Fast Multiple Organ Detection and Localization in Whole-Body MR Dixon Sequences

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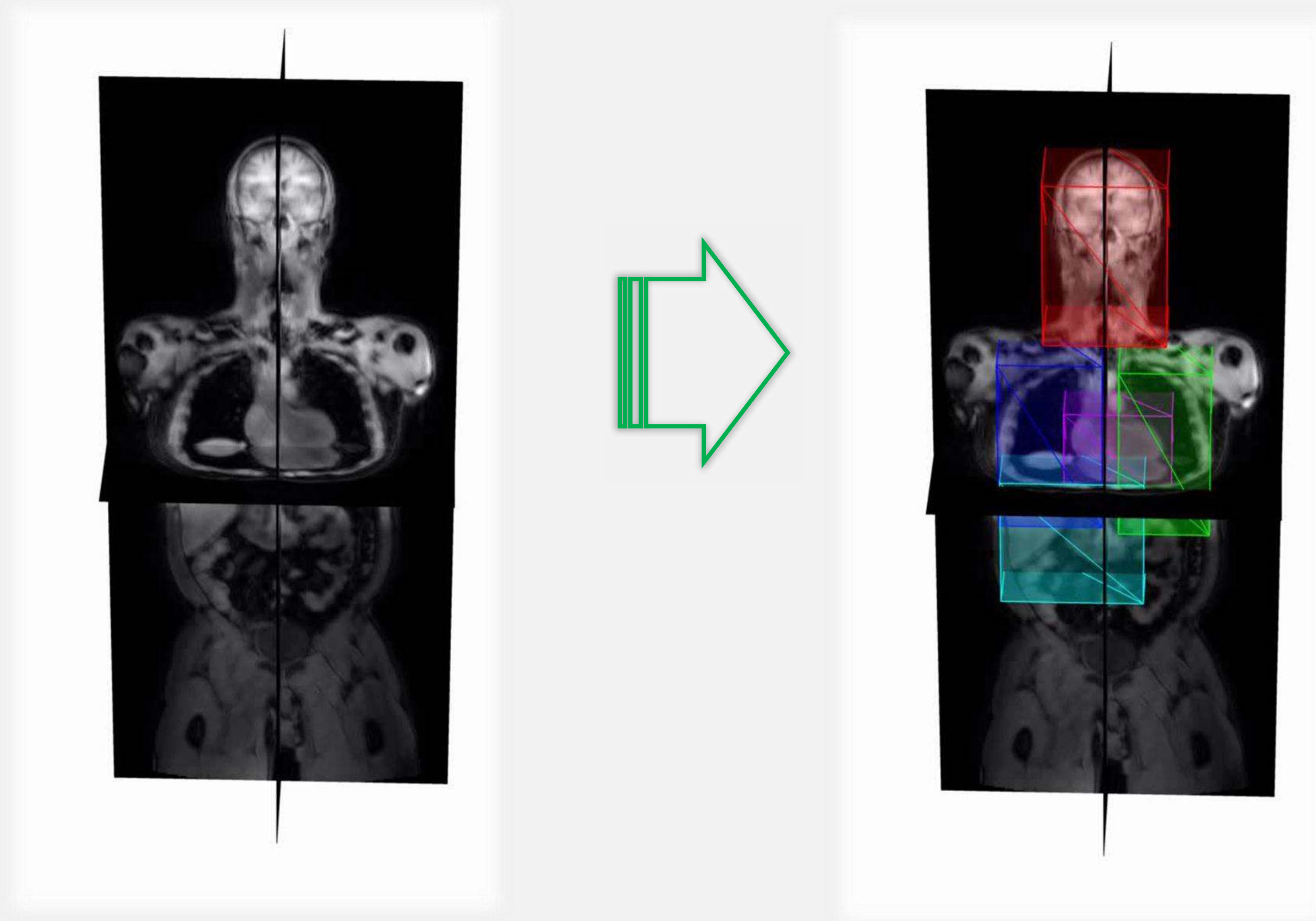
CAMP TUM

Microsoft Research Cambridge

MRINM

What it‘s all about...

Pauly et al., Fast Multiple Organ Detection and Localization



What it‘s all about...

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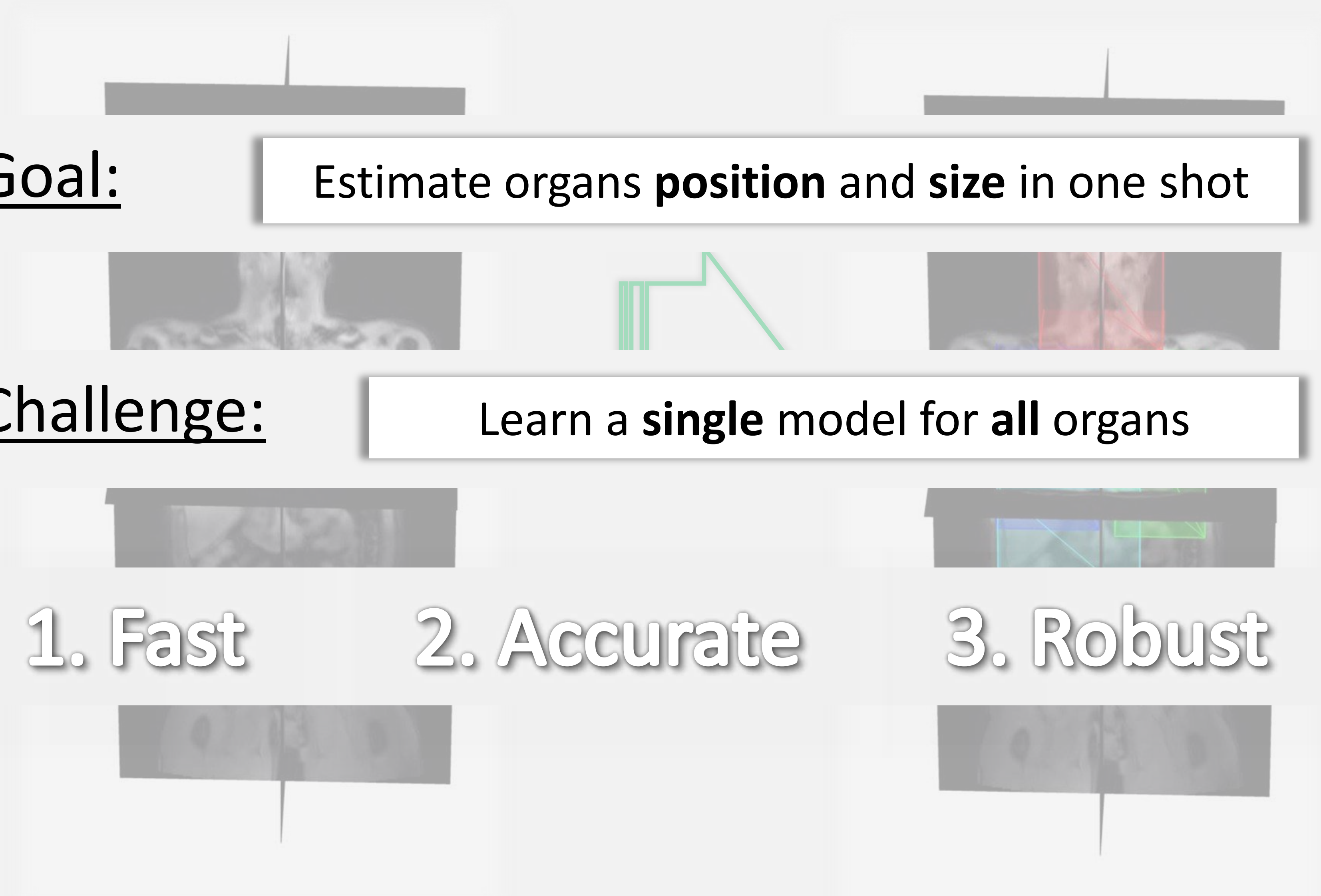


Goal: Estimate organs **position** and **size** in one shot

Challenge: Learn a **single** model for **all** organs

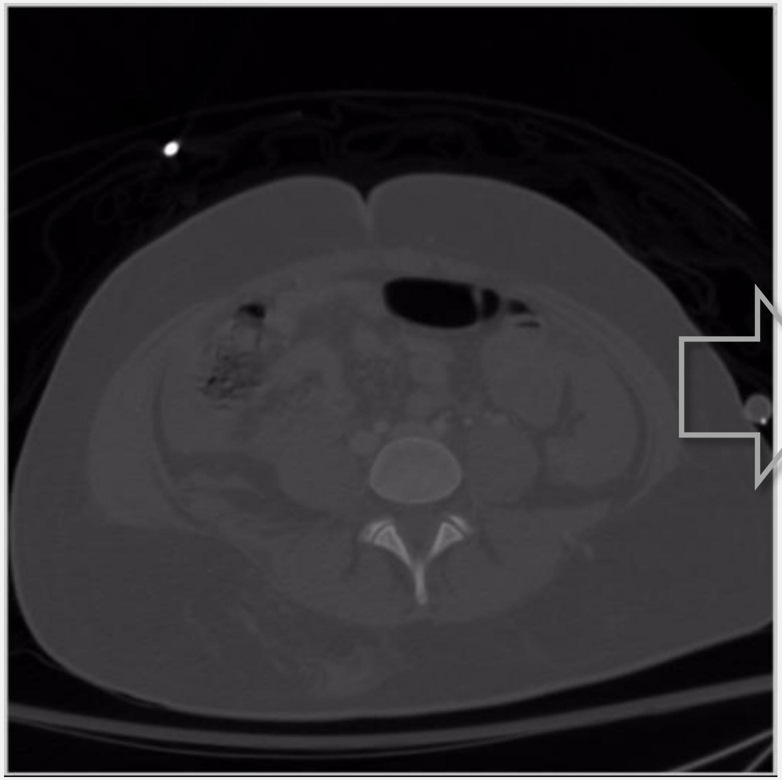
1. Fast
2. Accurate
3. Robust

Potential application...

