



# Deep Learning & Beyond:

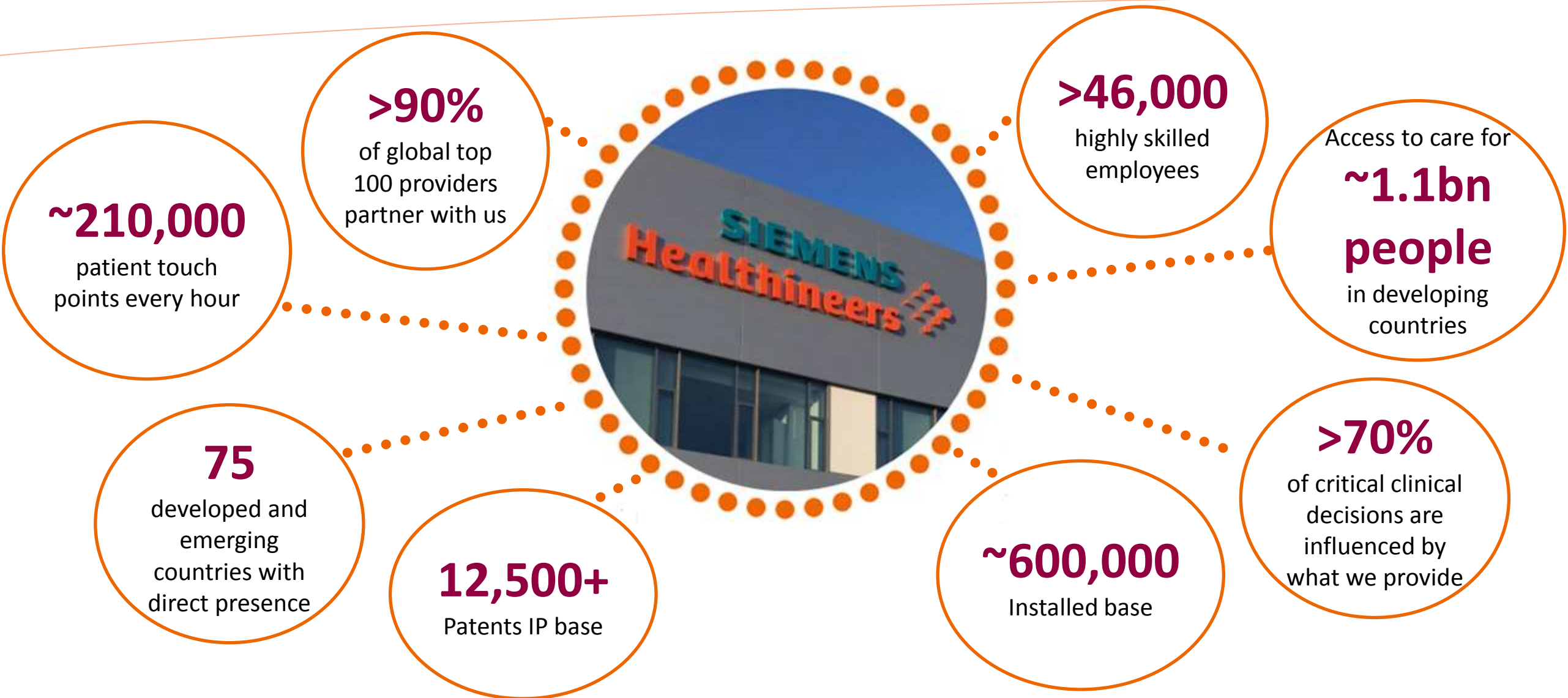
## Medical image recognition, segmentation and parsing

**S. Kevin Zhou, Ph.D.**

**Principal Key Expert of Image Analysis**

**Siemens Healthineers, Medical Imaging Technologies**

# A global leader in healthcare





# Innovations is the main driver

MRI 1980



MRI today



Data courtesy of CUBRIC, UK  
Cinematic Rendering: Research use only. Not for clinical use.

# Brain anatomy – MR 7T

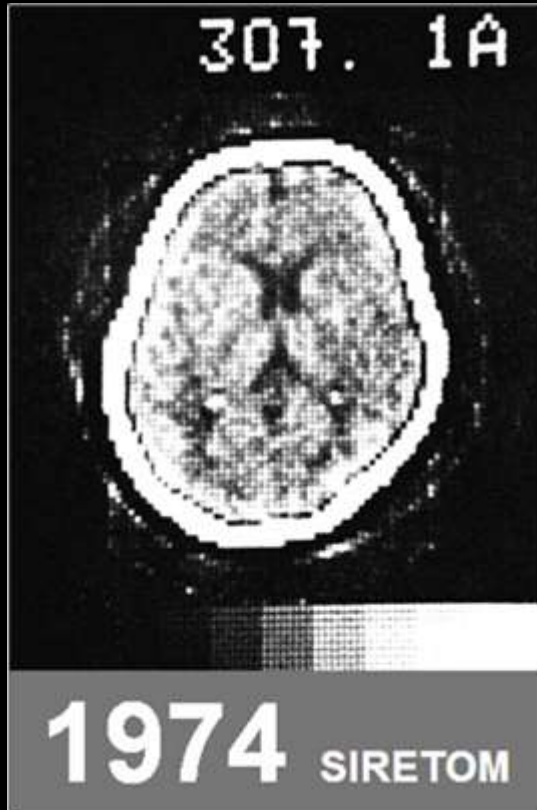
## Cinematic rendering



Data courtesy of Max Planck Institute Leipzig, Germany  
Cinematic Rendering: Research use only. Not for clinical use.



