Blood-vessels' lumen geometric modeling and quantification in 3D images

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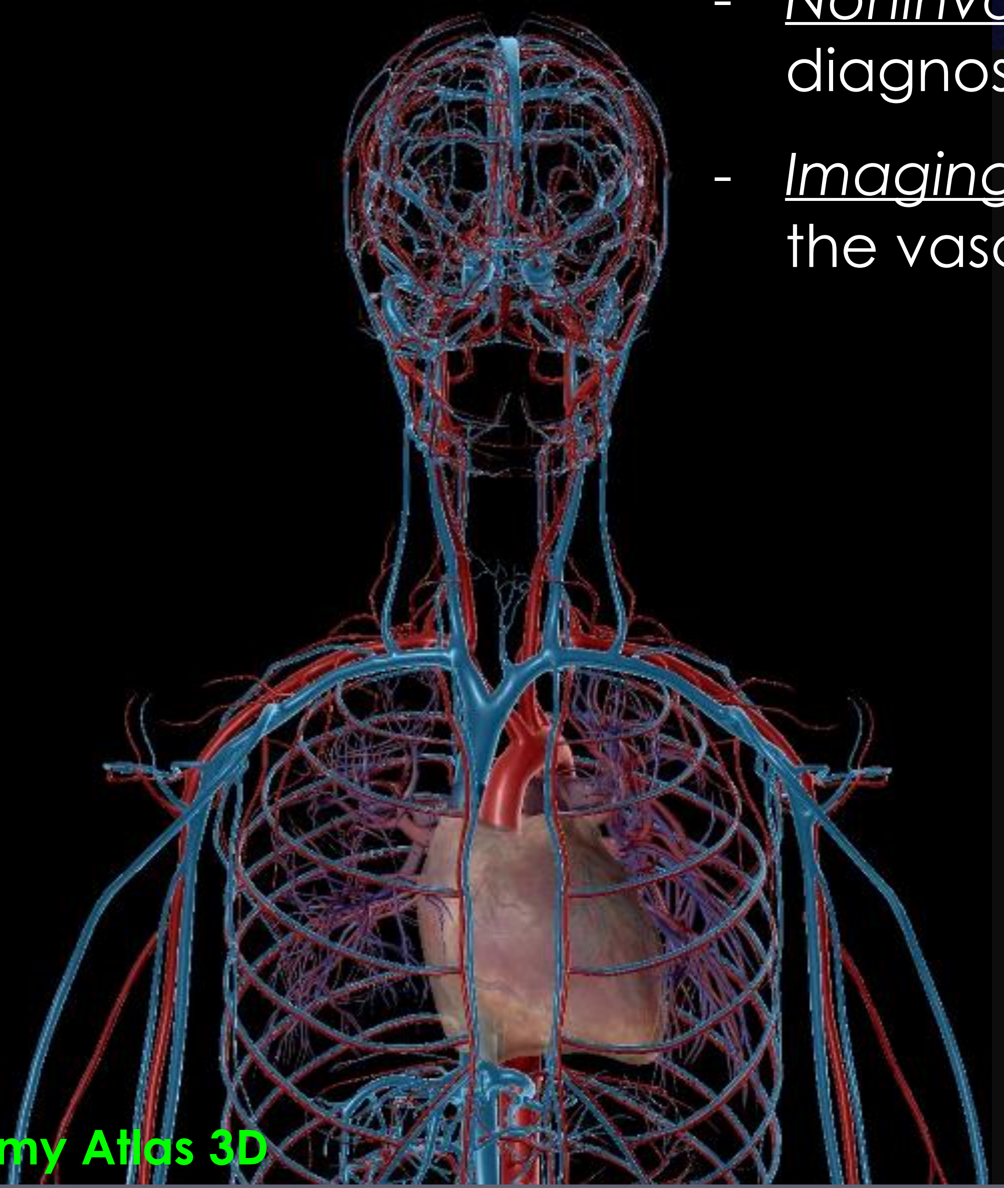
Overview

- Introduction
- Problem to solve
- Challenges
- Methods
- Examples
- Summary

Introduction

- Cardiovascular diseases are the leading cause of death worldwide [1].
- They originate mainly from blocked or excessive blood supply to tissues.

- *Noninvasive*, *objective* and *accurate* diagnostic techniques are searched for.
- *Imaging techniques* play a major role in the vascularity evaluation.

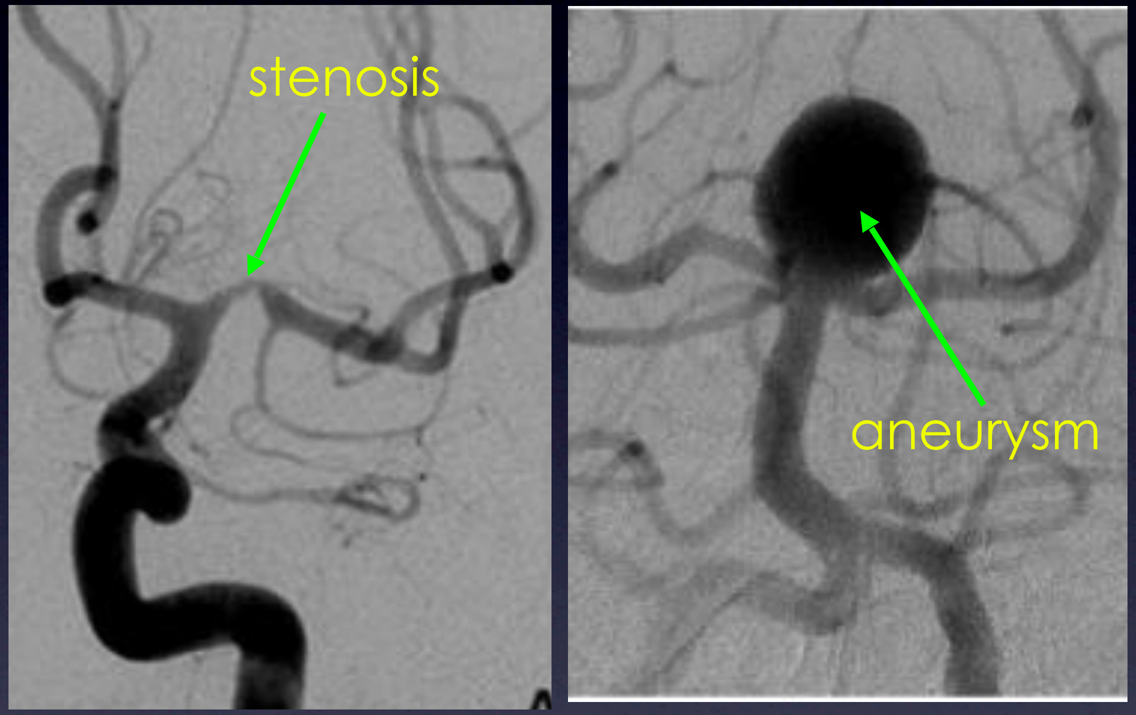


Visible Body, Human Anatomy Atlas 3D

Introduction

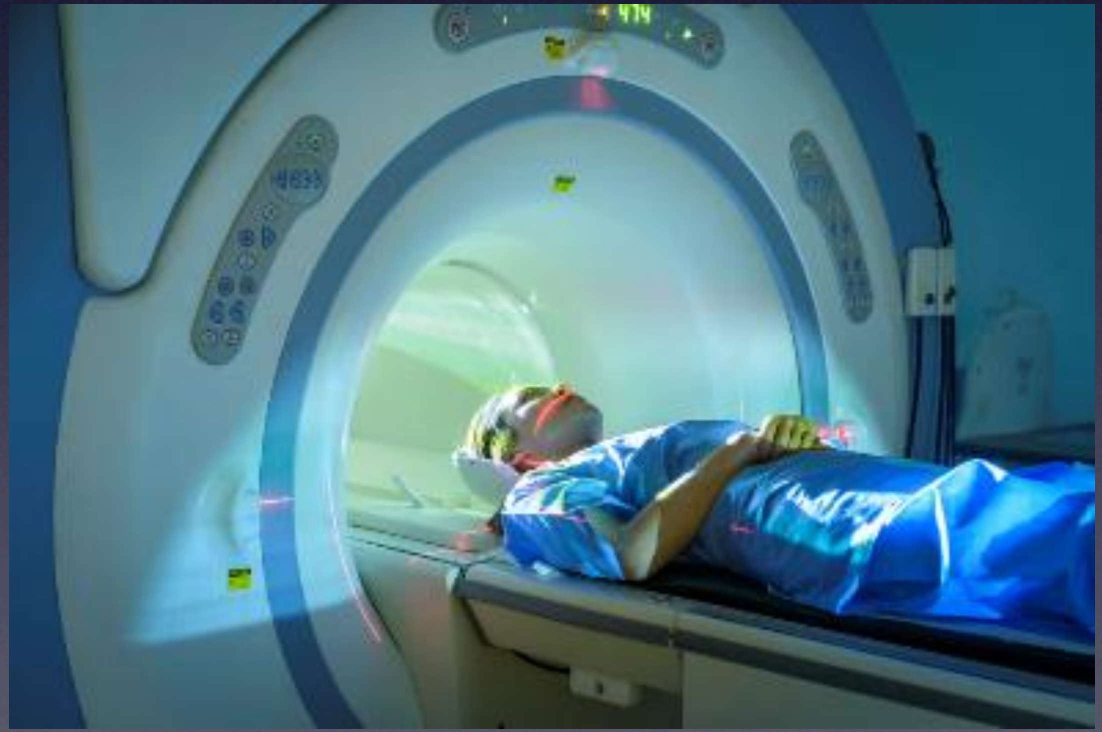
Personalized quantification of

- lumen centerline course,
- cross-section shape,
- deformations:



Medical imaging

Computed tomography angiography (CTA)

