

# MOUSE ARTERIAL WALL IMAGING AND ANALYSIS FROM SYNCHROTRON X-RAY MICROTOMOGRAPHY

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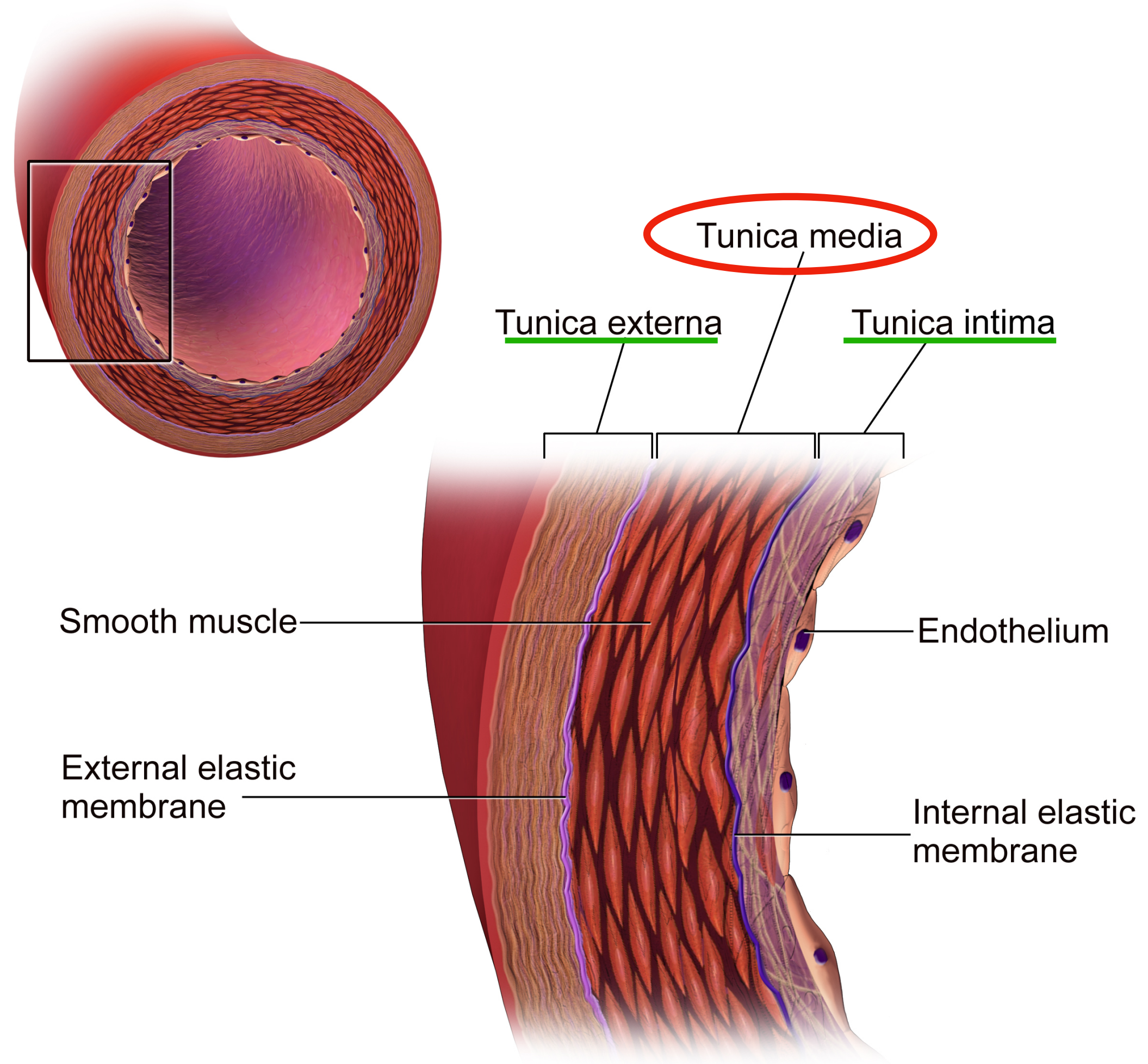
<sup>3</sup>Université de Reims Champagne Ardenne, LICIIS/LRC CEA DIGIT, 51100 Reims, France

<sup>4</sup>Synchrotron SOLEIL, 91192 Gif-sur-Yvette, France

October 19th, 2022

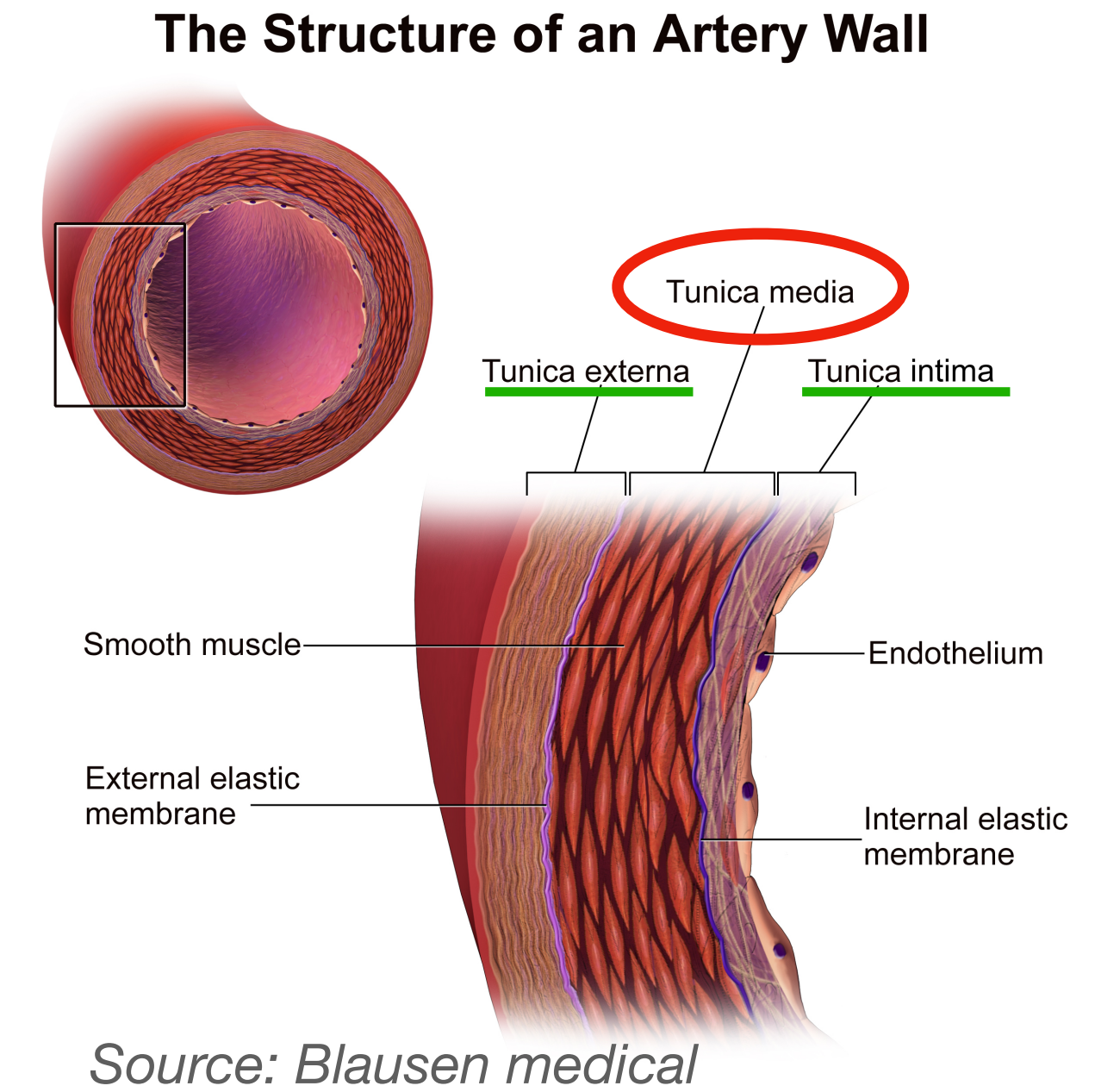
# Introduction

## The Structure of an Artery Wall



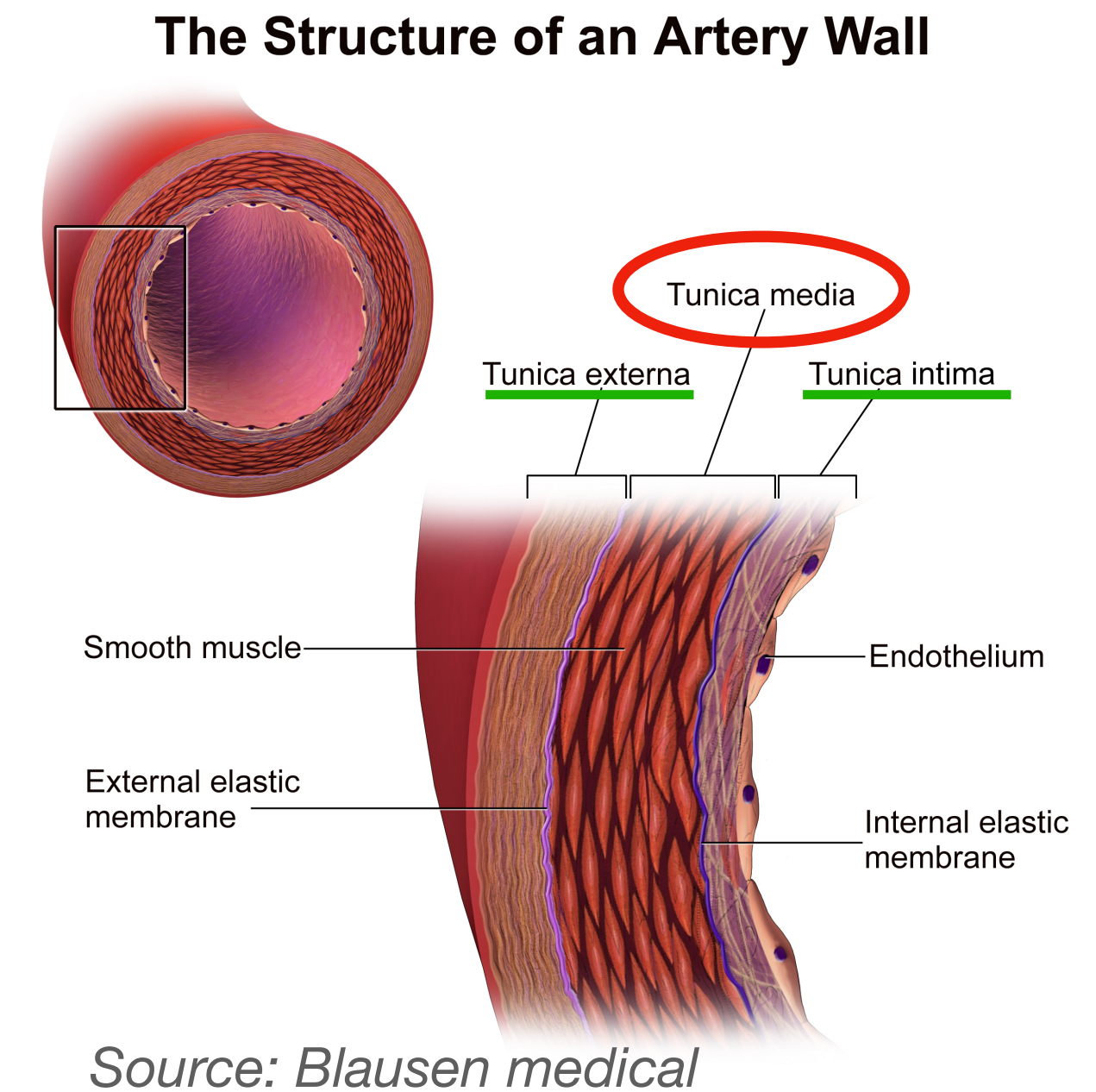
# Introduction

- **Elastic lamellae remodelling** are related to vascular diseases which can be precipitated by metabolic disorders, e.g. diabetes