# Computed Tomography at Siemens Healthineers 40+ years of Innovation



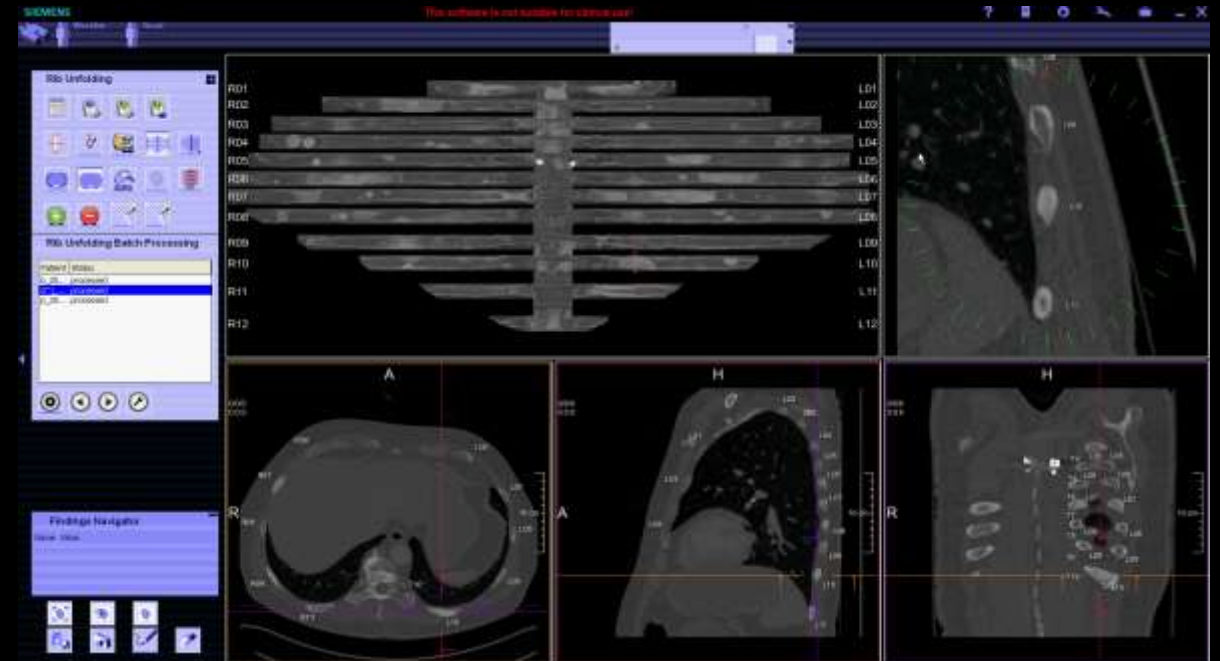


# Abdominal aneurysm and aortic stents

## Cinematic Rendering



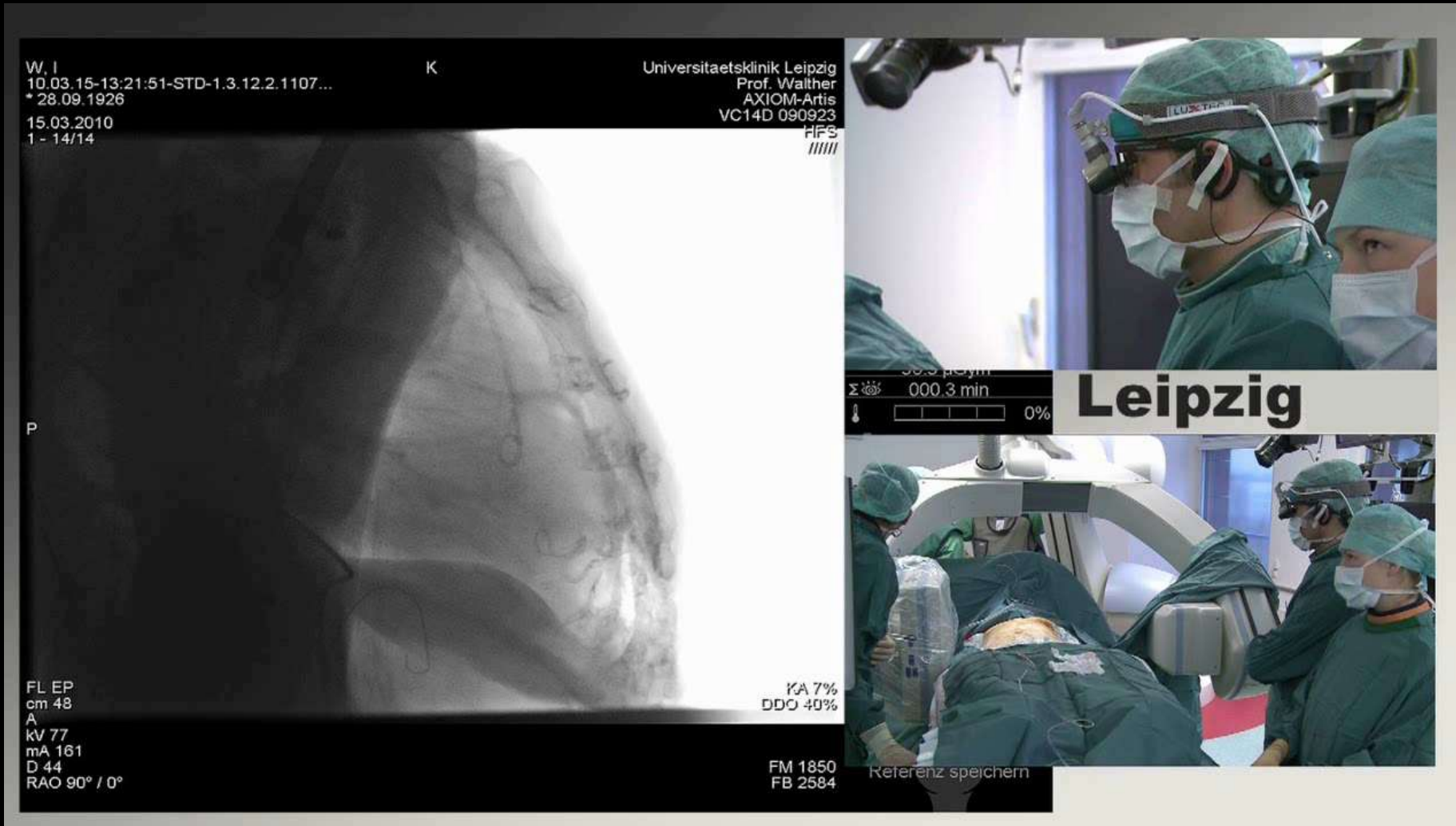
# Rib Unfolding



- Ringl H et al. The ribs unfolded - a CT visualization algorithm for fast detection of rib fractures: effect on sensitivity and specificity in trauma patients. Eur Radiol 2015; 25:1865-74
- This feature is based on research, and is not commercially available. Due to regulatory reasons its future availability cannot be guaranteed



# Transcatheter Aortic Valve Implantation



- The C-arm acquires 3D images by rotating around the patient
- The images are automatically reconstructed, segmented, and landmarks and the “perpendicularity ring” are detected

- Y. Zheng et al, Automatic Aorta Segmentation and Valve Landmark Detection in C-Arm CT for Transcatheter Valve Implantation, IEEE TMI 2013
- This feature is based on research, and is not commercially available. Due to regulatory reasons its future availability cannot be guaranteed.



# eSie Valves

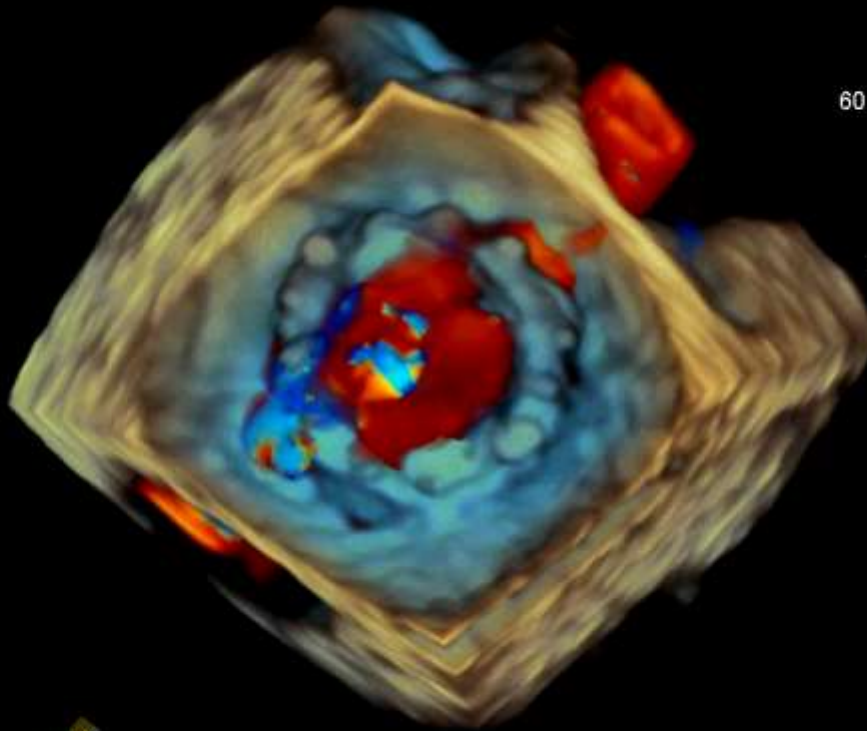


SIEMENS  
Healthineers

0dB / MI: 1.08 / TIS: 0.39 / TIB: 0.39  
/ TEE New\* / Z6Ms

08/14/2014 6:19 PM

Z6Ms



0.68 m/s  
0.68 m/s

14 vps  
60 bpm / General  
---4D---  
Gen  
-12 dB  
DR: 65 dB  
---Color---  
CDV / 3.3MHz  
-1.5 dB



0.61 m/s  
0.61 m/s

15 vps / 120 mm

Ann AP Diam 33.4 mm  
Ann AL-PM Diam 39.6 mm

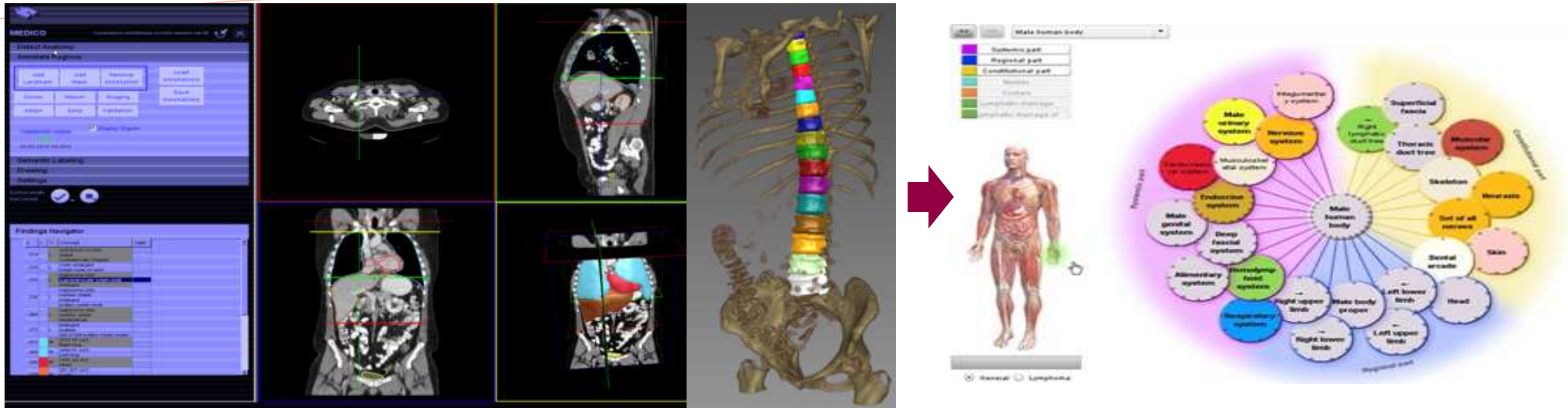


SIEMENS



True Volume TEE and Real-Time 3D Doppler  
Para-valvular Leakage

# Holy grail: Medical image parsing

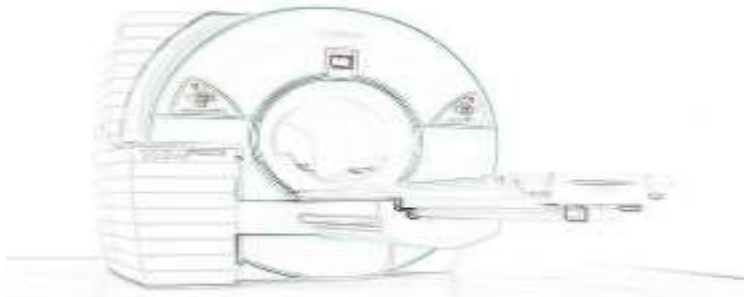


## Medical image parsing

- Assigning semantic labels to pixels or voxels
- Unifying detection, segmentation, and parsing



## Scanner



- Automated
- Personalized
- Consistent
- Fast
- Less radiation

## Reading



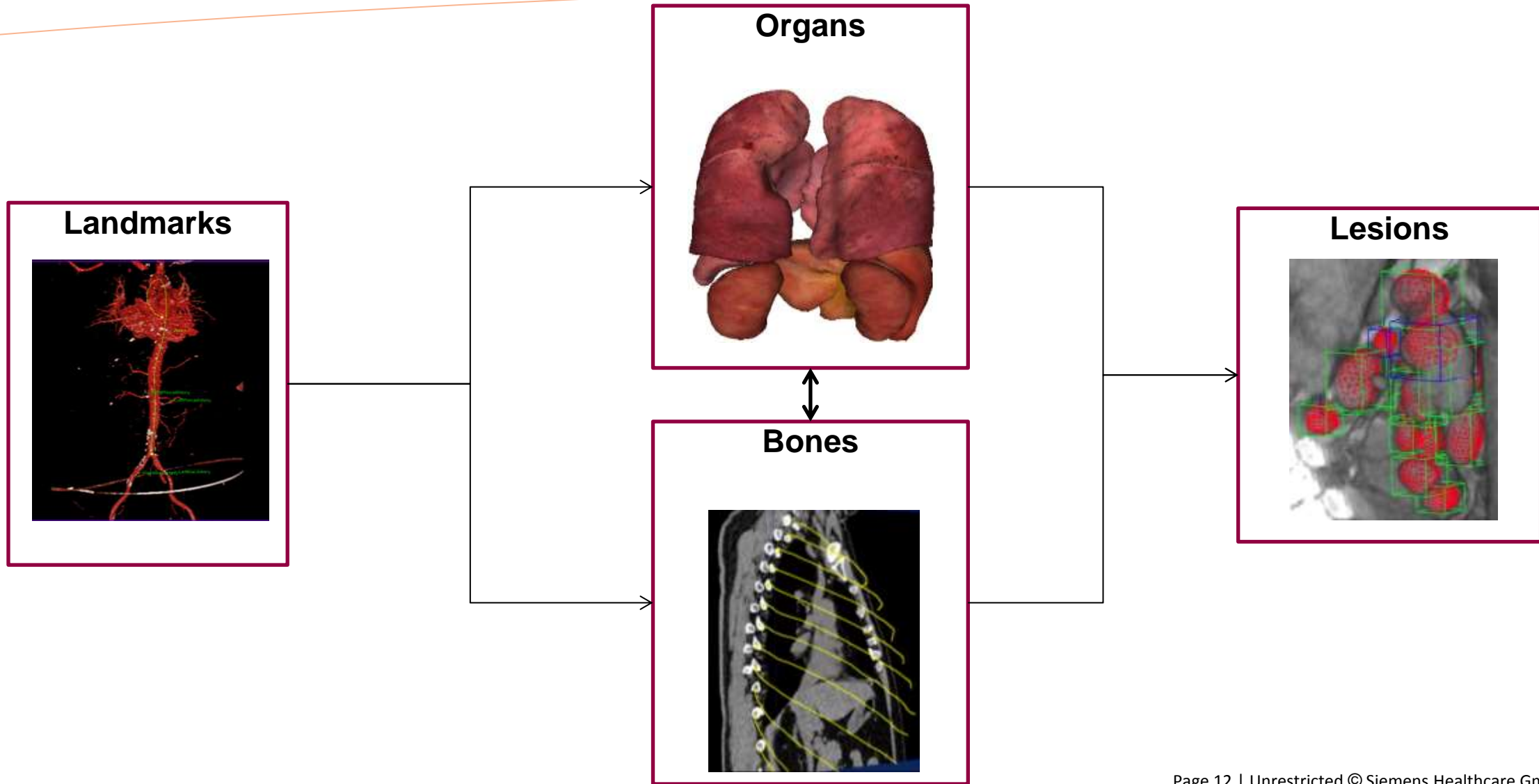
- Structured reading
- Streamlined workflow
- Semantic reporting

