



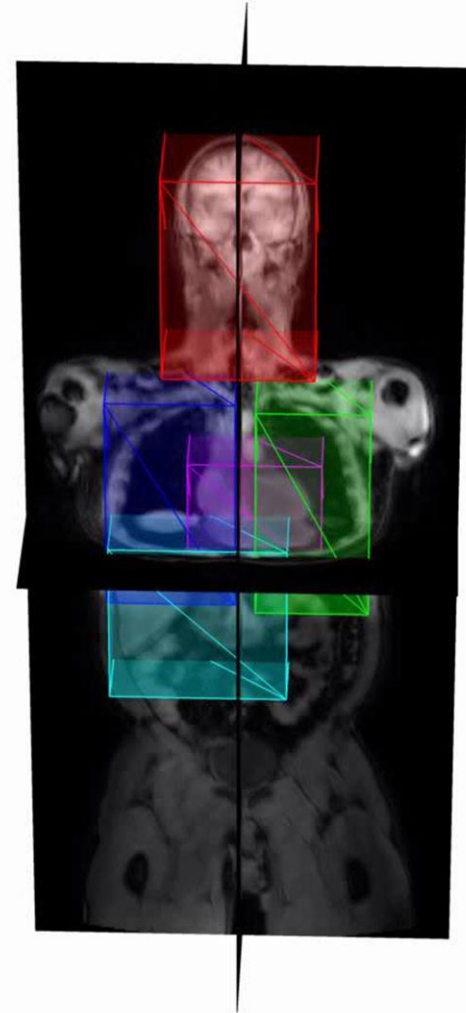
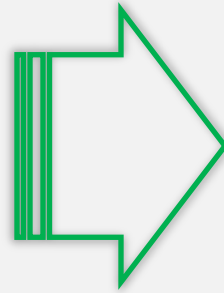
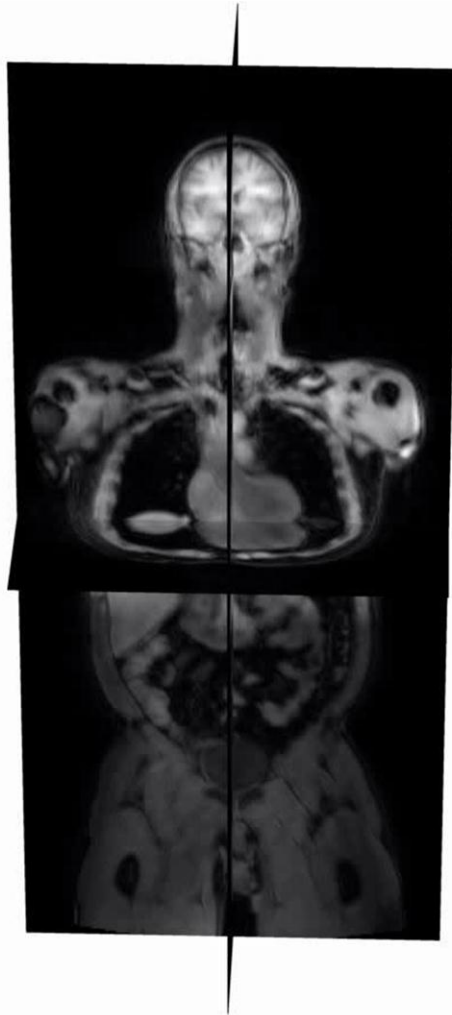
# Fast Multiple Organ Detection and Localization in Whole-Body MR Dixon Sequences

Olivier Pauly, Ben Glocker, Antonio Criminisi, Diana Mateus,  
Axel Martinez-Möller, Stephan Nekolla, and Nassir Navab



# What it's all about...

Pauly et al., Fast Multiple Organ Detection and Localization

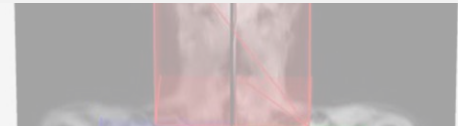


# What it's all about...

Pauly et al., Fast Multiple Organ Detection and Localization

Goal:

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



Challenge:

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



1. Fast

2. Accurate

3. Robust

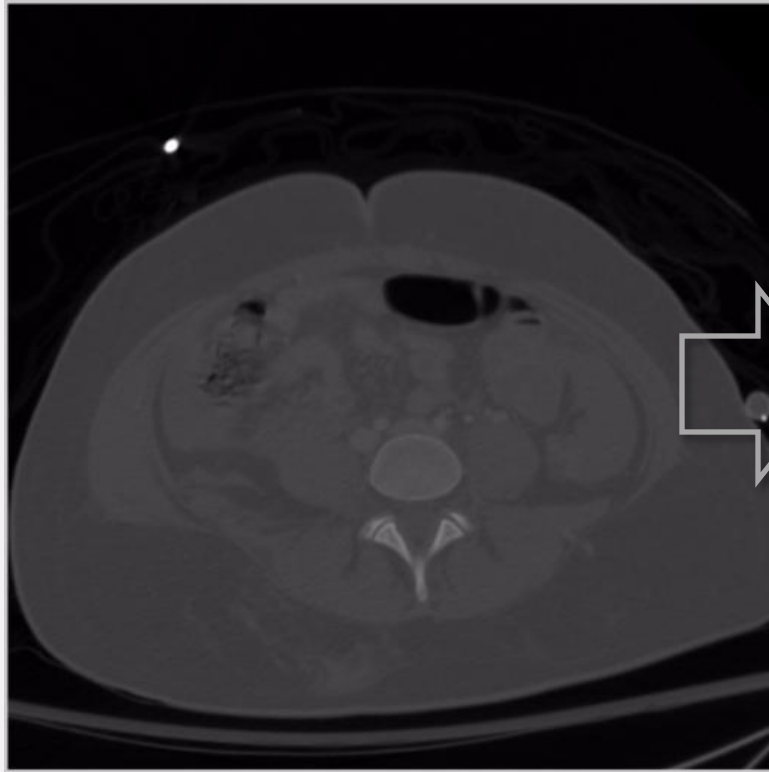


# Potential application...

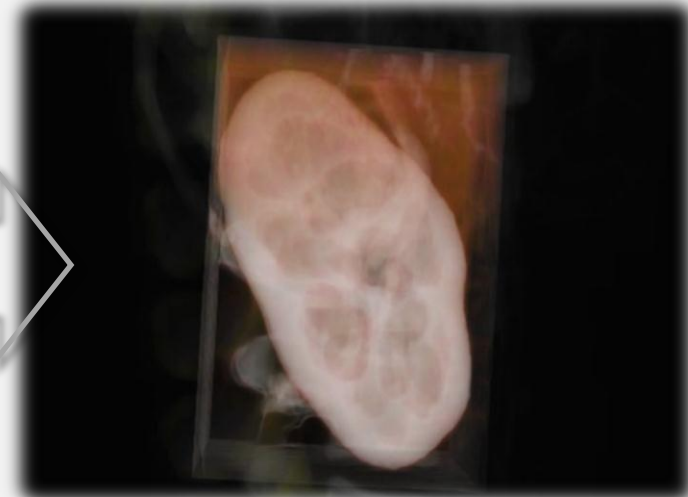
Pauly et al., Fast Multiple Organ Detection and Localization

Semantic navigation:

**Direct** navigation to **organs**



- Brain
- Heart
- Kidney (L)
- Kidney (R)
- Liver
- Lung (L)
- Lung (R)
- ...