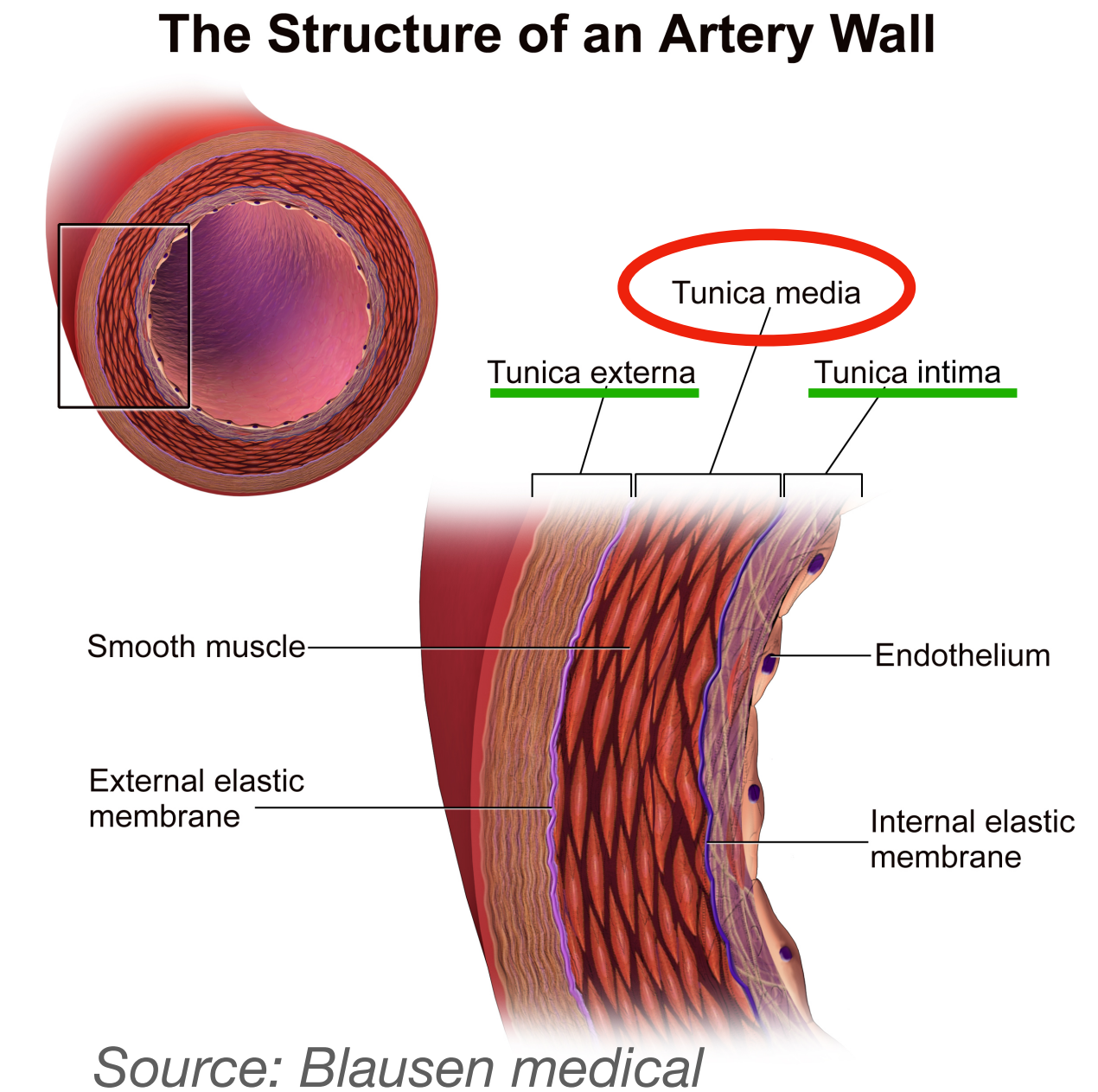


# Introduction

- **Elastic lamellae remodelling** are related to vascular diseases which can be precipitated by metabolic disorders, e.g. diabetes
  - Early identification of the very first stages of these diseases is extremely important to avoid irreversible damages on vessels
  - The proposed segmentation pipeline is a first step towards that goal



# Introduction



- **Elastic lamellae remodelling** are related to vascular diseases which can be precipitated by metabolic disorders, e.g. diabetes
  - Early identification of the very first stages of these diseases is extremely important to avoid irreversible damages on vessels
  - The proposed segmentation pipeline is a first step towards that goal
- **High-resolution synchrotron X-ray microtomography images** of mice aortae are used

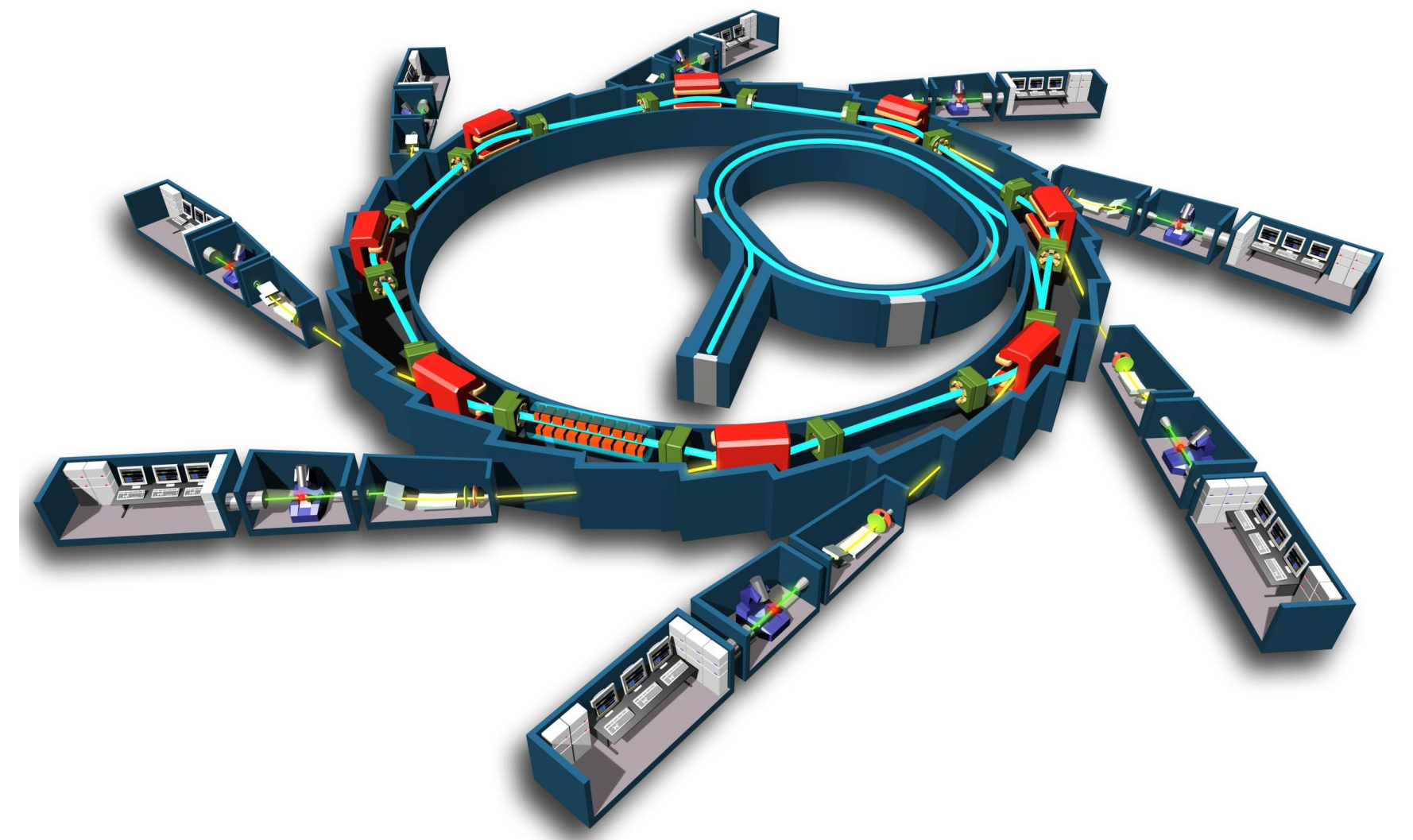
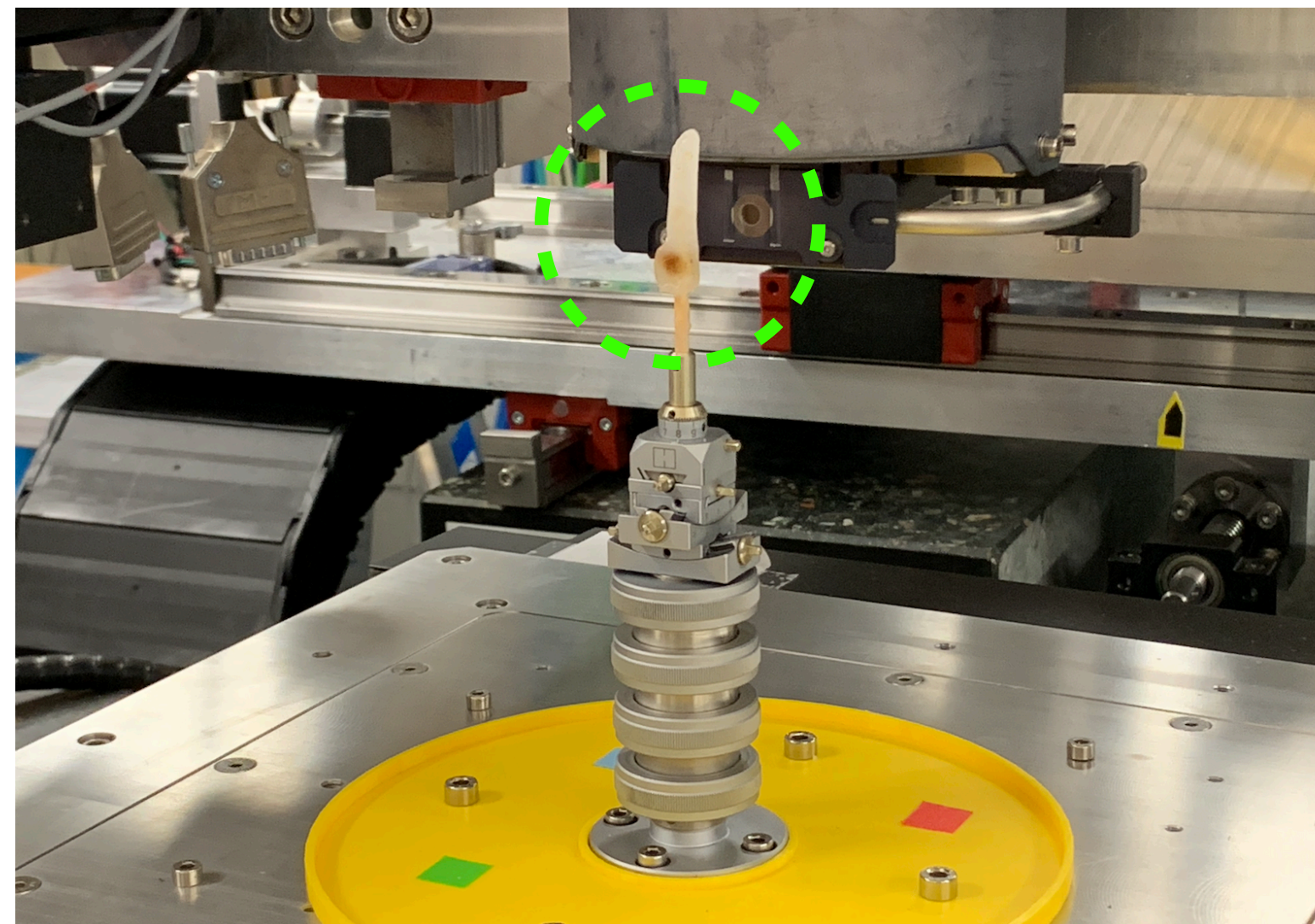
# Acquisition of images

- Tomographic image data acquired on the ANATOMIX beamline of the SOLEIL synchrotron



# Acquisition of images

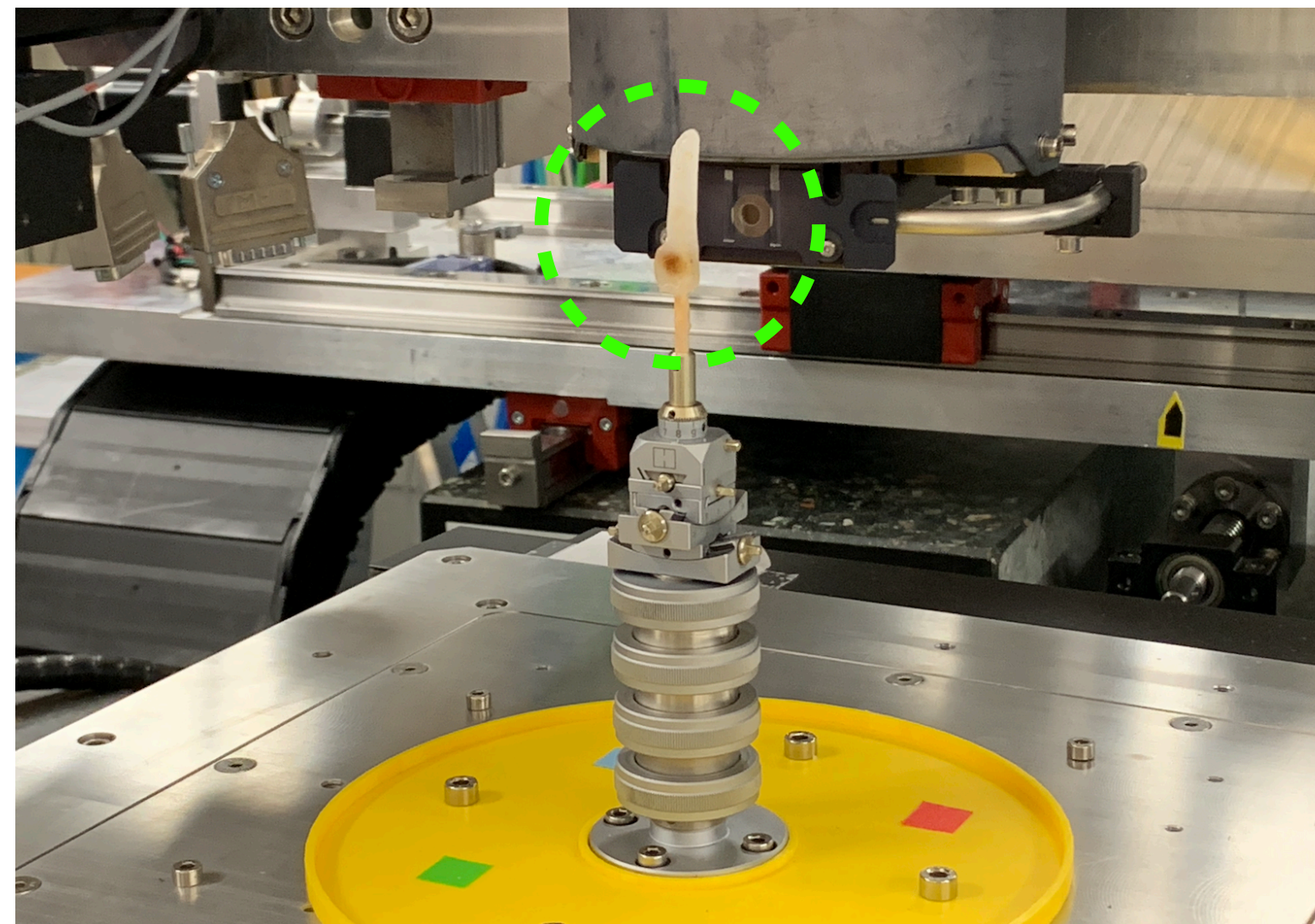
- Tomographic image data acquired on the ANATOMIX beamline of the SOLEIL synchrotron
- Mice aortae divided into 2 groups: **normal** (healthy) and **ill (diabetic)**