## Quantification



- Adv. measurements
- CAD
- Surgery planning
- Therapy prediction & monitoring

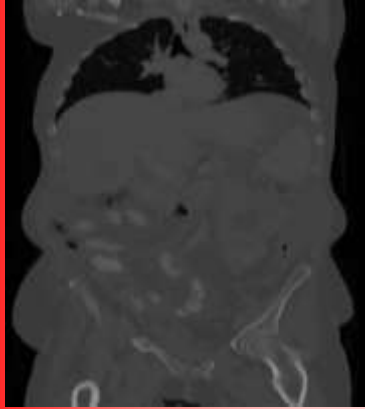
# Major parsing objects



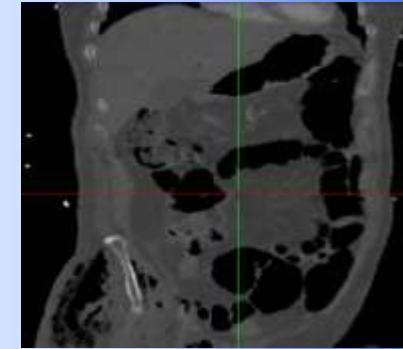


# Challenges

Image and shape variations



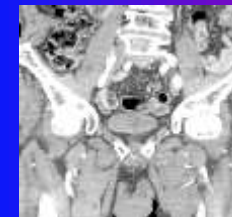
*Contrast*



*Pathologies*

- Deformed, missing, misleading context

*Context*

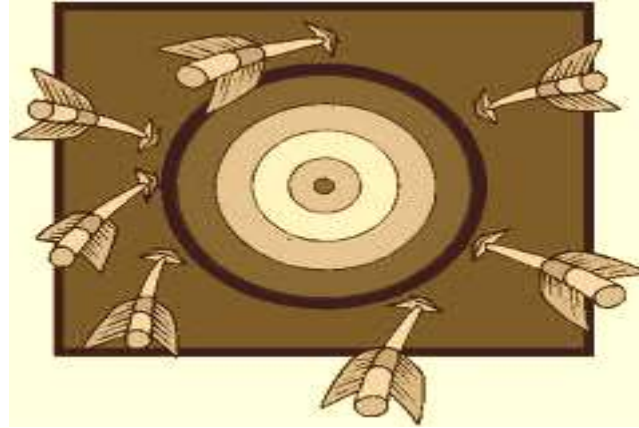


*Body Portions*

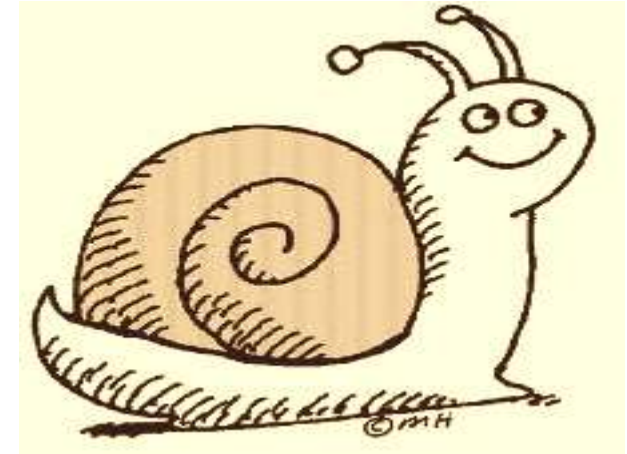
- Narrow FOV , Severe Occlusion



Robustness:  
*No outlier*



Accuracy:  
*Within inter-user  
variability*



Speed:  
*Less than a few  
seconds*





*Large Amount of  
Datasets*



*Anatomical  
Context*



**Machine  
Learning**



**Knowledge**

## Machine learning

- Supervised learning
  - Deep neural network
  - SVM, boosting, etc.
- Unsupervised learning
- (Deep) Reinforcement learning



## Knowledge

- Human anatomy
- Scanner protocol
- Prior constraints
- Math. theorems
  - Physics laws
  - Logic

# syngo.via CT bone reading



Oscar of invention

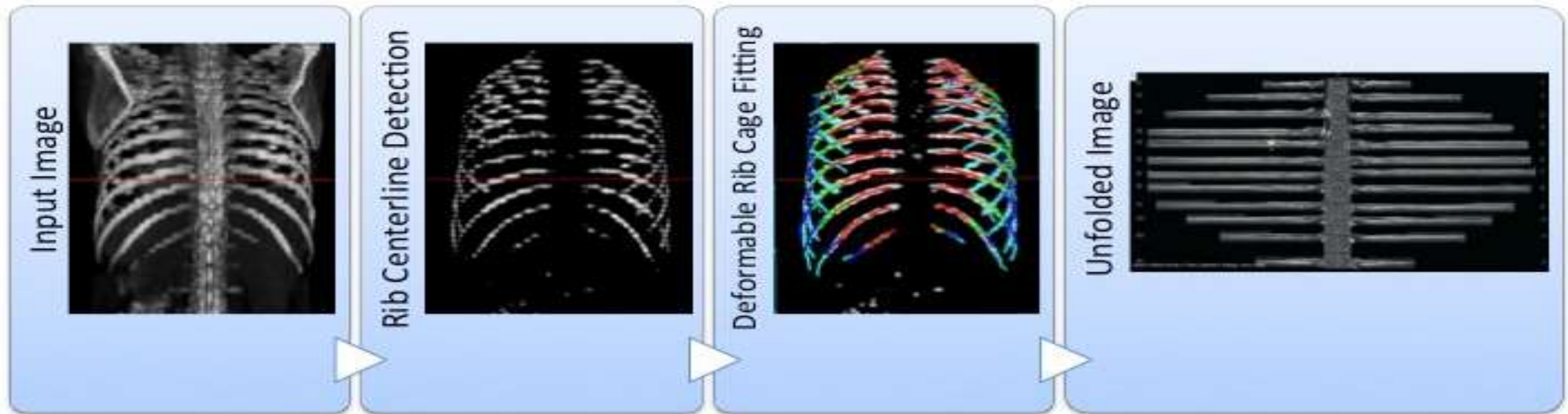


- Visualization of all ribs in one plane
- Automated numbering
- Reduces reading time
- Improves diagnostic sensitivity

- Patent US8989471 B2, Method and system for automatic rib centerline extraction using learning based deformable template matching.
- This feature is based on research, and is not commercially available. Due to regulatory reasons its future availability cannot be guaranteed.