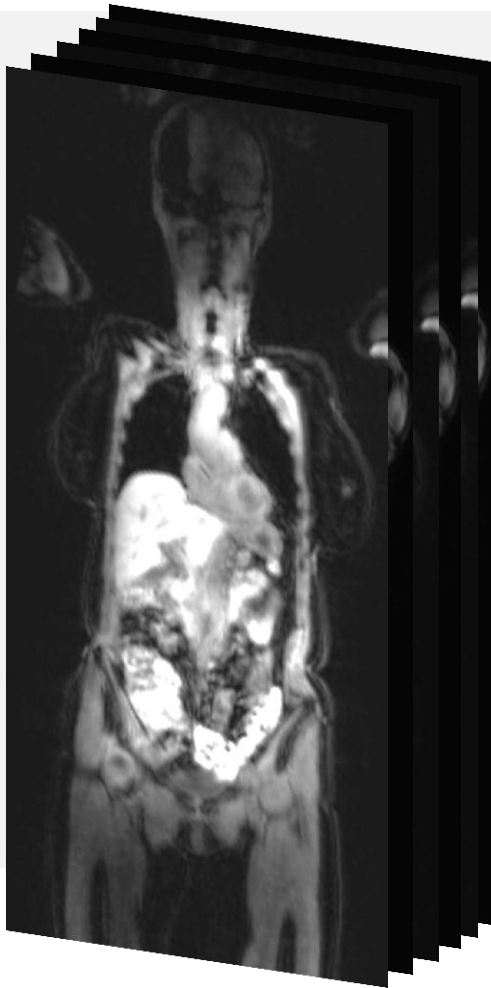


# Potential application...

Pauly et al., Fast Multiple Organ Detection and Localization

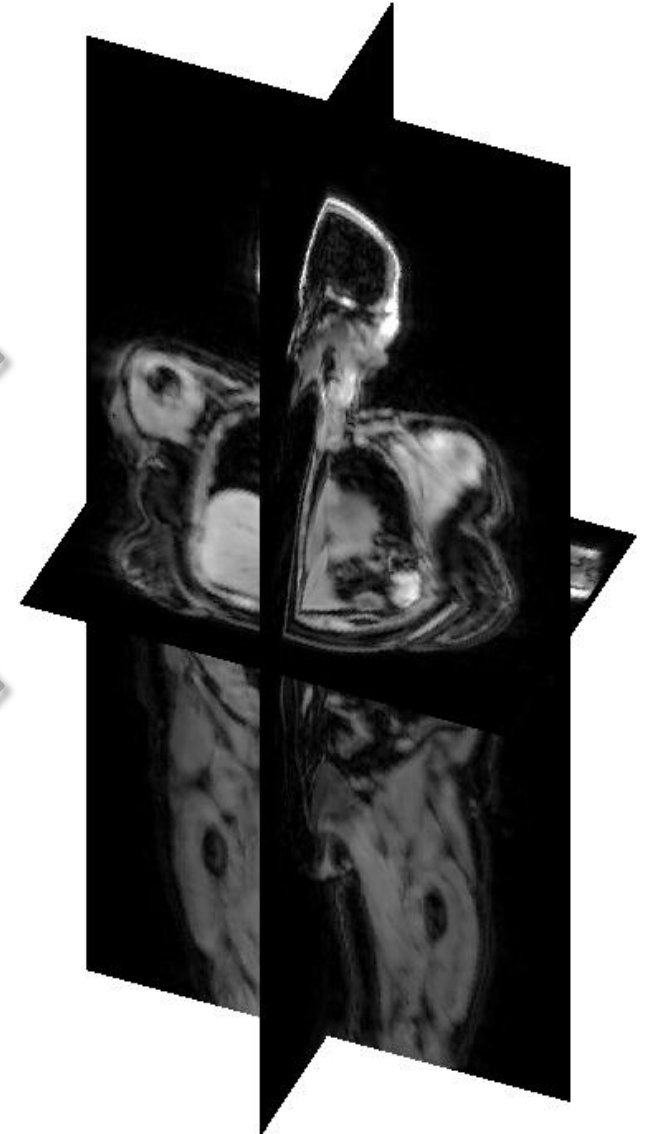
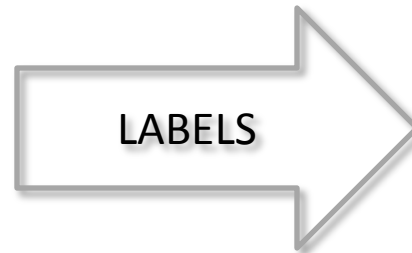
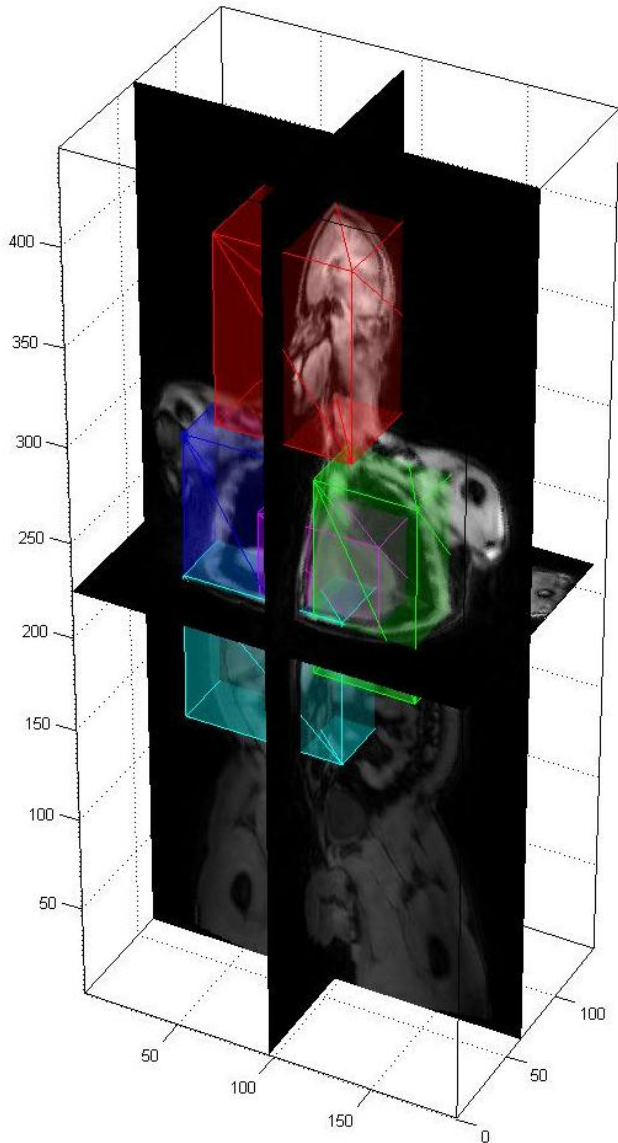
Database retrieval:

**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



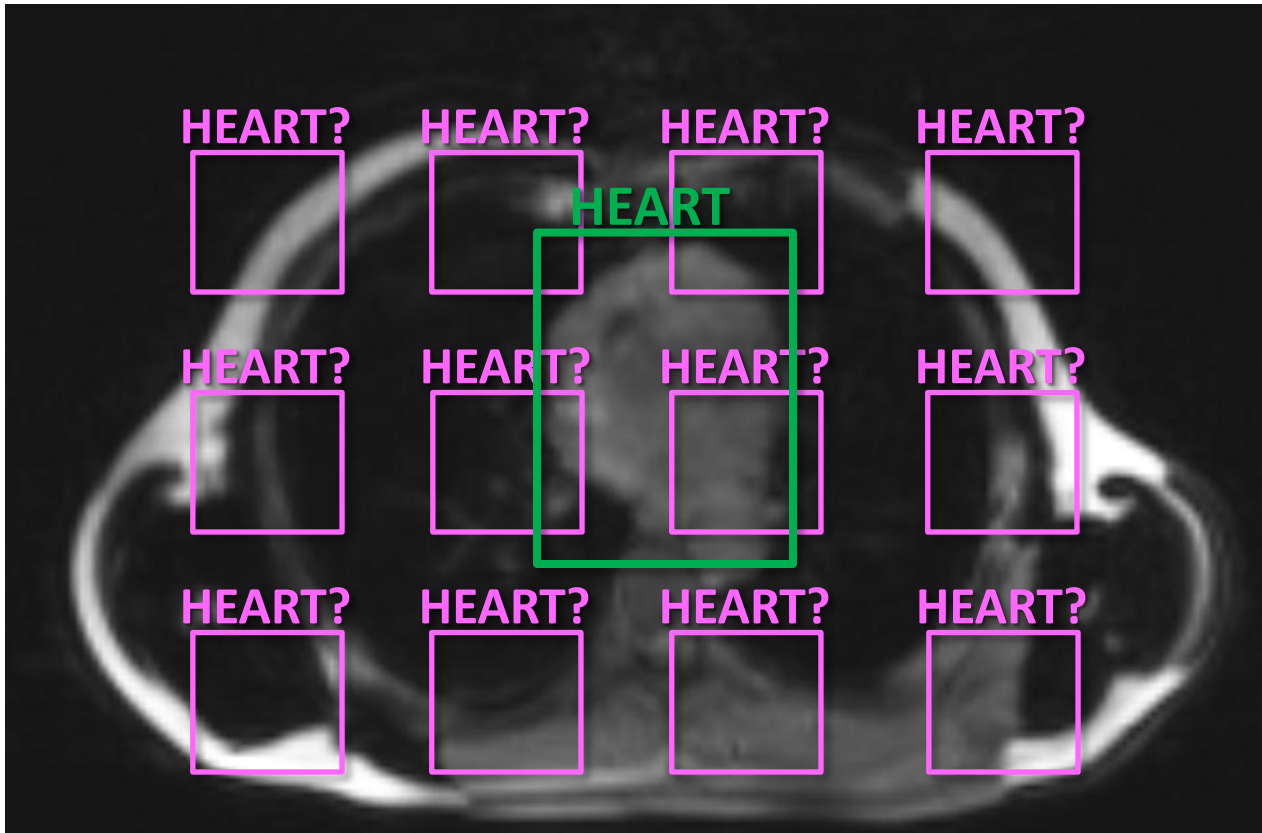
Non-linear : computationally expensive  
Large deformations

# 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





# 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



Requires a specialized classifier for each organ



Exhaustive search in 6D for each organ of interest

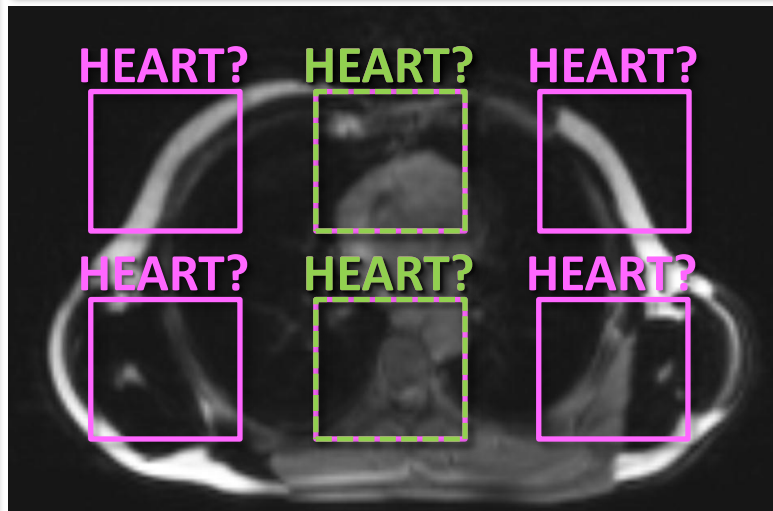
# Marginal Space Learning

Pauly et al., Fast Multiple Organ Detection and Localization

Learn sequentially  
in marginal spaces

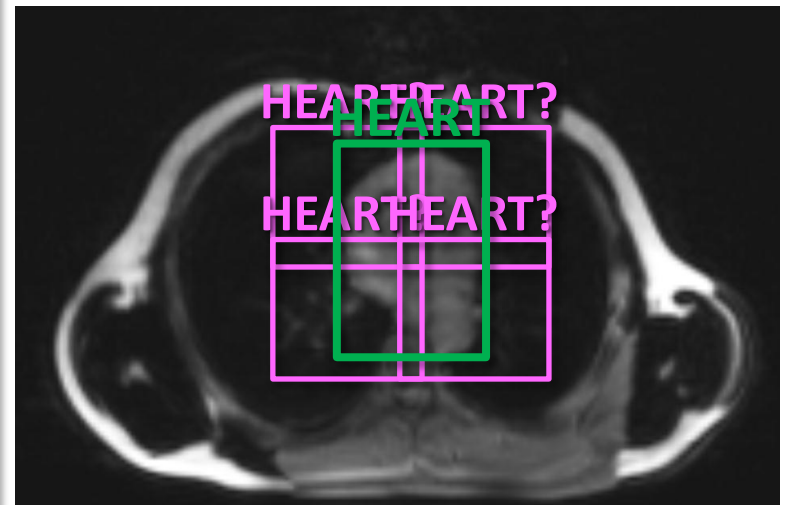
- ⊕ Exhaustive search in **position** parameters **only**
- ⊕ Refinement search in **position-size** parameters