Source: <https://fr.wikipedia.org/wiki/SOLEIL>

# Acquisition of images

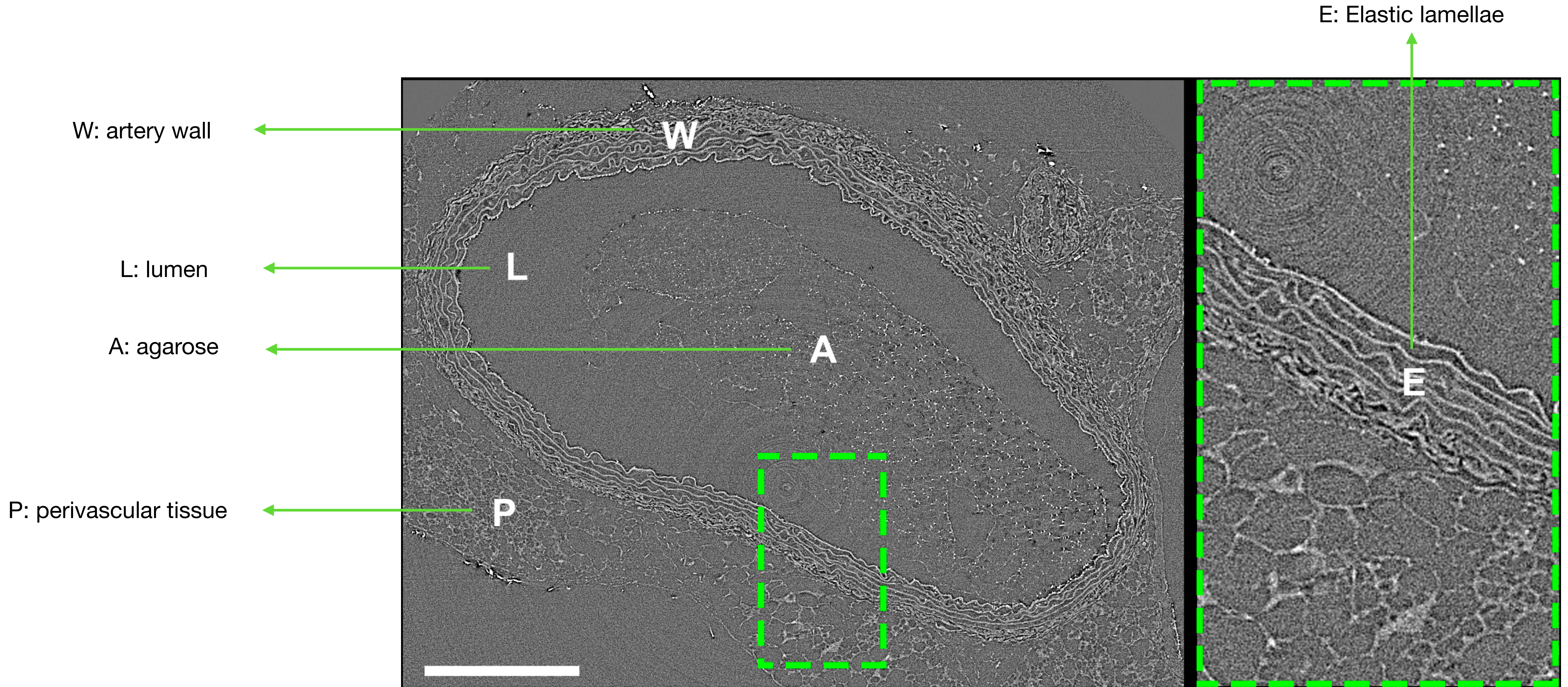
- Tomographic image data acquired on the ANATOMIX beamline of the SOLEIL synchrotron
- Mice aortae divided into 2 groups: **normal** (healthy) and **ill (diabetic)**
- Volume:  $2048^3$  voxels of size  $(0.65\mu m)^3$ 
  - 32 GB per stack



Source: <https://fr.wikipedia.org/wiki/SOLEIL>



# Image of an aorta

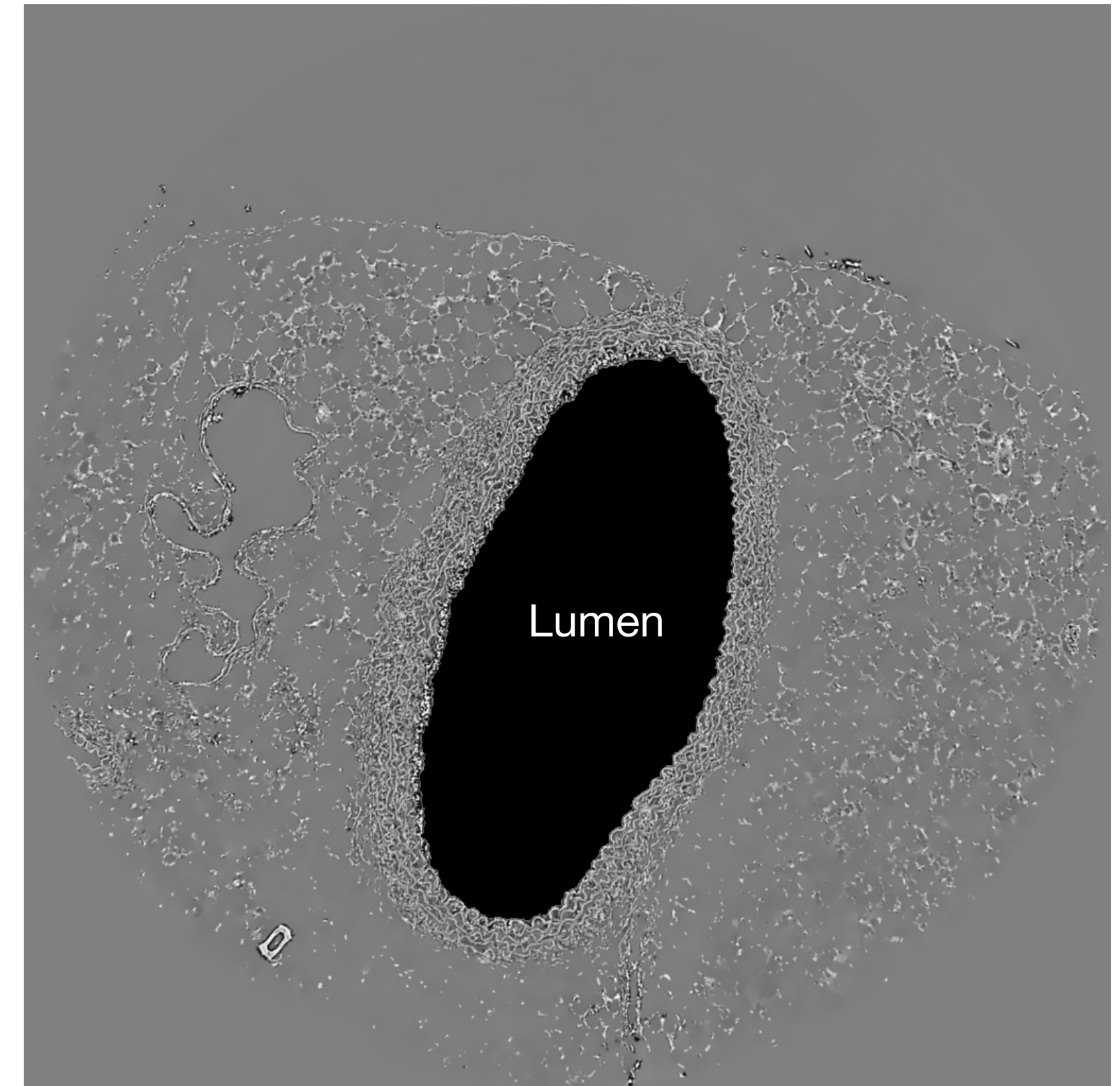
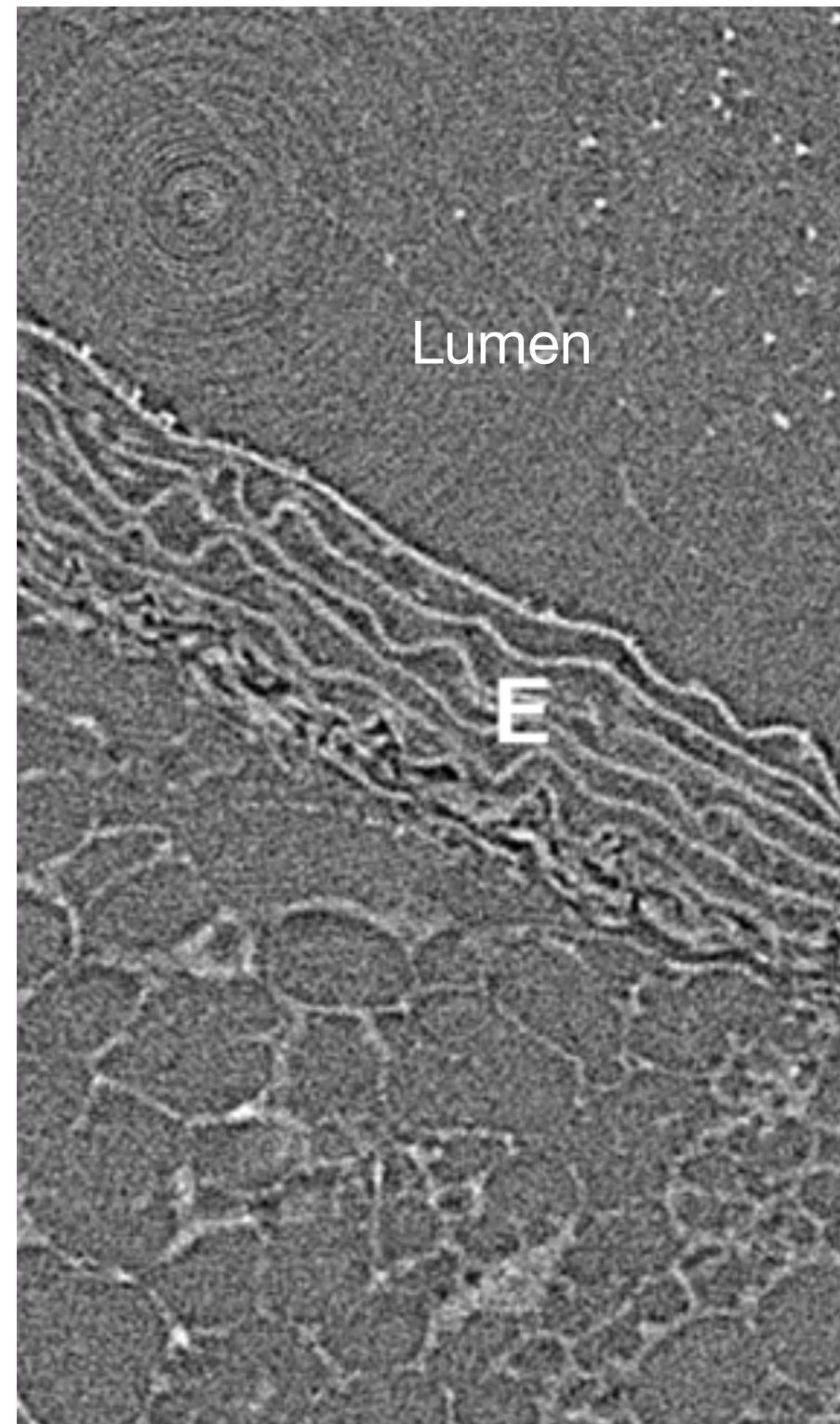