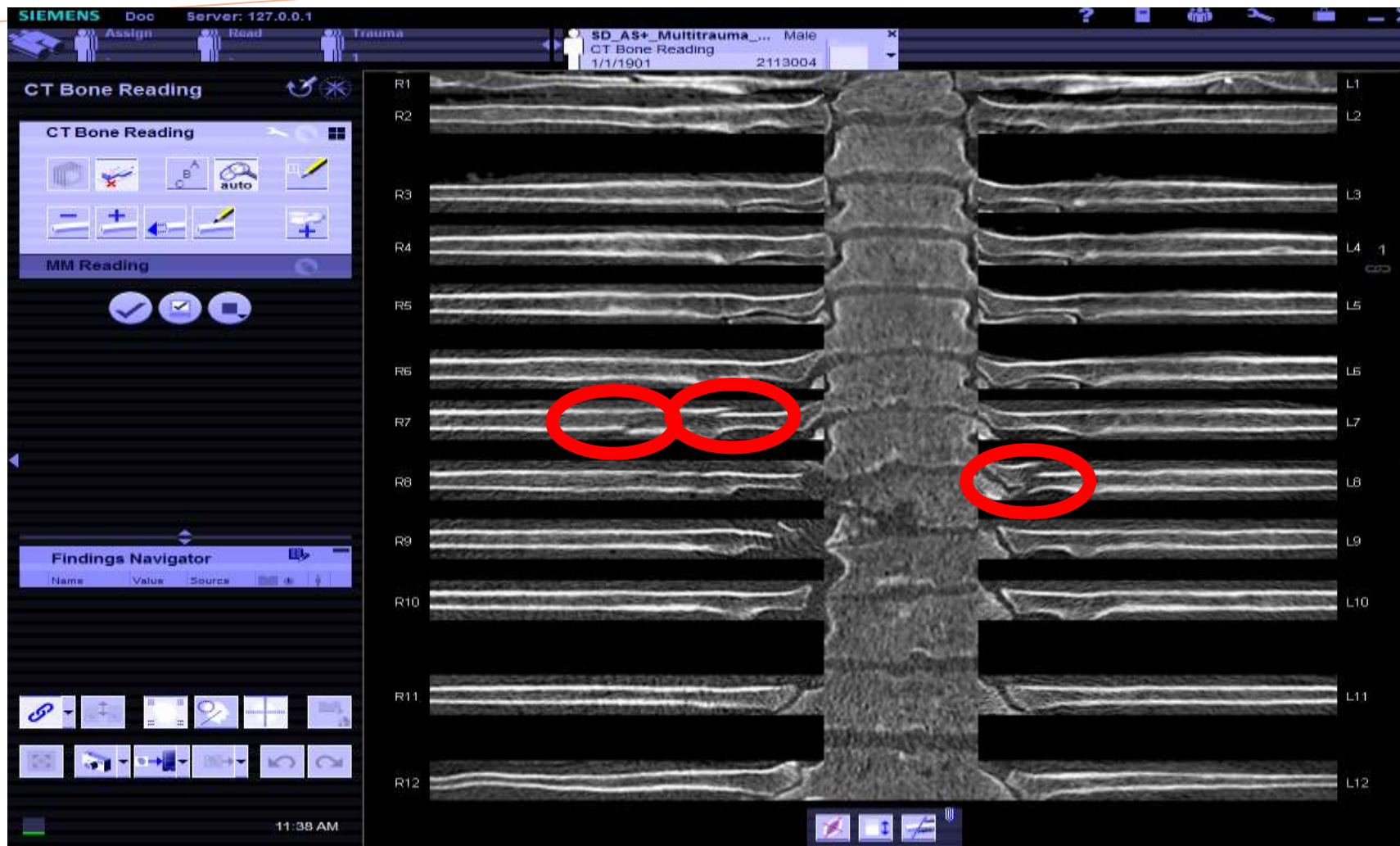


# ML + Rib cage model fitting

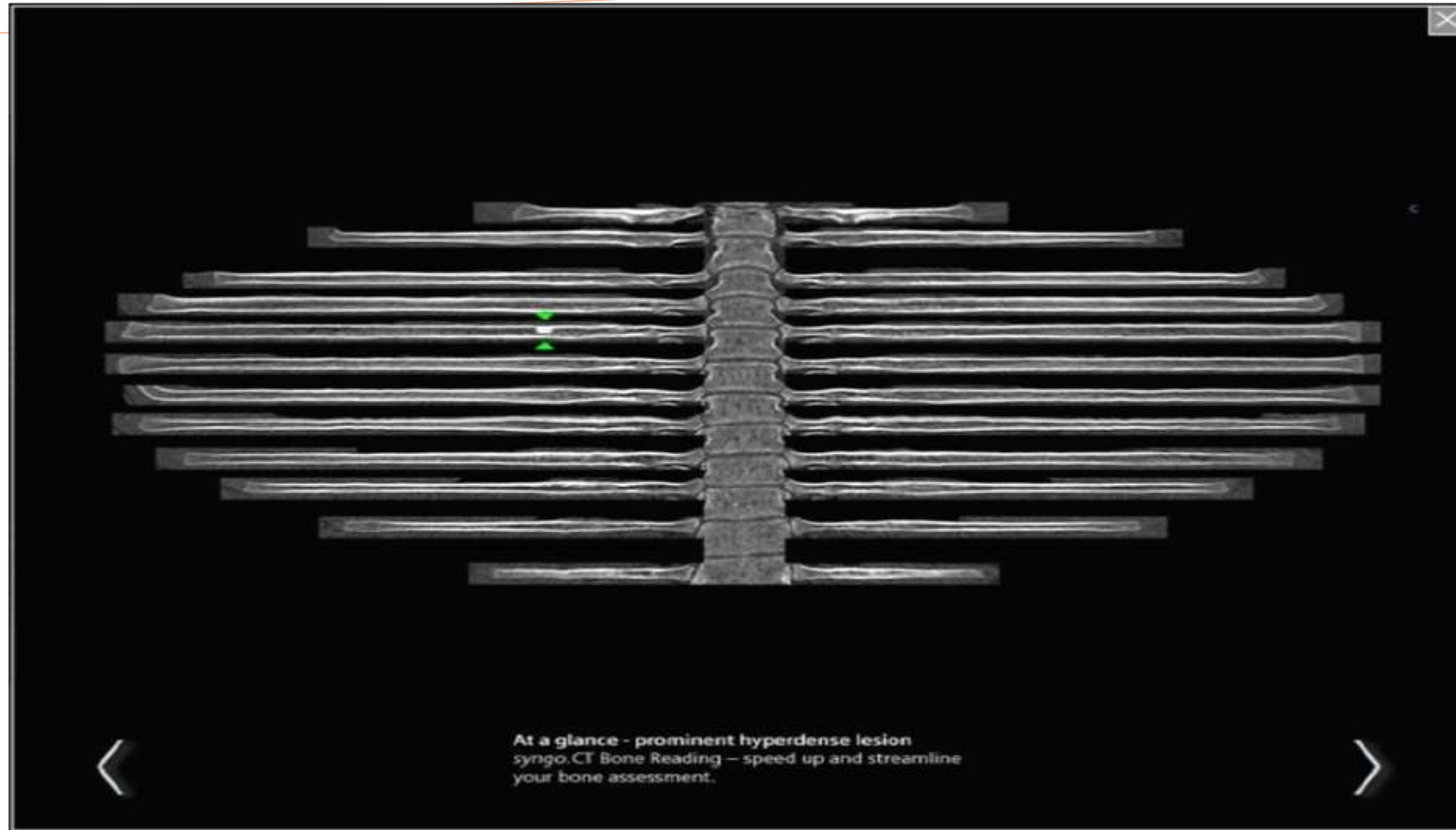


- Wu et al, "A learning based deformable template matching method for automatic rib centerline extraction and labeling in CT images," CVPR 2012.
- This feature is based on research, and is not commercially available. Due to regulatory reasons its future availability cannot be guaranteed.