Pauly et al., Fast Multiple Organ Detection and Localization

Semantic navigation:

Direct navigation to **organs**



Brain

Heart

Kidney (L)

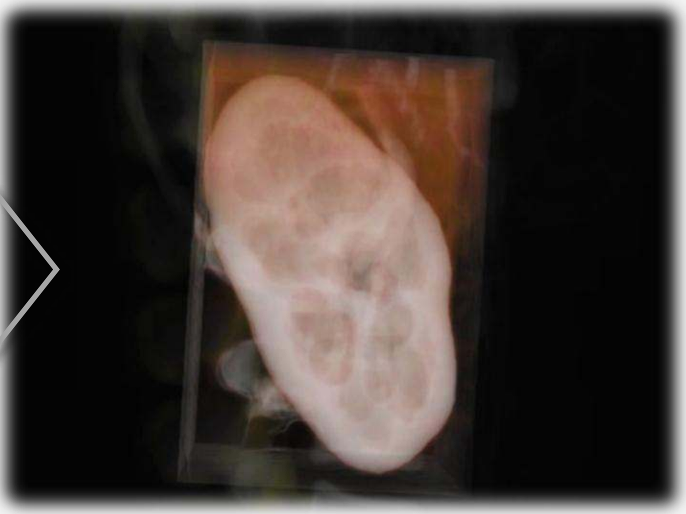
Kidney (R)

Liver

Lung (L)

Lung (R)

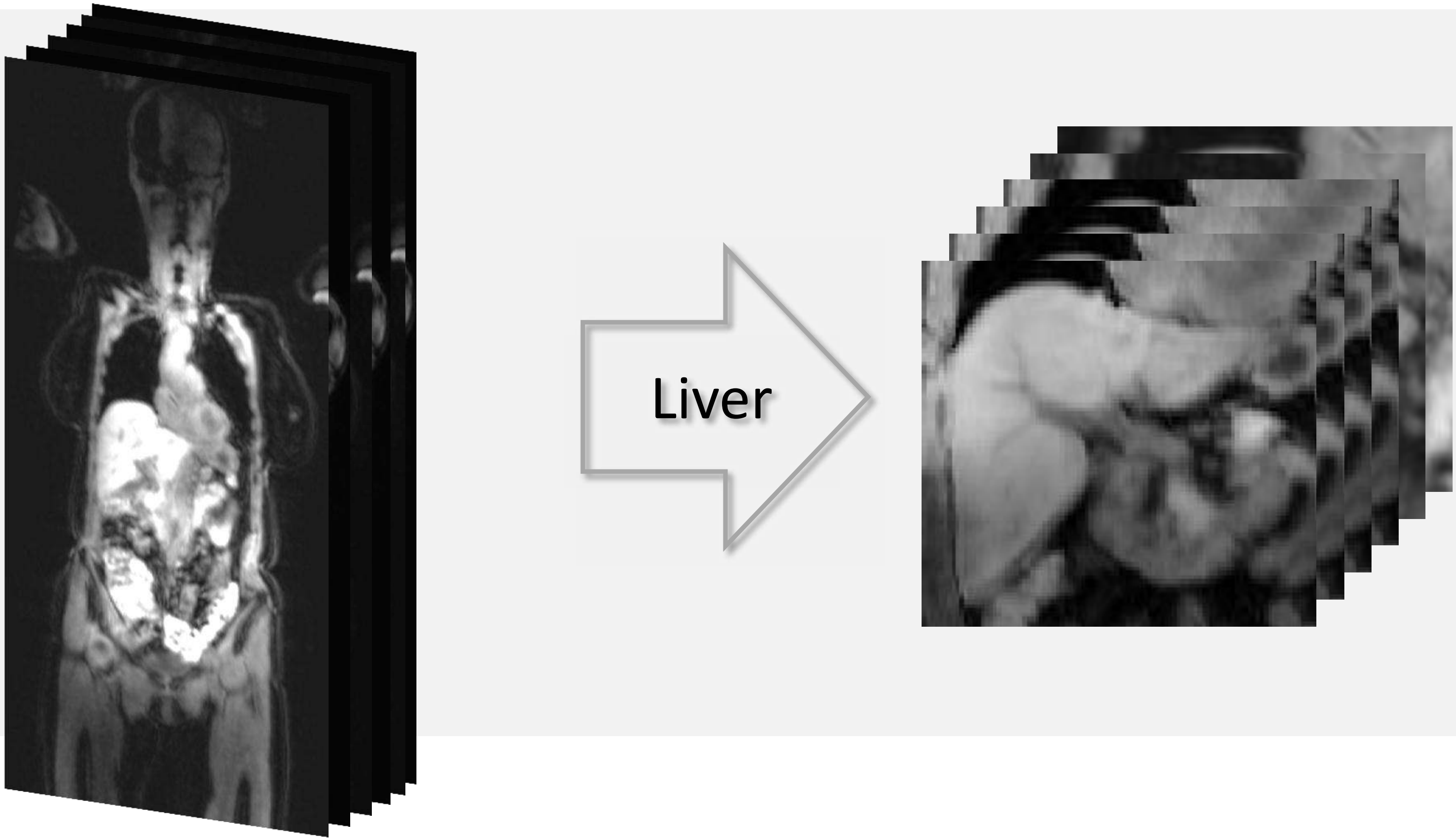
...



Potential application...

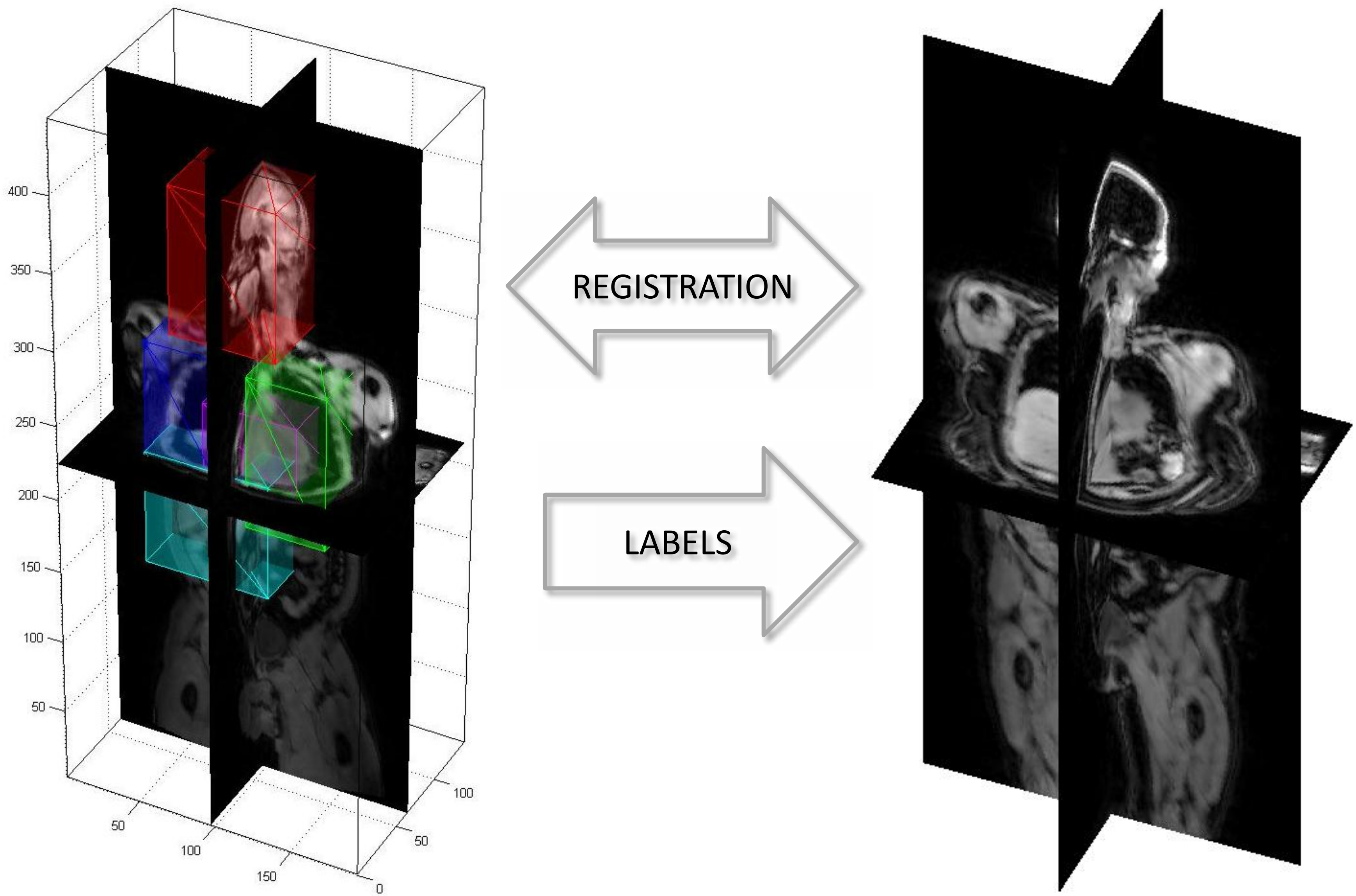
Database retrieval:

Retrieve organs of interest



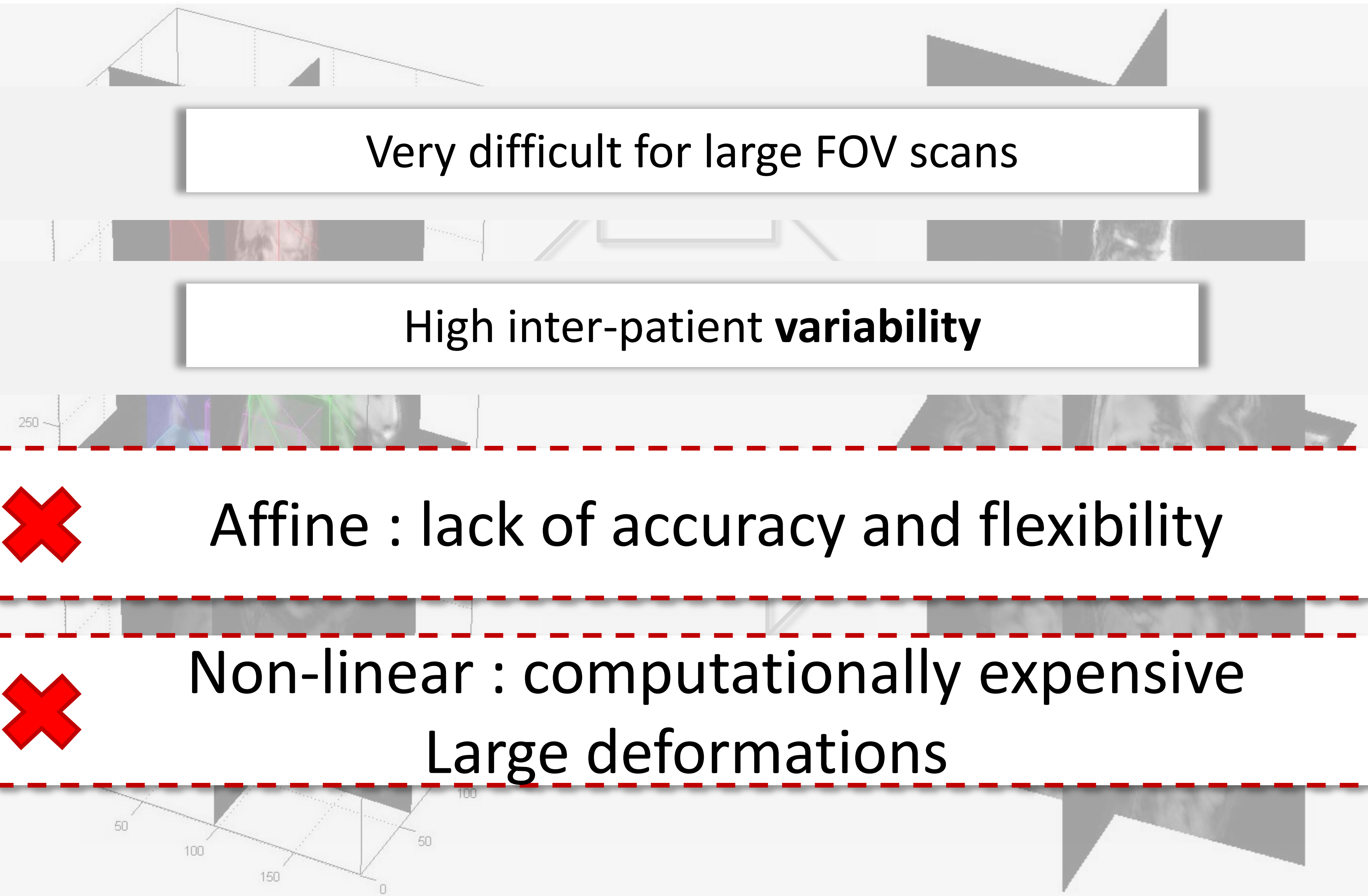
Atlas registration

Pauly et al., Fast Multiple Organ Detection and Localization



Atlas registration

Pauly et al., Fast Multiple Organ Detection and Localization



Very difficult for large FOV scans

High inter-patient **variability**

Affine : lack of accuracy and flexibility

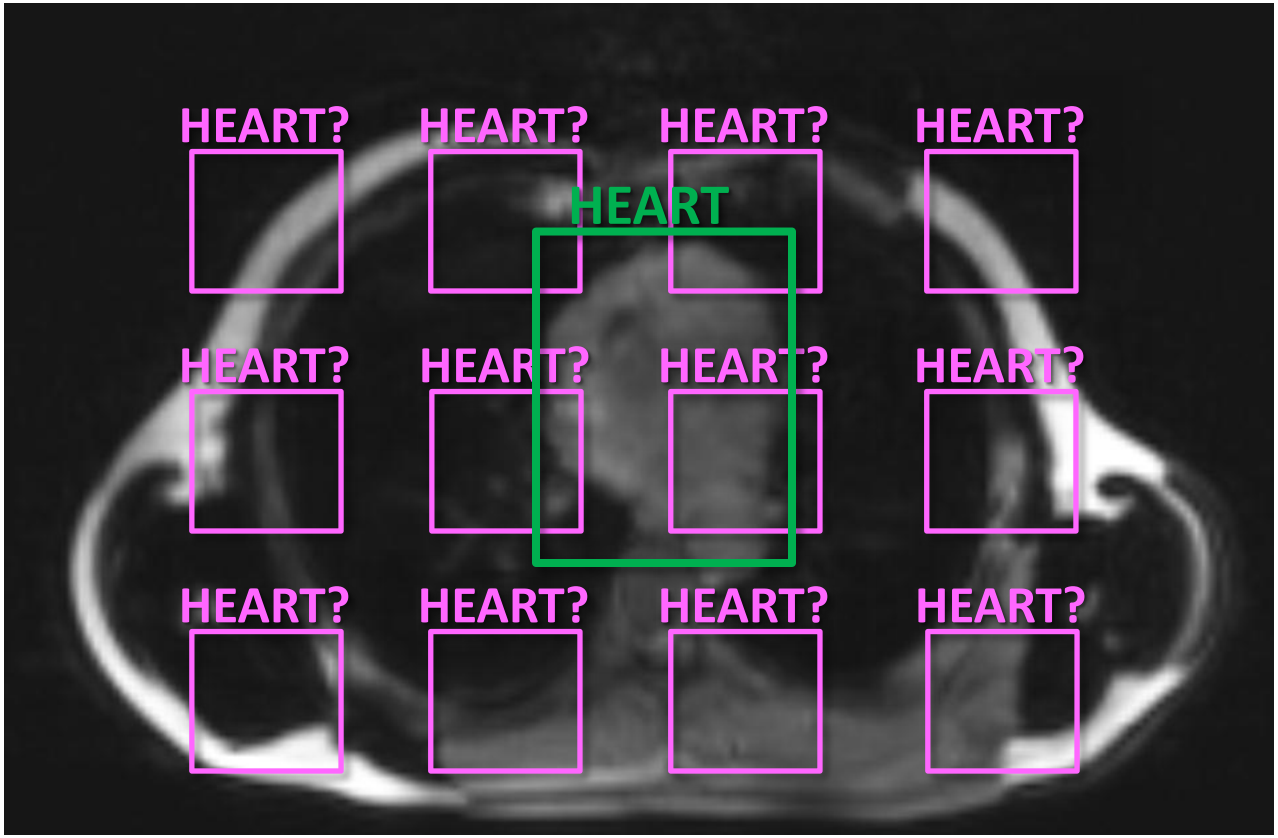
Non-linear : computationally expensive
Large deformations

Detection approach...

Pauly et al., Fast Multiple Organ Detection and Localization

Sliding Window

- **Exhaustive search** in position-size parameters
- A **classifier** evaluates each position-size candidate



*P. Viola and M. Jones, **Rapid object detection using a boosted cascade of simple features,** CVPR 2001.*

Detection approach...