**Classifier1: Position**



best candidates

**Classifier 2: Position+Size**



# 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



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

# Towards multiple organ detection?

Pauly et al., Fast Multiple Organ Detection and Localization

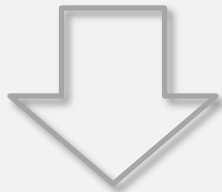
Detection Organ of interest? YES / NO



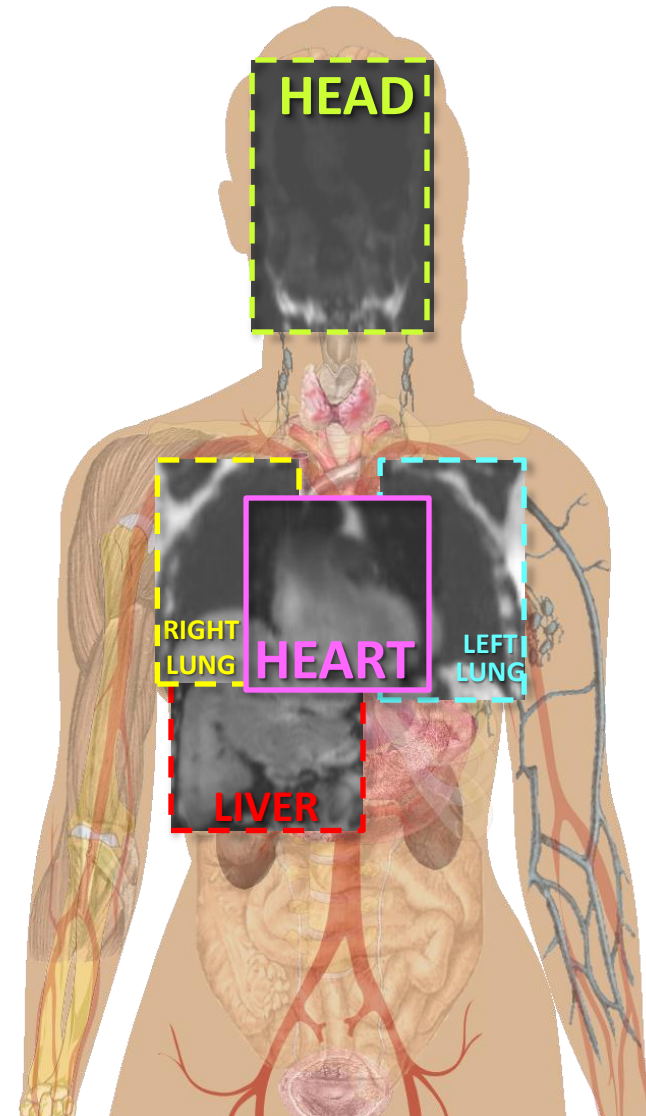
Human body = well known anatomy



Medical Imaging = standard procedure



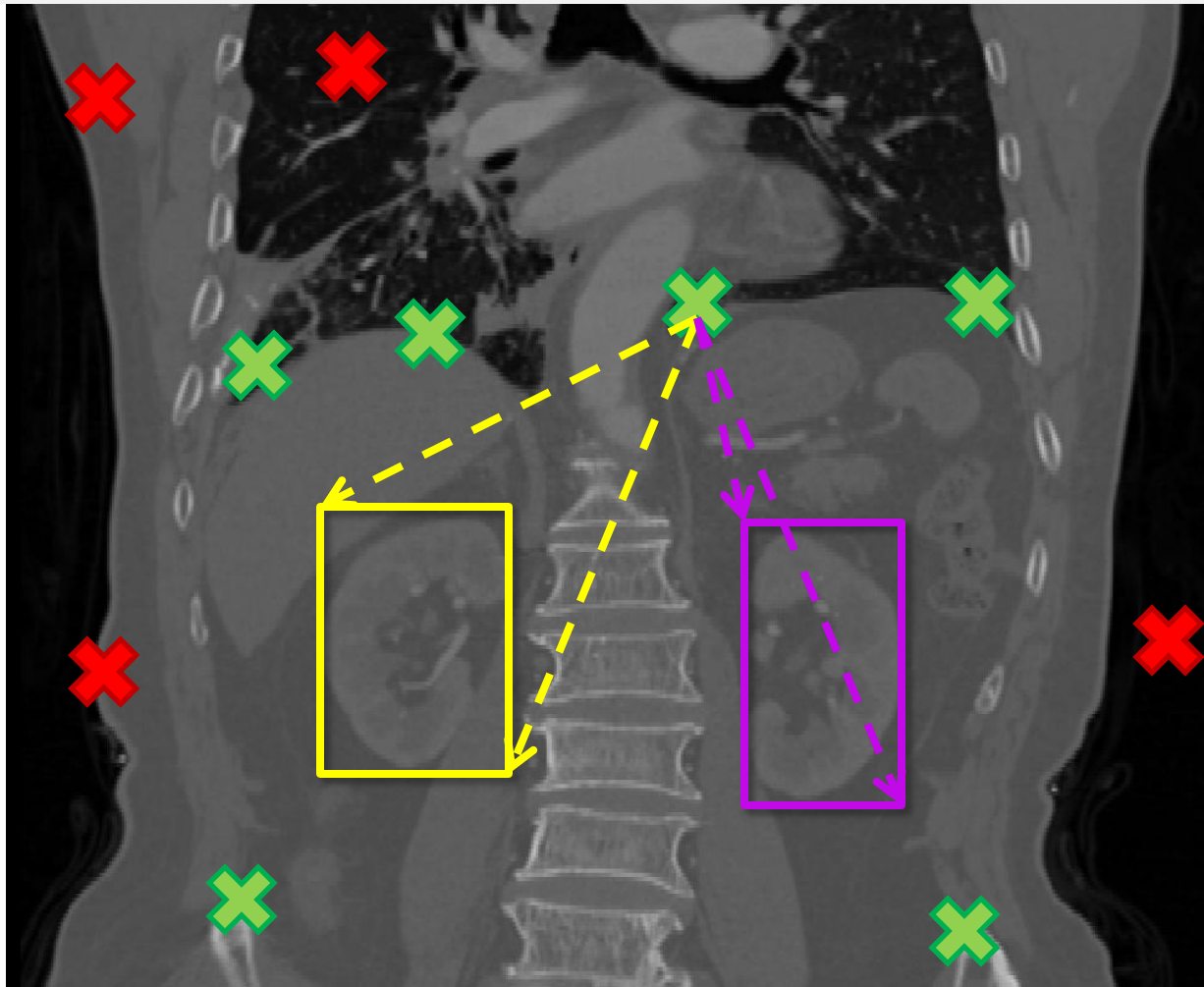
**Prior knowledge on the relative positions of all organs!**