# Fractures

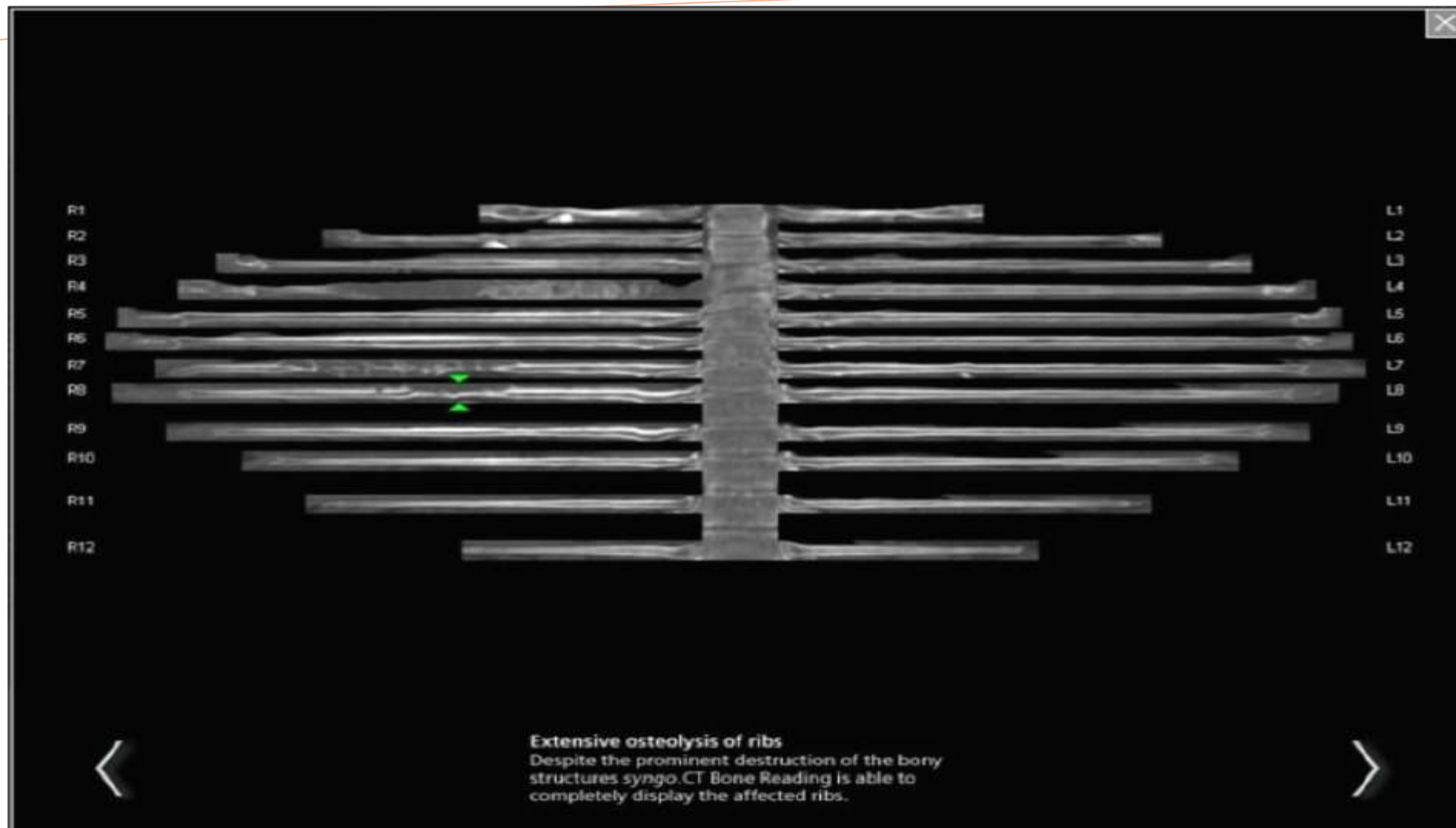


# Hyperdense lesion

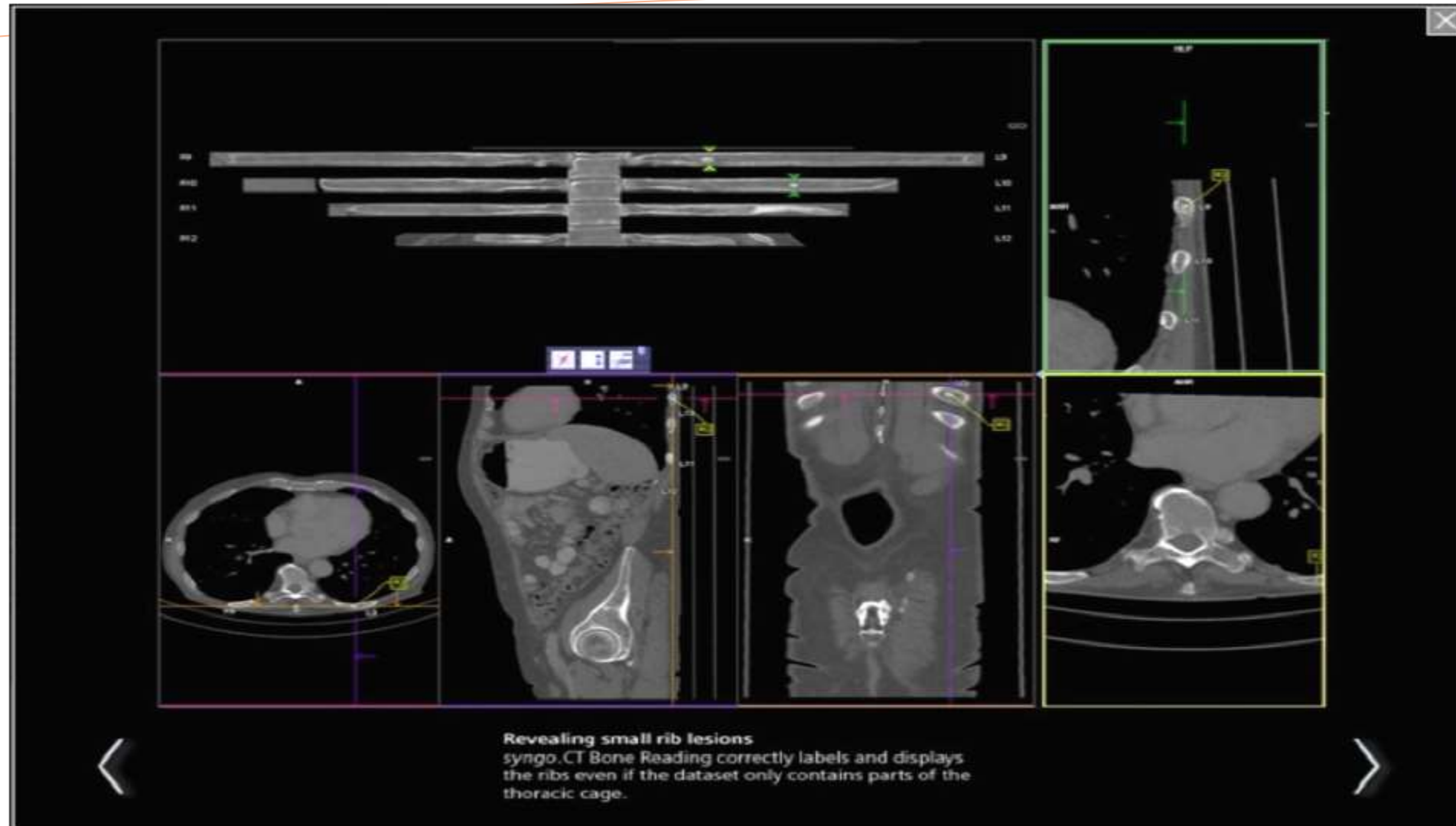




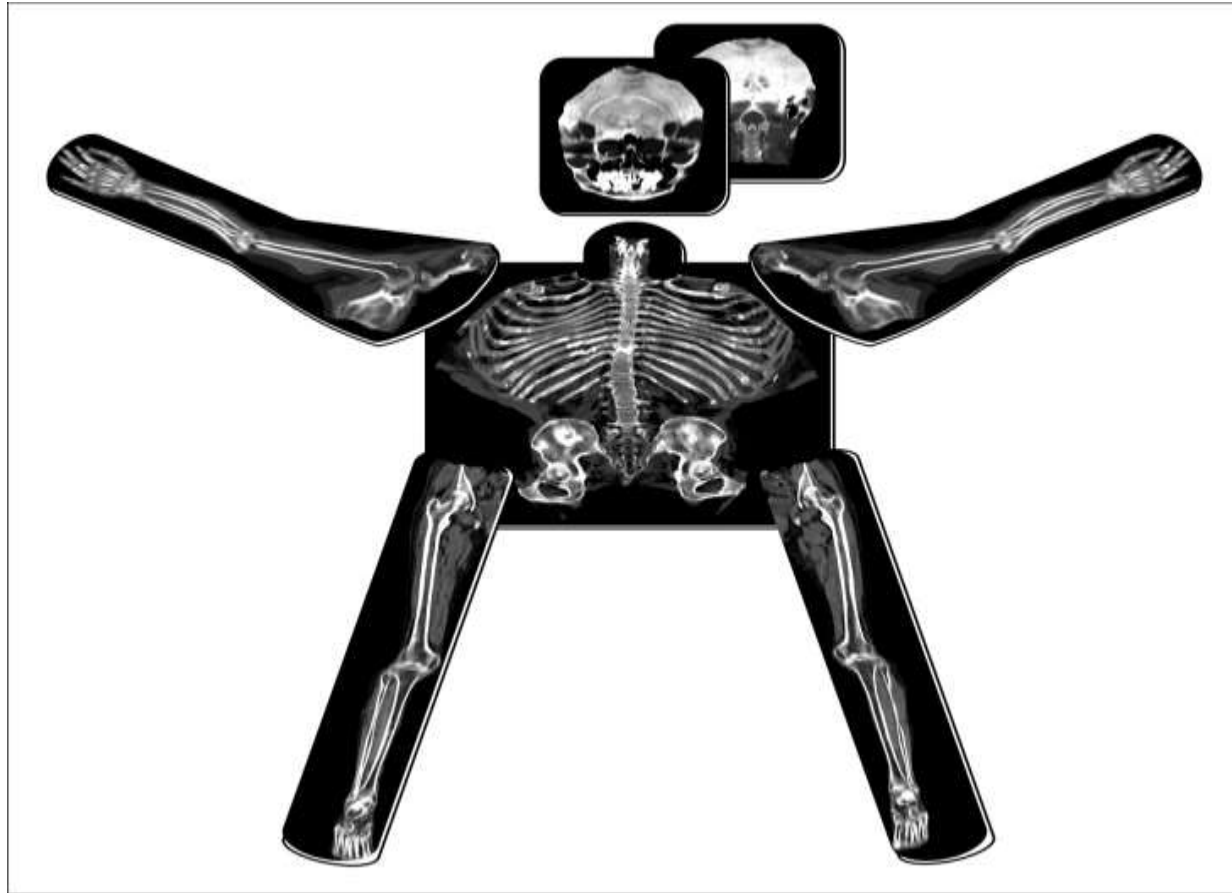
# Osteolysis



# Incomplete rib cage



# Skeleton unfolding



- Patent US9558568 B2: Visualization method for a human skeleton from a medical scan
- This feature is based on research, and is not commercially available. Due to regulatory reasons its future availability cannot be guaranteed.



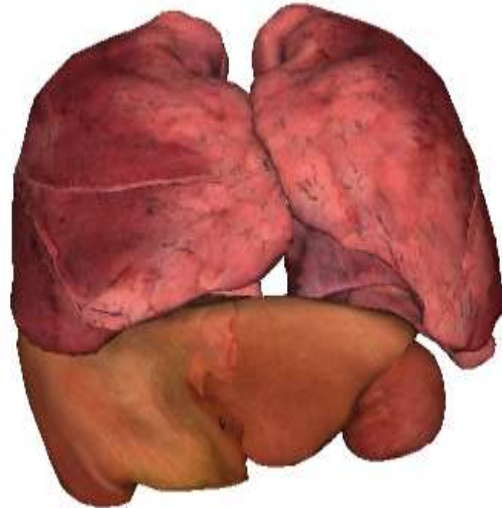


*Unitary / Local Context*



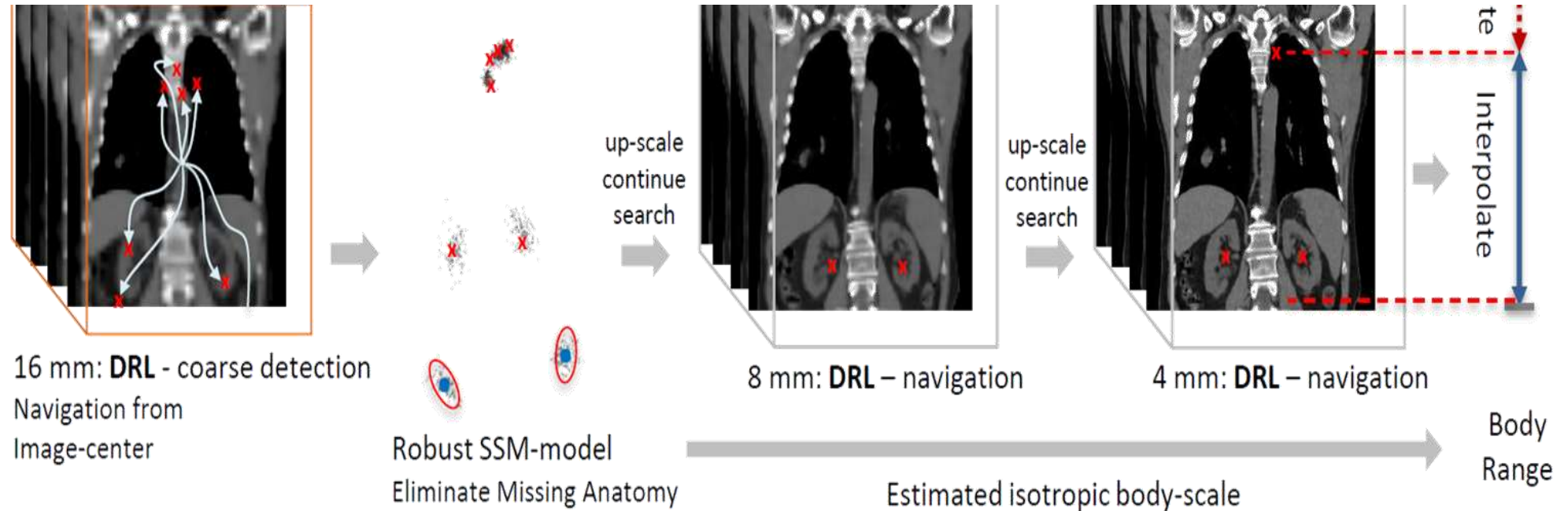
*Holistic / Global Context*

# Rapid multi-organ segmentation



- **Accuracy: ~ inter-user variability**
- **Running time: 1-2 seconds**
- US Patent 7949173, "Method and system for regression-based object detection in medical Images"
- Lay et al, "Rapid multi-organ segmentation using context integration and discriminative models," IPMI 2013.
- This feature is based on research, and is not commercially available. Due to regulatory reasons its future availability cannot be guaranteed.