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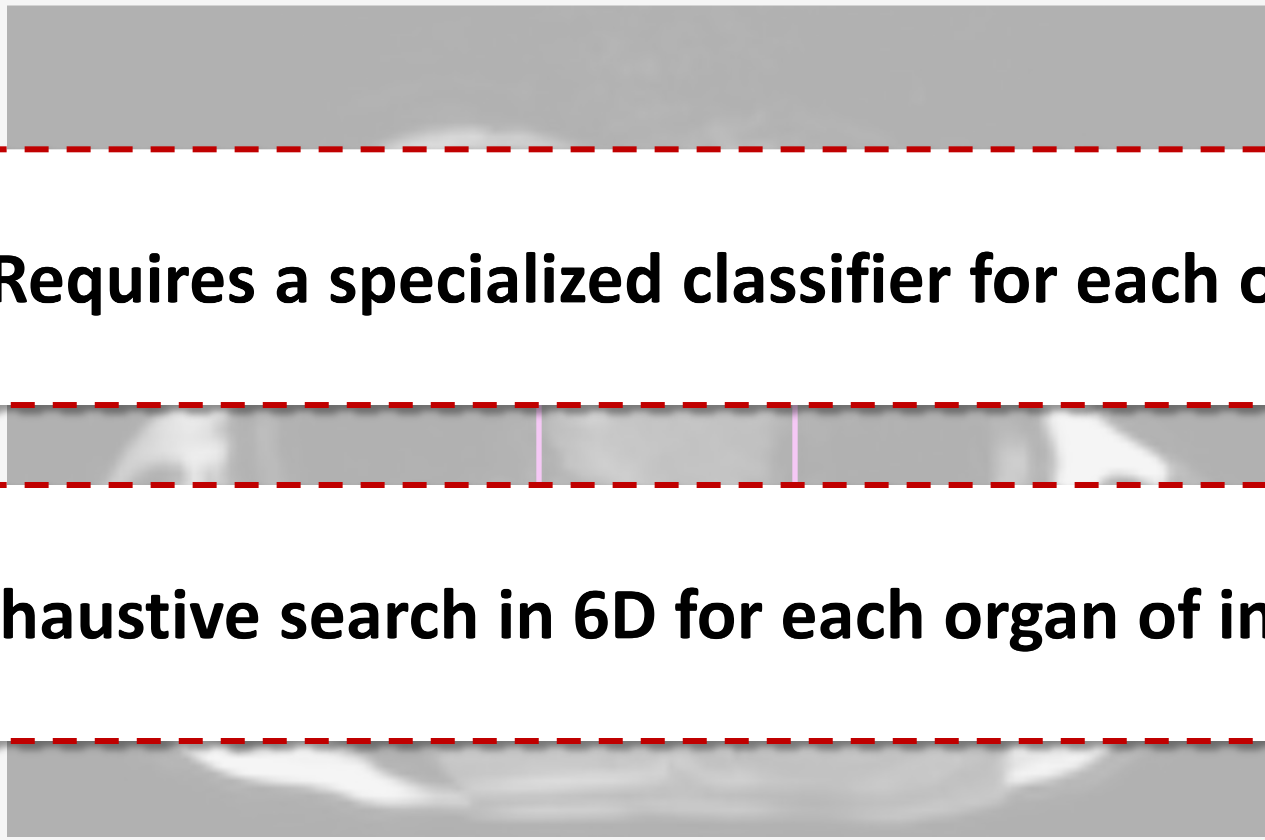


✖ **Requires a specialized classifier for each organ**

✖ **Exhaustive search in 6D for each organ of interest**

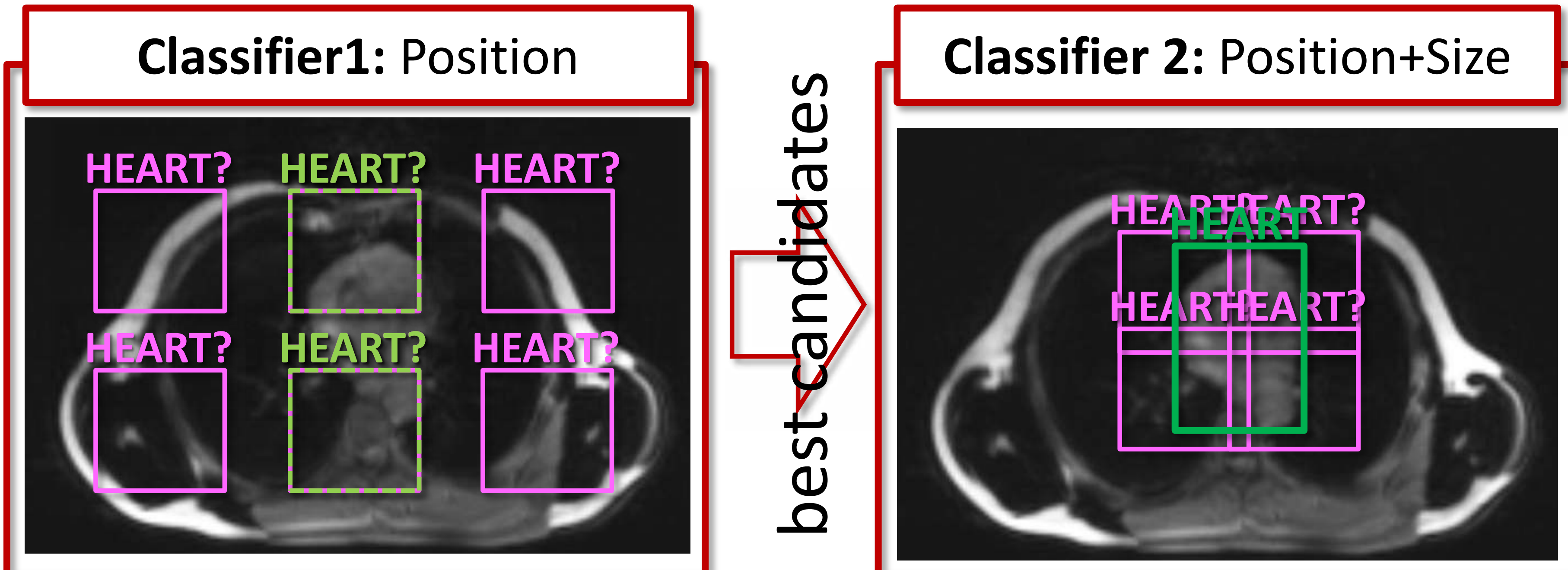
*P. Viola and M. Jones, **Rapid object detection using a boosted cascade of simple features,** CVPR 2001.*

Marginal Space Learning

Pauly et al., Fast Multiple Organ Detection and Localization

Learn sequentially in marginal spaces

- **Exhaustive search** in **position** parameters **only**
- **Refinement** search in **position-size** parameters



*Zheng, Barbu, Georgescu et al.: **Four-Chamber Heart Modeling and Automatic Segmentation for 3D Cardiac CT Volumes using Marginal Space Learning and Steerable Features**, IEEE TMI (2008)*

Marginal Space Learning

Learn sequentially in marginal spaces

- **Exhaustive search** in **position** parameters **only**
- **Refinement** search in **position-size** parameters

More Efficient Organ localization

Need to train a cascade of classifiers: one classifier for each marginal step

„Real“ multi-organ MSL intractable:
- Search space too high-dimensional
- Increasing complexity of the cascade

Y. Zheng, B. Georgescu, D. Comaniciu: ***Marginal Space Learning for Efficient Detection of 2D/3D Anatomical Structures in Medical Images****, IPMI 2009*

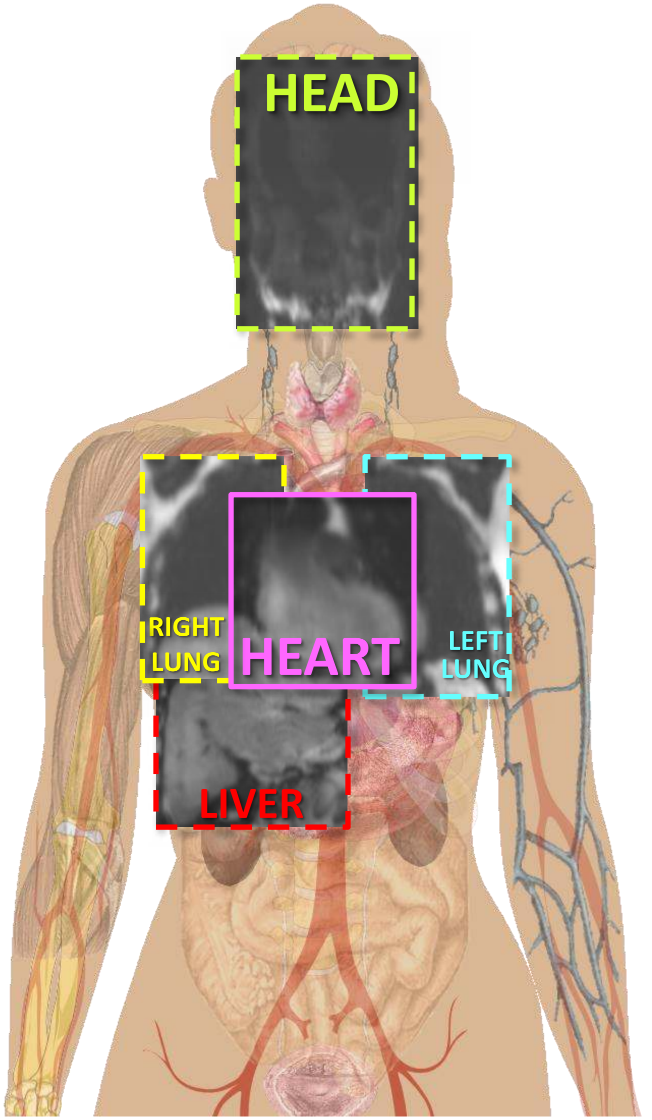
Towards multiple organ detection?