# Our regression approach

Pauly et al., Fast Multiple Organ Detection and Localization

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



## Ex: Kidneys

-  Left Kidney
-  Right Kidney
-  High confidence
-  Low confidence

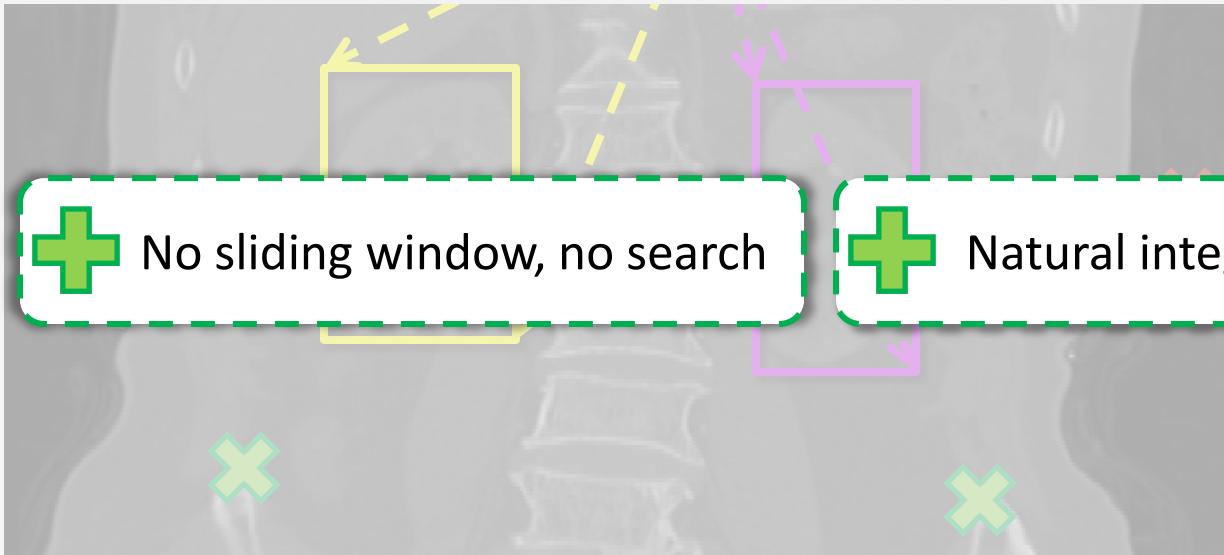
# Our regression approach

Pauly et al., Fast Multiple Organ Detection and Localization

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

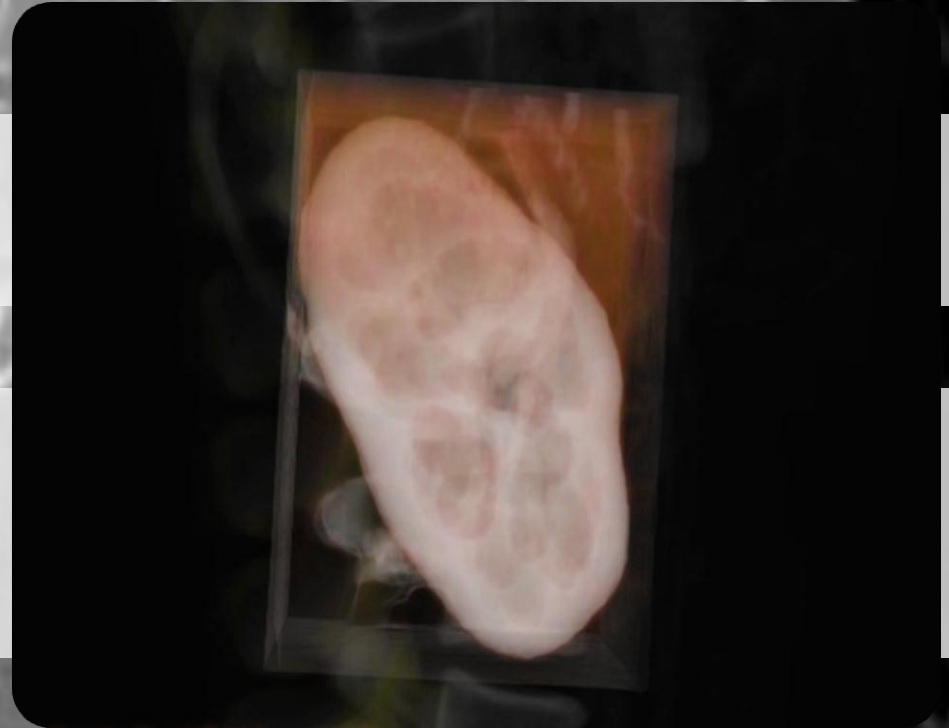
Pauly et al., Fast Multiple Organ Detection and Localization

Our previous work:

Organ localization in CT studies

Regression forests

Features based  
on Hounsfield units



# Our contributions in this paper

Pauly et al., Fast Multiple Organ Detection and Localization

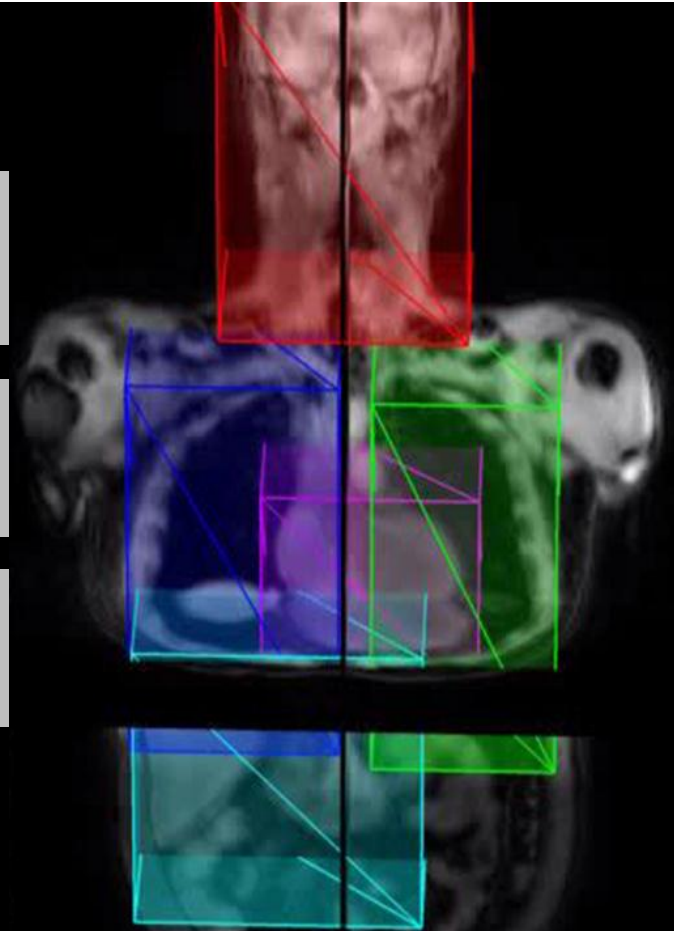
Our current work:

Multi-channel whole-body MR

Regression ferns

3D LBP-like features

Comparison with forests





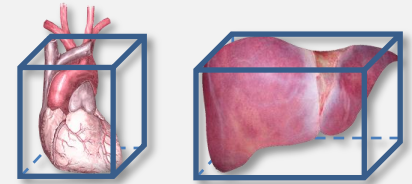
# Organ localization as a regression task

Pauly et al., Fast Multiple Organ Detection and Localization

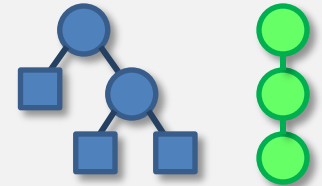
1. Input feature space



2. Output prediction space



3. Regression Ferns



# 1. Input feature space

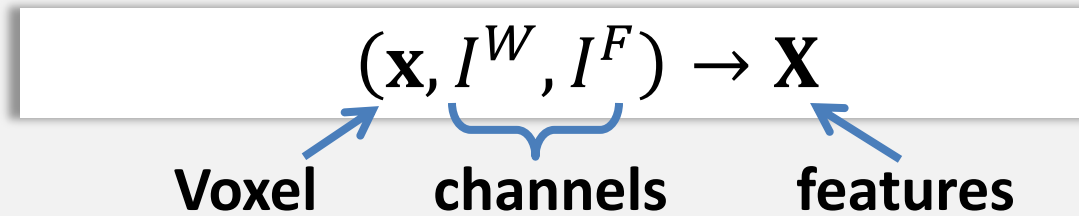
INPUT SPACE

REGRESSION

OUTPUT SPACE

Pauly et al., Fast Multiple Organ Detection and Localization

## 3D multi-scale LBP-like features



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

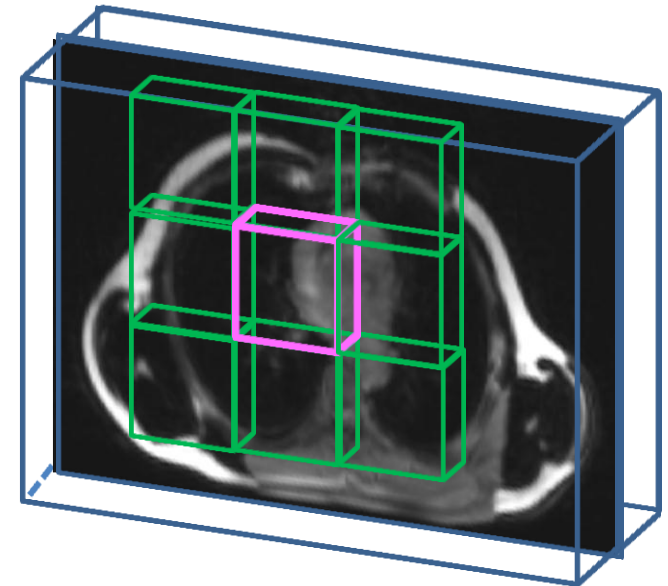
$\mathbf{X} = (1\ 0\ 0\ 1\ \dots\ 0\ 1)$



