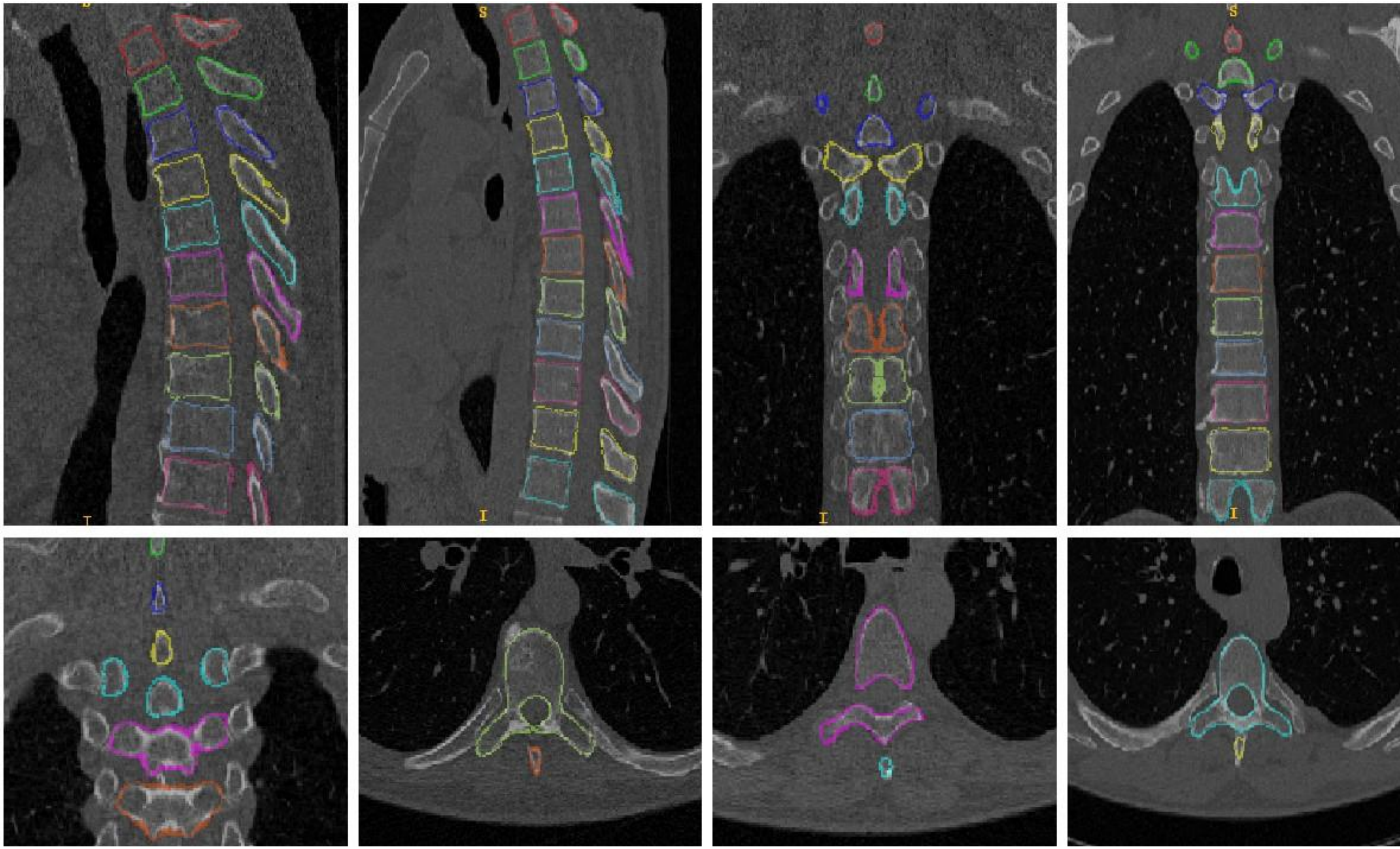
The Art of Low-level Learning (How Greedy You Can be?, **Bias versus Variance!!**)