Pauly et al., Fast Multiple Organ Detection and Localization

Detection Organ of interest? ***YES*** / ***NO***

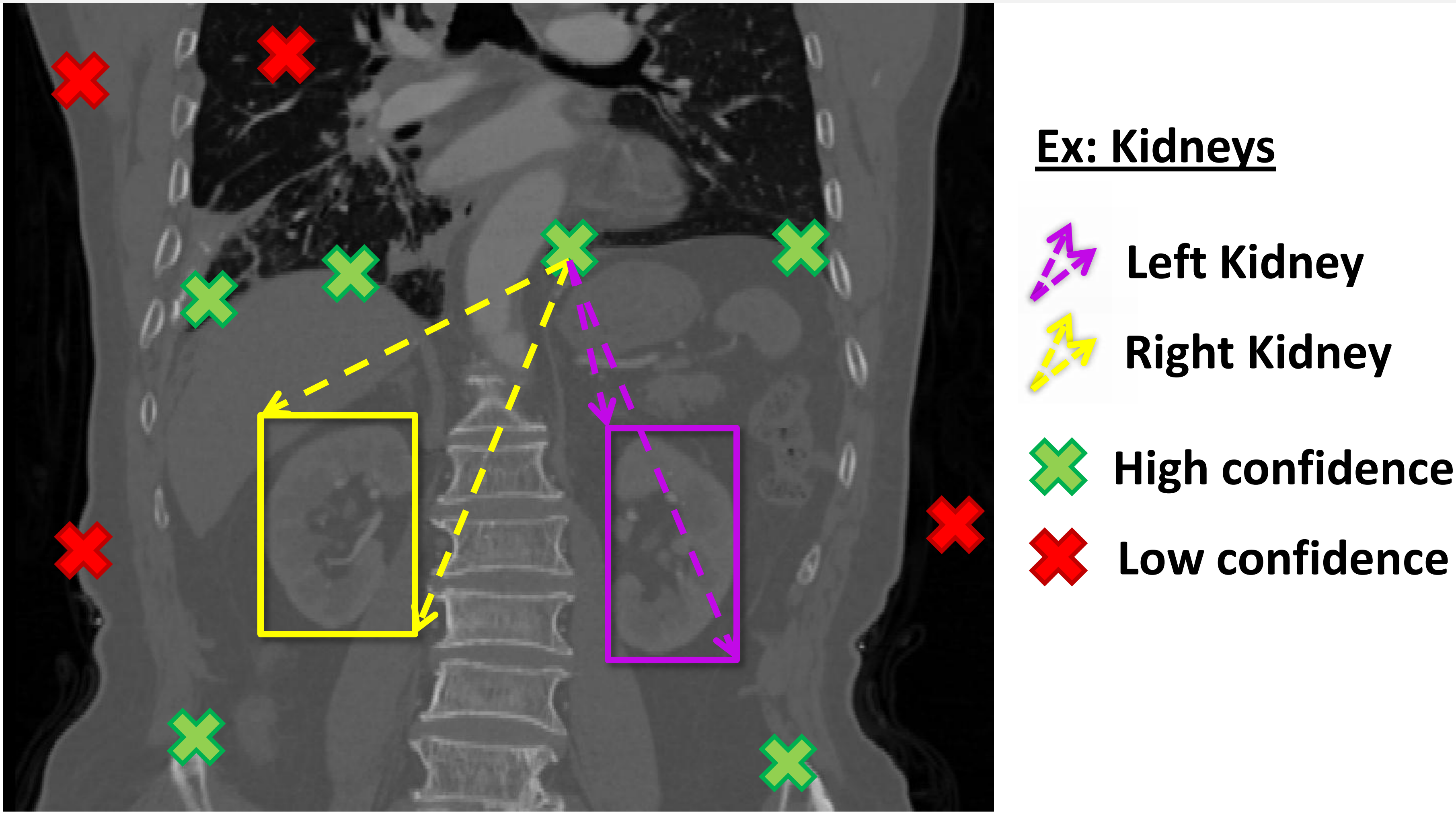
- Human body = well known anatomy
- Medical Imaging = standard procedure

Prior knowledge on the relative positions of all organs!



Our **regression** approach

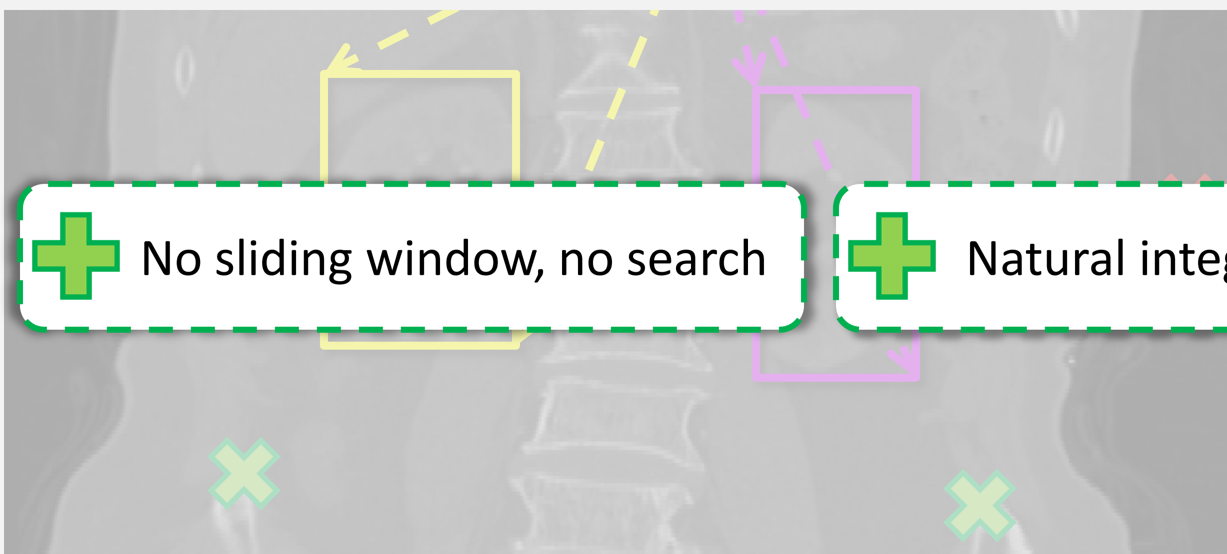
Learn a **probabilistic** mapping from **voxels** to **all organ bounding boxes**



Our **regression** approach

Learn a **probabilistic** mapping from **voxels** to **all organ bounding boxes**

Discover implicitly anatomical **key landmarks**
which best predict organ positions



Not confident

No sliding window, no search

Natural integration of multiple organs

Our contributions in this paper

<u>Our previous work:</u> Organ localization in CT studies

Regression forests

Features based
on Hounsfield units

A. Criminisi, J. Shotton, D. Robertson and E. Konukoglu: ***Regression Forests for Efficient Anatomy Detection and Localization in CT Studies****, MCV workshop, MICCAI 2010*