# Multi-scale deep RL for 3D body markers



Validated on **2305 CT volumes**

Focus on robustness: **No failures!**

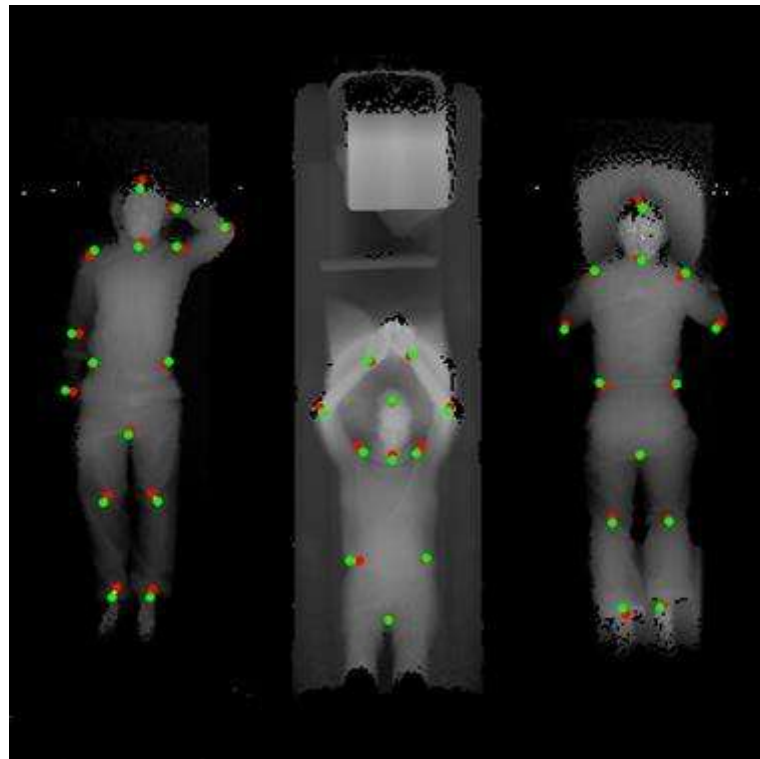
Real time speed: 0.8s (8 body markers)

Comparison with other Deep Learning & SADNN

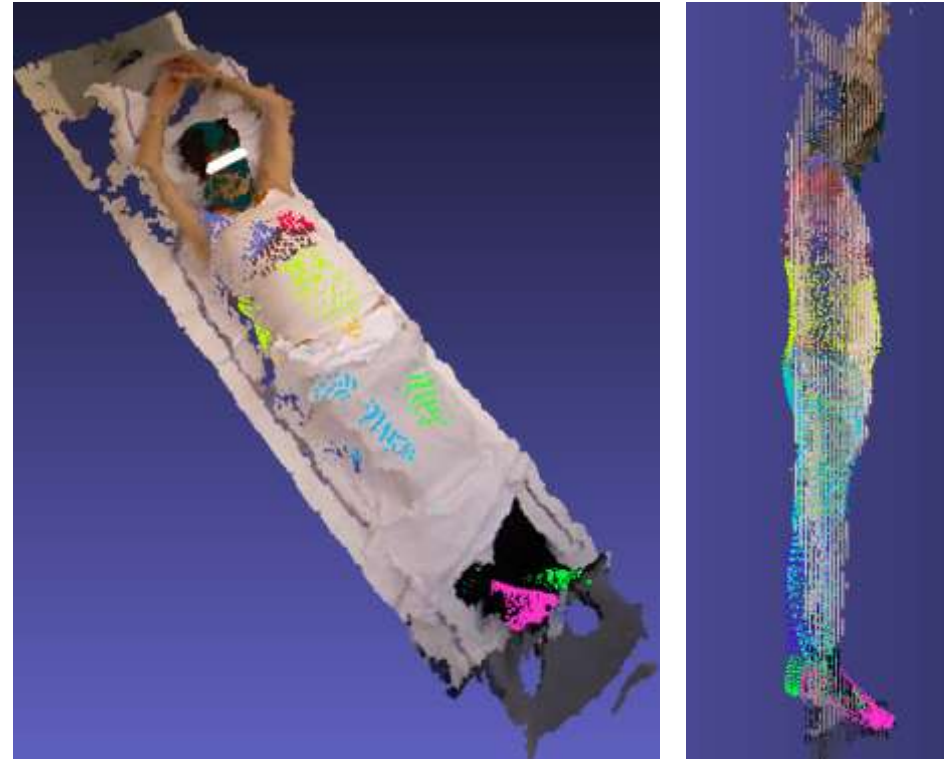
- Ghesu et al., Robust Multi-Scale Anatomical Landmark Detection in Incomplete 3D-CT Data, Medical Image Analysis, MICCAI 2017
- This feature is based on research, and is not commercially available. Due to regulatory reasons its future availability cannot be guaranteed.



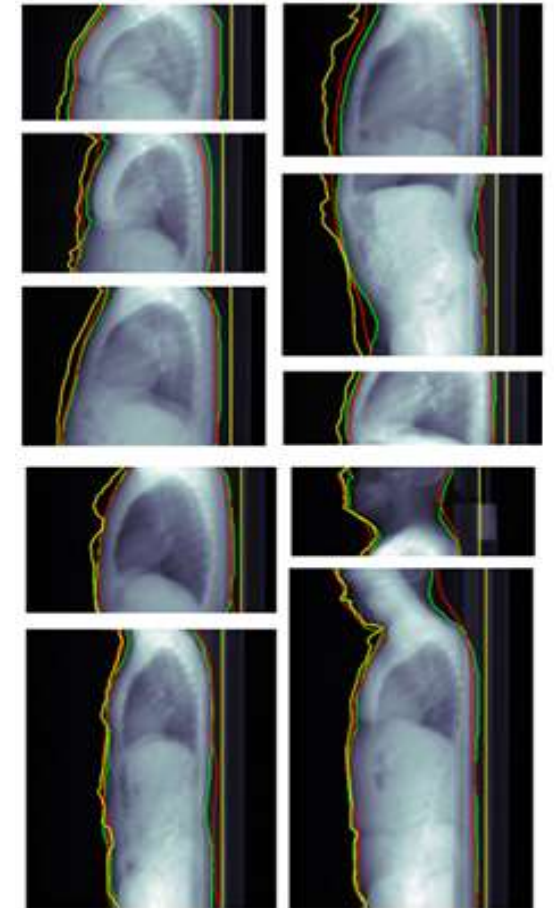
# DARWIN – AI-based patient specific avatar modeling



**Pose & bodymarkers**



**Mesh representation**



**Validation through  
CT imaging**

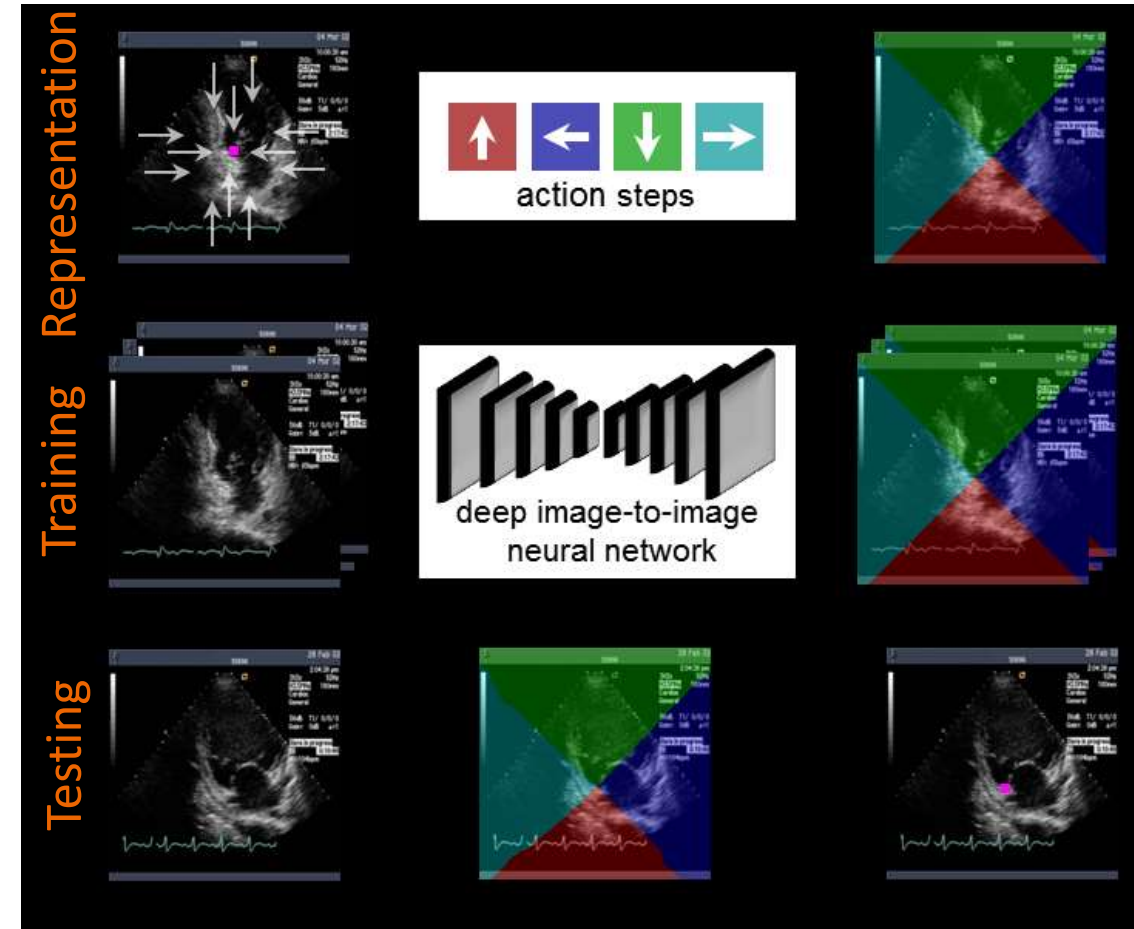
- Singh, et al. DARWIN: Deformable Patient Avatar Representation With Deep Image Network, MICCAI 2017.
- This feature is based on research, and is not commercially available. Due to regulatory reasons its future availability cannot be guaranteed.