Patient-level accuracy and performance



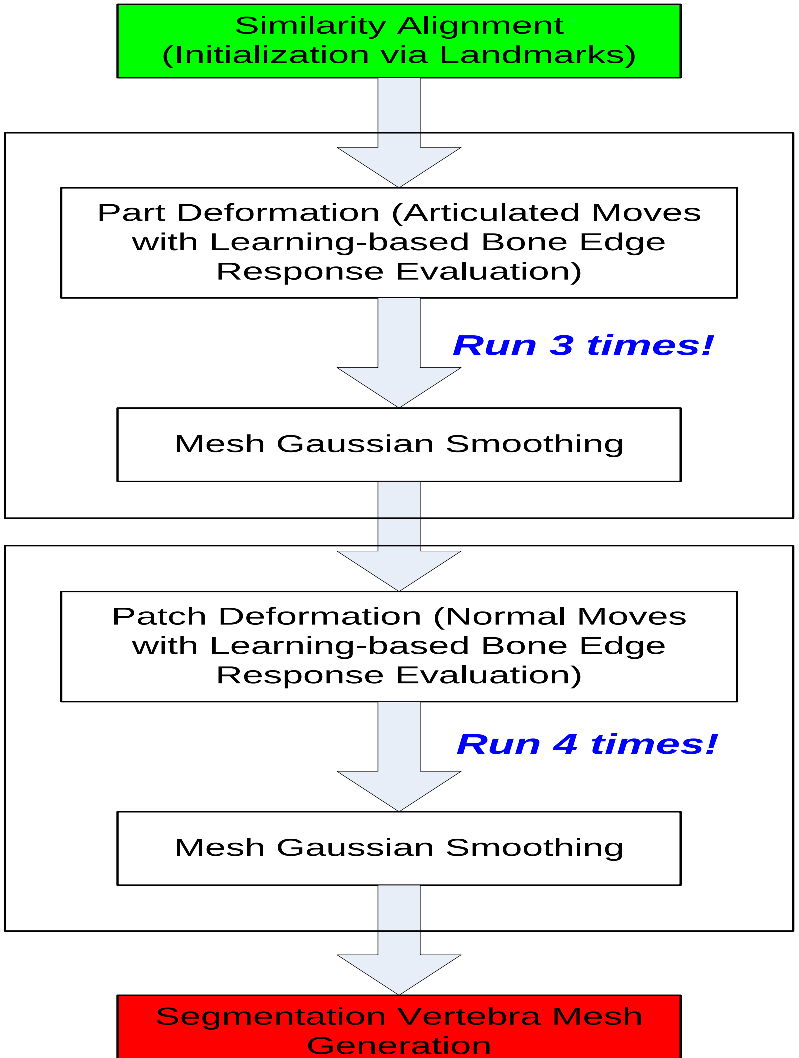
Vertebra Segmentation & Identification (MICCAI'10)

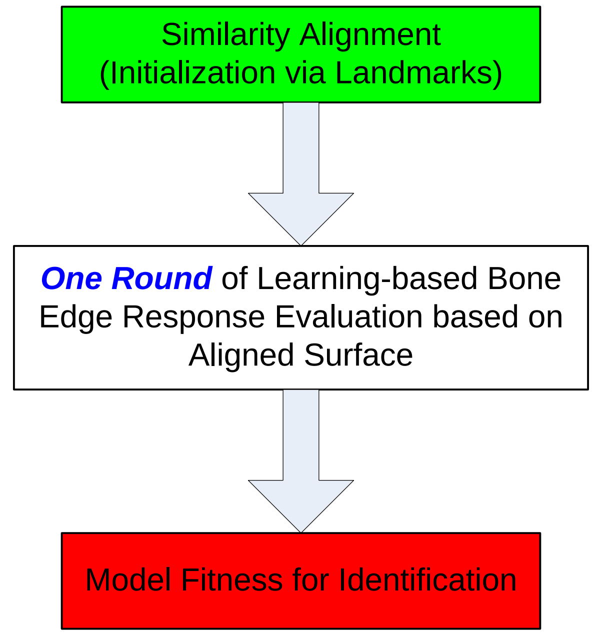


Methods Overview

- Vertebrae Segmentation
  - Learning-based edge detector
  - Hierarchical deformation scheme
  - Convergence field (enforced at bony structure for robustness of alignment)
- Vertebrae Identification
  - Mean Shapes
  - Single vertebra identification
  - Vertebrae string identification

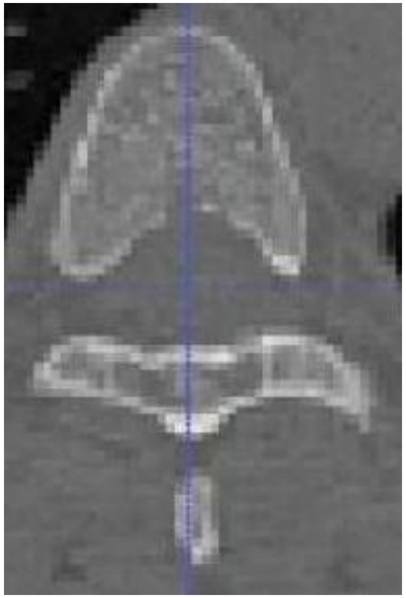
System Flowchart

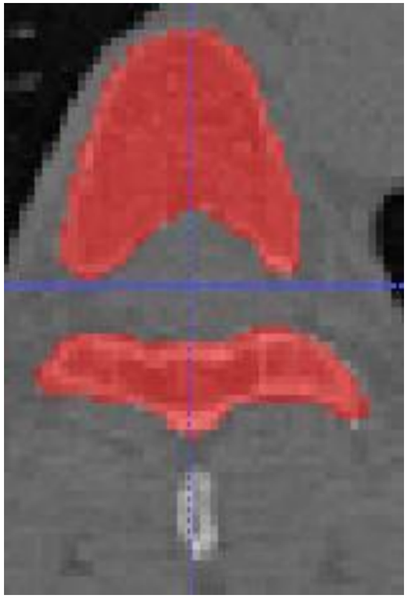


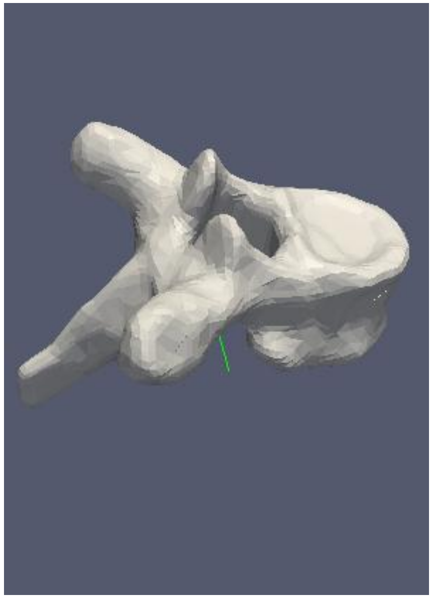


Surface template generation (training phase)