Characterize  
Relative  
intensity changes



Multi-scale for  
Inter-patient  
variability



# 2. Output space

INPUT SPACE

REGRESSION

OUTPUT SPACE

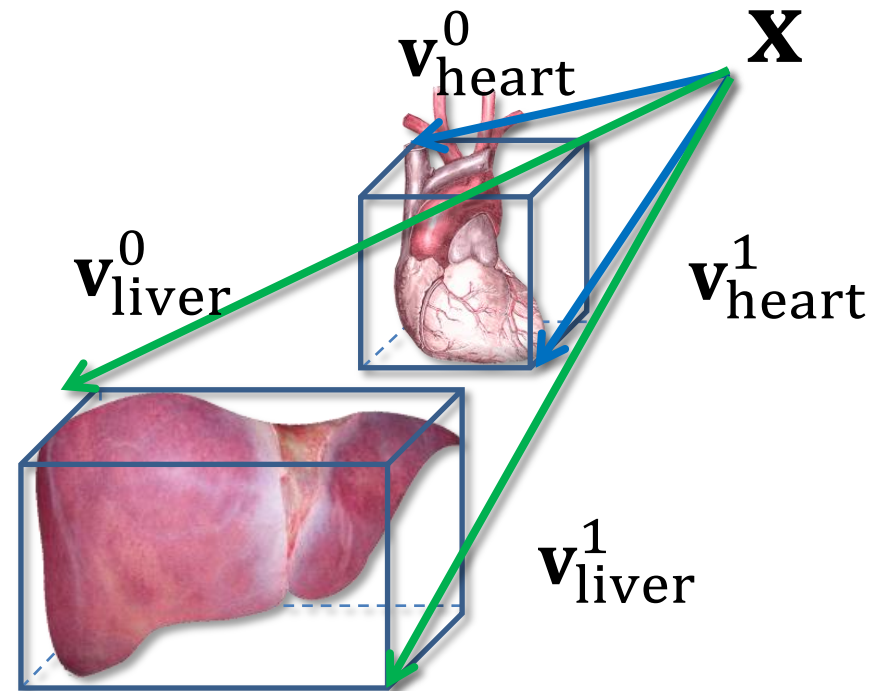
Pauly et al., Fast Multiple Organ Detection and Localization

Relative displacement between voxel and organ bounding box

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

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

⋮



For all  $K$  organs:

$$\mathbf{V} = (\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k, \dots, \mathbf{v}_K)$$

$$\mathbb{R}^{6 \times K}$$

# 3. Regression Ferns

INPUT  
SPACE

REGRESSION

OUTPUT  
SPACE

Pauly et al., Fast Multiple Organ Detection and Localization

Goal:

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

Features

Displacements

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

# 3. Regression Ferns

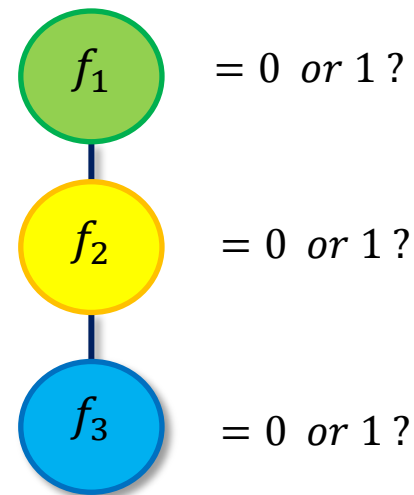
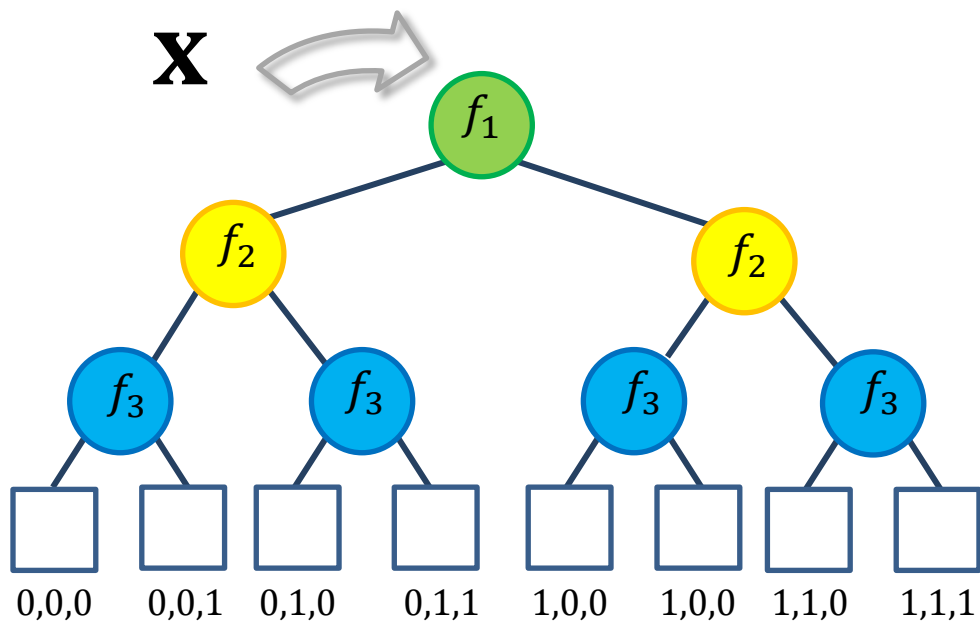
INPUT SPACE