# Landmark detection using DI2IN + supervised action map

- Novel representation -- supervised action map
- Deep image2image network (DI2IN)

		PBT		DRL		I2I		SAC	
		lmk1	lmk2	lmk1	lmk2	lmk1	lmk2	lmk1	lmk2
CA	mean	10.45	13.85	7.69	10.02	6.73	9.02	<b>6.31</b>	<b>8.01</b>
	50%	5.74	8.11	5.43	7.63	5.00	6.40	<b>4.35</b>	<b>5.88</b>
	80%	11.11	16.18	9.33	13.73	8.54	11.40	<b>7.54</b>	<b>10.83</b>
OB	mean	59.23	130.66	29.99	32.45	30.07	21.97	<b>14.94</b>	<b>16.76</b>
	50%	35.31	139.49	11.69	13.17	5.39	6.08	<b>4.85</b>	<b>5.91</b>
	80%	109.84	193.64	43.98	45.76	13.34	15.54	<b>11.76</b>	<b>13.67</b>

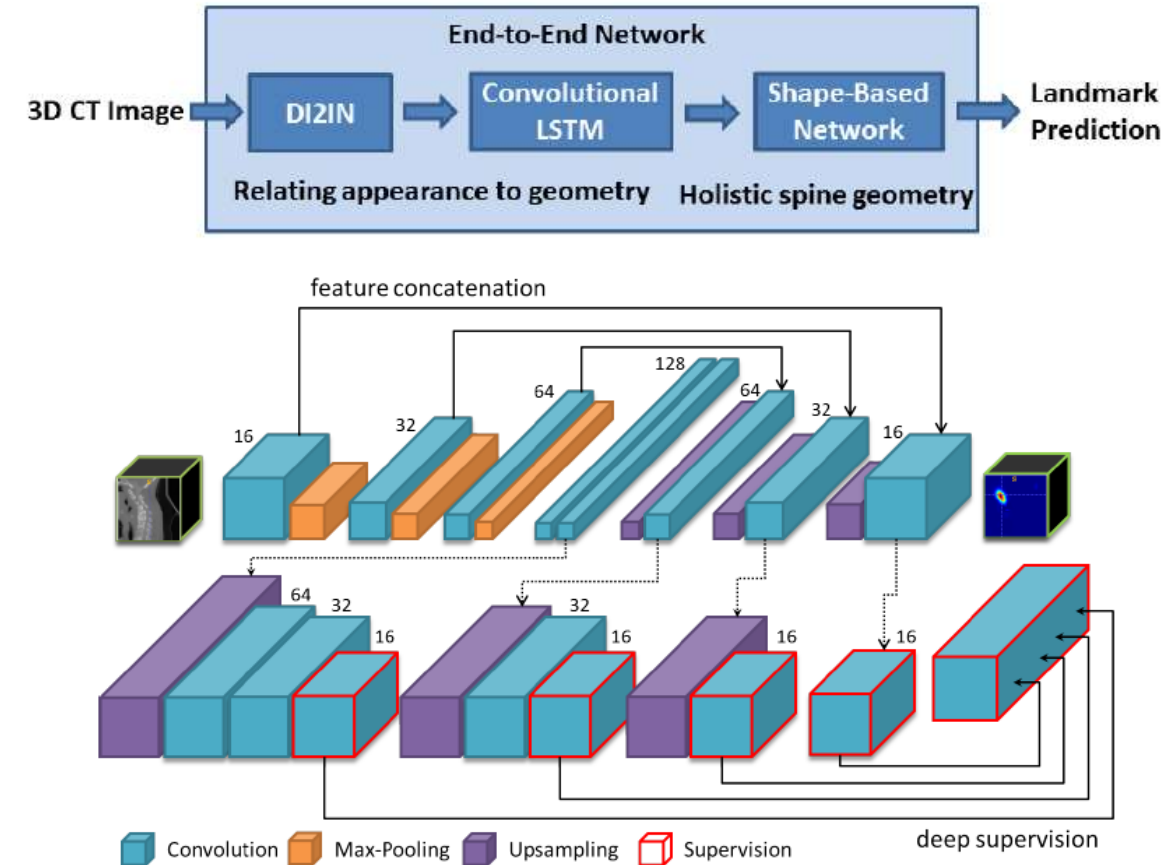


- Xu et al., Supervised Action Classifier: Approaching Landmark Detection as Image Partitioning, MICCAI 2017.
- This feature is based on research, and is not commercially available. Due to regulatory reasons its future availability cannot be guaranteed.

# Vertebral landmark detection using deep image2image recurrent network

- DL + shape constraints
- Reducing failure rate by 14% compared to best method on public benchmarking data set

Region	Method	Set 1			Set 2		
		Mean	Std	Id.Rates	Mean	Std	Id.Rates
All	Glocker <i>et al.</i> [2]	12.4	11.2	70%	13.2	17.8	74%
	Suzani <i>et al</i> [4]	18.2	11.4	-	-	-	-
	Chen <i>et al.</i> [3]	-	-	-	8.8	13.0	84%
	Our method	10.6	<b>8.7</b>	78%	8.7	8.5	85%
	Our method +1000	<b>9.0</b>	8.8	<b>83%</b>	<b>6.9</b>	<b>7.6</b>	<b>89%</b>



- Yang et al., Deep Image-to-Image Recurrent Network with Shape Basis Learning for Automatic Vertebra Labeling in Large-Scale 3D CT Volumes, MICCAI 2017
- This feature is based on research, and is not commercially available. Due to regulatory reasons its future availability cannot be guaranteed.

# Adversarial Image2Image Network for Organ Contouring

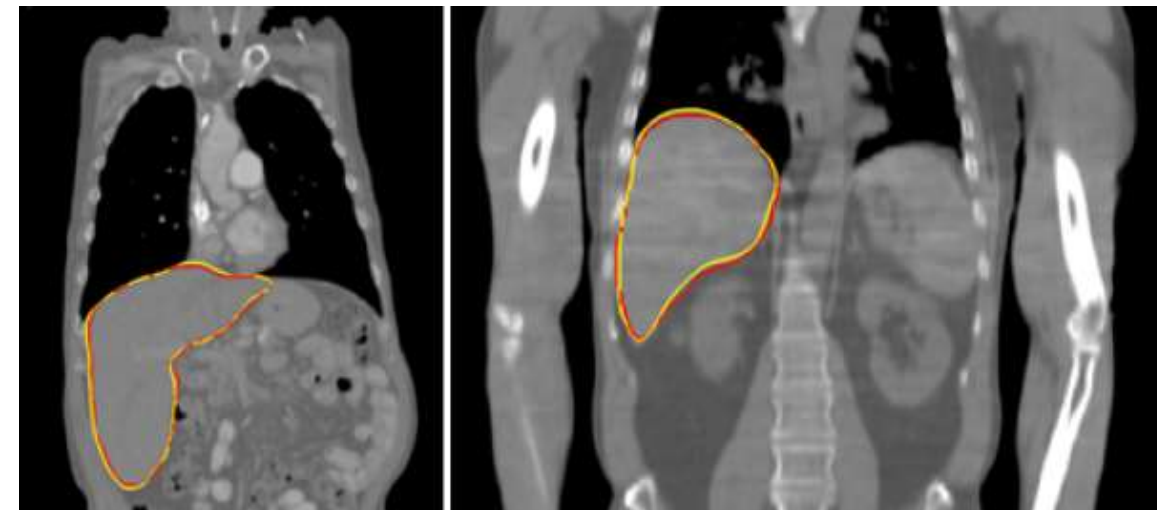
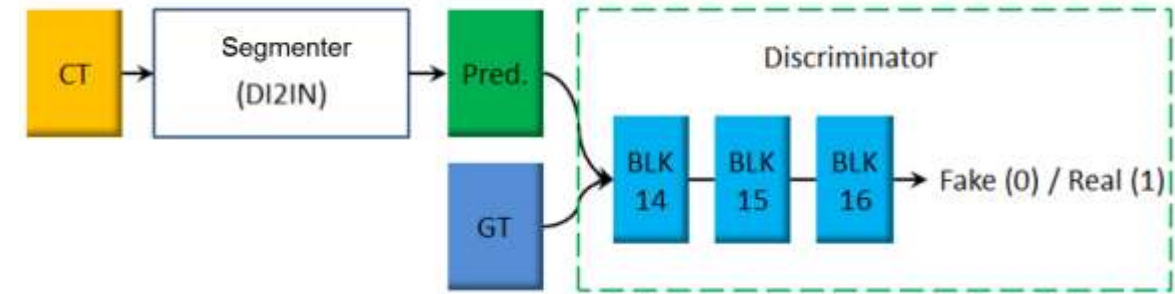
## Adversarial Image-to-Image Network

- Using segmentation (DI2IN) and discriminative models to improve segmentation performance

### Liver segmentation

- 34% error reduction when using 1000 CT data sets

Method	ASD (mm)			
	Mean	Std	Max	Median
Ling <i>et al.</i> (400) [5]	2.95	5.07	37.45	2.01
DI2IN (400)	2.38	1.31	10.35	2.0
DI2IN-AN (400)	2.09	0.94	7.94	1.88
DI2IN (1000)	2.15	0.81	6.51	1.95
DI2IN-AN (1000)	<b>1.95</b>	<b>0.75</b>	<b>6.48</b>	<b>1.81</b>