Original 3D CT image → Pre-processing → Manual segmentation → Surface generation



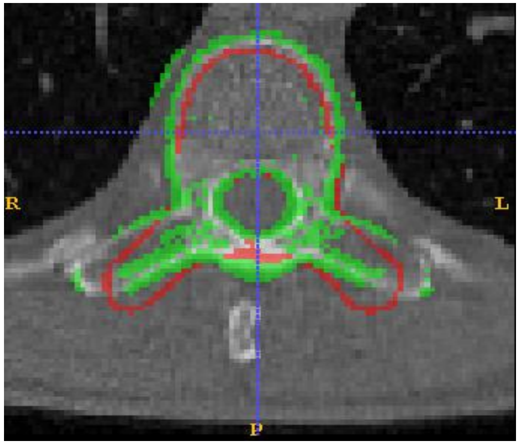


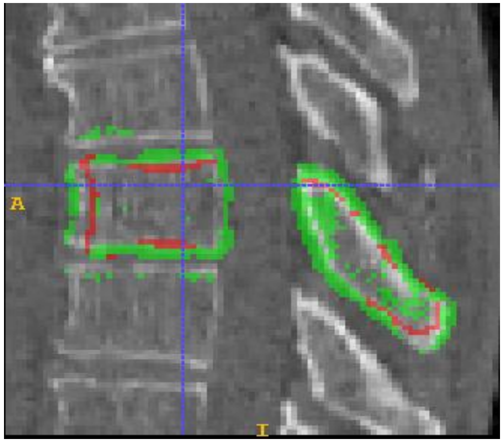


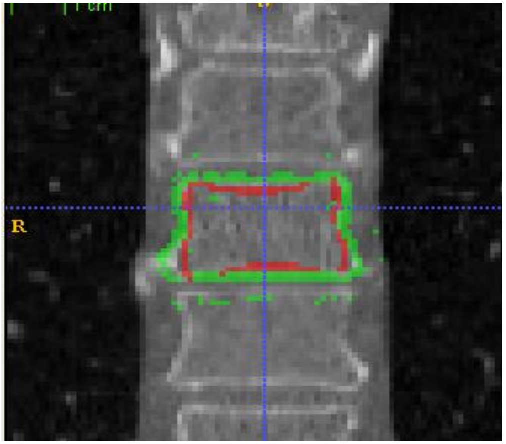
Edge response map

➢Generate response map by learned edge detectors
- optimally combine image features to detect object-specific edge
- more discriminative and robust
- Indicates edge likelihood (probability map)
- Informative but noisy

➢Hierarchical deformation strategy
- Sub-region deformation
- Patch deformation
- Individual vertex deformation



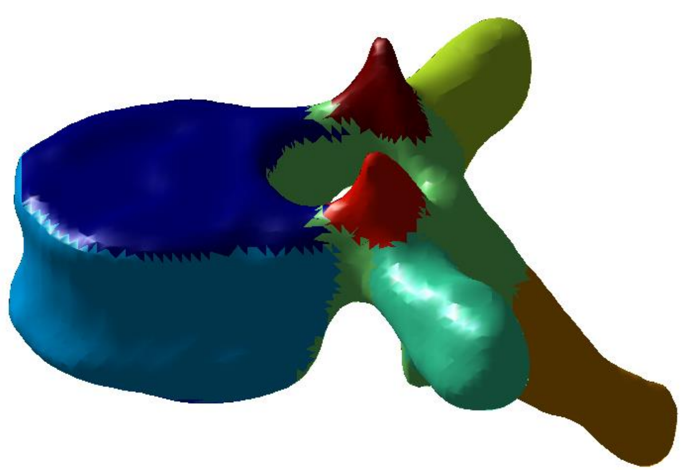


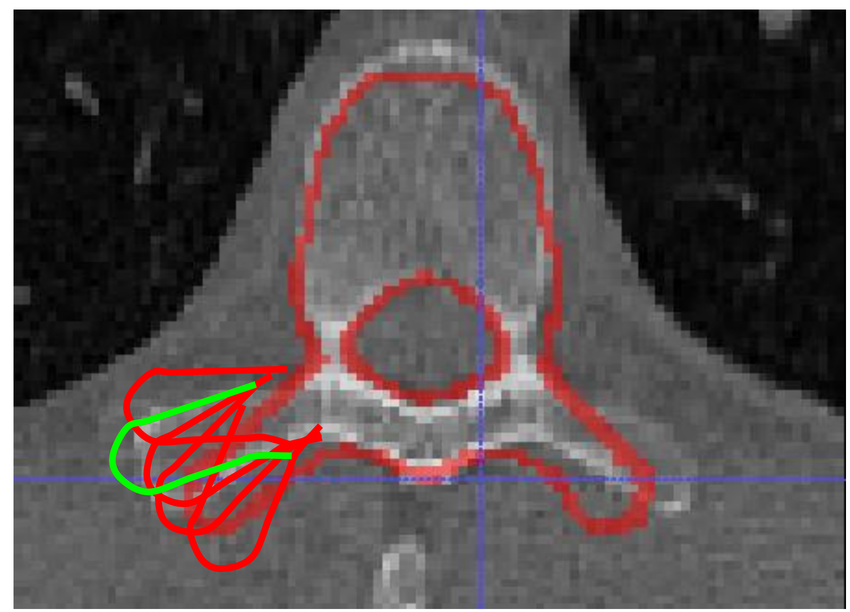


Sub-region deformation

Sub-region deformation

- Divide the surface to 12 subregions
- Vertices in the same subregion deform together as a team
- Rigid transformation with the strongest “edge ” likelihood is the target position.