# Pipeline of the segmentation

- Preprocessing: to eliminate noise while highlighting useful details

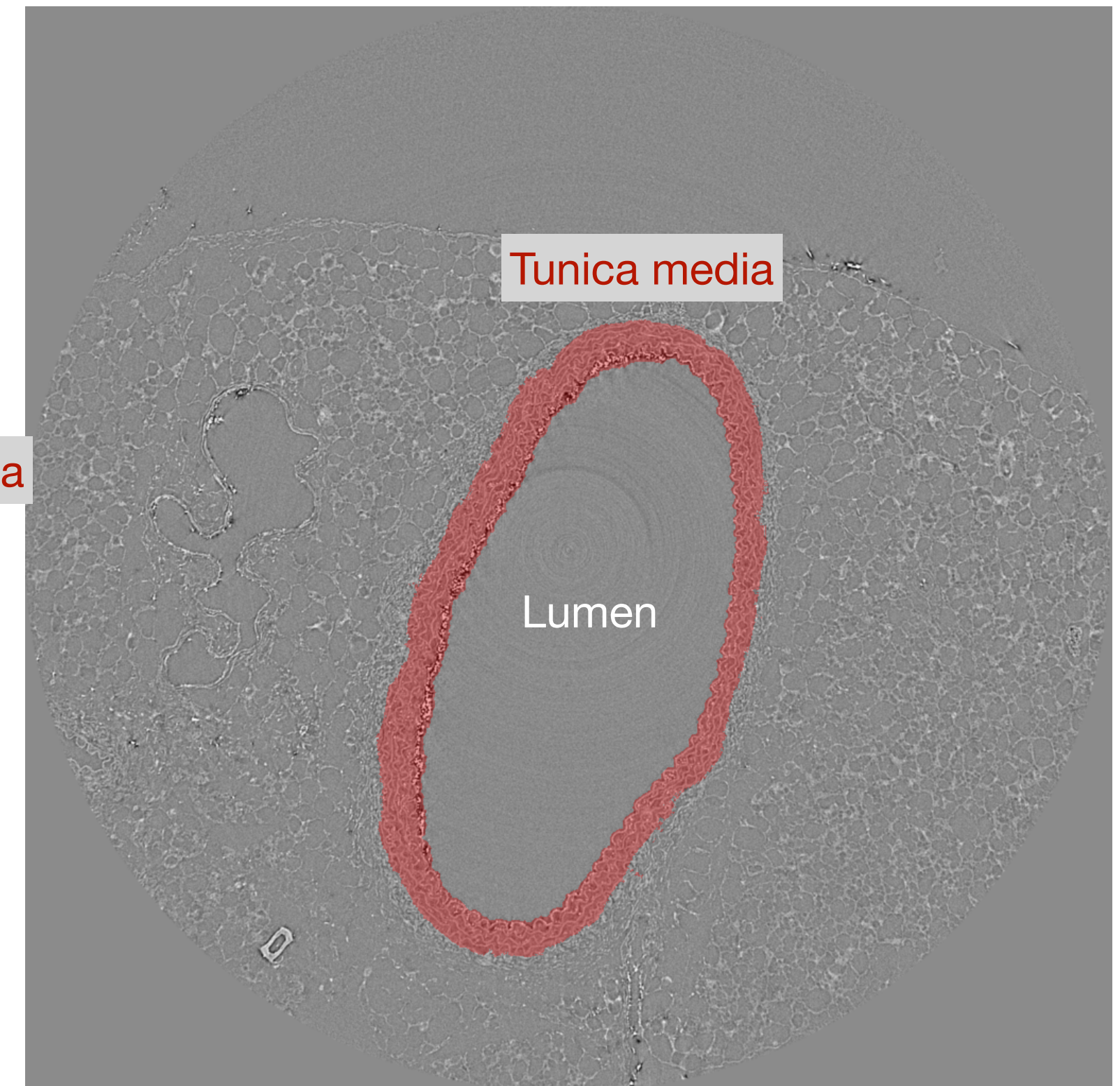
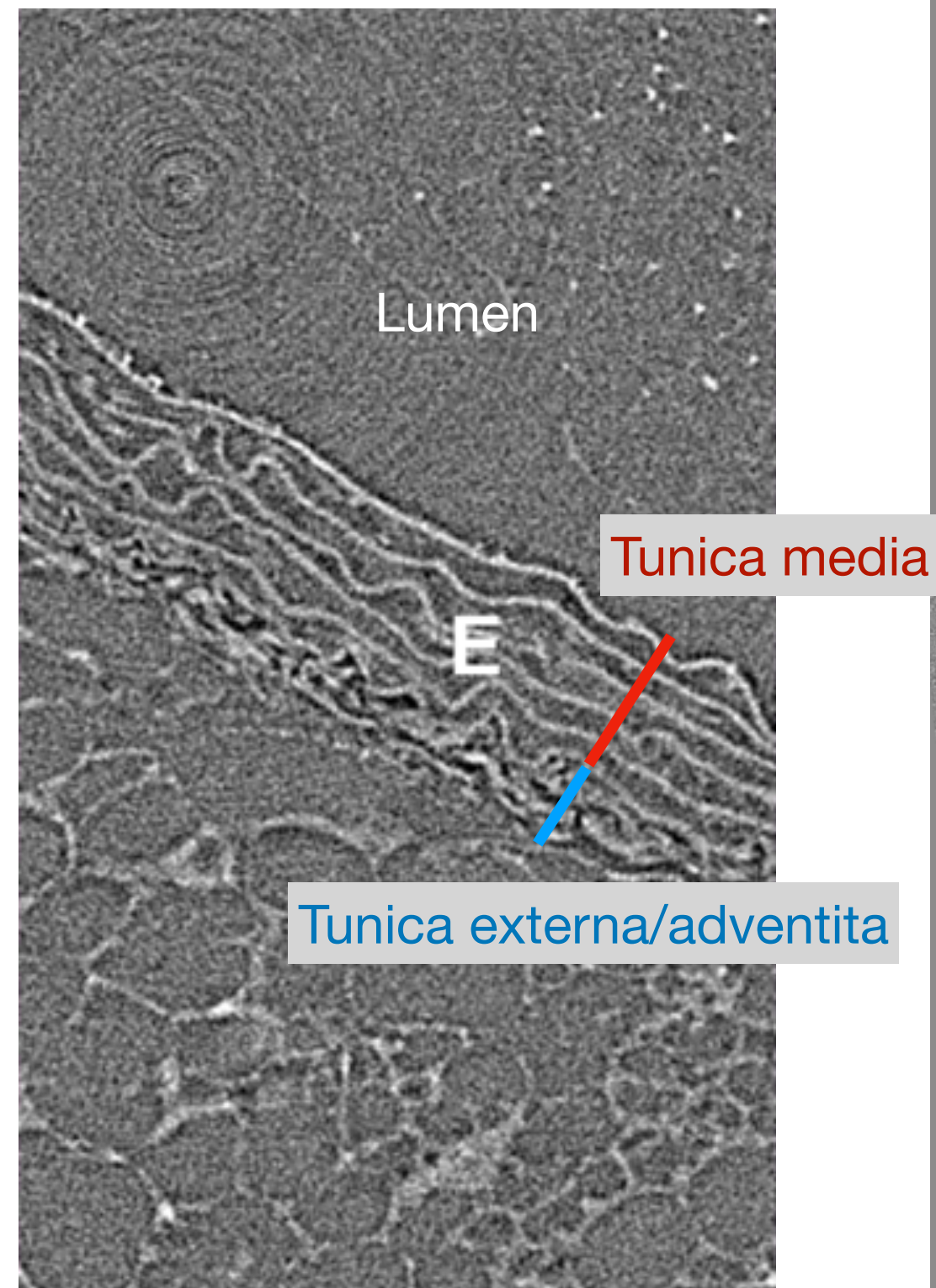
# Pipeline of the segmentation

- Preprocessing: to eliminate noise while highlighting useful details
- Segmentation of the lumen



# Pipeline of the segmentation

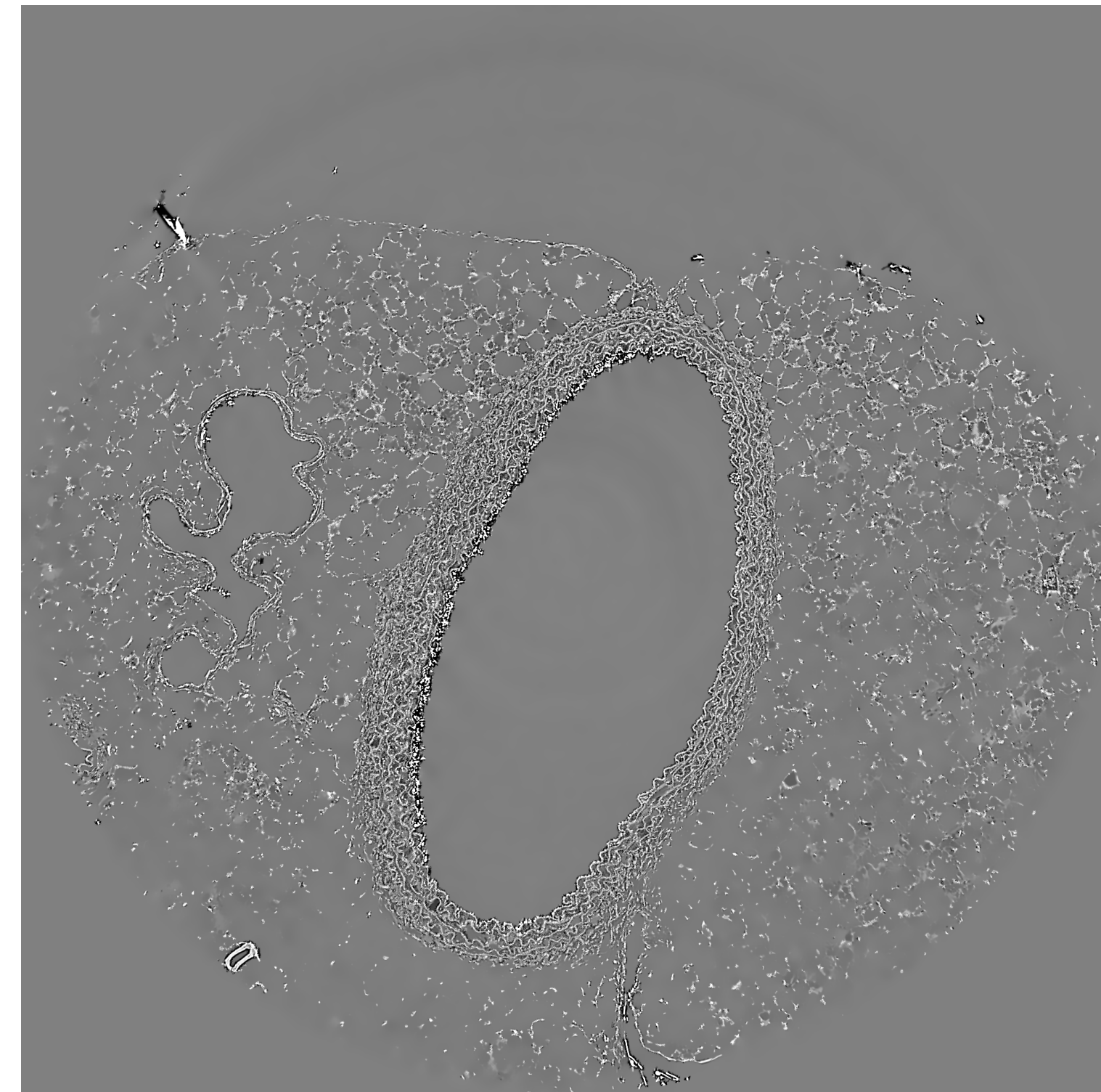
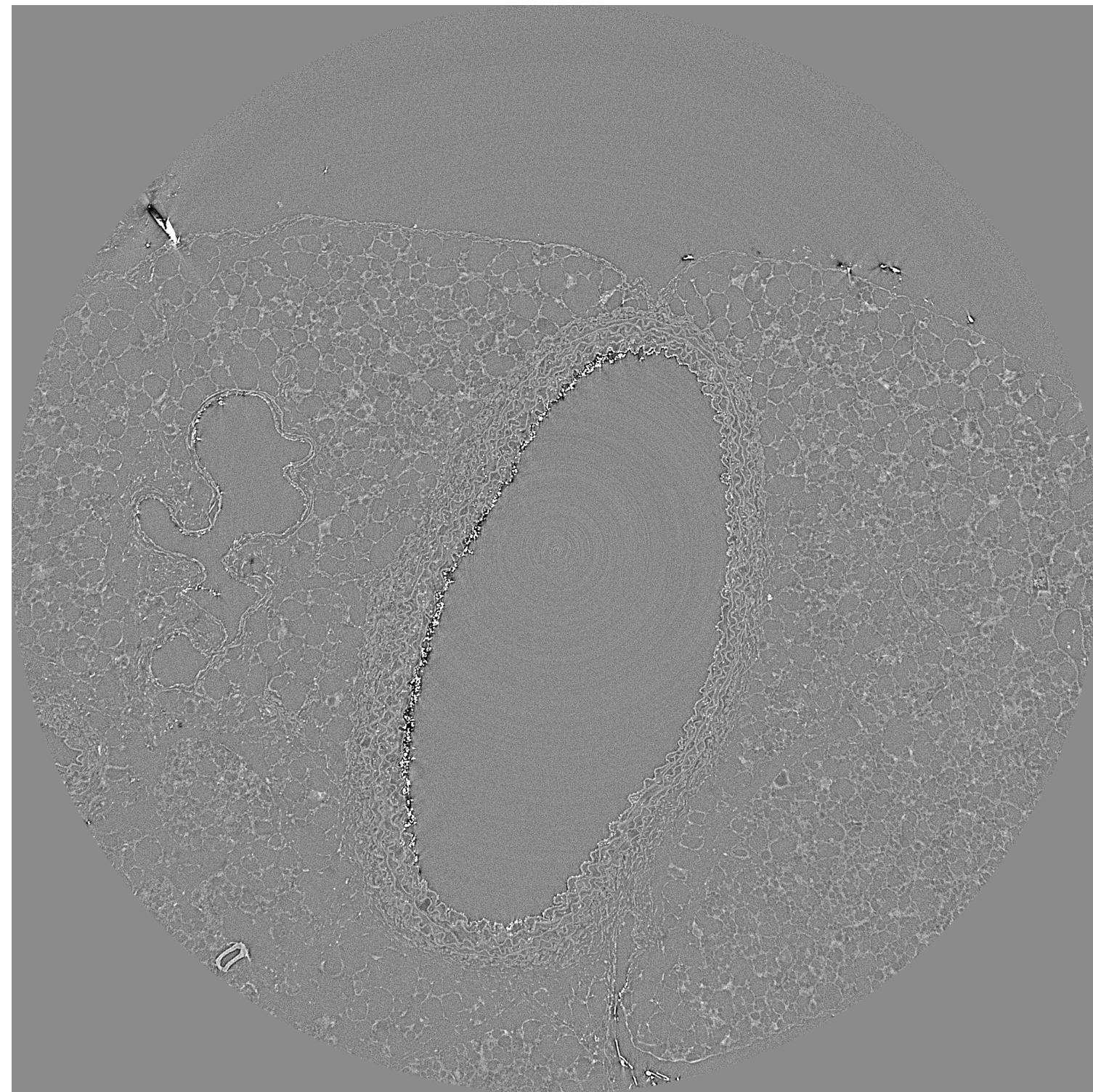
- Preprocessing: to eliminate noise while highlighting useful details
- Segmentation of the lumen
- Texture classification based on deep learning