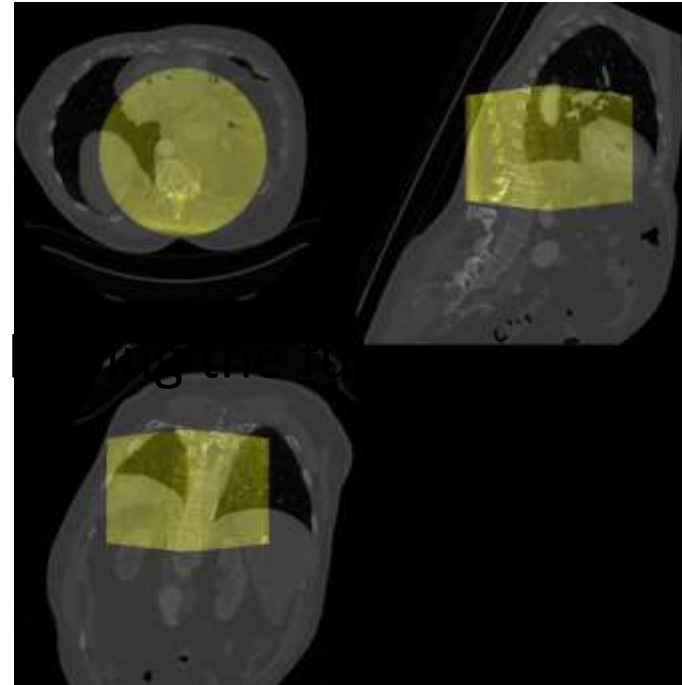
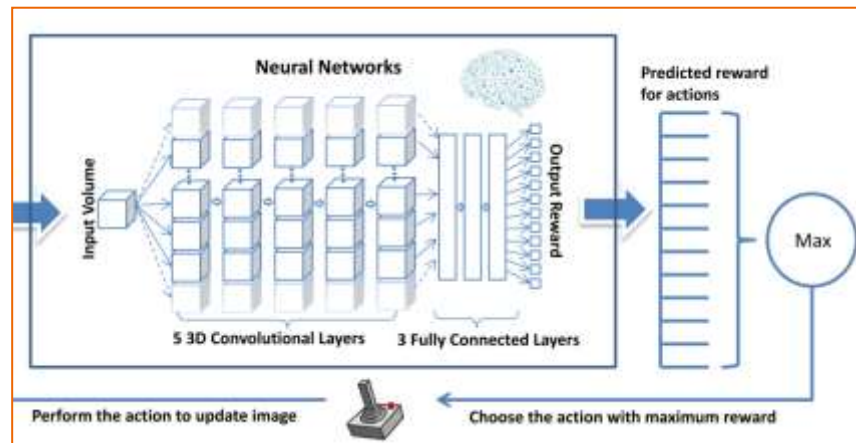


Data courtesy of Universitätsspital Basel

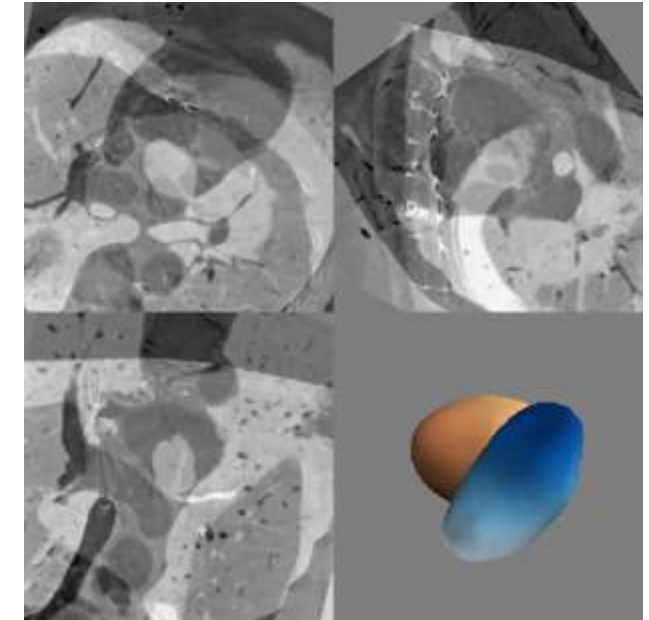
# Robust multi-modality image fusion – within seconds

## Artificial agent trained using DRL

- Applies to 3D/3D rigid/deformable registration, 2D/3D (multi-agents)
- Trained on 5M training pairs



CT/DynaCT Spine



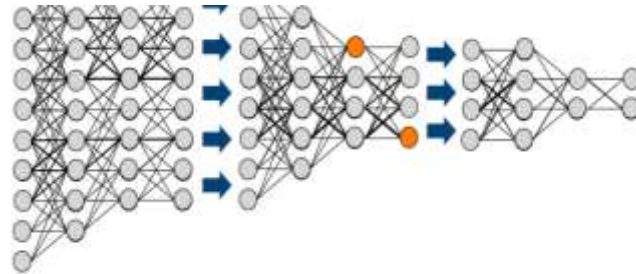
CT/DynaCT Heart

- Liao et al., An Artificial Agent for Robust Image Registration, AAAI 2017.
- This feature is based on research, and is not commercially available. Due to regulatory reasons its future availability cannot be guaranteed.



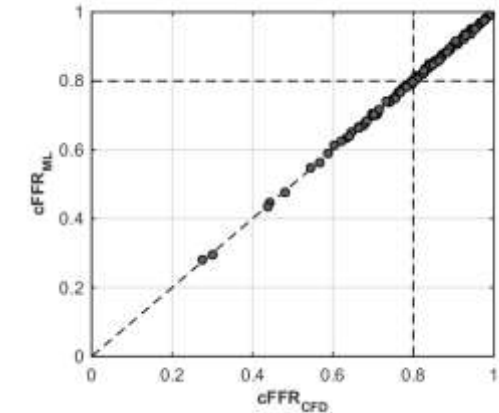
# Deep-Learning based cFFR

## Offline training phase



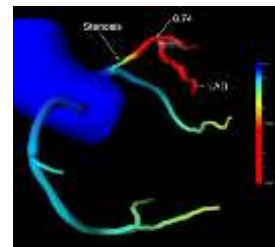
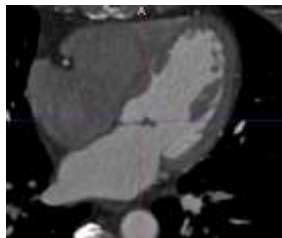
cFFR model  
 $\text{FFR}(\mathbf{x})$

12,000 unique vessel trees with > 1,000,000 coronary segments  
> 10 million locations with CFD based flow results



99.98% Correlation between deep-learning based cFFR and CFD

## Deployment



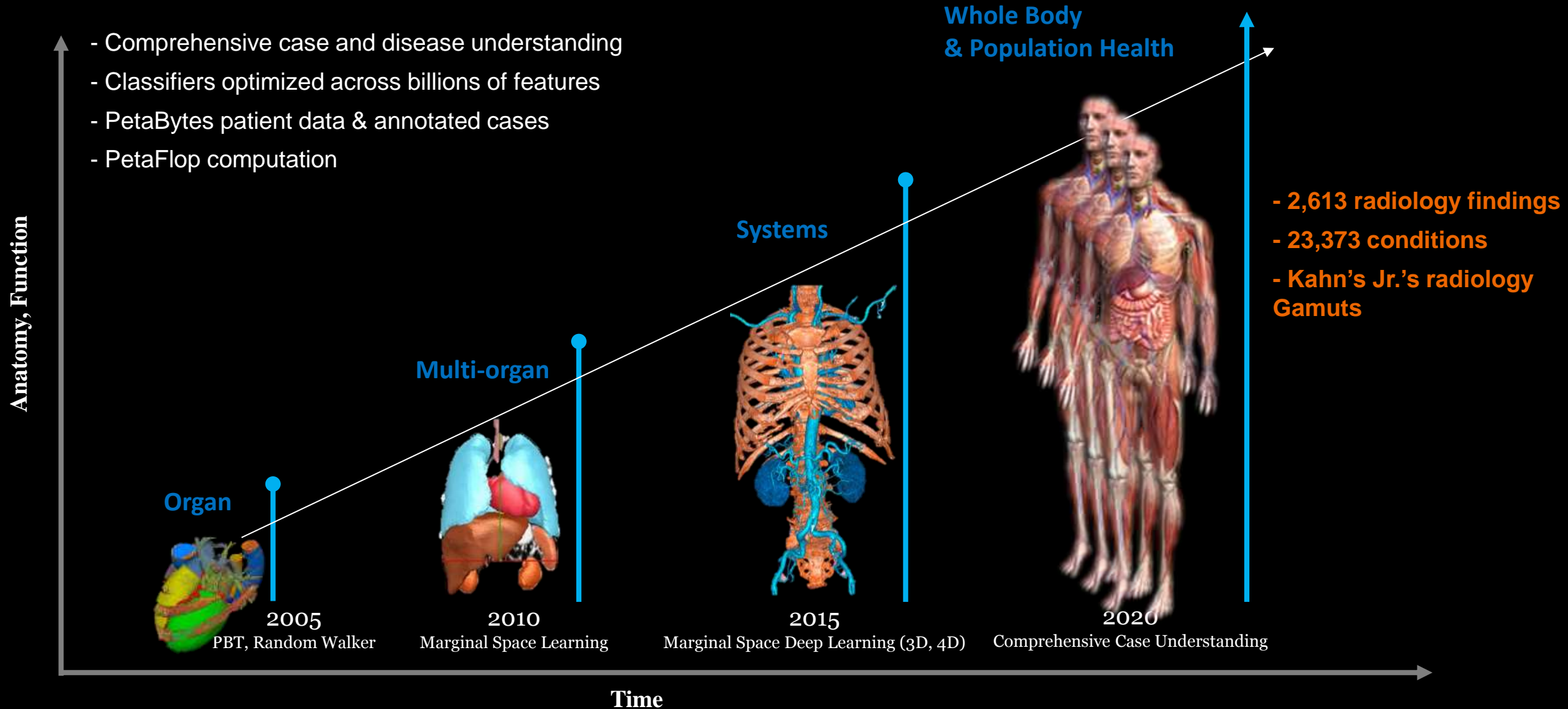
Radiologist-driven workflow

Workstation based

Real-time FFR update **after lumen correction/editing**

- Itu et al., A machine-learning approach for computation of fractional flow reserve from coronary computed tomography. J Appl Physiol 121: 42–52, 2016
- This feature is based on research, and is not commercially available. Due to regulatory reasons its future availability cannot be guaranteed. Page 32 | Unrestricted © Siemens Healthcare GmbH, 2017

# From local analysis to whole body, population health and systems medicine



**THANKS!**

**WE ARE RECRUITING!!!**

<https://www.siemens.com/us/en/home/company/jobs.html>

**Towards  
Digital twin –**  
lifelong, personalized  
physiological model  
updated with each  
scan, exam



**Patient-centric,  
holistic  
treatment**

• This feature is based on research, and is not commercially available. Due to regulatory reasons its future availability cannot be guaranteed.