Calculate response at this position

Maximum response

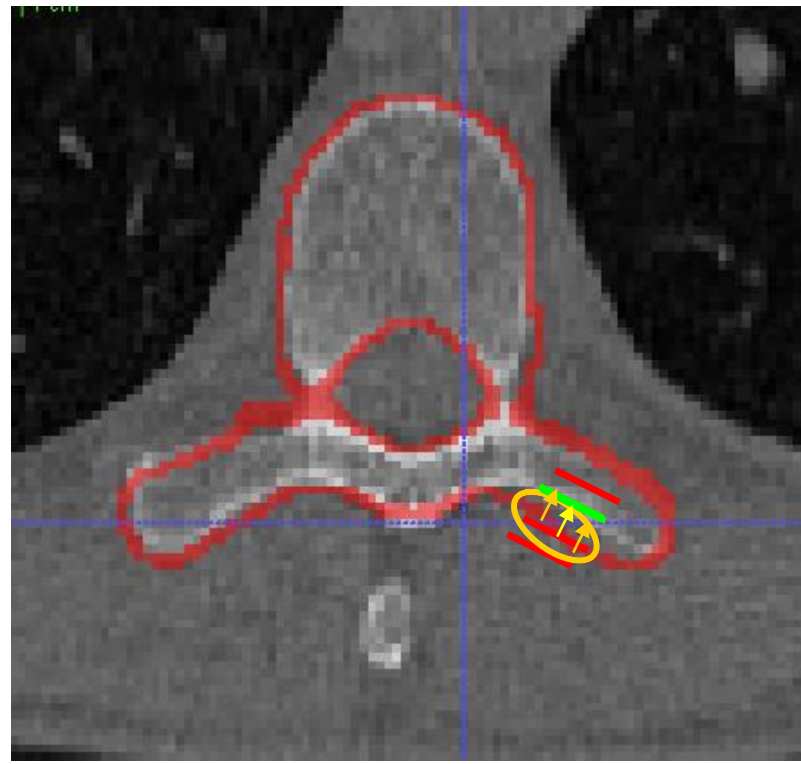
Patch deformation

Patch deformation

- Move a patch to a number of positions along its normal direction, and calculate the responses at these positions. Position with strongest response is the target position.