# Pipeline of the segmentation

## Preprocessing

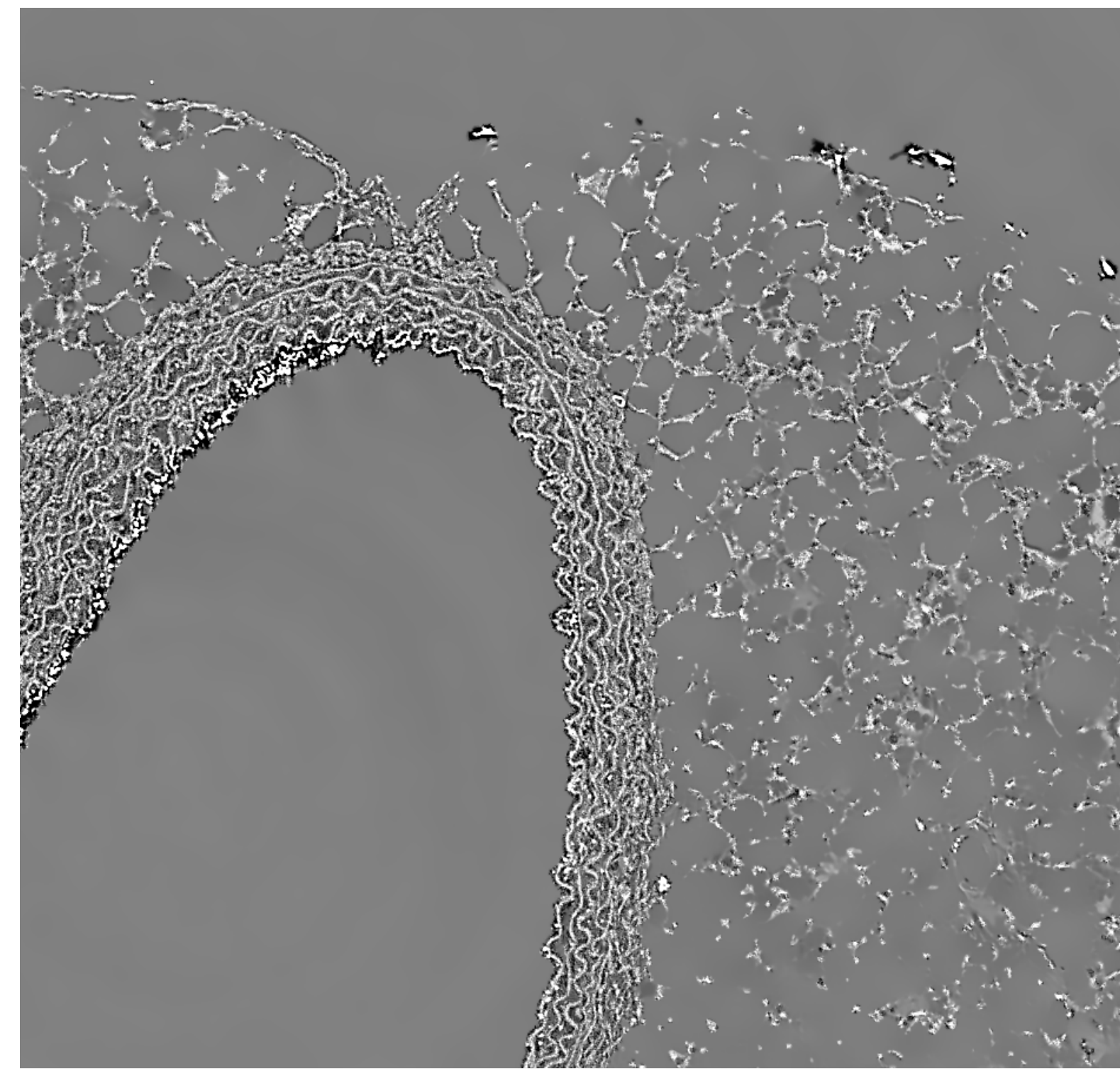
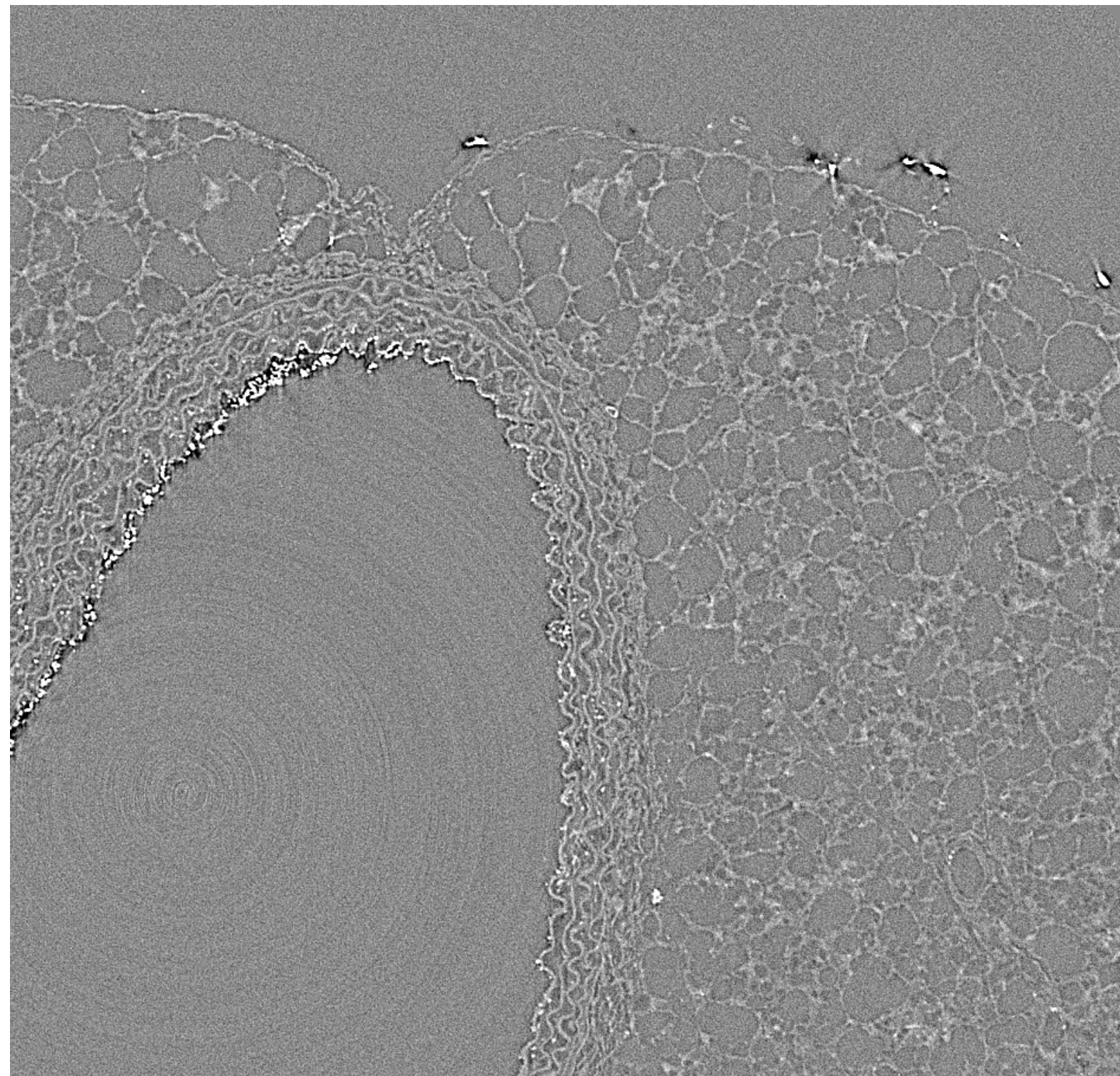
- Bilateral filtering + Contrast enhancement + Non-local means filtering



# Pipeline of the segmentation

## Preprocessing

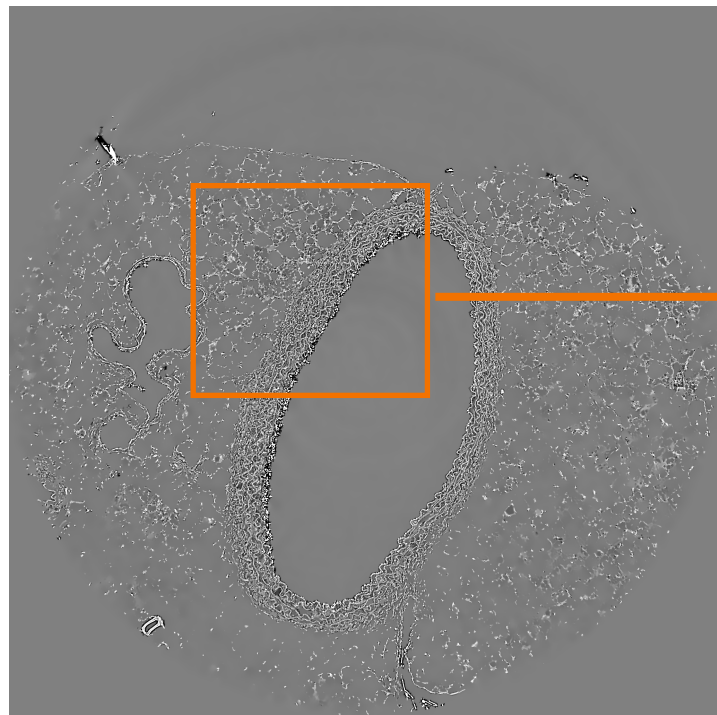
- Bilateral filtering + Contrast enhancement + Non-local means filtering