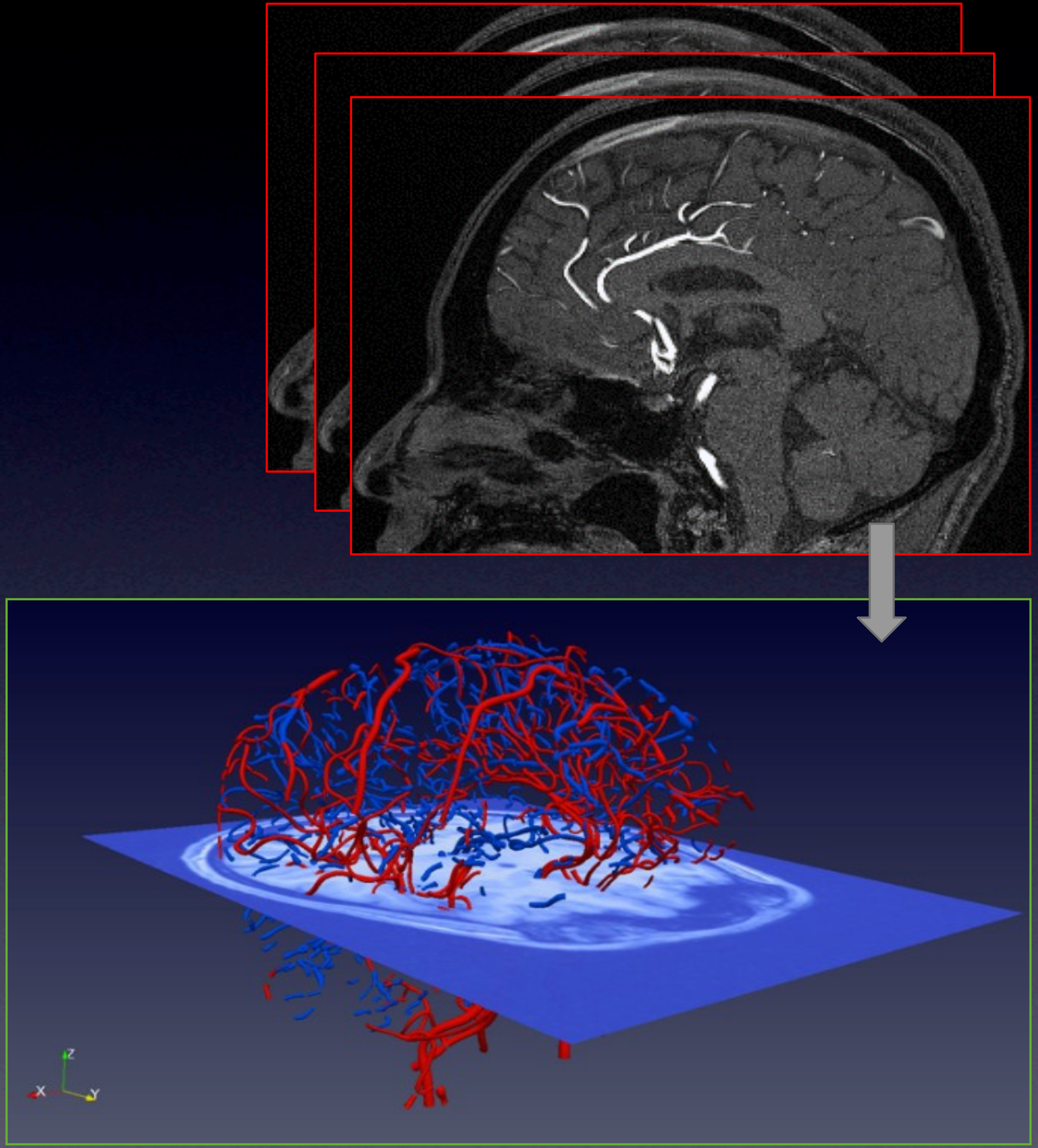


Magnetic resonance angiography (MRA)

Problem to solve

Lumen geometry reconstruction
of blood vessel trees
given their 3D discrete image

Example
Human brain arteries in ToF MRI

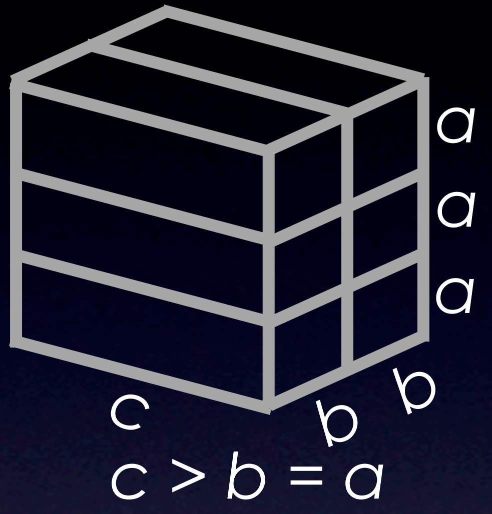


Geometric model
- curved tubes (between n-furcations)
- circular/non-circular cross-sections,
- the diameter varies along the centerline

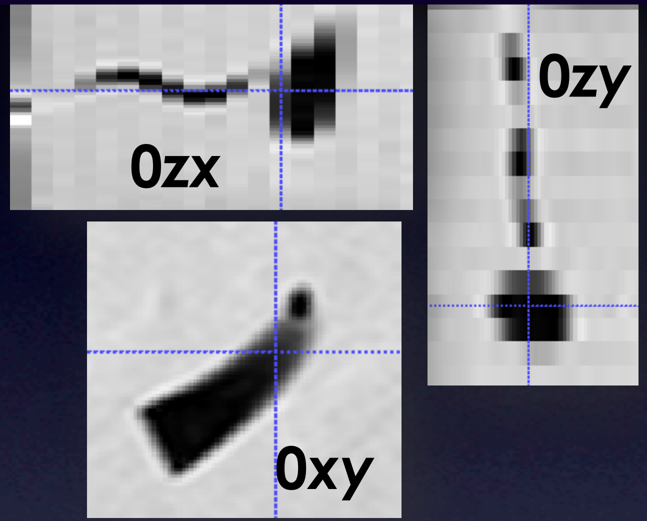
Basis for
- diagnostic quantification,
- blood-flow simulation,
- surgery planning/execution,
- education, ...

Challenges

Discretization, voxel anisotropy



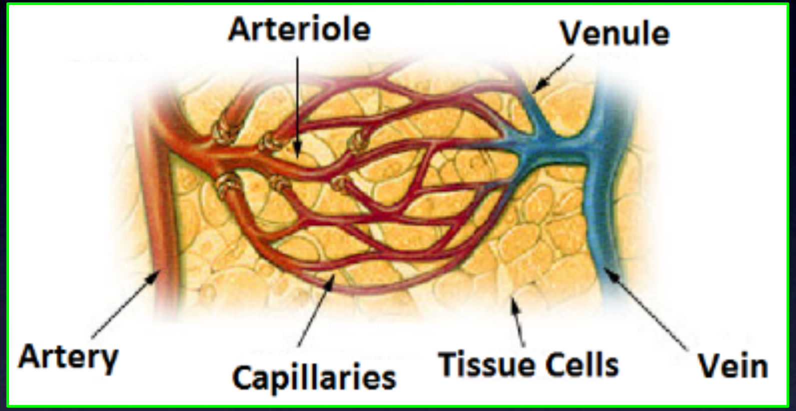
T2w MRI, coronal thick-plane
0.33mm x 0.33mm x 2.2mm



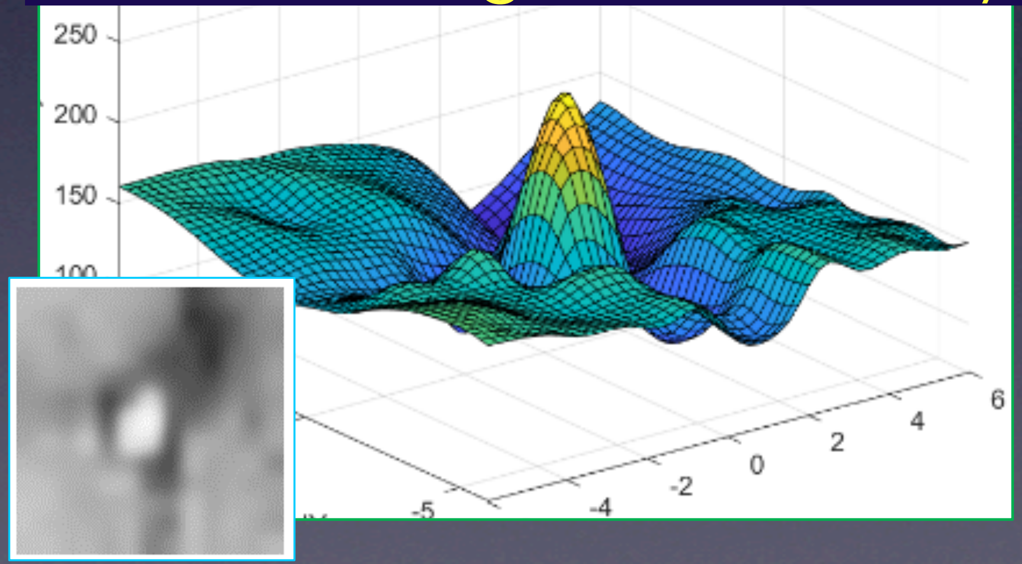
The scales

$\min\{a,b\} \approx 300\ \mu m$

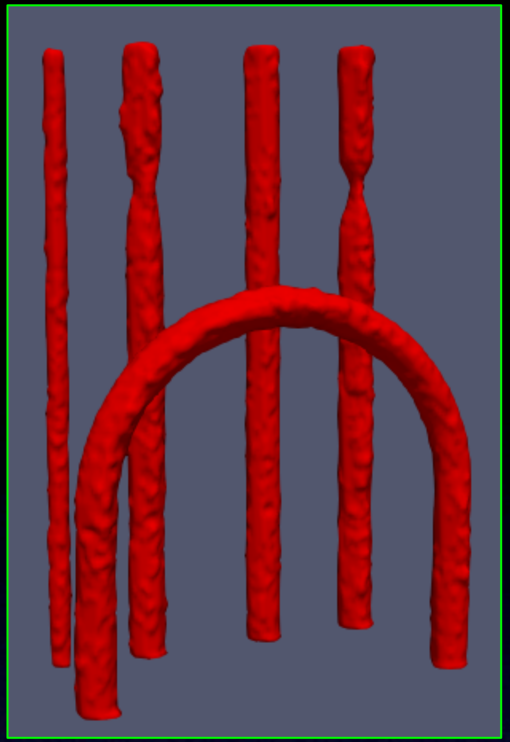
$D \in [10\ \mu m, 40\ mm]$

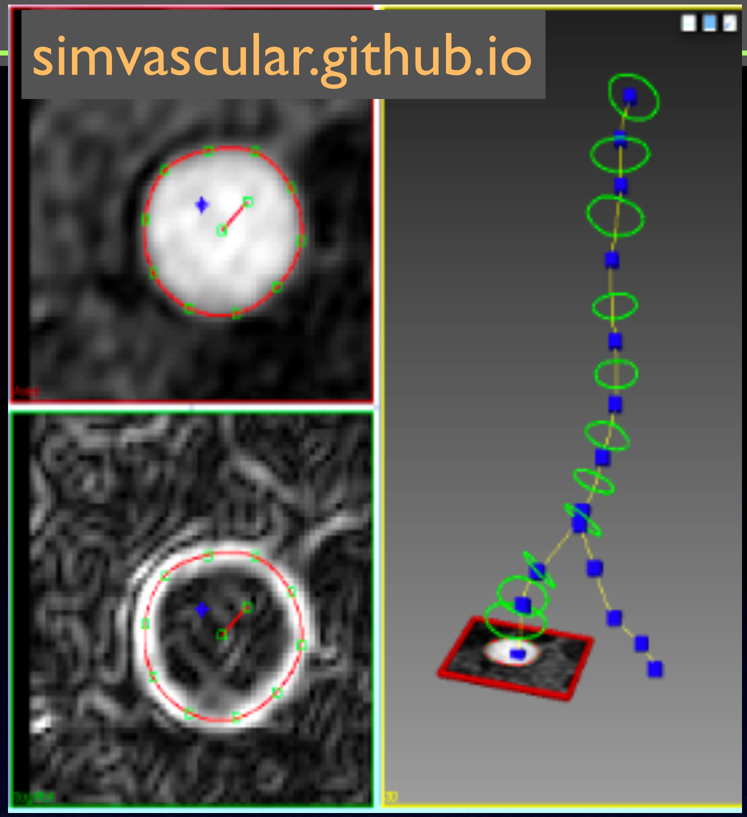


Uneven background intensity



Noise (SNR)