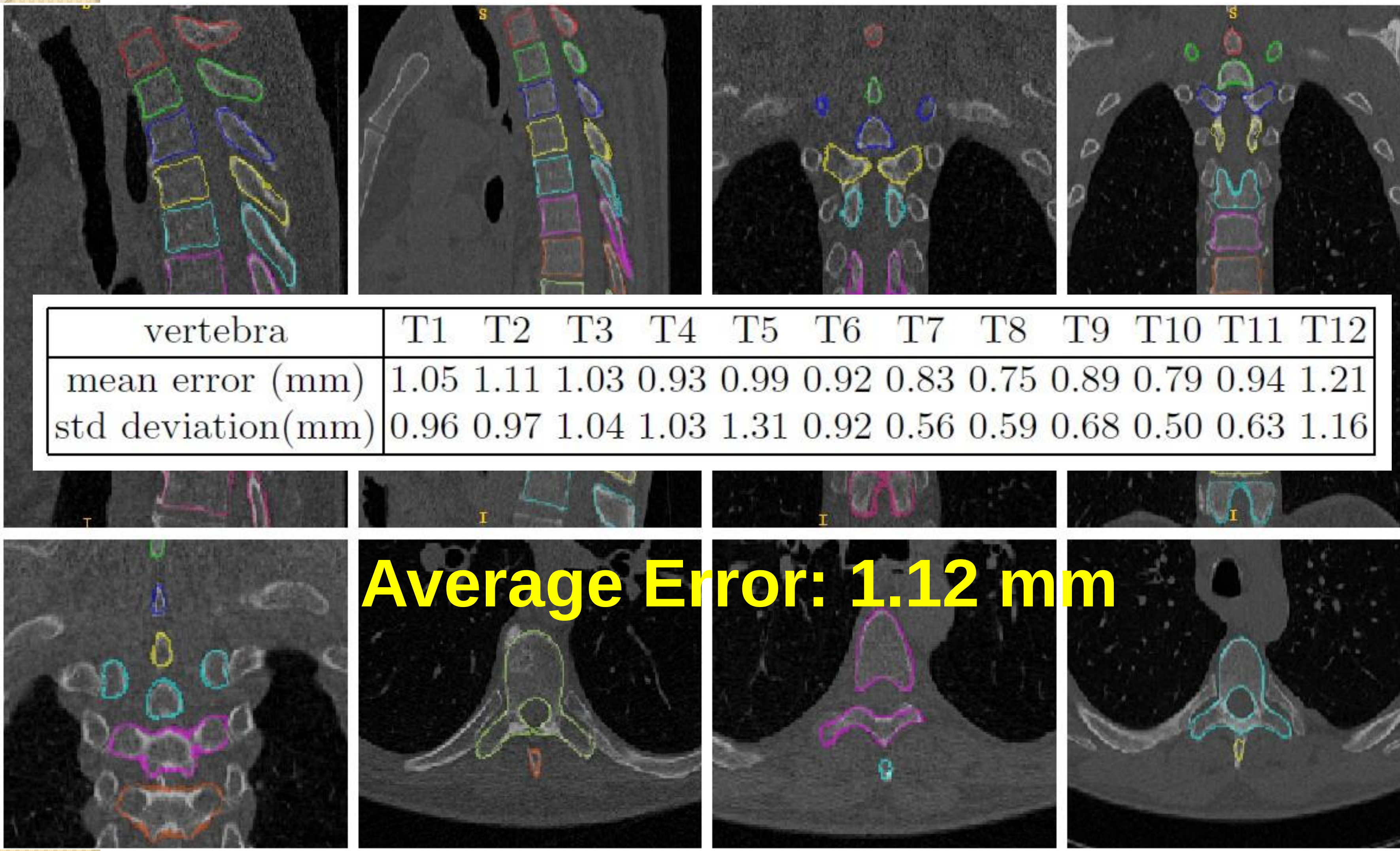
Individual vertices deformation

- Move each vertex to a position with highest edge likelihood



Calculate responses at these position
Maximum response at this position

Segmentation Accuracy Results

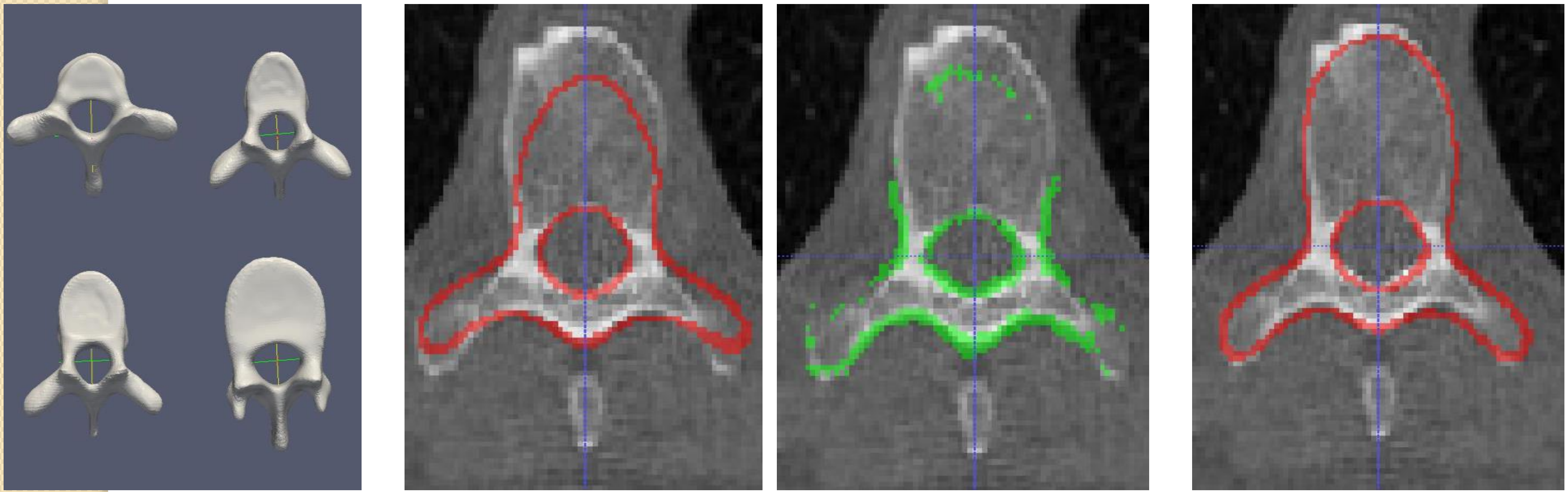


vertebra	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12
mean error (mm)	1.05	1.11	1.03	0.93	0.99	0.92	0.83	0.75	0.89	0.79	0.94	1.21
std deviation(mm)	0.96	0.97	1.04	1.03	1.31	0.92	0.56	0.59	0.68	0.50	0.63	1.16