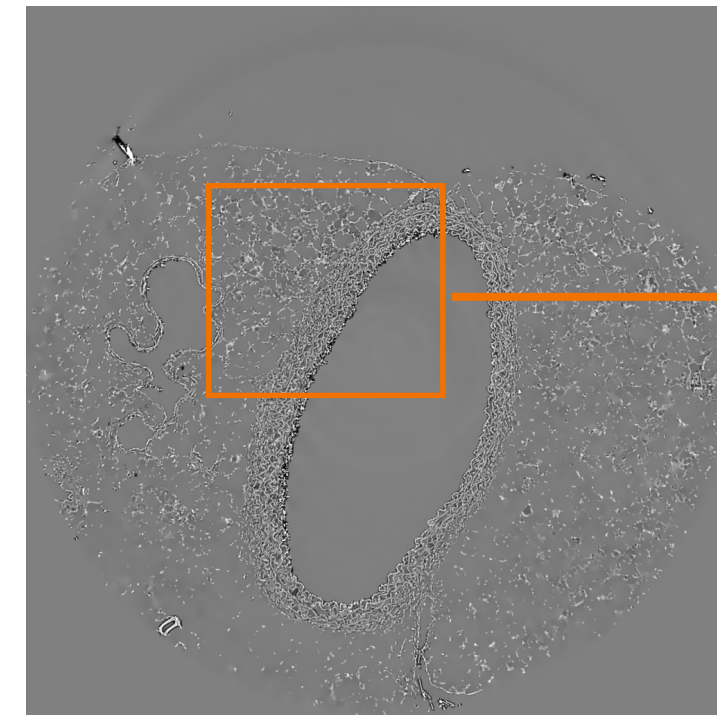
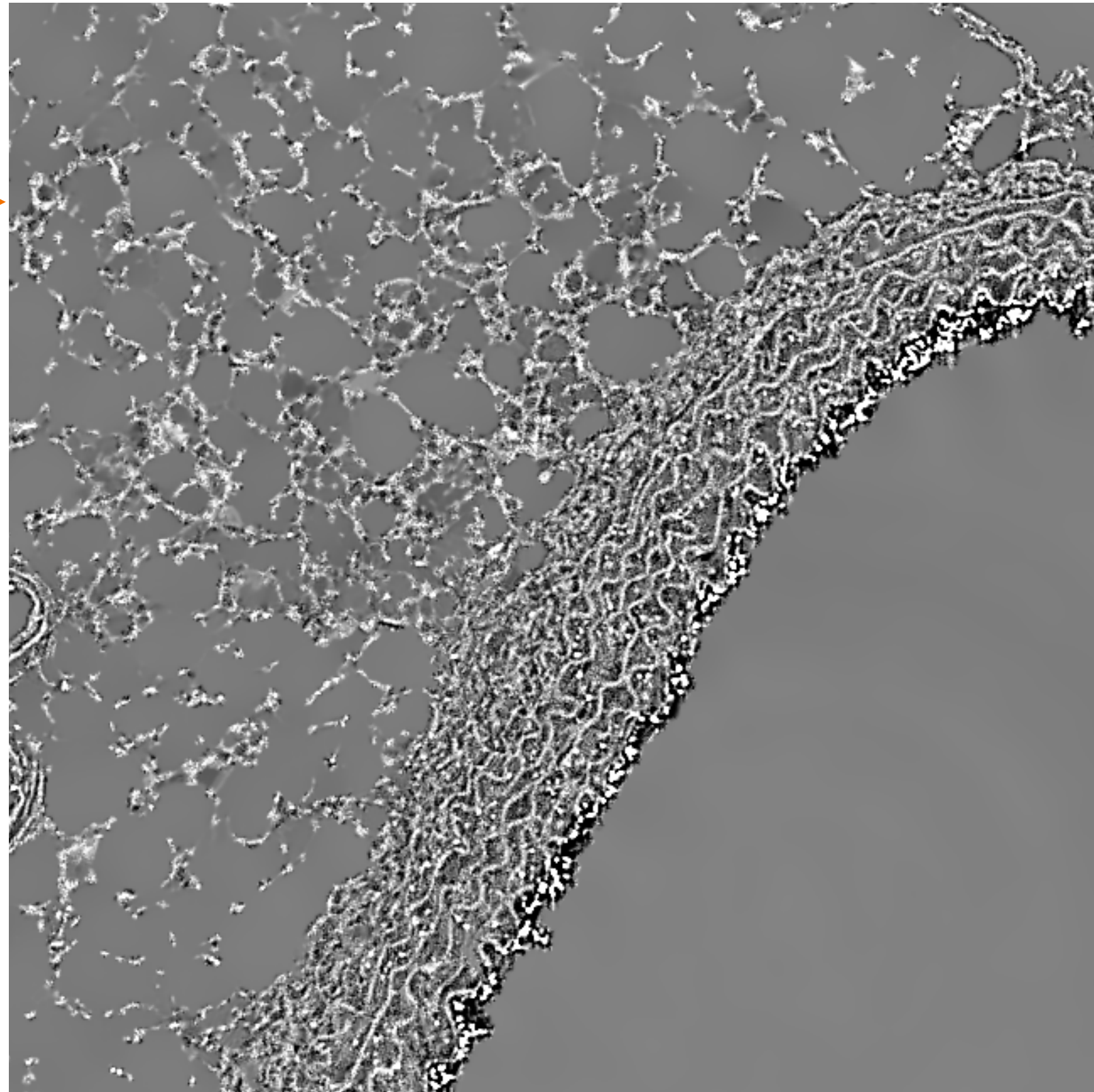
# Pipeline of the segmentation

## Segmentation of the lumen

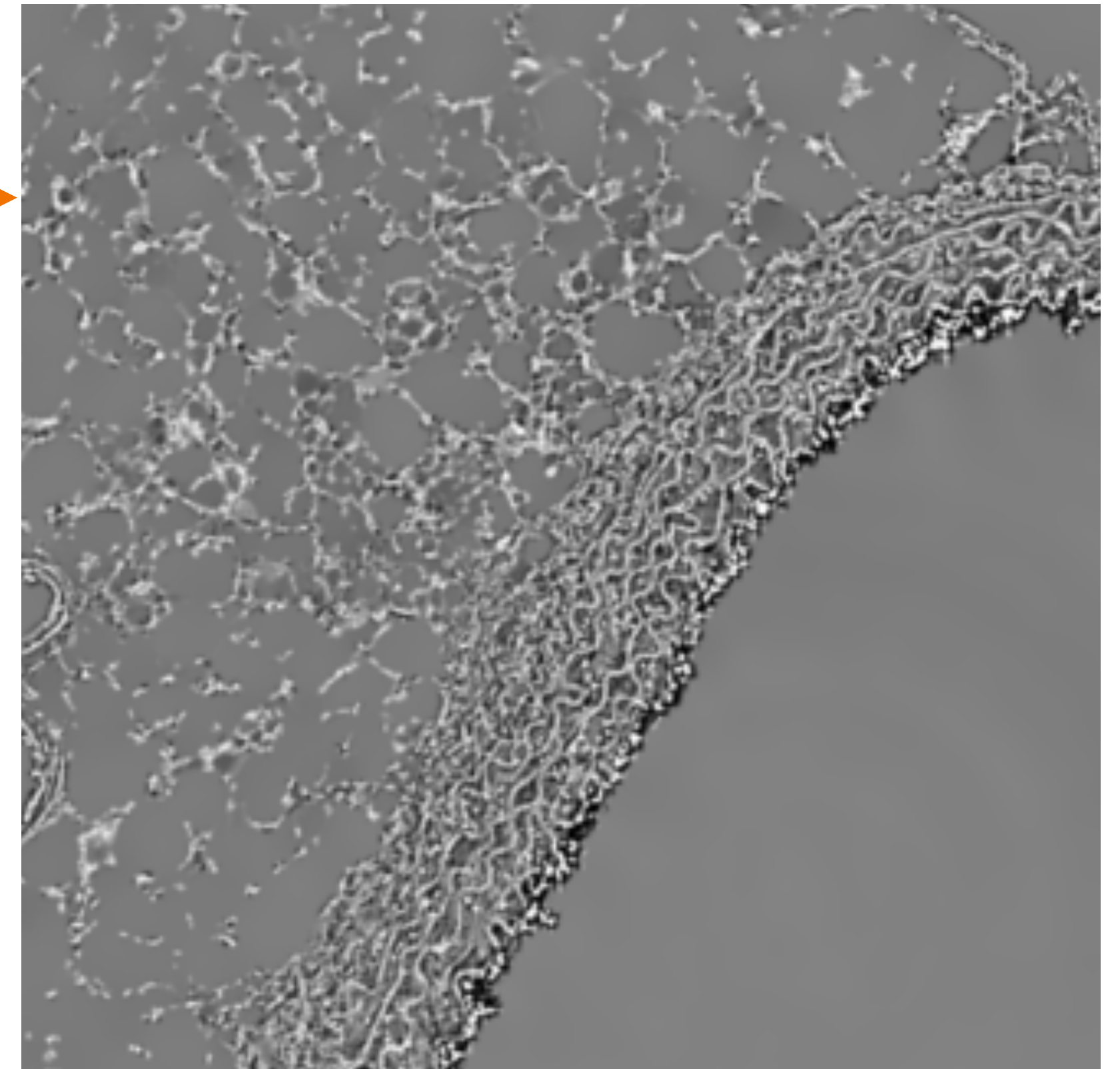
- Rescaling images according to a Gaussian scale-space paradigm



2048\*2048



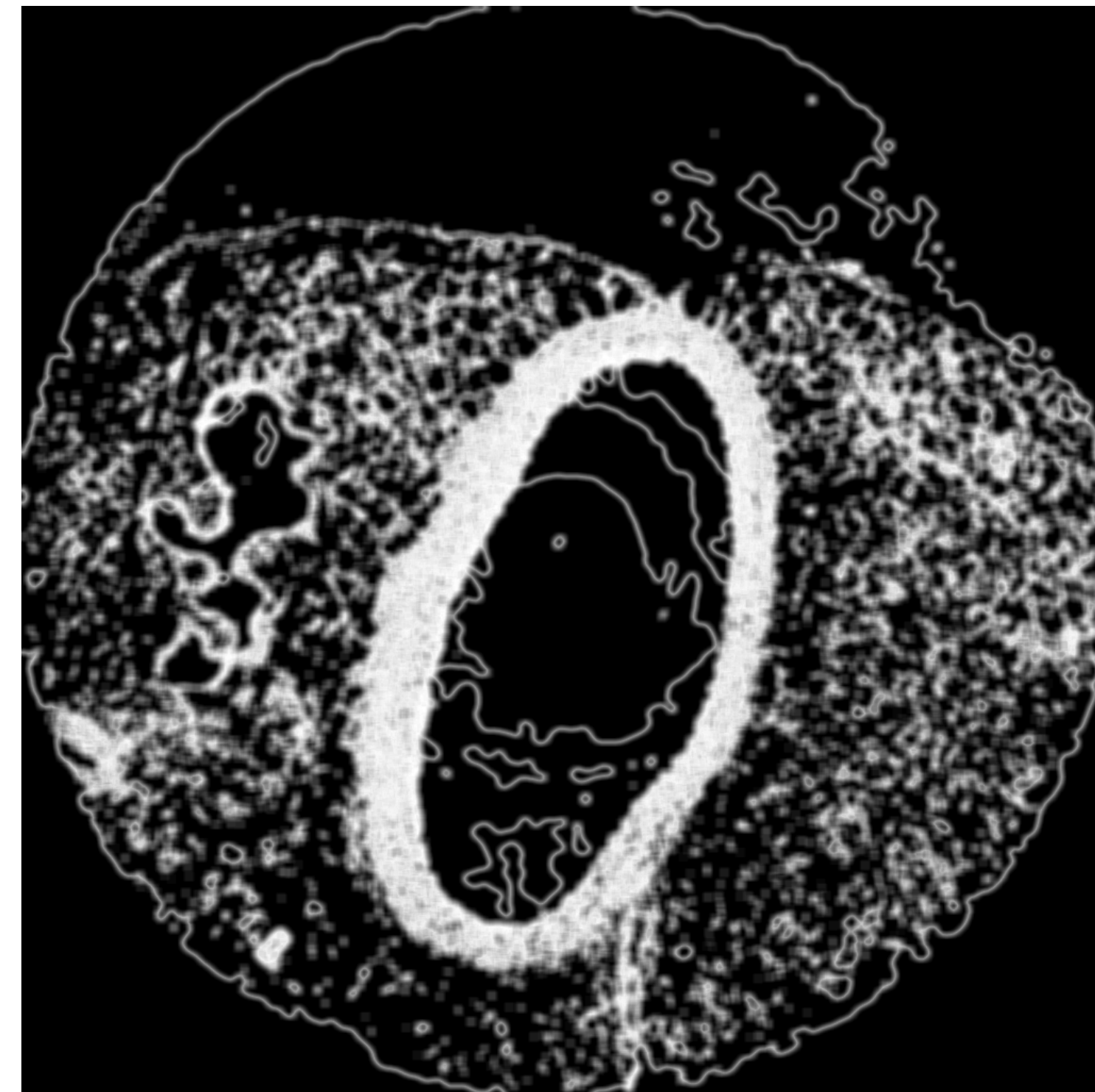
1024\*1024



# Pipeline of the segmentation

## Segmentation of the lumen

- Co-occurrence matrix for each pixel  $x$ :  $M(x) \in \mathcal{M}_{8 \times 8}(\mathbb{N})$  with pixel values quantified to 8 bins
- $F(x) = \max M(x)$