Our contributions in this paper

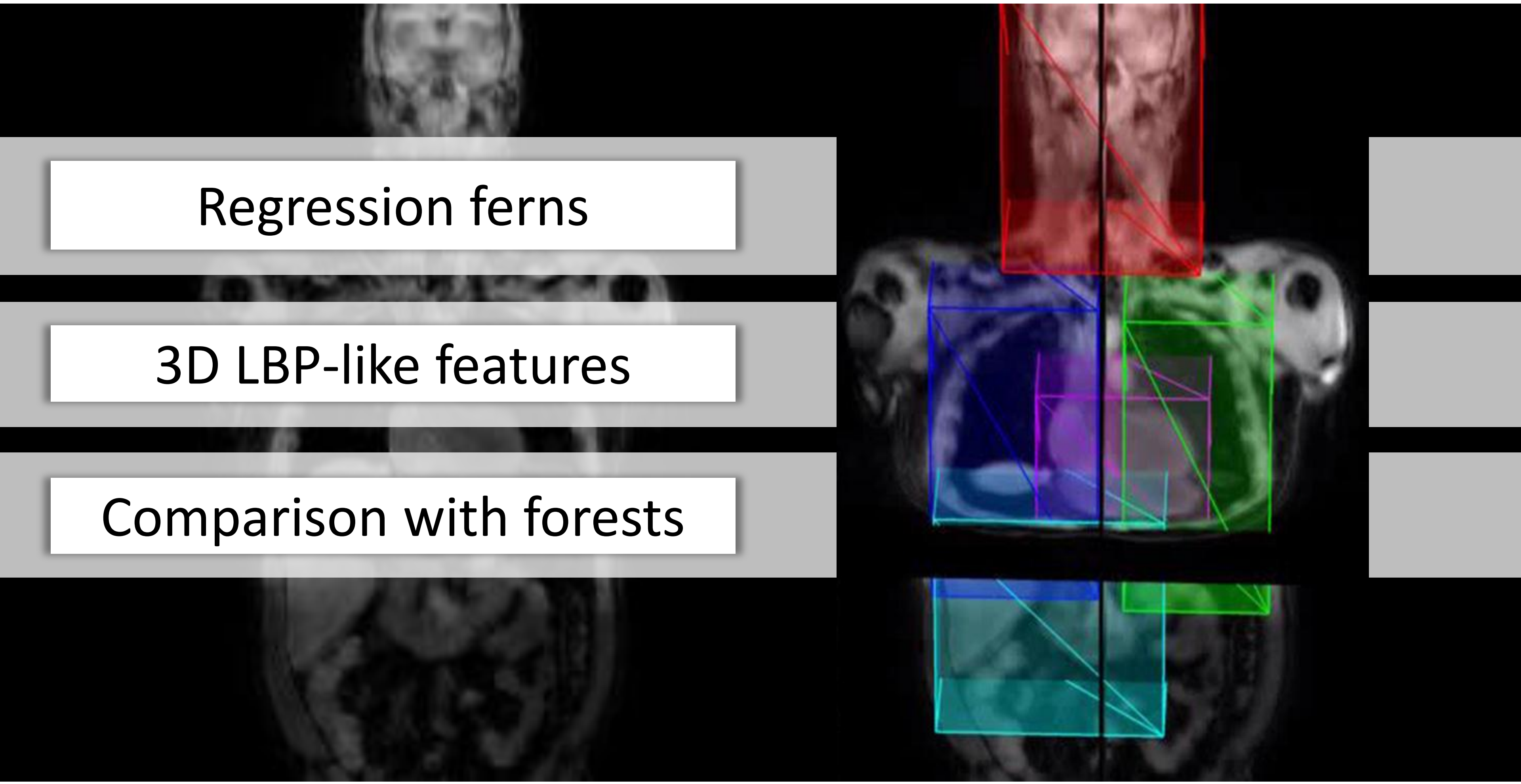
<u>Our current work:</u>

Multi-channel whole-body MR

Regression ferns

3D LBP-like features

Comparison with forests



Organ localization as a regression task

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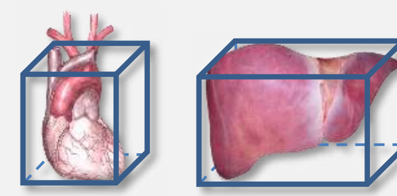
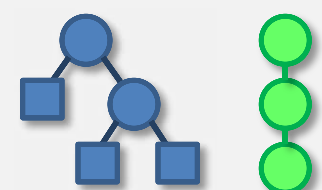
1. Input feature space

2. Output prediction space



3. Regression Ferns



1. Input feature space

INPUT SPACE → REGRESSION → OUTPUT SPACE

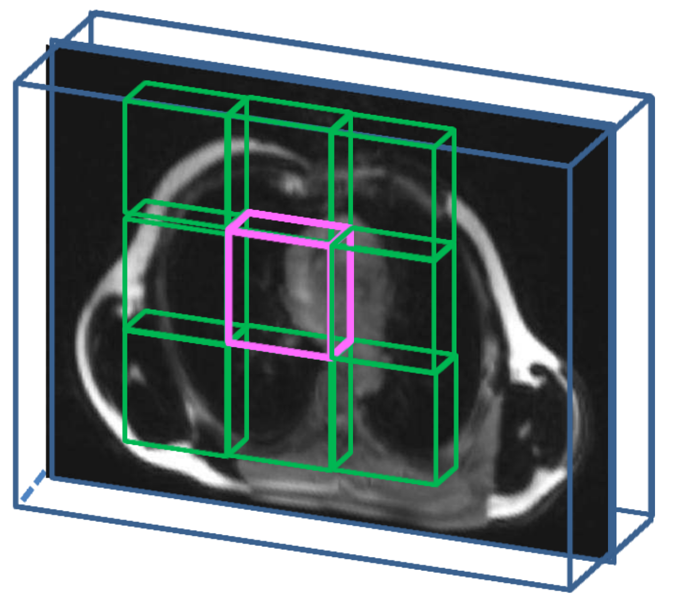
Pauly et al., Fast Multiple Organ Detection and Localization

3D multi-scale LBP-like features

$$(\underset{\text{Voxel}}{\mathbf{x}}, \underbrace{I^W, I^F}_{\text{channels}}) \rightarrow \underset{\text{features}}{\mathbf{X}}$$

mean( ) > mean( ) = 0 or 1 ?

$$\mathbf{X} = (\mathbf{1\ 0\ 0\ 1\ \ldots 0\ 1})$$



+ Characterize Relative intensity changes

+ Multi-scale for Inter-patient variability

2. Output space

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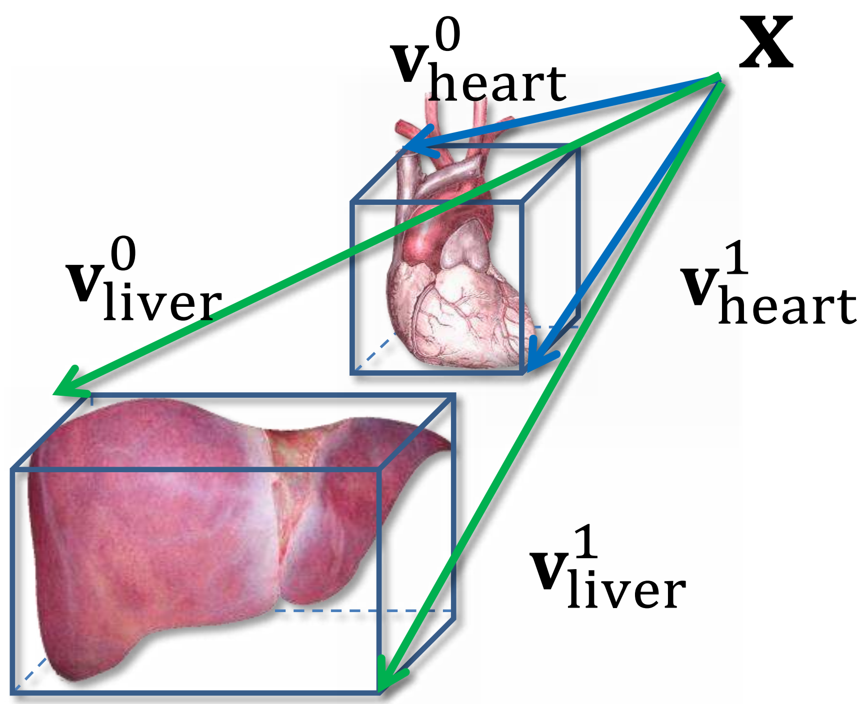
Relative displacement between **voxel** and **organ bounding box**

$$\mathbf{v}_{\text{heart}} = (\mathbf{v}_{\text{heart}}^{0}, \mathbf{v}_{\text{heart}}^{1})$$

$$\mathbf{v}_{\text{liver}} = (\mathbf{v}_{\text{liver}}^{0}, \mathbf{v}_{\text{liver}}^{1})$$

$$\vdots$$



For all K organs:

$$\mathbf{V} = (\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k, \dots, \mathbf{v}_K) \qquad \mathbb{R}^{6\mathrm{x}K}$$

3. Regression Ferns

INPUT SPACE | REGRESSION | OUTPUT SPACE

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Goal: Given $\mathbf{X}$, we want to predict $\mathbf{V}$

Features

Displacements

Learn $p(\mathbf{V} \mid \mathbf{X})$ over the full feature space

Difficult task

Use regression ferns to **divide** and **conquer**:

1. **Subdivide** the input feature space in „cells“ $\{C_t\}_{t=1}^{T}$

2. Learn $p(\mathbf{V} \mid \mathbf{X})$ in **each cell** using a simple model

3. Regression Ferns

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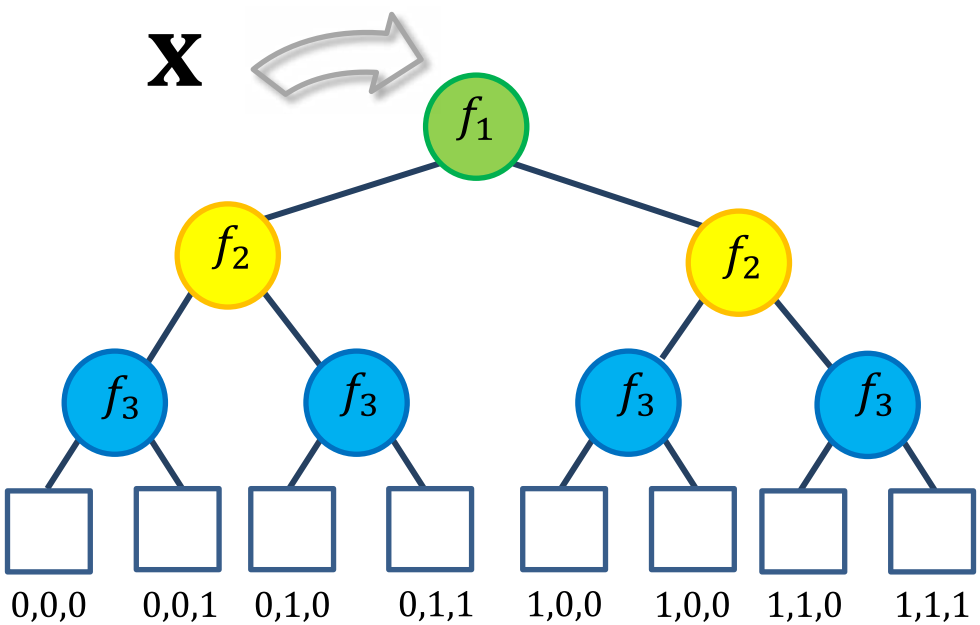
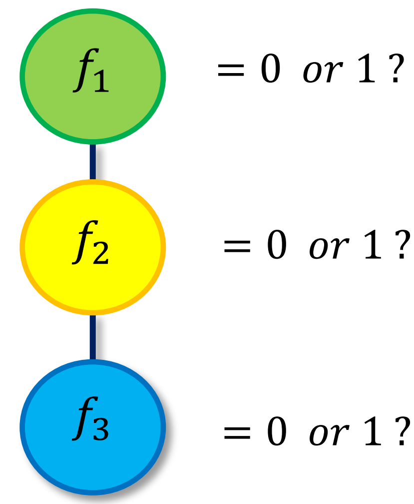
Random fern = constrained random tree