Modeling of vascular structures in 3D images

Two main approaches [2,3,5,6]

3D lumen binary segmentation

- ✗ loss of information due to binarization [9]
- ✗ voxelized surface needs further smoothing

2D cross-section analysis along approximated centerline

- ✓ no intermediate binary segmentation
- ✓ incorporation of *a priori* knowledge, for robustness [2]

Methods and algorithms

Level-set techniques [7]

- ✗ long-lasting computations

CNNs [8]

- ✗ need for annotated data

Image model fitting [9,17]

- ✓ subpixel accuracy
- ✗ computationally demanding, local minima

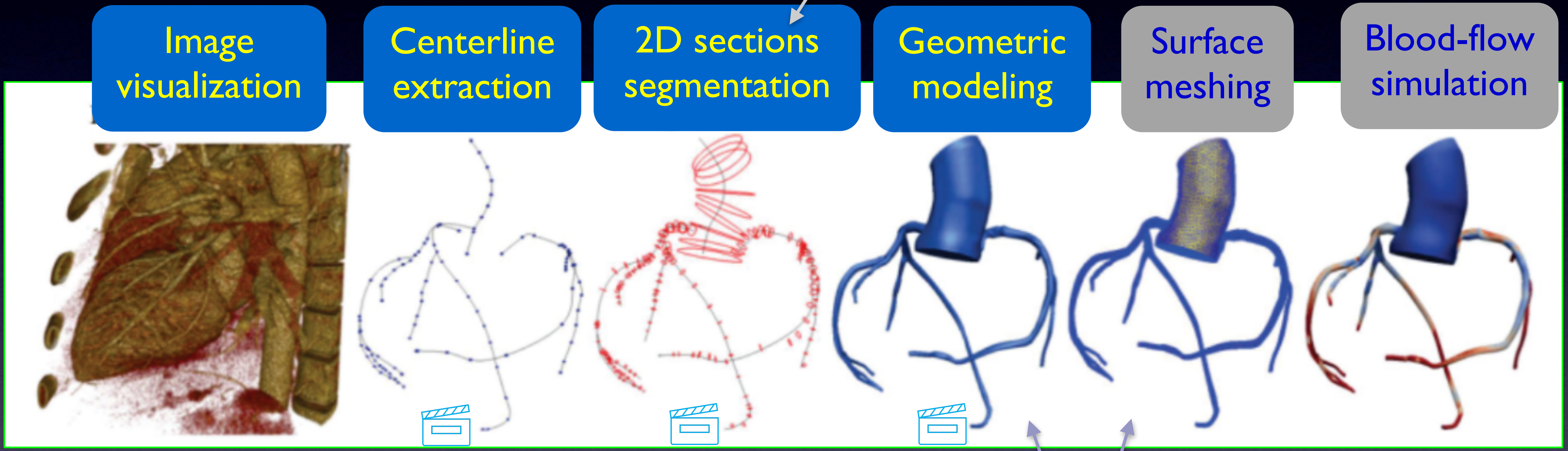
CNN-based parameter estimation [21]

- ✓ subpixel accuracy
- ✓ robustness to background elements
- ✓ very short recall time
- ✓ can be trained on synthetic images

Centerline-based interactive pipeline [22]

SimVascular
simvascular.github.io/

lumen contour delineation



. DICOM
. NIfTI
. ...

https://www.pre-scient.com/knowledge-center/geometric-modelling/geometric-modeling.html

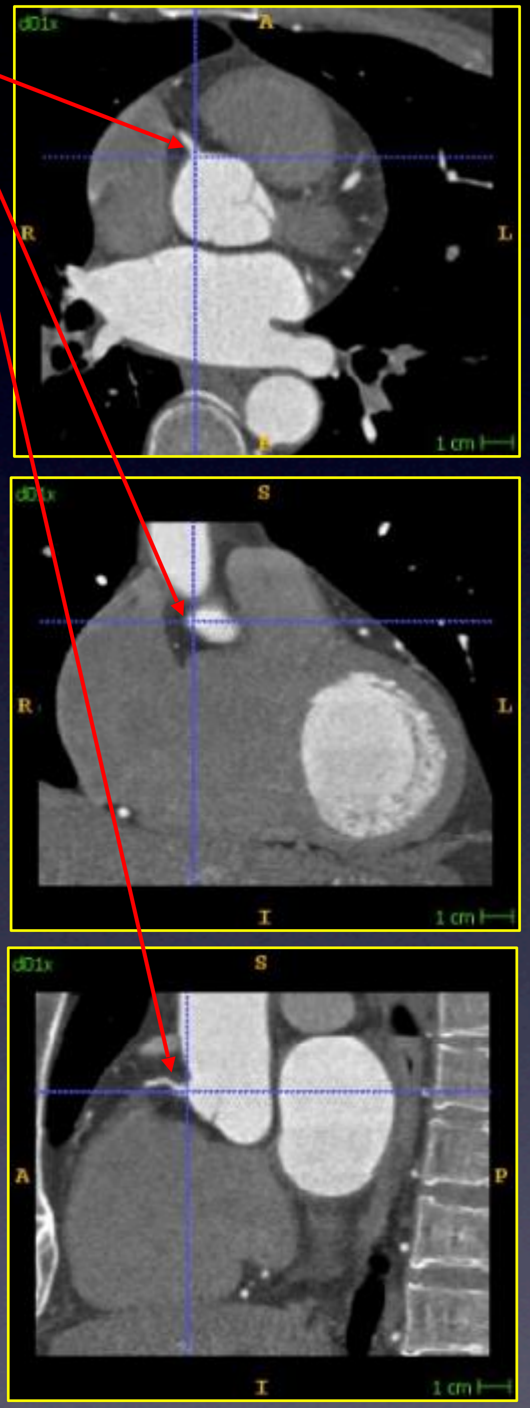
https://community.cadence.com/cadence_blogs_8/b/cfd/posts/hurdling-geometry-model-challenges-for-cfd-mesh-generation

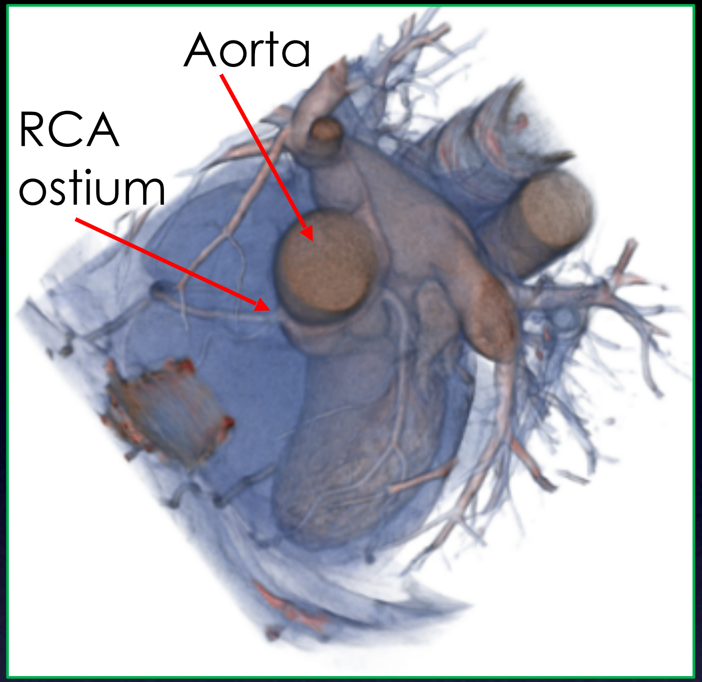
Centerline-based automated pipeline [9,21]

Coronary arteries

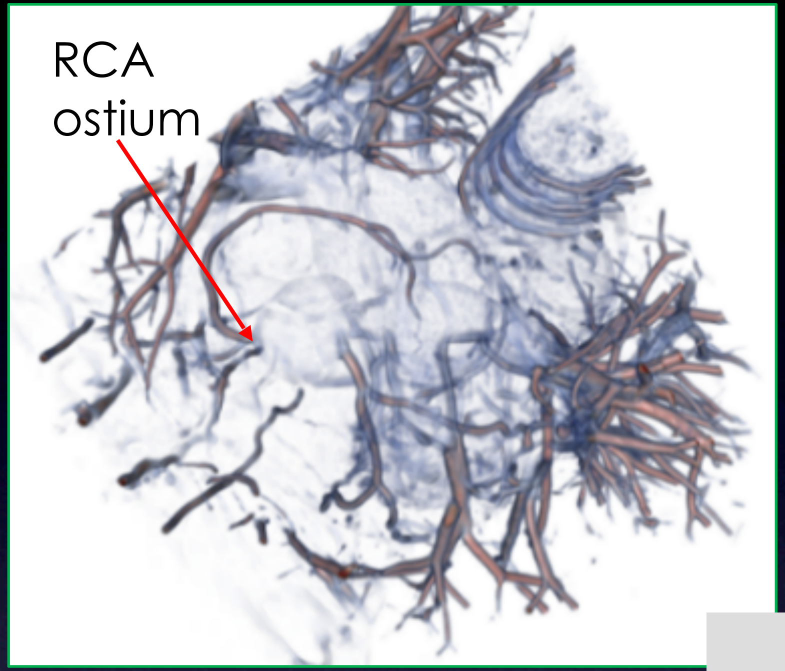
Contrast-enhanced CT [4]