Average Error: 1.12 mm

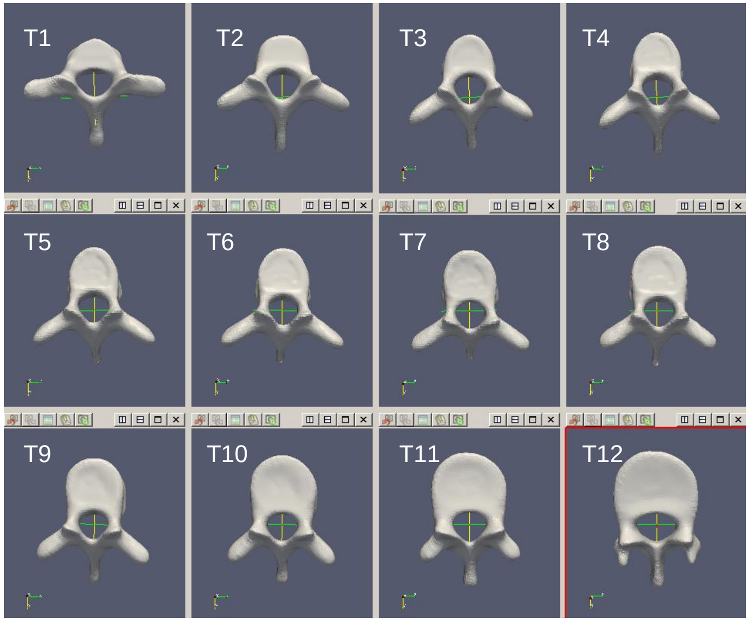
Identification: framework

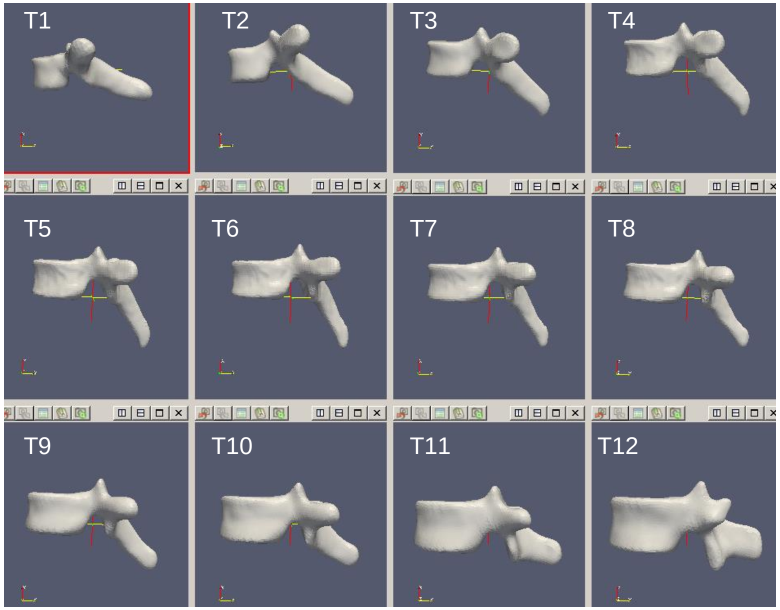
Compute mean shapes → Mean shape to new image → Compute response → Which has maximum response



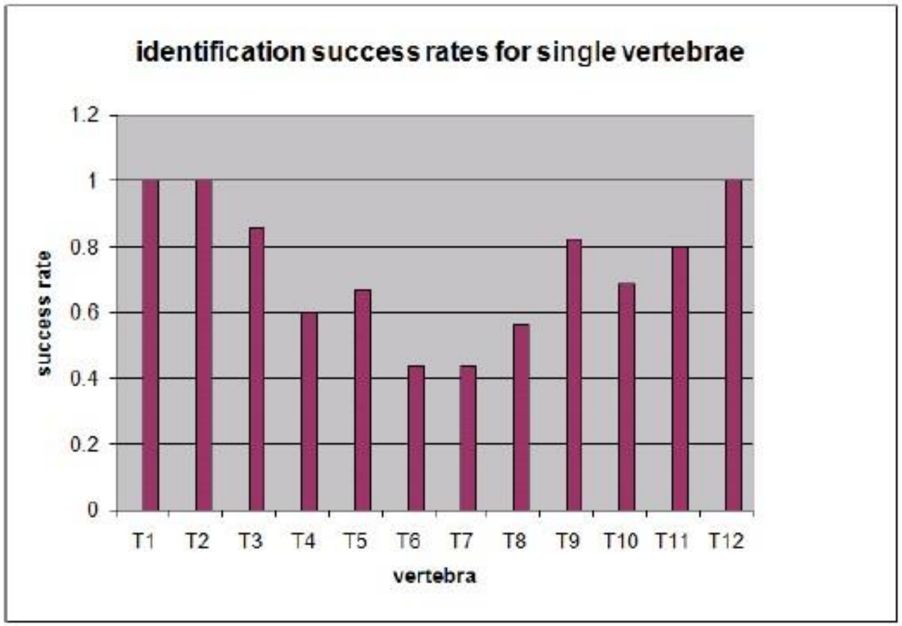
Mean shapes

- The segmentation method is applied on 40 CT volumes
- Surface meshes of thoracic vertebrae are obtained
- Vertex correspondence across meshes are directly available
- Mean vertebrae shapes are computed (four-fold cross validation)