+ Faster training
No explicit data splitting

+ More compact
structure

3. Regression Ferns

INPUT SPACE | **REGRESSION** | OUTPUT SPACE

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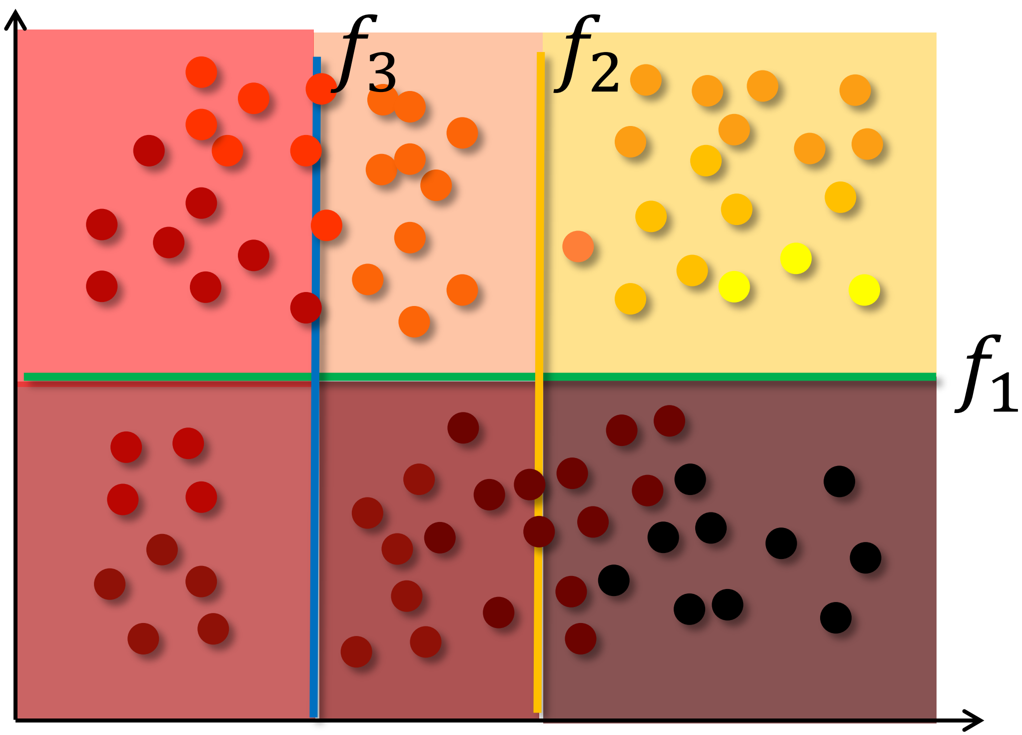
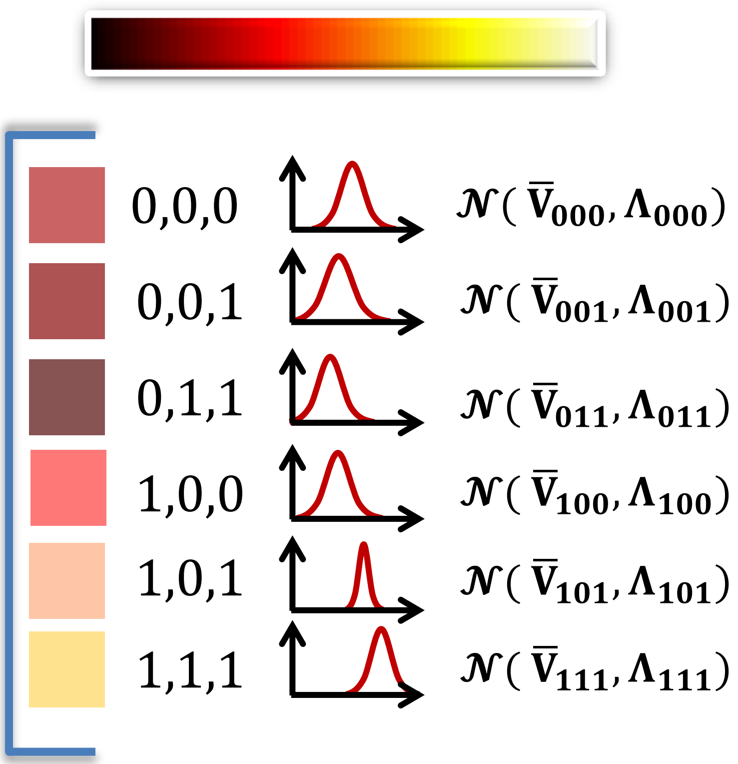
1. Partition input space

2. Learn p(V|X)

Input feature space



Output values



3. Regression Ferns

INPUT SPACE | REGRESSION | OUTPUT SPACE

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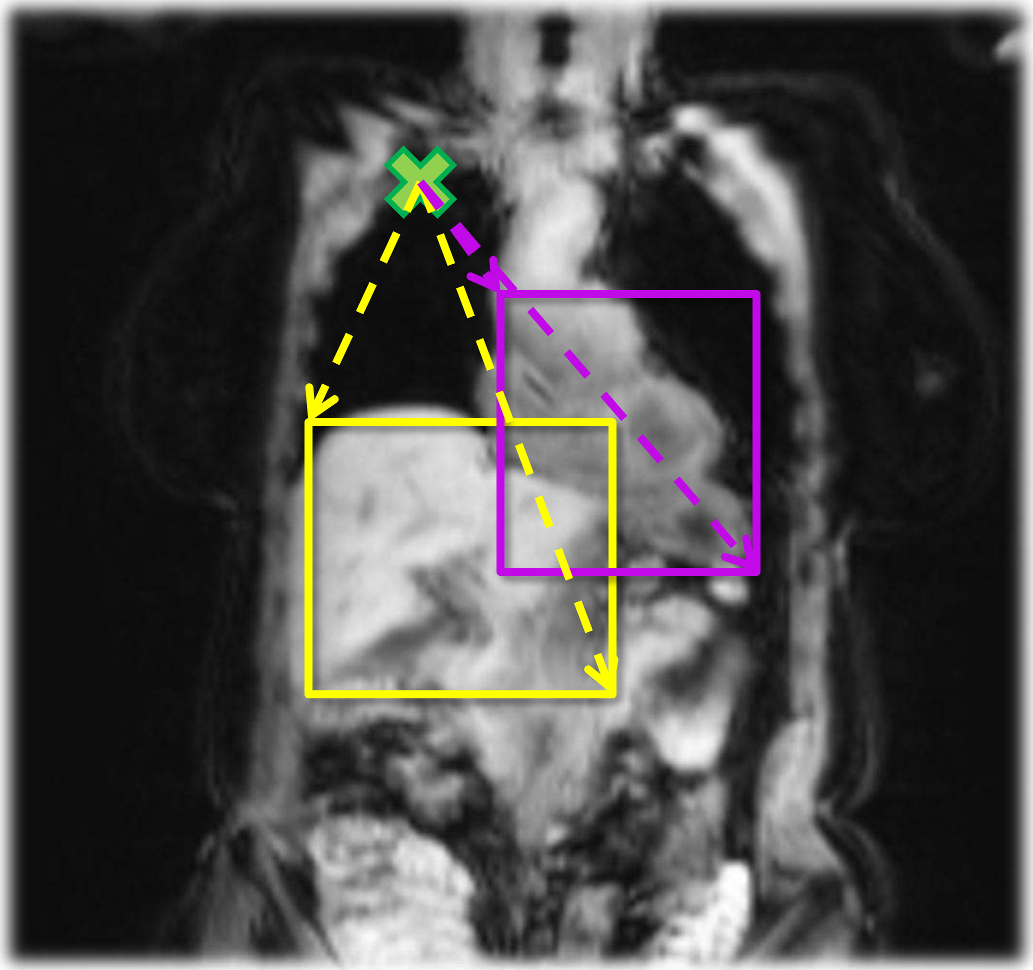
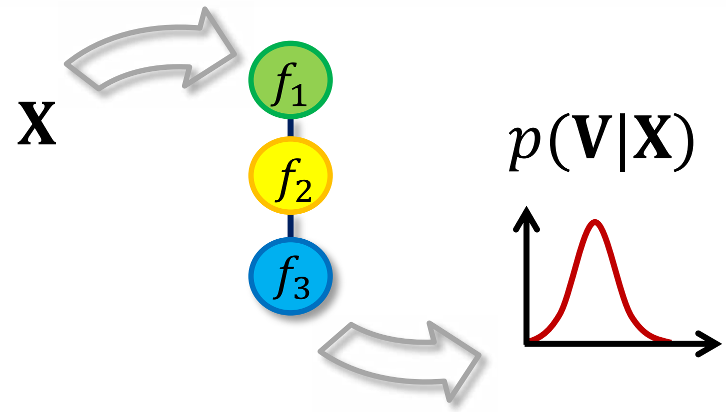
Each voxel: probabilistic prediction for all organ bounding boxes