RCA ostium



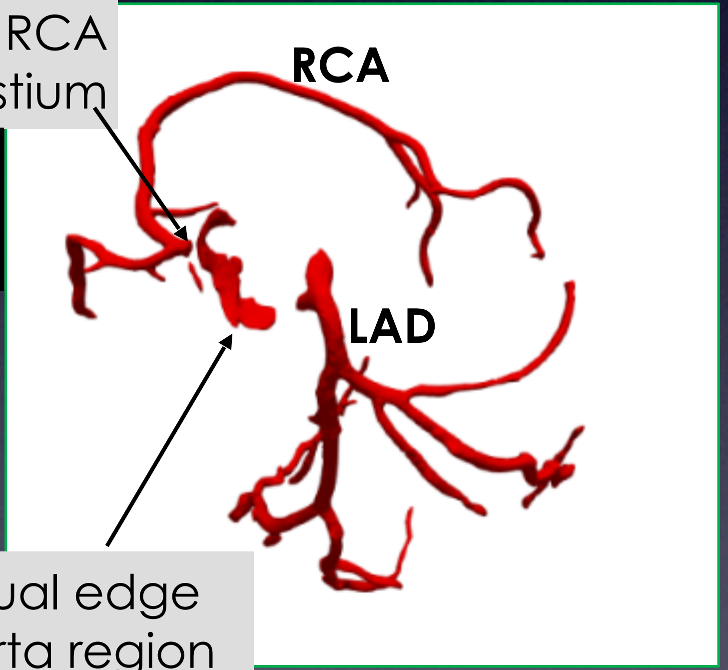


Vesselness filtering [10,15,16]



3D region-growing

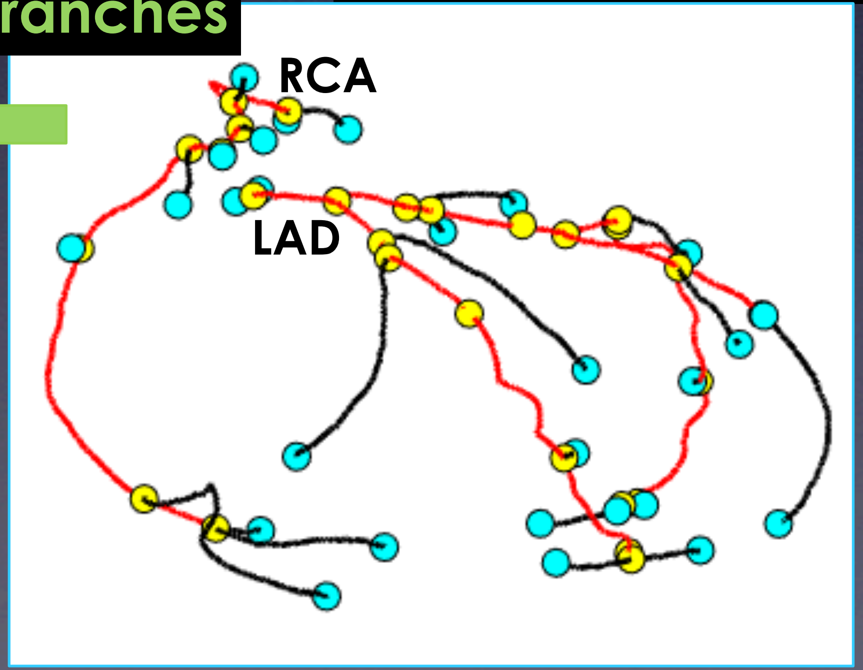
RCA ostium



Residual edge of aorta region

RCA - right coronary artery
LAD - left anterior descending

- 3D binary thinning,
- skeleton tree parsing [23]



Smooth approximation of binary skeleton branches

3D image resampling on cross-section planes

Methods

Image formation model [9,21]

- Scanner assumed to be a linear space-invariant system

$$F(x,y) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(u,v)h\left(x-u, y-v\right) dv du \qquad (1)$$

where $f(x,y;\, a,b,R,d_x,d_y)$ is the lumen intensity distribution

$h(x,y;\, w)$ is an isotropic Gaussian impulse response.

Model parameters

- a : background intensity
- b : intensity step
- R : lumen radius
- w : 2D Gaussian blur
- d_x, d_y : centerline shift

- 2D cross-section intensity at a point (i, j)

$$I(i,j;\theta;\sigma) = a + bF(R, w, i\Delta_s - d_x, j\Delta_s - d_y) + \epsilon(\sigma) \qquad (2)$$

where Δ_s is the sampling interval.

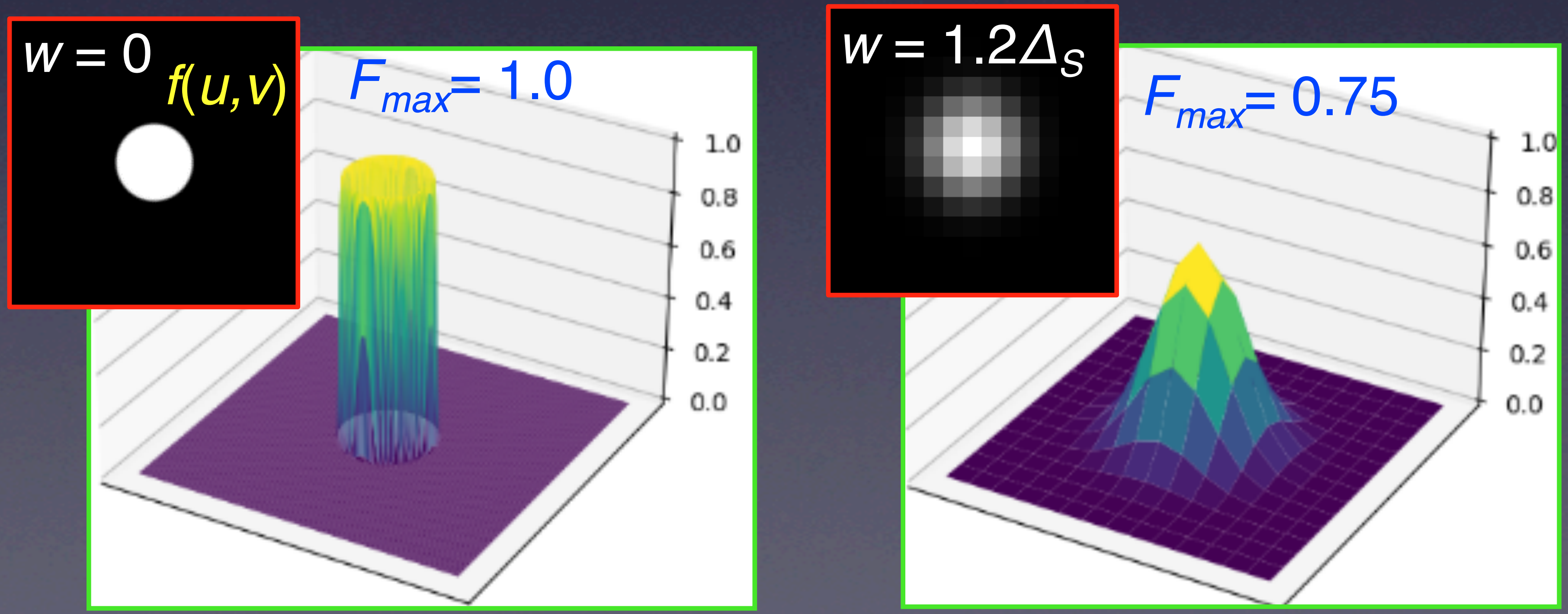
Random noise ϵ

- zero mean
- standard deviation σ

Parameter vector

$\theta = (a, b, R, w, d_x, d_y)$

$R = 2.0\Delta_S$
$a = 0$
$b = 1$
$d_x = 0$
$d_y = 0$



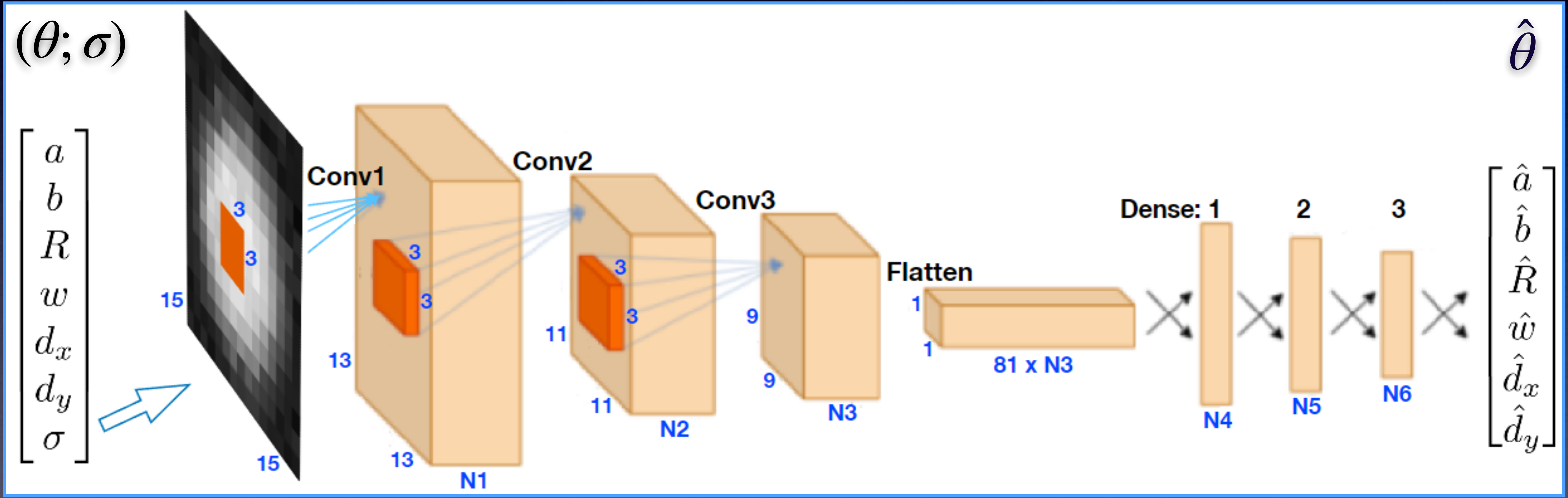
CNN-based lumen parameters estimation [21,13]