REGRESSION

OUTPUT SPACE

Pauly et al., Fast Multiple Organ Detection and Localization

Random fern = constrained random tree



Faster training  
No explicit data splitting



More compact  
structure

# 3. Regression Ferns

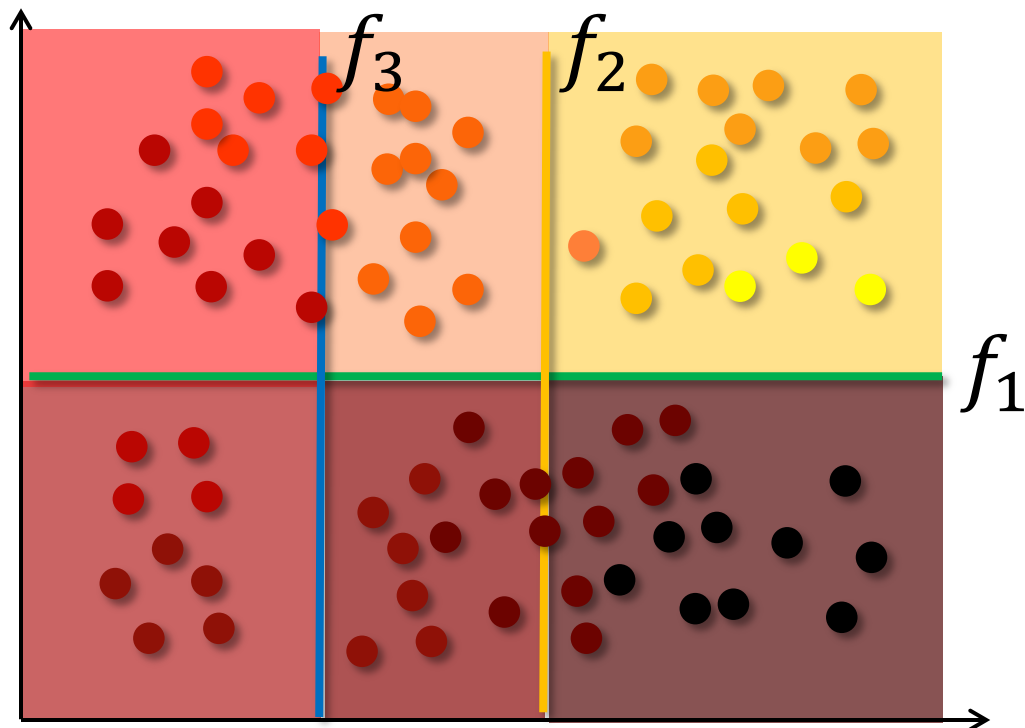


Pauly et al., Fast Multiple Organ Detection and Localization

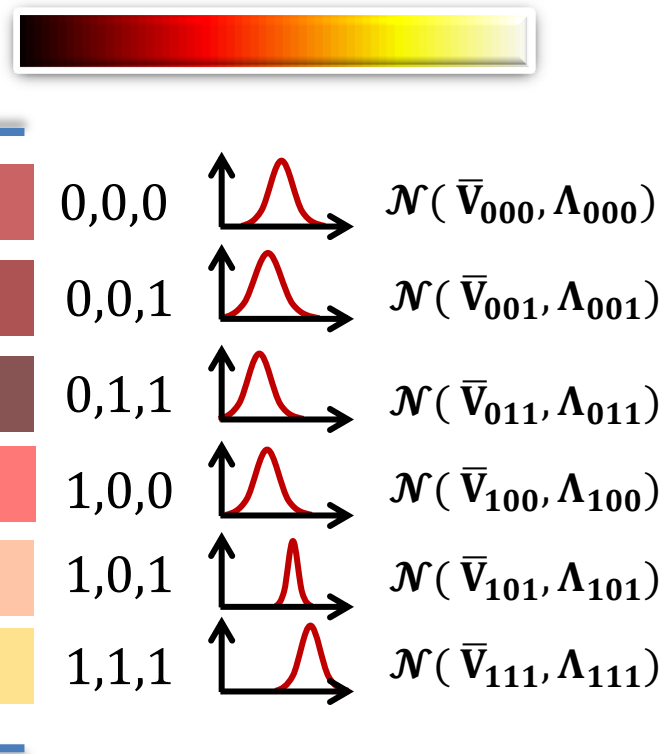
## 1. Partition input space

## 2. Learn $p(V|X)$

Input feature space



Output values



# 3. Regression Ferns

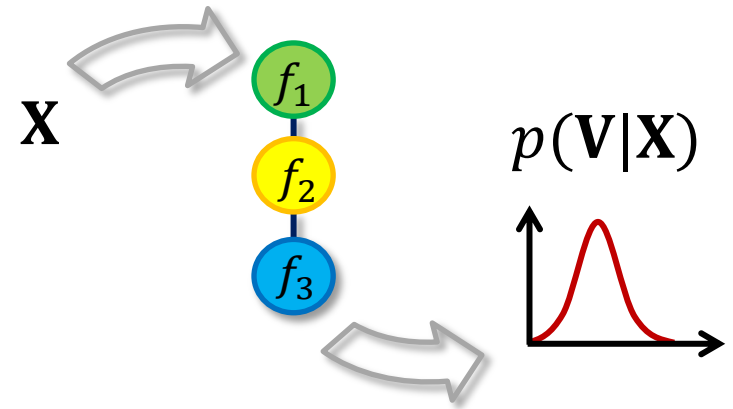
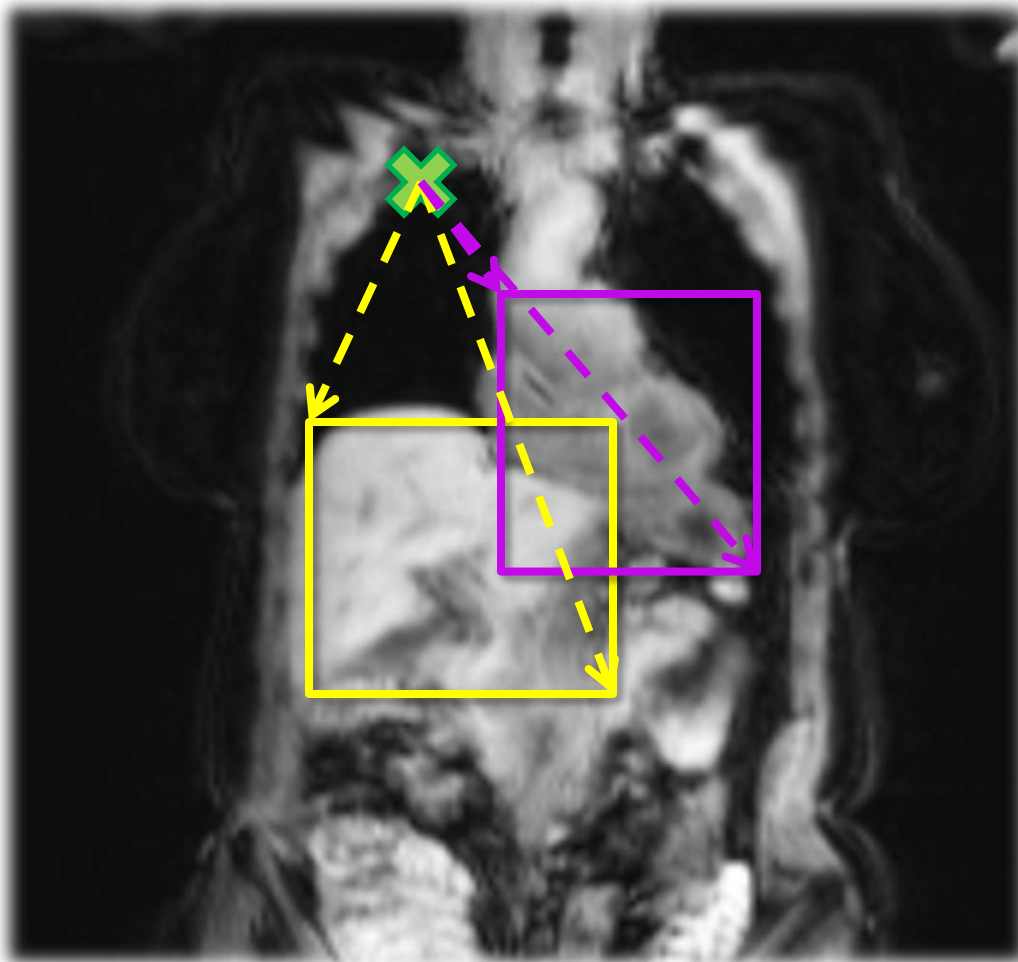
INPUT SPACE

REGRESSION

OUTPUT SPACE

Pauly et al., Fast Multiple Organ Detection and Localization

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:  $p(\mathbf{V} | \mathbf{X}) = \mathcal{N}_t(\mathbf{V} | \bar{\mathbf{V}}_t, \Lambda_t)$