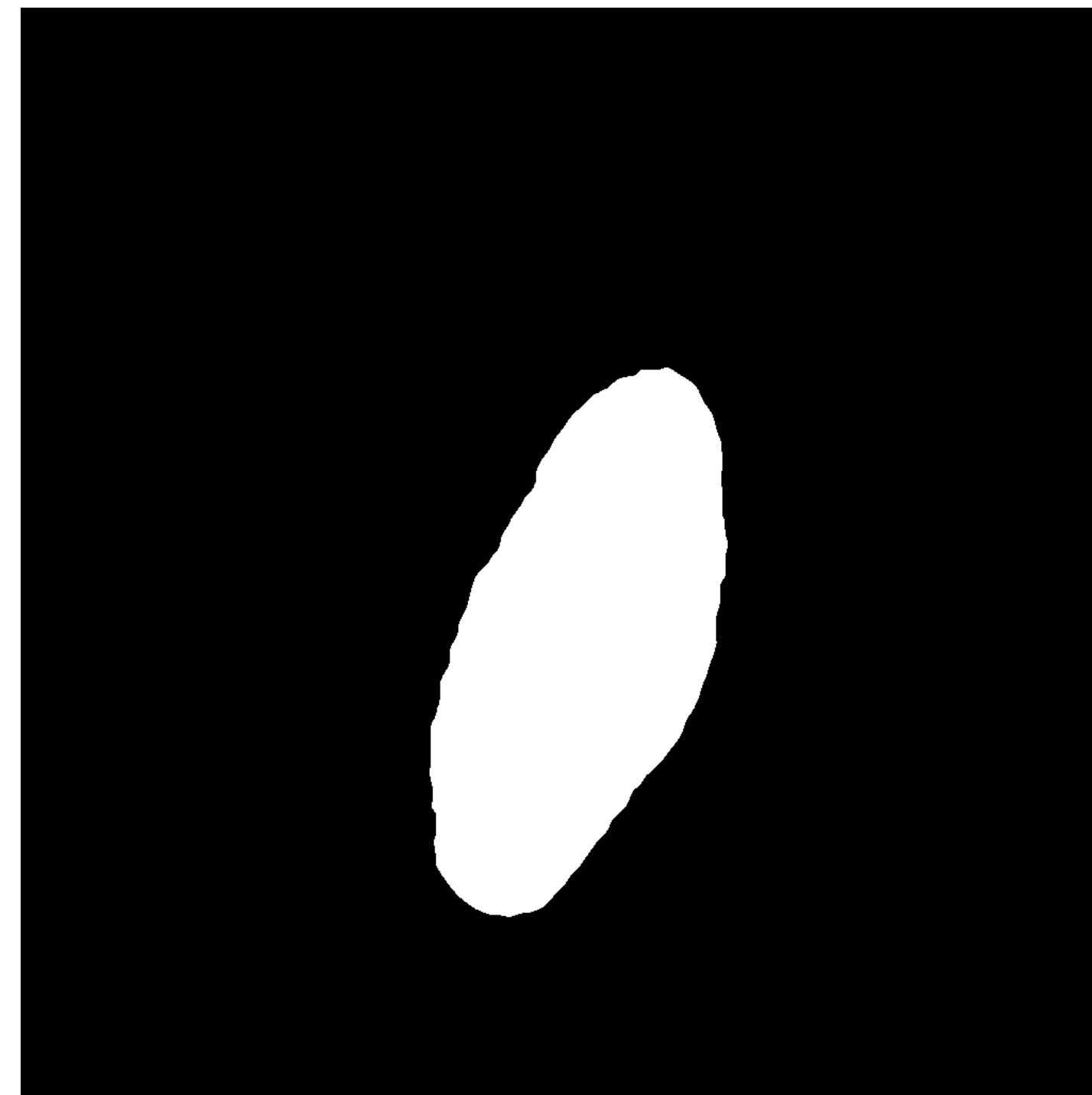
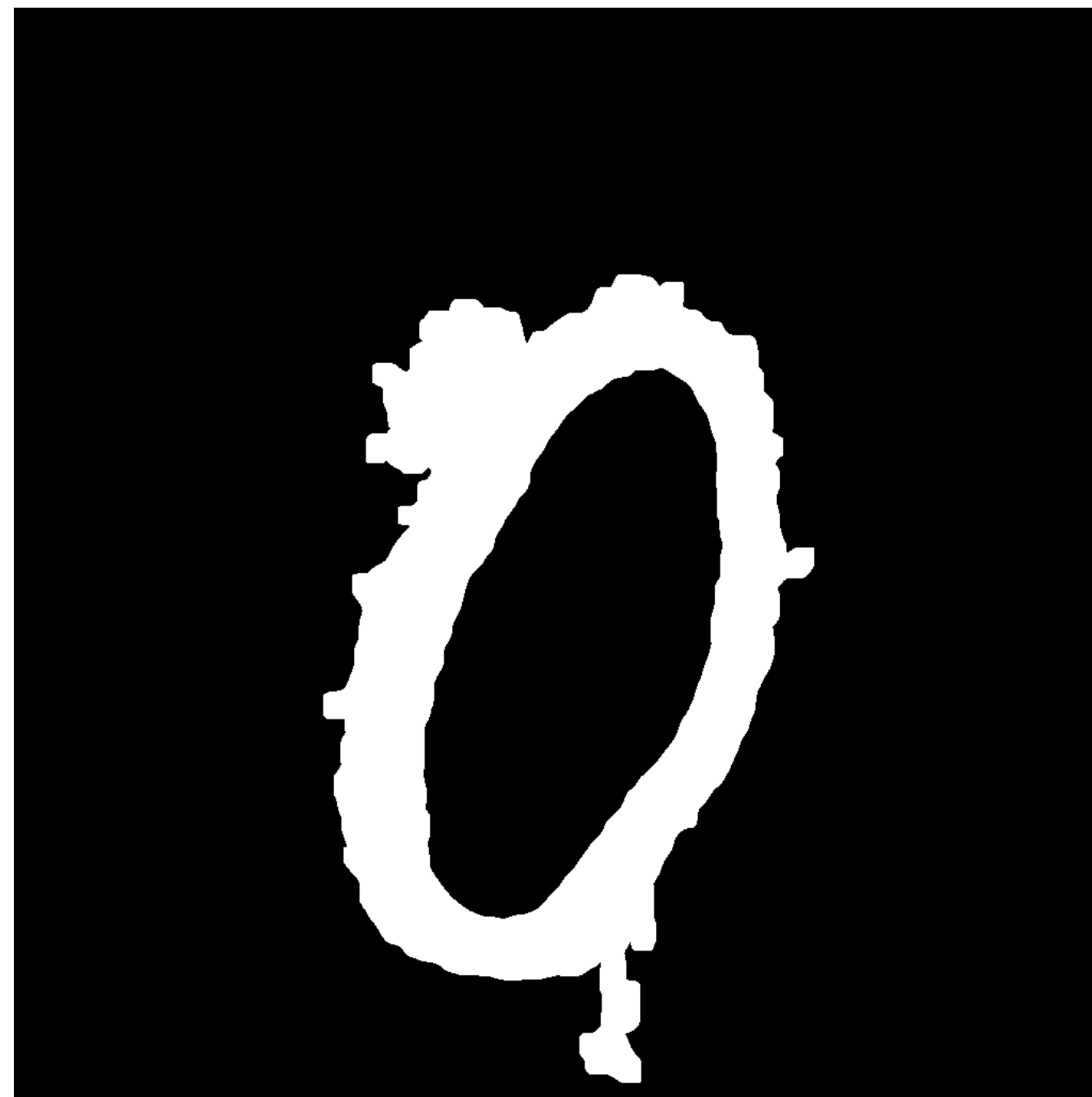




# Pipeline of the segmentation

## Segmentation of the lumen

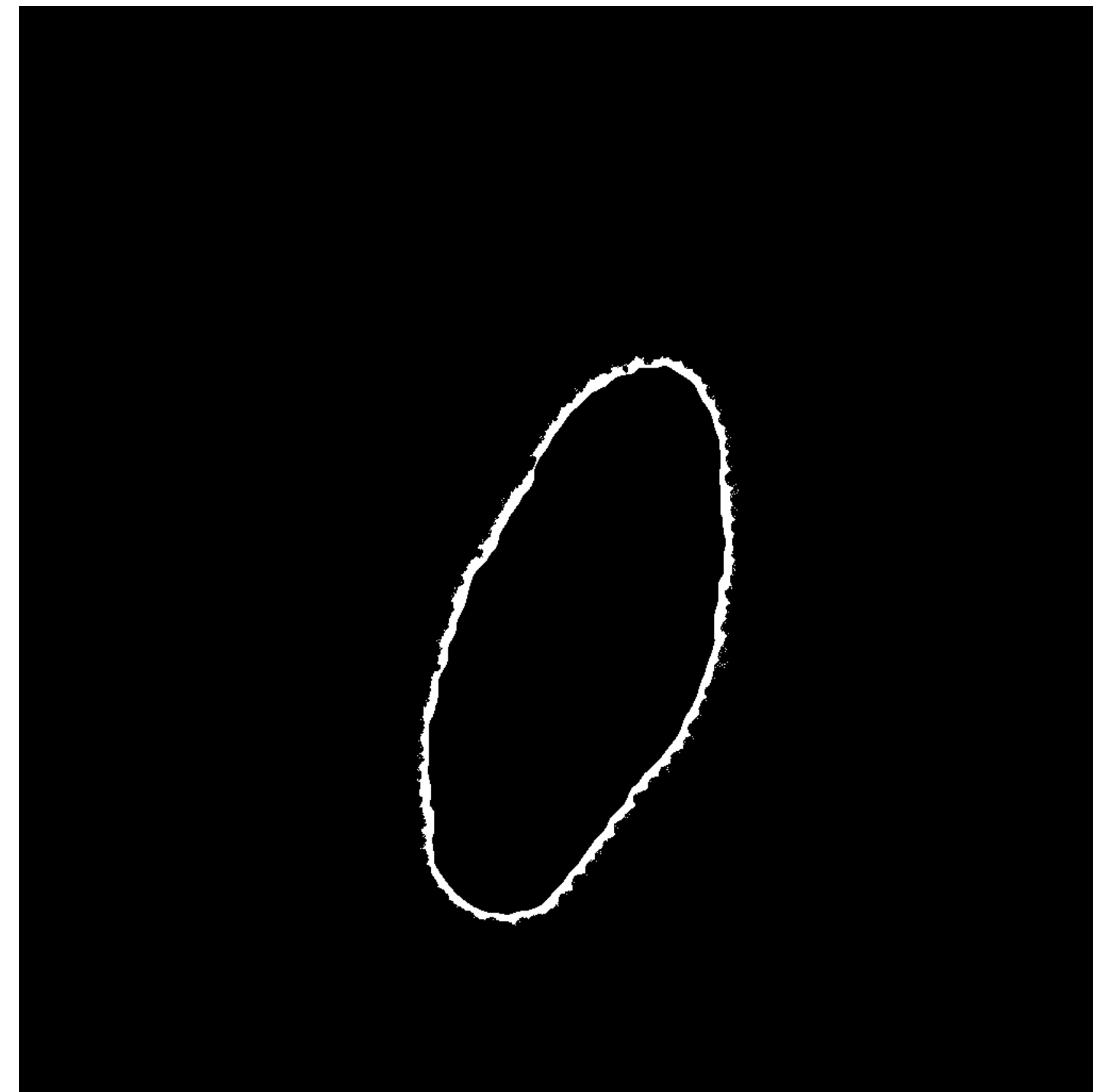
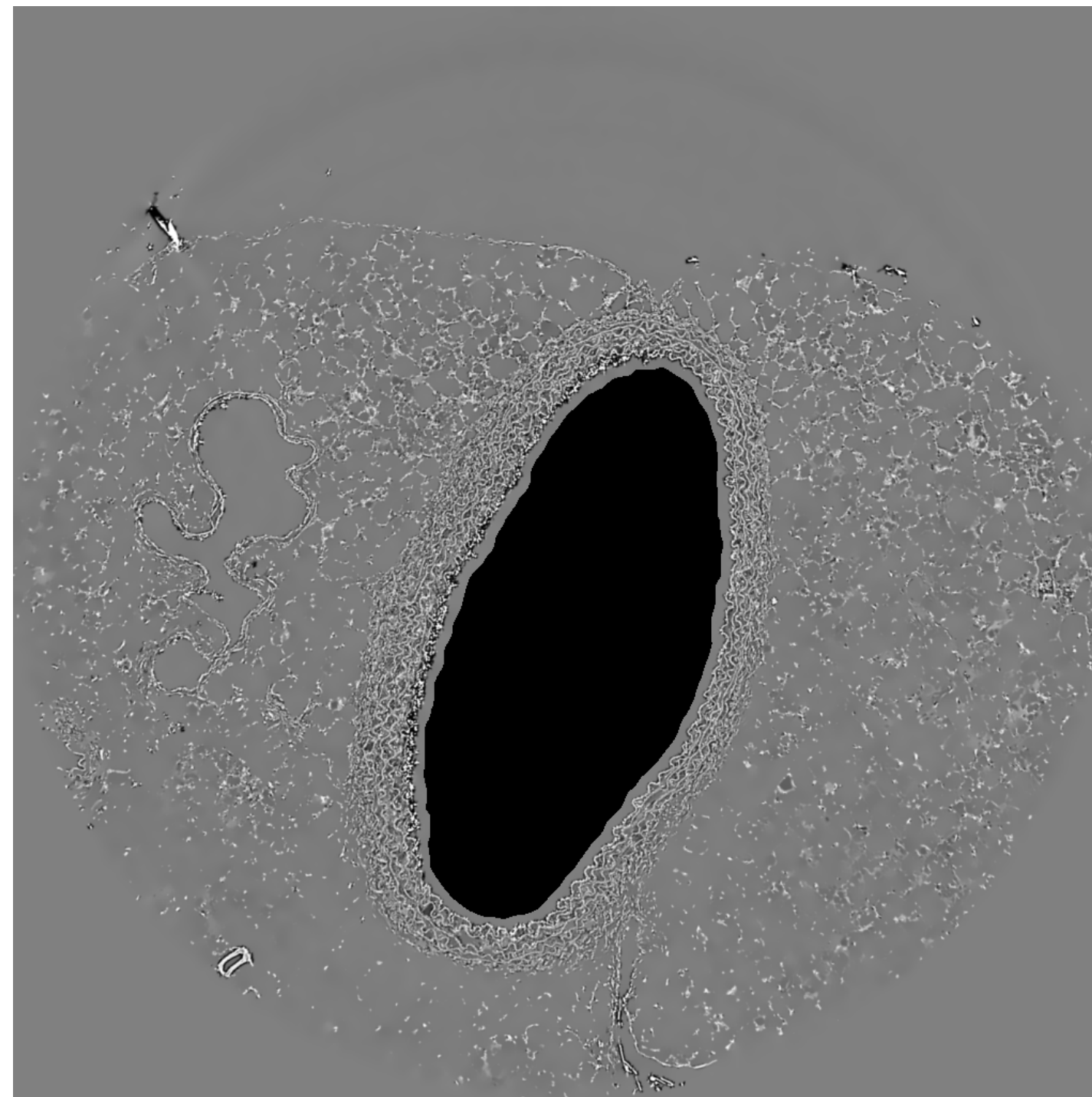
- Filtering -> Thresholding -> Dilation -> Selection of region according to the area