Transfer learning

A set of 2D images is computed

$$I_m = I(m, \theta_m, \sigma), \quad m \in \{1,...,M\}$$

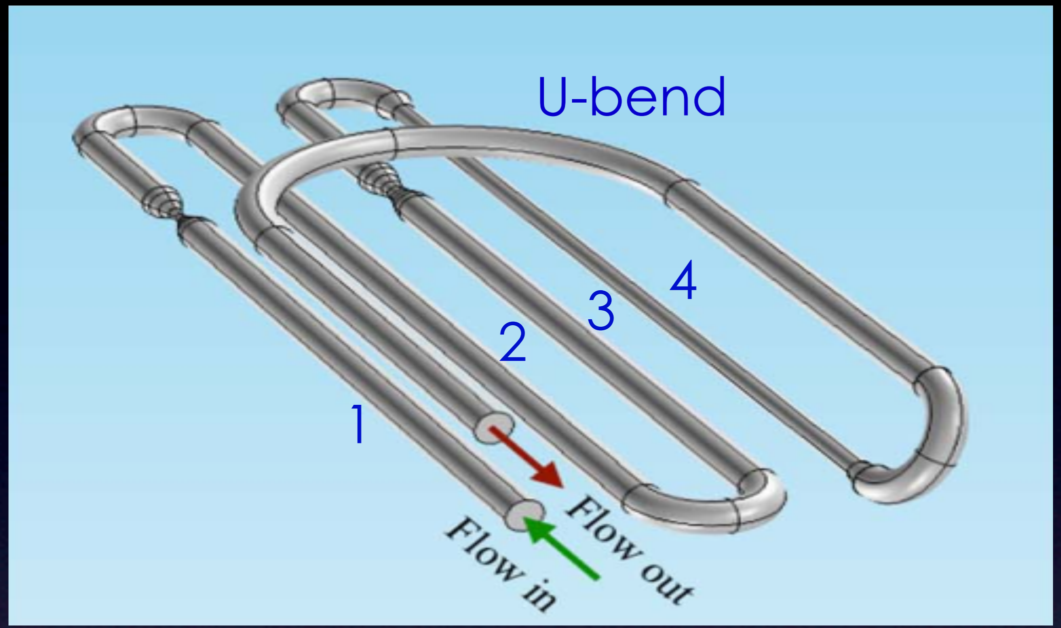
for known model parameters θ_m and noise standard deviation σ.



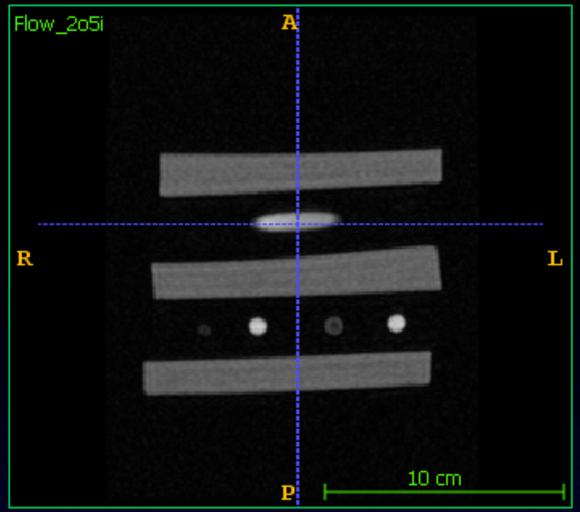
N1, …, N6 - channels count

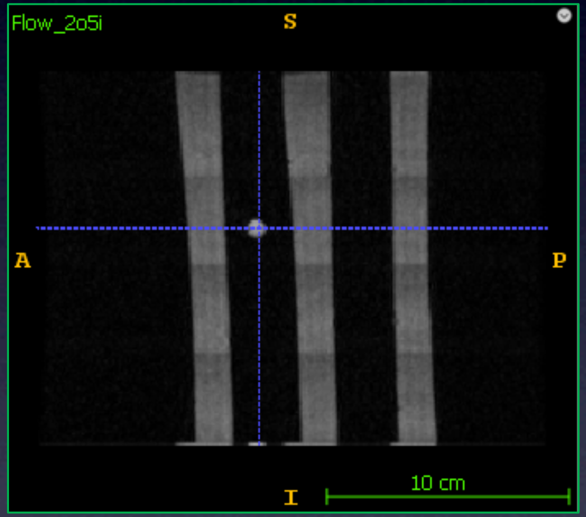
Example 1

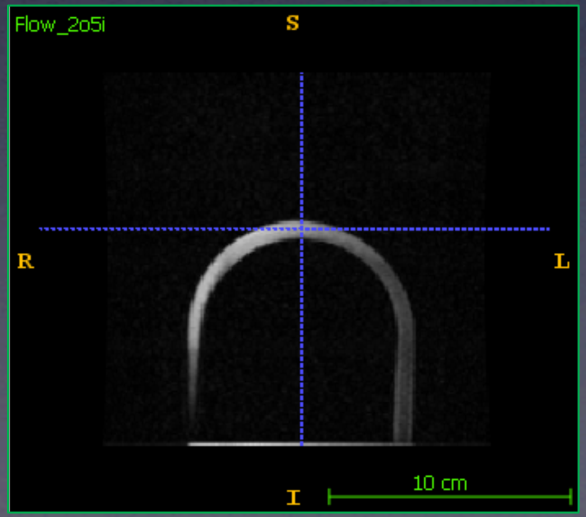
Blood-flow phantom 3D ToF MRI [14]



U-bend pipe inner radius: 4 mm

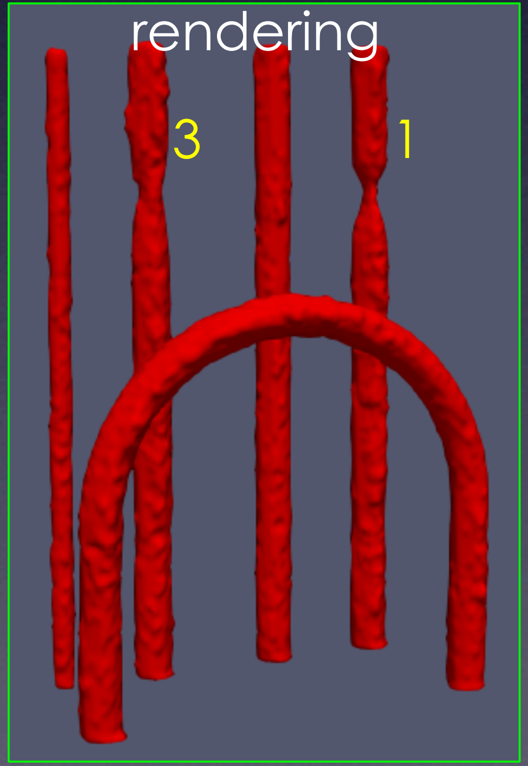




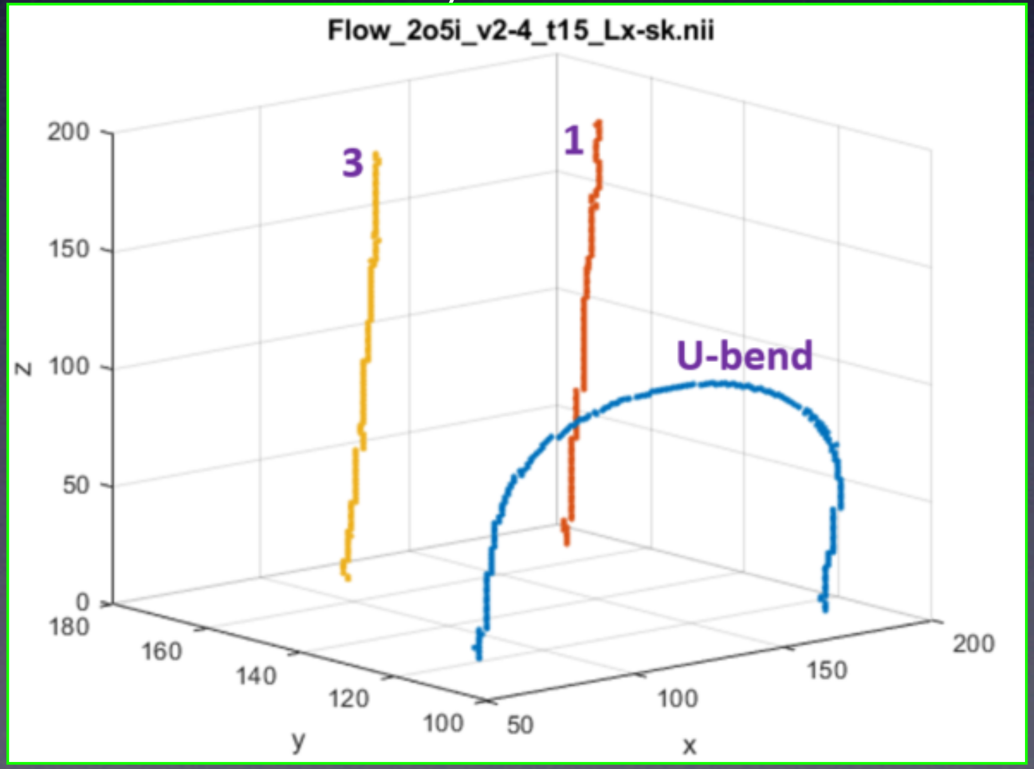


- MR-QA123 Quality Assurance Flow Phantom Set (Shelley)
- CardioFlow 1000 MR pump, 2.5 ml/s
- GE Signa HDxt 1.5 T scanner
- estimated *PSNR* = 30 dB
- voxels: 0.82mm x 0.82mm x 1.01mm

3D segmentation rendering



Binary skeletons



Results [21]

Blood-flow phantom ToF MRA

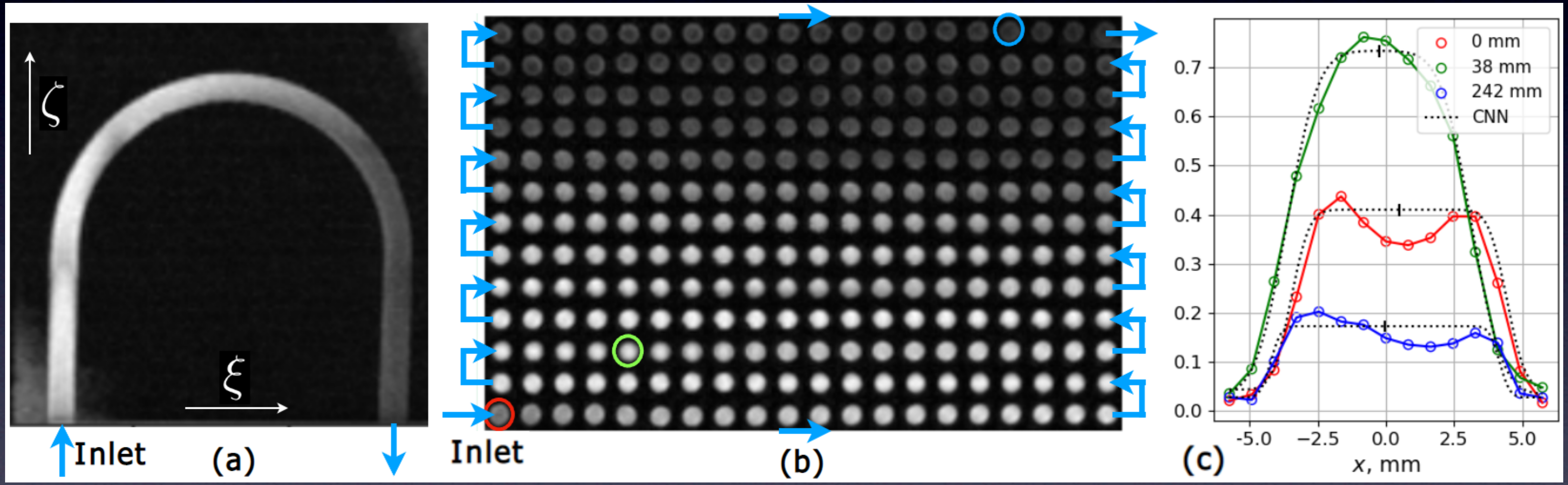
PC, MS Windows 11
16GB RAM, Intel™ i5-8300H CPU @ 2300 MHz
NVIDIA GeForce GTX 1050, 4GB GPU
Keras and *Scipy* Python libraries