Voxel: $\mathbf{x} = (x, y, z)$

Feature: $(\mathbf{x}, I^W, I^F) \rightarrow \mathbf{X}$

Leaf: $p(\mathbf{V} \mid \mathbf{X}) = \mathcal{N}_t(\mathbf{V} \mid \bar{\mathbf{V}}_t, \boldsymbol{\Lambda}_t)$

Node: $f(\mathbf{X}, \boldsymbol{\theta}, \tau)\colon\ \mathbf{X} \cdot \boldsymbol{\theta} \le \tau$

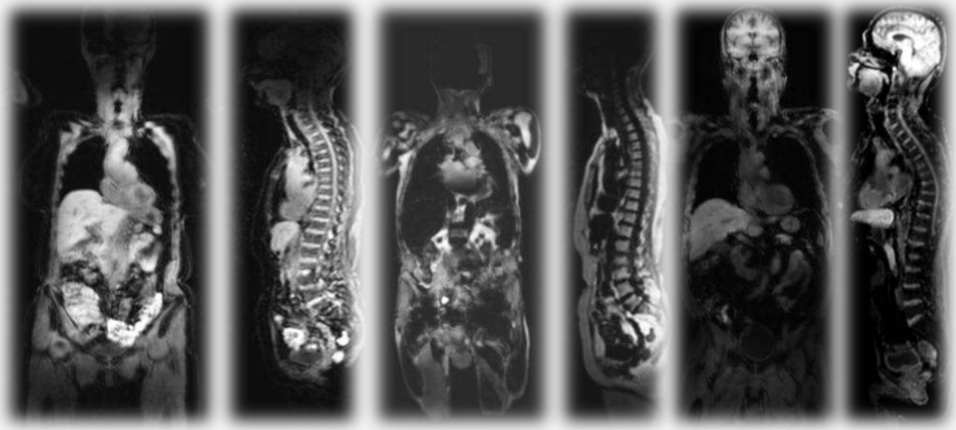
Experiments and Results

Experiments

Data

33 cancer patients

Head, heart, lungs,liver



Cross-validation

Random Ferns

Random Forests

20 patients for **training**
13 patients for **testing**

Multi-atlas registration

20 patients as **multiple atlas**
1 patient for testing
Best patient from atlas

Results

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MEAN LOCALIZATION ERRORS (mm)						
Organs	**Head**	**Left lung**	**Right lung**	**Liver**	**Heart**	**Overall**
Random ferns	9.82 ± 8.07	14.95 ± 11.35	16.12 ± 11.73	18.69 ± 13.77	15.17 ± 11.70	$\mathbf{14.95 \pm 11.33}$
Random forests	10.02 ± 8.15	14.78 ± 11.72	16.20 ± 12.14	18.99 ± 13.88	15.28 ± 11.89	$\mathbf{15.06 \pm 11.55}$
Atlas lower bound	18.00 ± 14.45	14.94 ± 11.54	15.02 ± 13.69	18.13 ± 16.26	13.31 ± 11.03	$\mathbf{15.88 \pm 13.40}$
Atlas upper bound	70.25 ± 34.23	60.78 ± 29.47	63.95 ± 30.13	70.59 ± 32.88	60.38 ± 28.90	$\mathbf{65.19 \pm 31.12}$
Atlas Mean	35.10 ± 13.17	30.41 ± 11.39	29.85 ± 12.62	31.74 ± 13.49	29.82 ± 12.23	$\mathbf{31.38 \pm 12.58}$

Size: 192 x 124 x 443 Pixel spacing: 2.6mm x 2.6mm x 2.6mm

Accuracy

Best overall accuracy

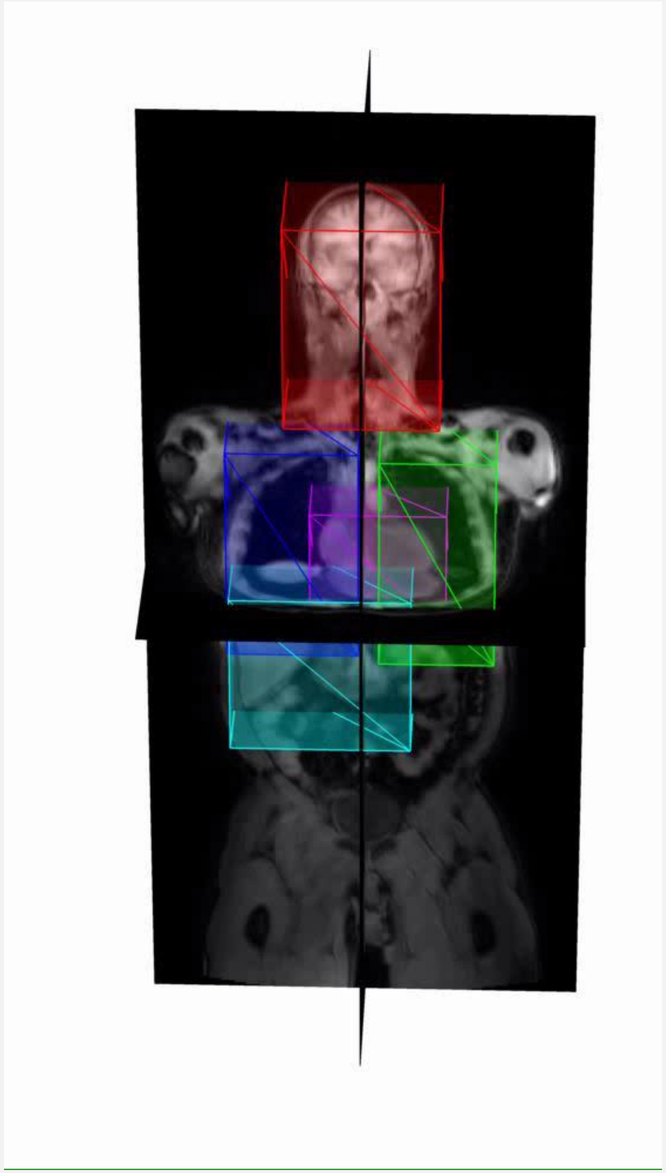
Lower standard deviation

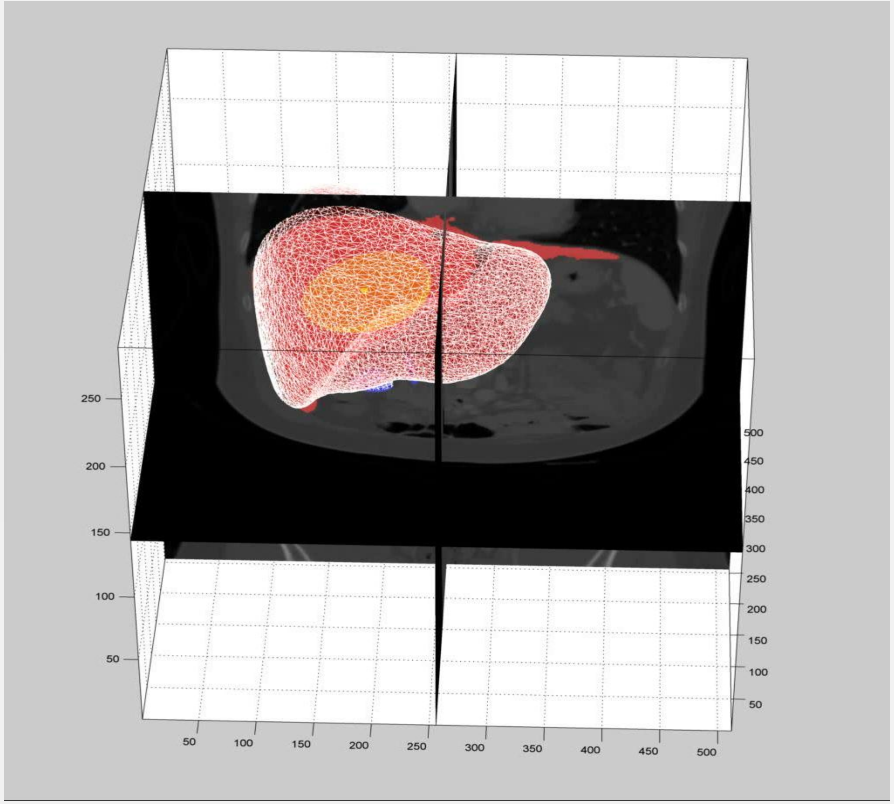
Speed

Ferns: training/testing times of a few seconds

Forests: training/testing times of a few minutes

Conclusion





Thank you for your attention

Microsoft Research Inner Eye project
http://research.microsoft.com/en-us/projects/medicalimageanalysis/

Computer Aided Medical Procedures
http://campar.in.tum.de

Nuklearmedizin, Klinikum Rechts der Isar
http://www.nuk.med.tu-muenchen.de/

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