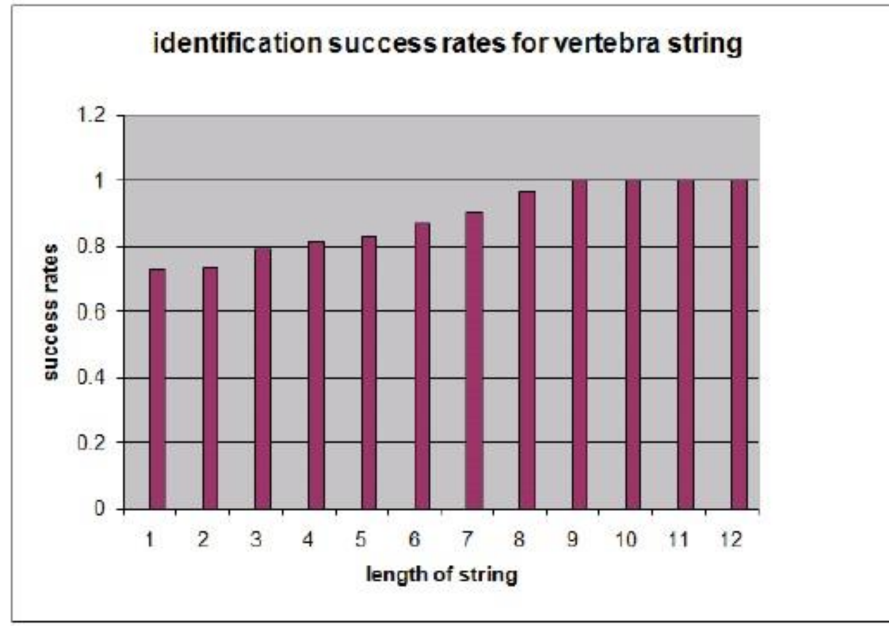




Results (compared favorably with the state-of-the-art!)