Image simulation
for transfer learning

$$0 \le a \le 0.3$$
$$0.1 \le b \le 1.1$$
$$1 \le R/\Delta_s \le 6$$
$$0.3 \le w/\Delta_s \le 1.5$$
$$-1.2 \le d_x/\Delta_s \le 1.2$$
$$-1.2 \le d_y/\Delta_s \le 1.2$$
$$\sigma \approx 0.032$$

M = 60 000 (training set)
M_V = 20 000 (validation set)
M_T = 20 000 (test set)

U-bend MIP image | 260 cross-sections along the centerline | Intensity profiles

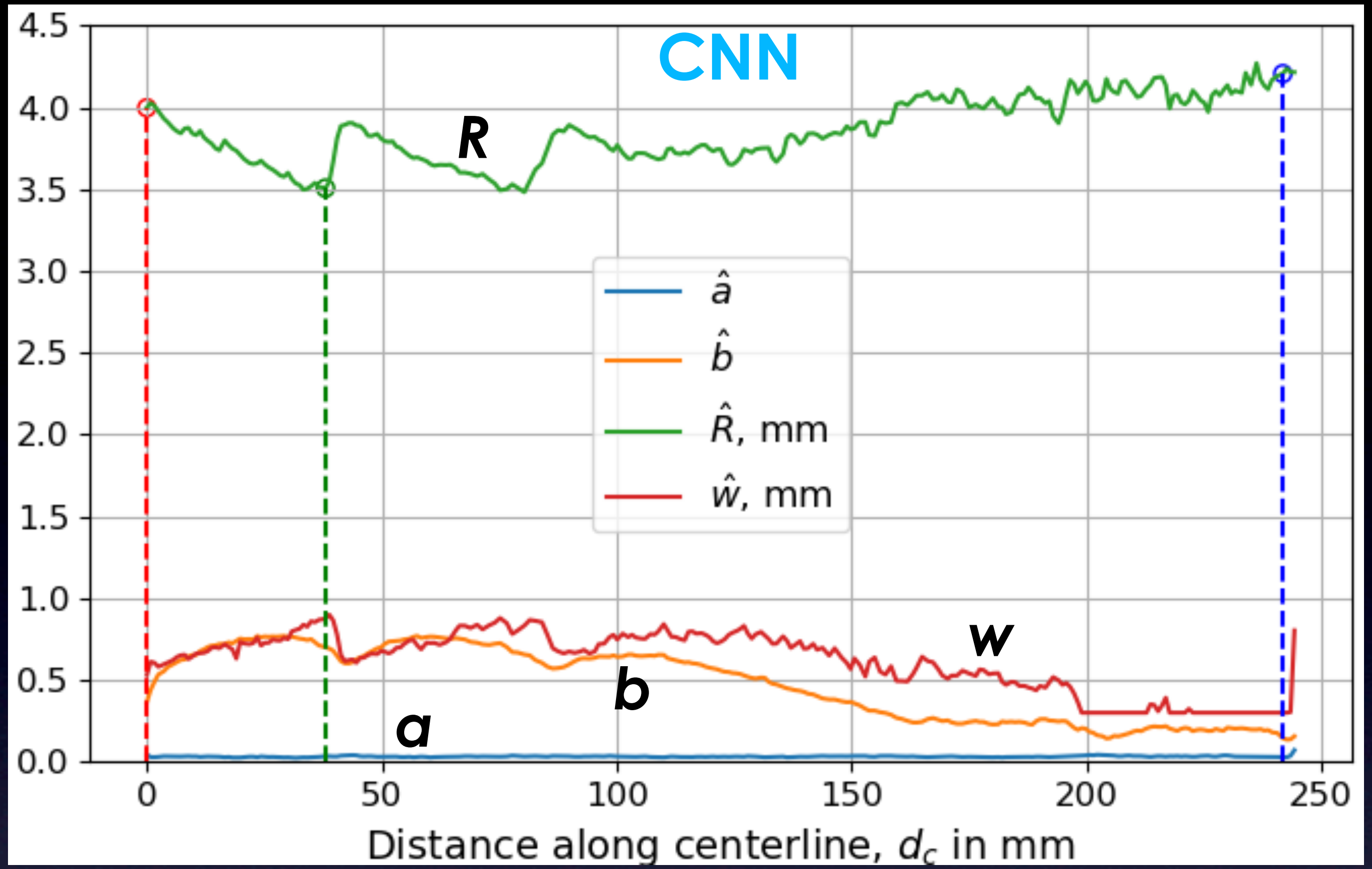


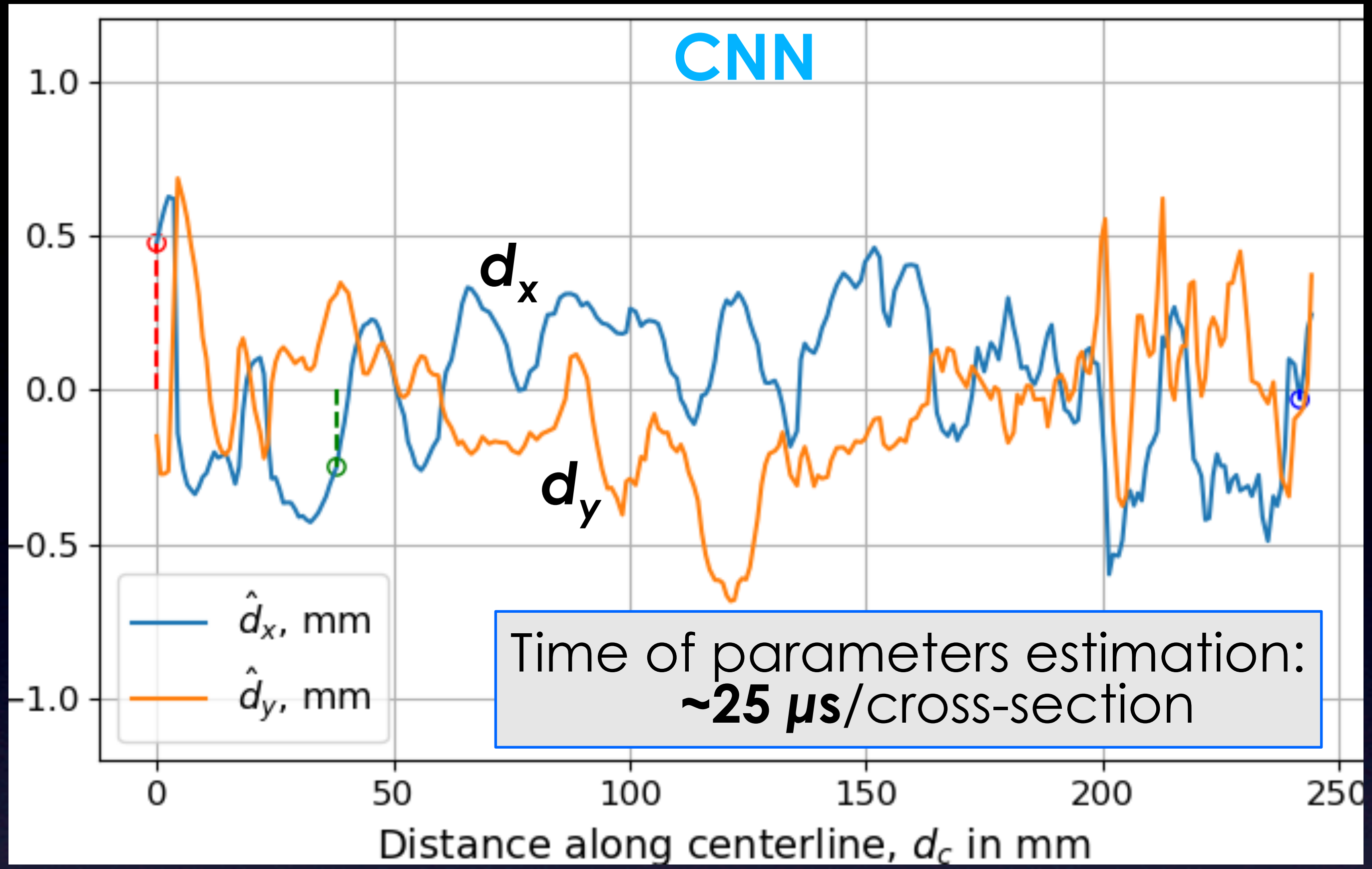
- Adam weight ϕ optimization
- ~1 hr of training up to the time of validation error increase, for a single-parameter output and (32,32,32,32,16,8) CNN channels

The sampling interval
Δ_s = 0.82 mm

Results [21]