Node:  $f(\mathbf{X}, \theta, \tau): \mathbf{X} \cdot \theta \leq \tau$

---

# Experiments and Results

---

Pauly et al., Fast Multiple Organ Detection and Localization



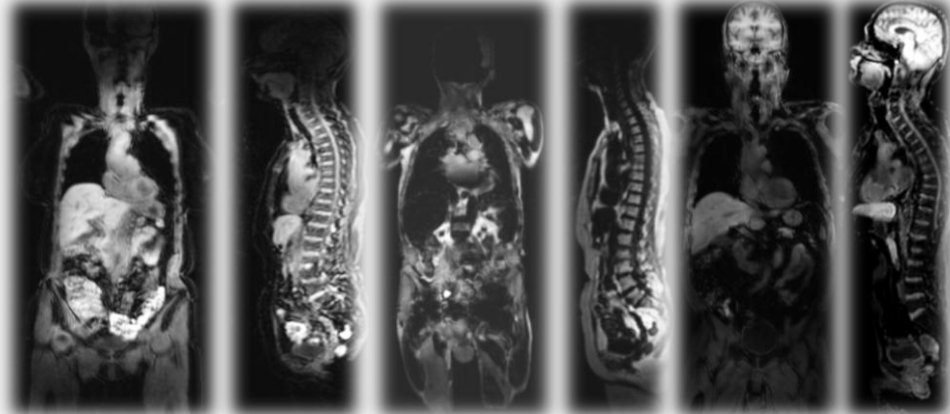
# Experiments

Pauly et al., Fast Multiple Organ Detection and Localization

## Data

**33 cancer patients**

**Head, heart,  
lungs, liver**



## Cross- validation

**Random Ferns**

**Random Forests**

**Multi-atlas  
registration**

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

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

# Results

Pauly et al., Fast Multiple Organ Detection and Localization

## MEAN LOCALIZATION ERRORS (mm)

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

Size: 192 x 124 x 443

Pixel spacing: 2.6mm x 2.6mm x 2.6mm

Accuracy

Best overall accuracy

Lower standard deviation

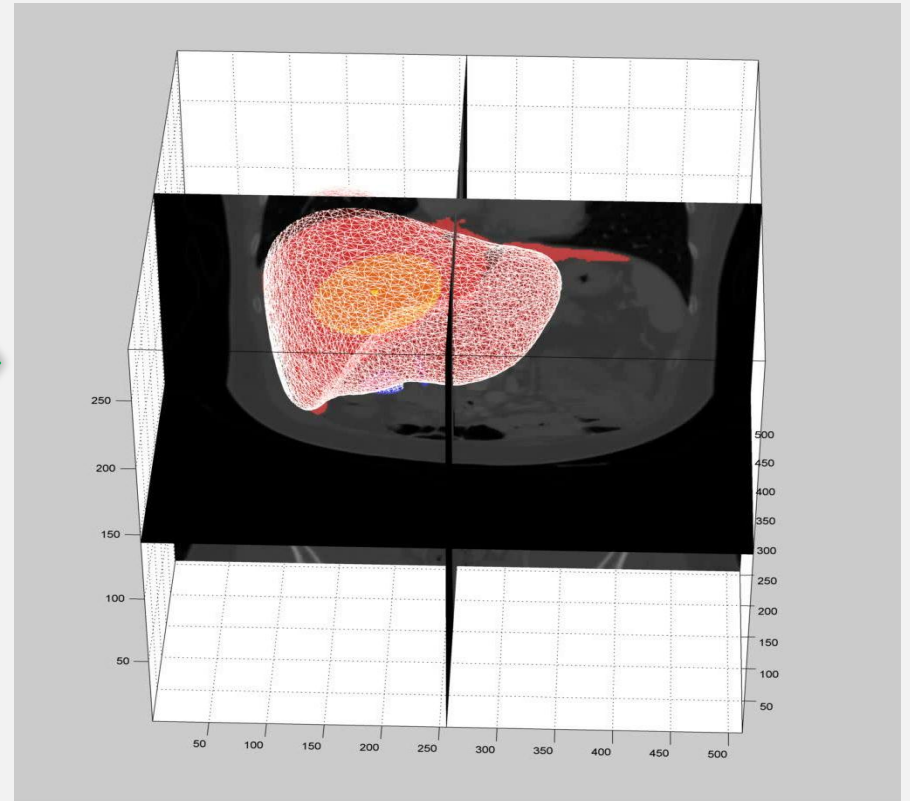
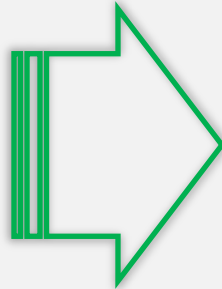
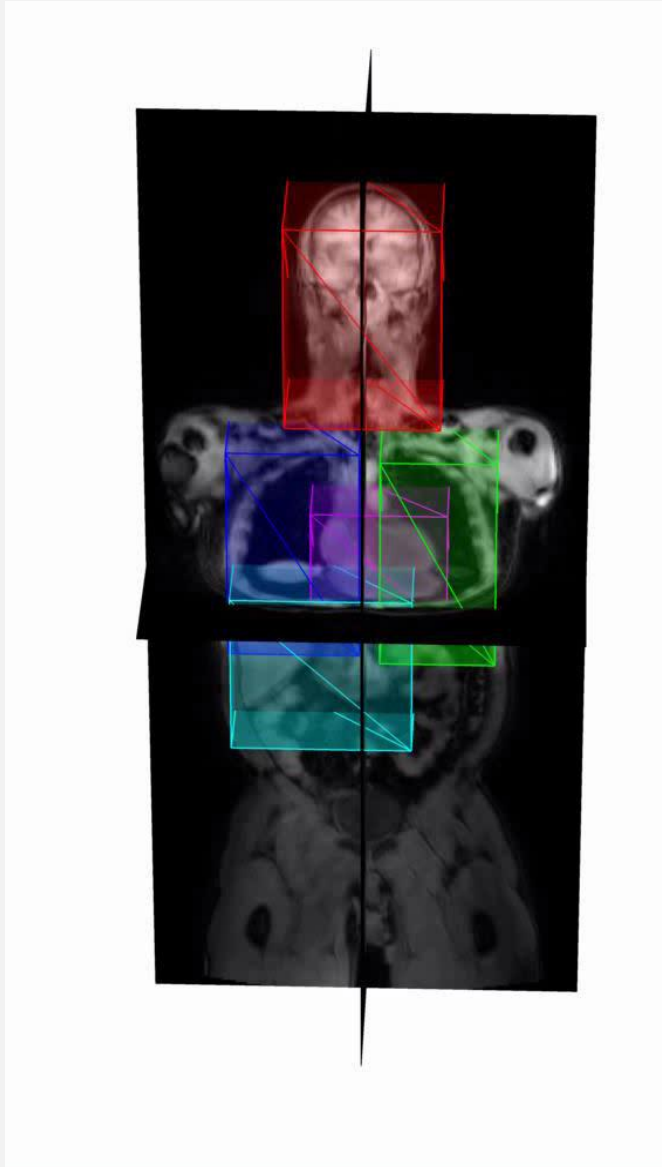
Speed

Ferns: training/testing times of a few seconds

Forests: training/testing times of a few minutes

# Conclusion

Pauly et al., Fast Multiple Organ Detection and Localization



# Thank you for your attention

Pauly et al., Fast Multiple Organ Detection and Localization



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/>



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

Olivier Pauly, Ben Glocker, Antonio Criminisi, Diana Mateus,  
Axel Martinez-Möller, Stephan Nekolla, and Nassir Navab