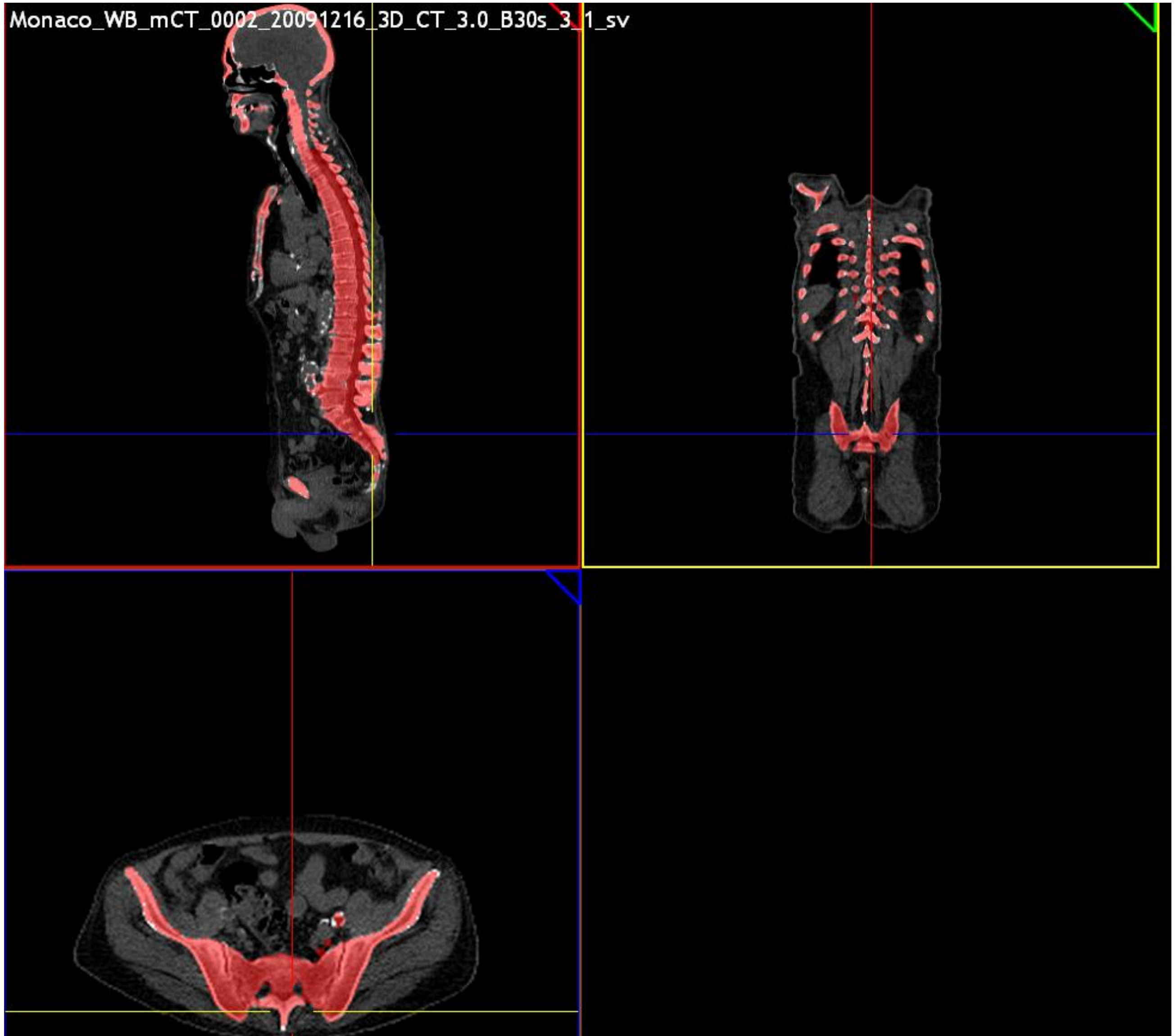
individual success rates



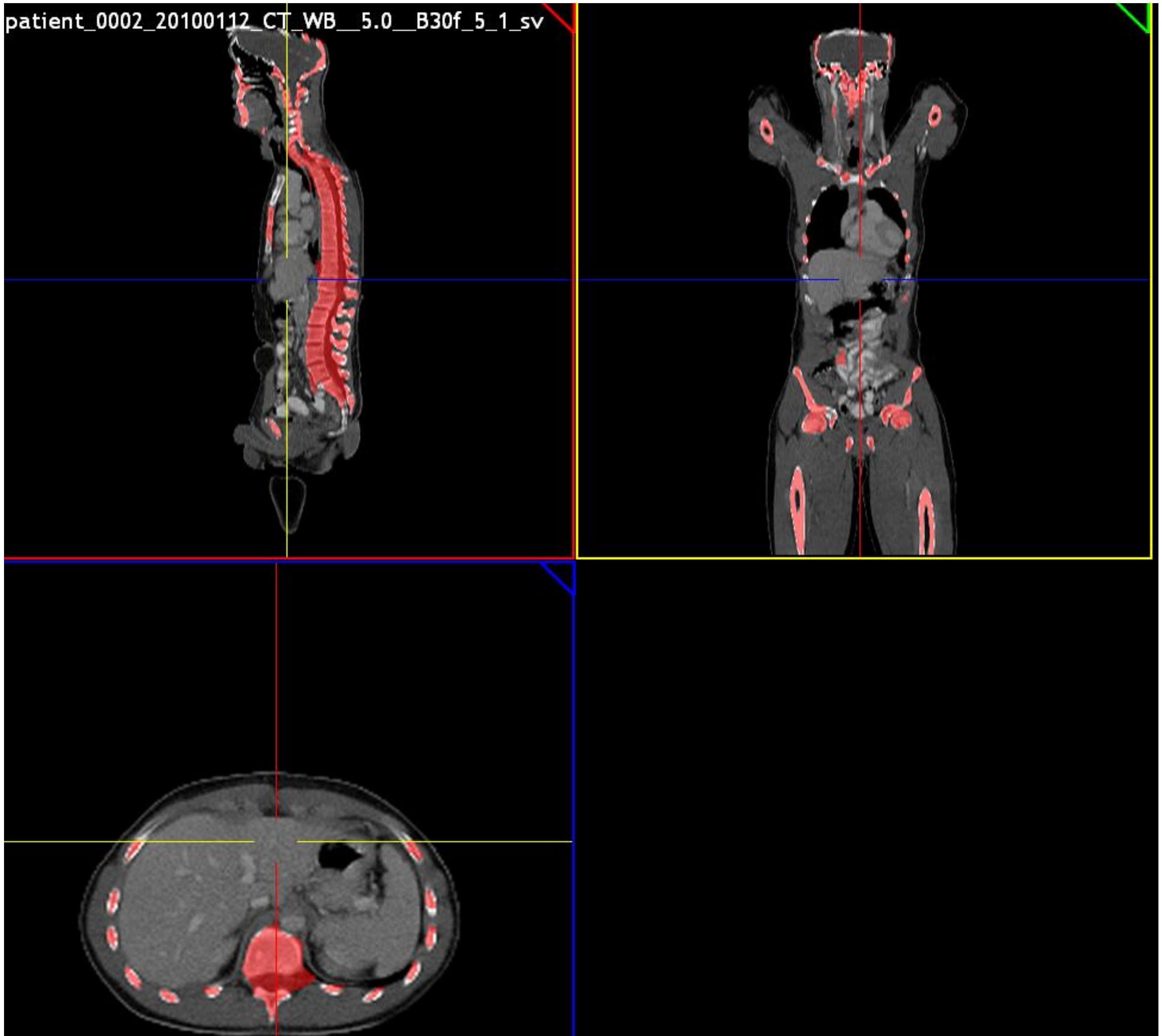
string success rates

- Hierarchical Segmentation and Identification of Thoracic Vertebra Using Learning-based Edge Detection and Coarse-to-fine Deformable Model, Ma, Lu, Zhan, Zhou, Salganicoff, Krishnan, MICCAI 2010 (Oral)

Flexible Structure Labeling & Masking



Supervoxel graph, weakly supervised learning, regional recognition & feature description, classifier fusion …



Short Messages

- Trend of more merging activities of modern computer vision and medical image understanding & semantic imaging → MICCAI/CVPR MCV workshops
- Computer vision can help though non-trivial (no silver bullet)!!
- Image or Visual Representation is equally important, if not more, to algorithms in computer vision and medical imaging (art side of computer vision). → better understanding of the problem!
  - It is not all about science, but science-guided arts!
- Statistical, principled quantitative systematic performance progression!! How I can do better than yesterday, stochastically guaranteed?
- Better image structure encoding and full-range <Image-Image>; <Image-Text> Context Learning → Full Body Imaging/non-Imaging (image data, annotation & clinical reports) Parsing → NLP, talking pictures in CVPR …
- CAD 2.0 ??
- Go Cloud! CAD-S and what will change the algorithm and data?
  - Never do something cheap?

Acknowledgement

- Thanks to my colleagues, collaborators, mentors and interns!
- Video on Depth based object tracking…
- Make dirty, difficult things work!
- Enable radiologist's experience, knowledge, vision & insights to be computable reliably, in a high performance setting!