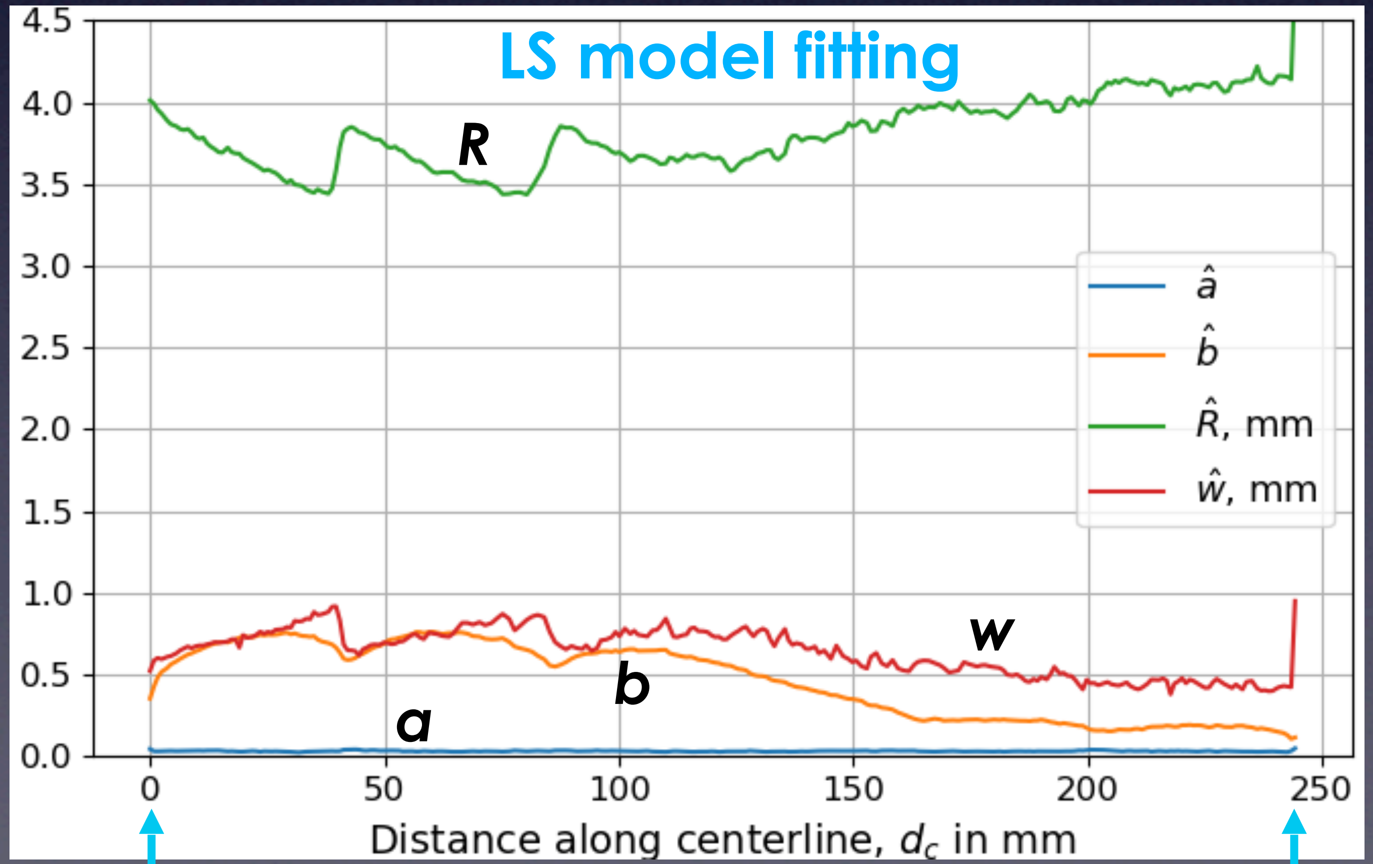
Blood-flow phantom ToF MRA

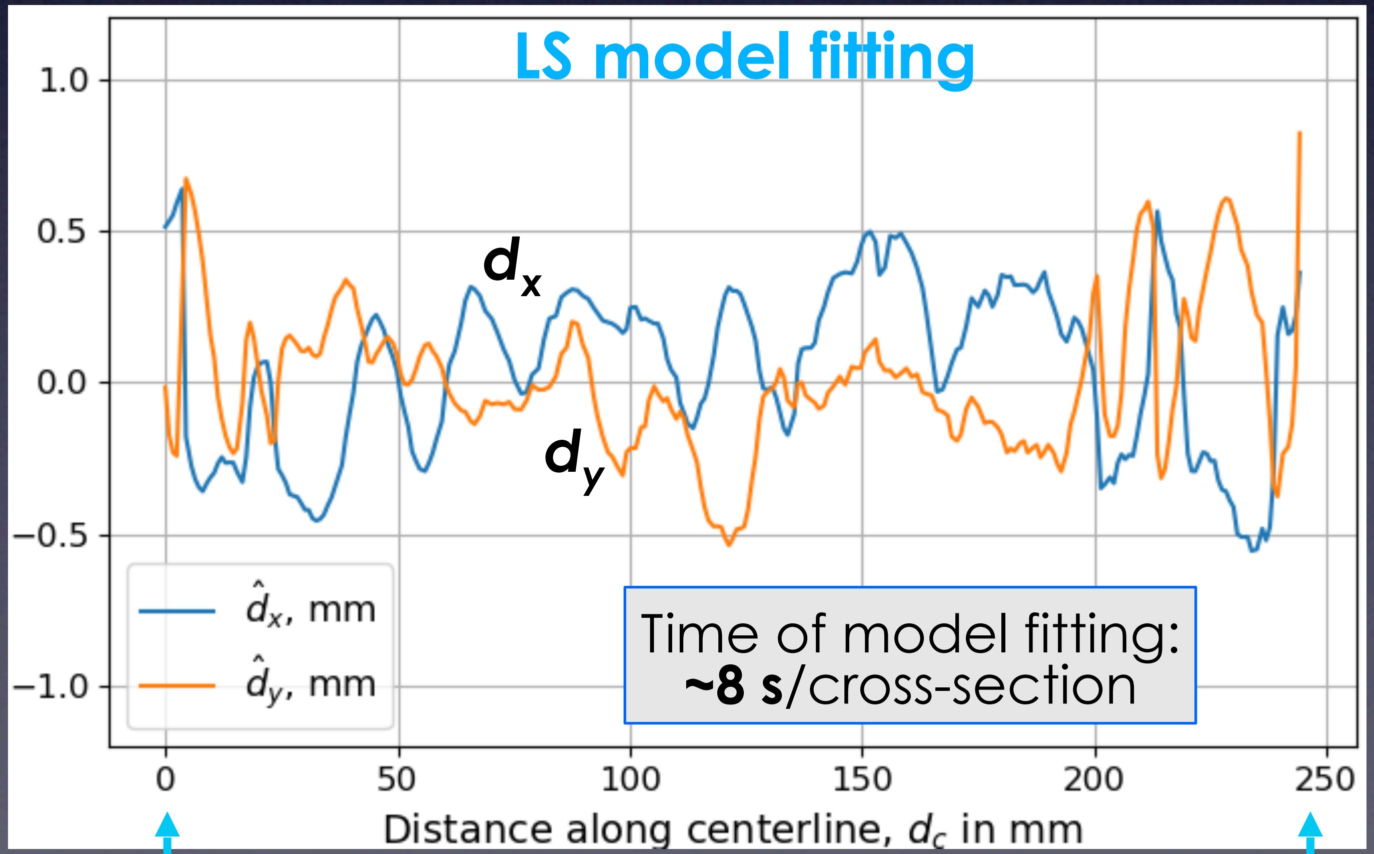




Comparison

- Equally high accuracy
- CNN much faster





Inlet Outlet Inlet Outlet

The sampling interval $\Delta_s = 0.82$ mm

Example 2

Coronary arteries in CE CTA [4,21]

- Rotterdam Coronary Artery Algorithms Evaluation Framework
- 17 datasets annotated by 3 observers
- voxels of different size: e.g. 0.3mm x 0.3mm x 0.4mm, 0.37mm x 0.37mm x 0.45mm, 0.43mm x 0.43mm x 0.25mm, ...

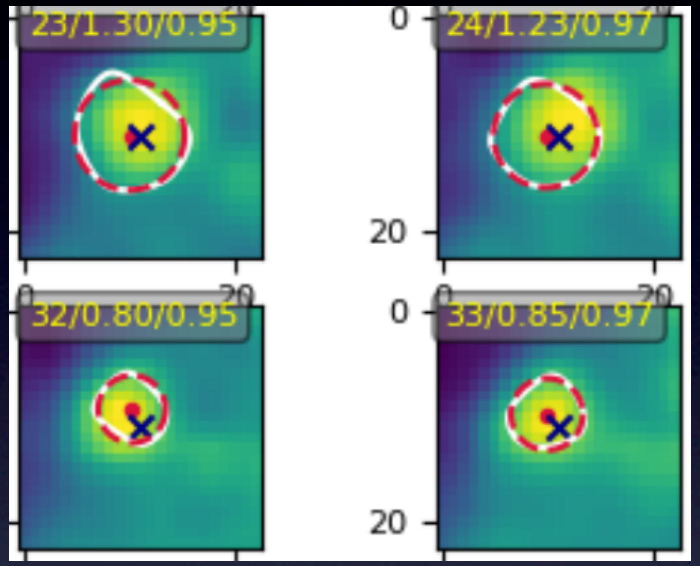
Black cross: centerline intersection point
White line: contour marked by observer
Red dot: center of mass of the contour
Dashed red line: equivalent circle of radius

$$\rho = \sqrt{A/\pi} \qquad (3)$$

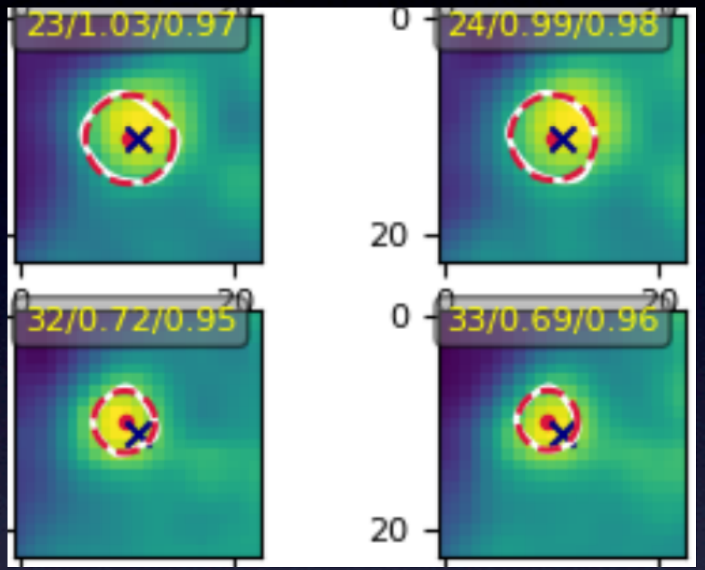
where A is the area inside contour.

Values of (3) were substituted for radius R in (2).

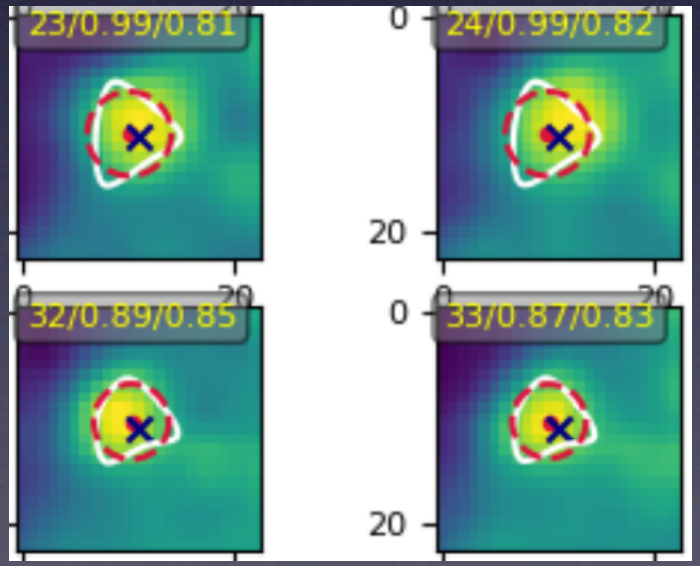
LS model fitting --> errors and excessive computation time.



Observer #1



Observer #2



Observer #3

- The background intensity changes significantly across the image.
- The shape of marked contours differs much between the observers.

Results [21]

Equivalent radius of coronary arteries

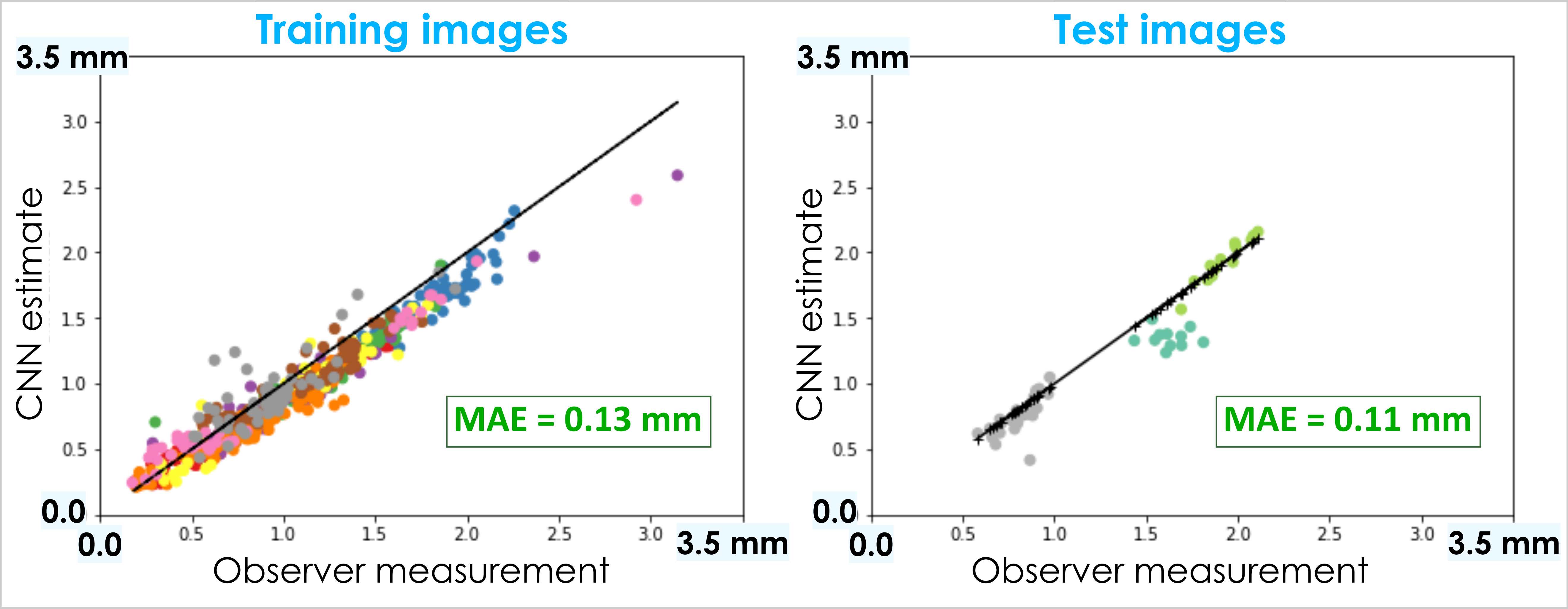
The CNN was trained on real, nonideal images to reduce the estimator sensitivity to spurious objects in the background.

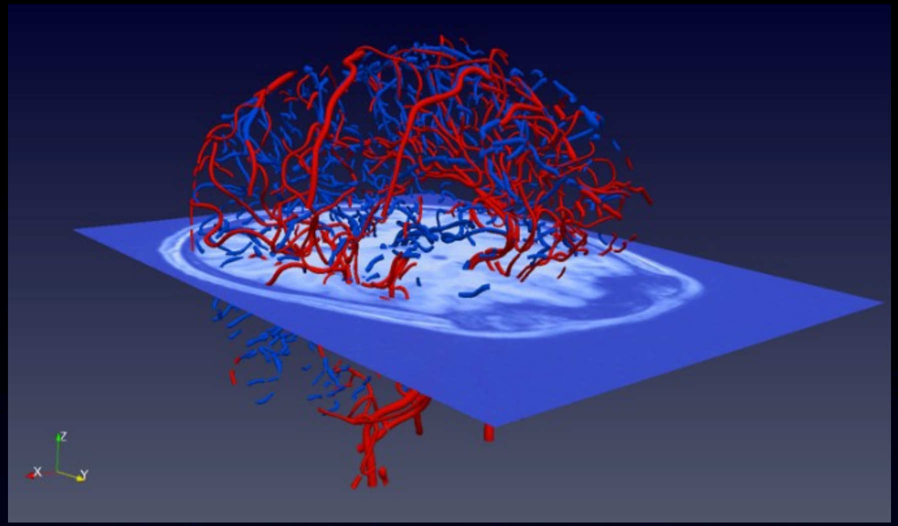
Training set: 558 sections of arteries segments annotated by Observer #1

Test set: 51 sections

The sampling interval
$\Delta_s = 0.45$ mm

Center of mass shift estimation:
MAE < 0.09 mm
(another experiment, not shown here)





Summary

1.Methods involving binary segmentation fail in performing the thin-branches extraction and quantification tasks.

2. Centerline-based image-formation-model fitting offers subvoxel accuracy, robustness to image nonidealities, and modularity for better processing control.

3. The CNN-based model parameters estimation is promising in terms of speed, accuracy, robustness and flexibility.

Future research

Automated 3D blood-vessel image processing methods, taking account of

. vessel centerline tracking [11],
. anatomical markers detection (e.g. ostia),
. non-circular cross-sections (e.g. stenoses),
. denoising,
. superresolution [20].

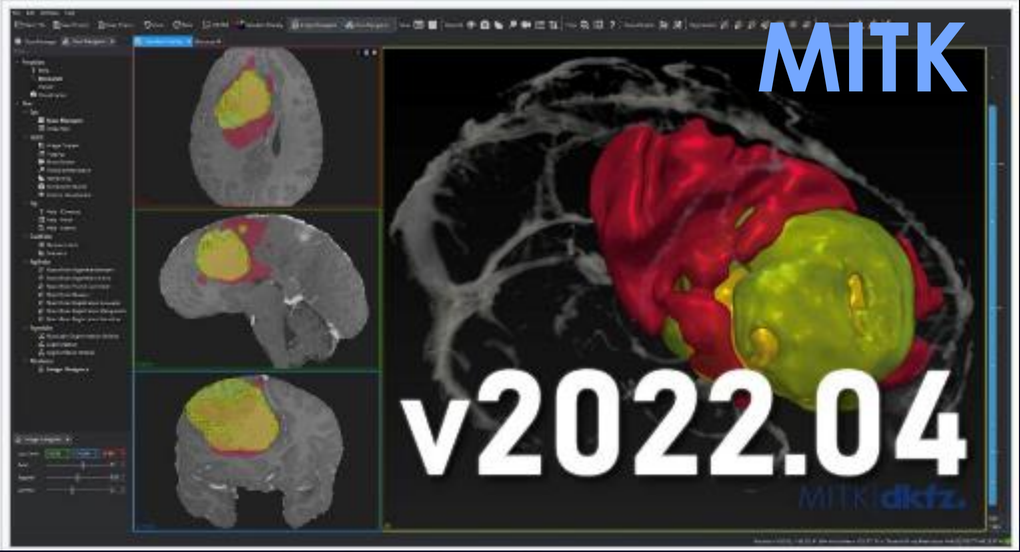
.Multiplatform
.Interactive

Free software (visualization/segmentation/analysis)

itk-SNAP
itksnap.org/
University of Pennsylvania

SimVascular
simvascular.github.io/
Stanford Medicine, Berkeley University of California, QSMSC, NSF, SimTK

MITK v2022.04



mitk.org/
German Cancer Research Center

Convert3D

Harvard University
slicer.org/
3DSlicer

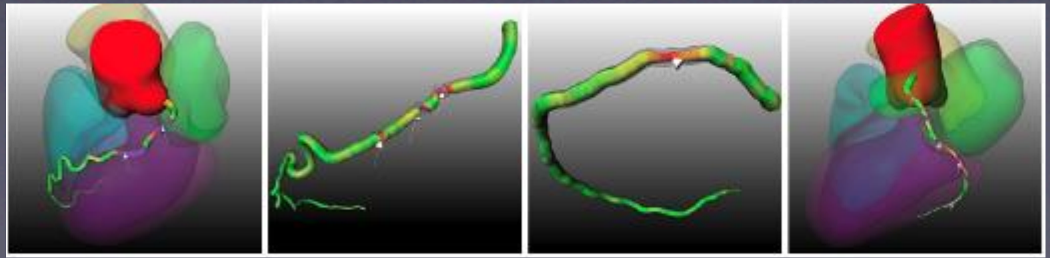
MeshLab
meshlab.net

ParaView
paraview.org/

kitware Glance
kitware.github.io/glance/

Blood-vessel image datasets

Kirisli et al.: Standardized evaluation framework for evaluating coronary artery stenosis detection, stenosis quantification and lumen segmentation algorithms in computed tomography angiography, Medical Image Analysis 17 (2013) 859-876



PAVES
https://paves.grand-challenge.org/

NITRC NeuroImaging Tools & Resources Collaboratory
https://www.nitrc.org/projects/icbmmra/
Magnetic Resonance Angiography Atlas Dataset

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Acknowledgment

The collaboration with

Dr. Artur Klepaczko
Dr. Marek Kociński
Prof. Michał Strzelecki
Prof. Piotr Szczypiński
} *Lodz University of Technology Institute of Electronics*

Dr. Marcin Elgalal
Prof. Agata Majos
} *Medical University of Lodz Department of Radiology*

Dr. Andreas Deistung
Prof. Jürgen R. Reichenbach
} *F. Schiller University in Jena Medical Physics Group*

Prof. Arvid Lundervold } *University of Bergen Department of Biomedicine*

Prof. Carlos Vinhais } *Polytechnic Institute of Porto ISEP School of Engineering*

is much appreciated.

Parts of this work were supported by *Polish National Science Center* under *Grant No. 2013/08/M/ST7/00943*.