# Pipeline of the segmentation

## Segmentation of the lumen

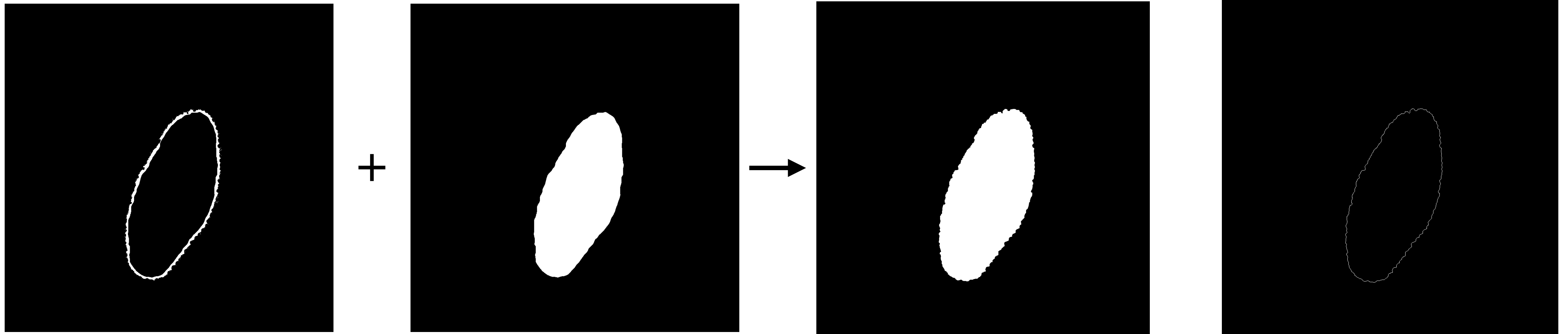
- A region growing approach



# Pipeline of the segmentation

## Segmentation of the lumen

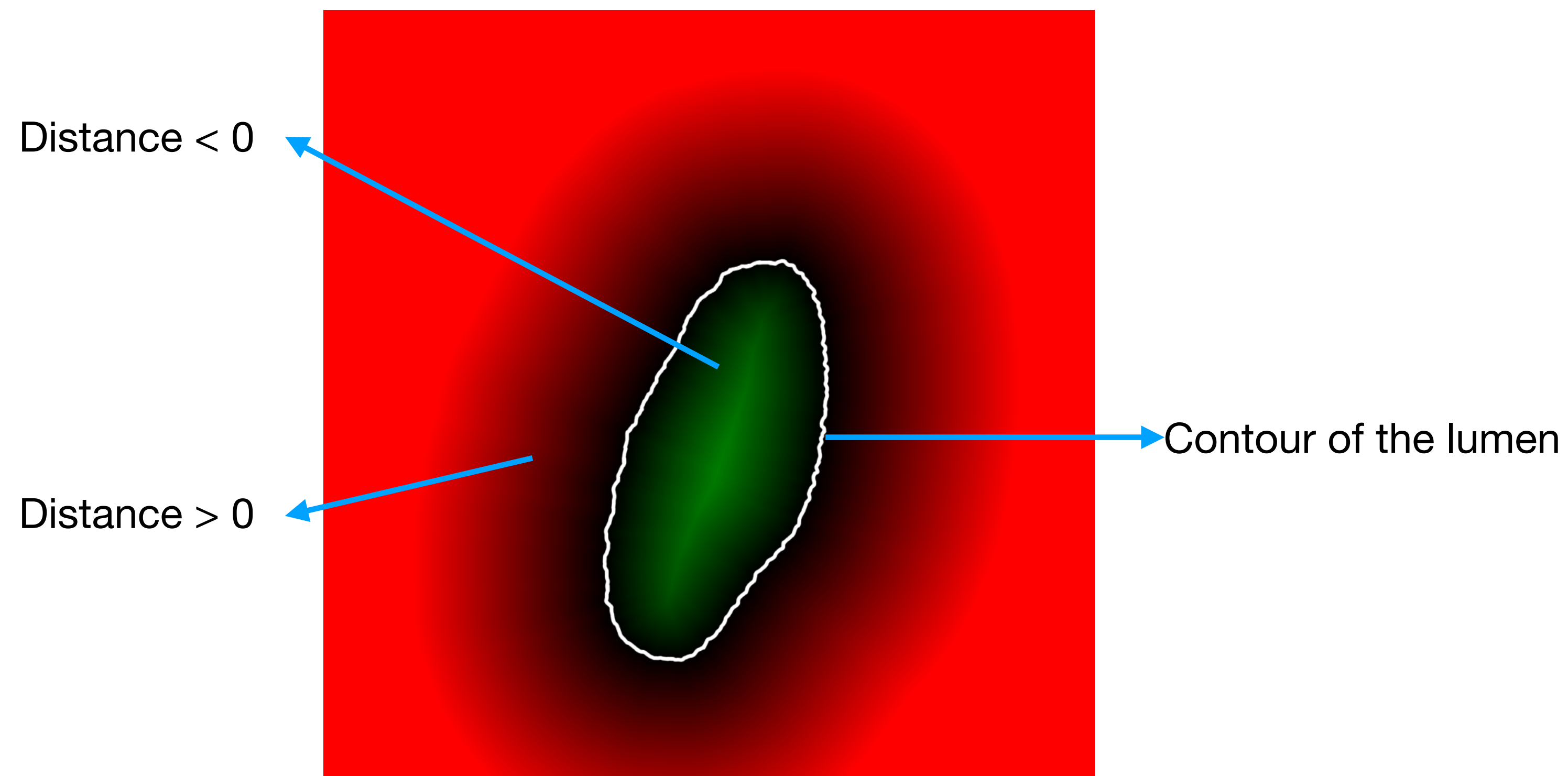
- A region growing approach



# Pipeline of the segmentation

## Distance map & Normal vector field

- Distance map: the distance between any pixel and the contour of the lumen



# Pipeline of the segmentation

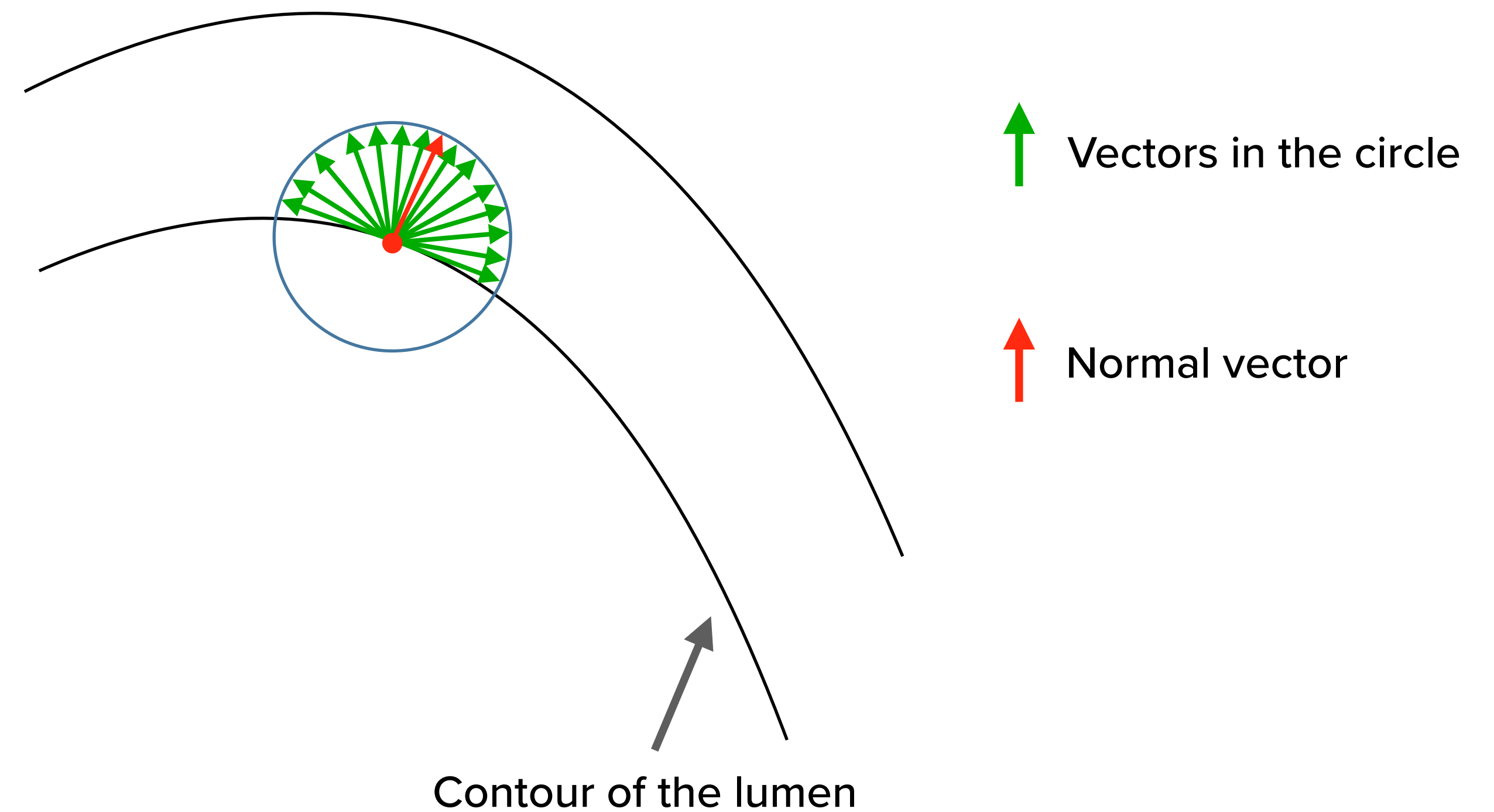
## Distance map & Normal vector field

- Normal vector field

$$\vec{n}(x) = \frac{\sum_{y \in \bar{L} \cap B(x, \rho_0)} (x - y)}{|\sum_{y \in \bar{L} \cap B(x, \rho_0)} (x - y)|}$$

$\bar{L}$ : area outside the lumen

$B(x, \rho_0)$ : the ball of center  $x$  and radius  $\rho_0$

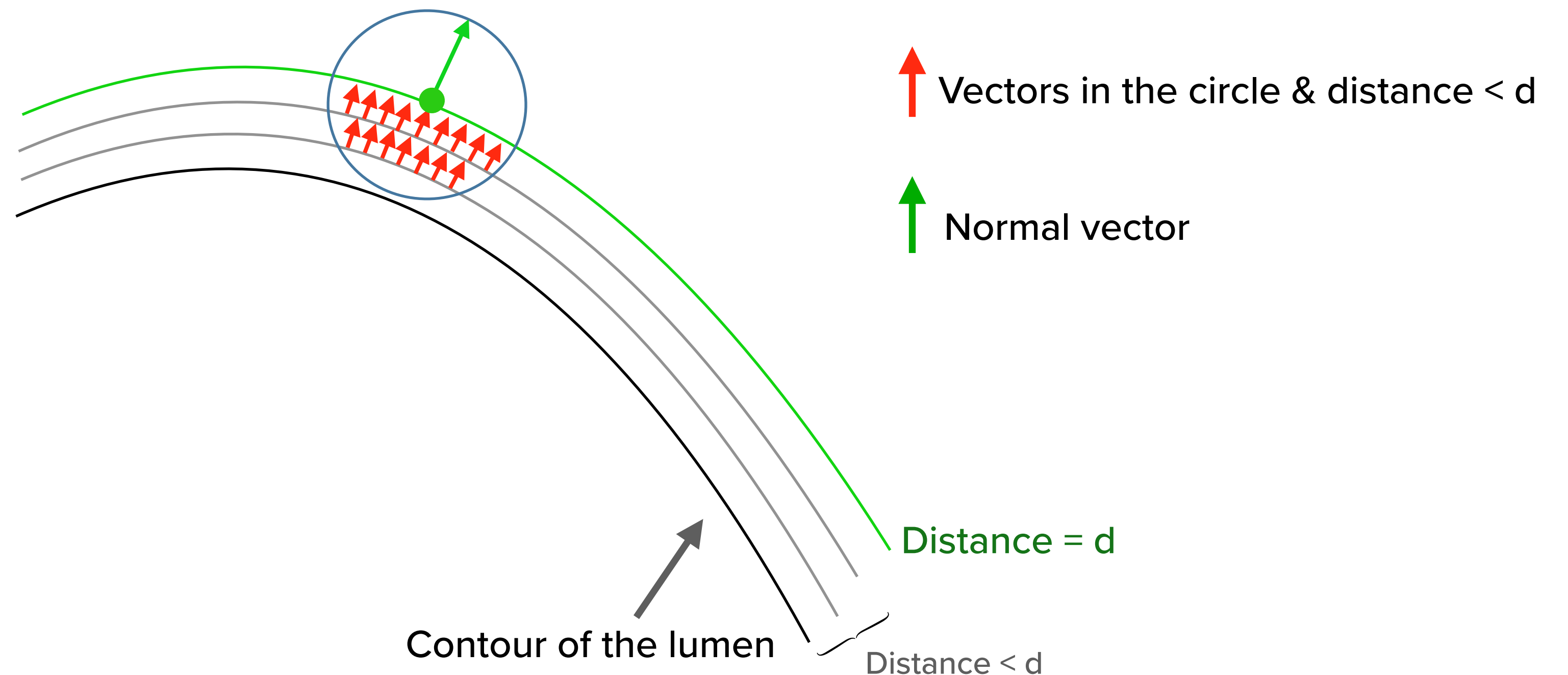


# Pipeline of the segmentation

## Distance map & Normal vector field

- Normal vector field

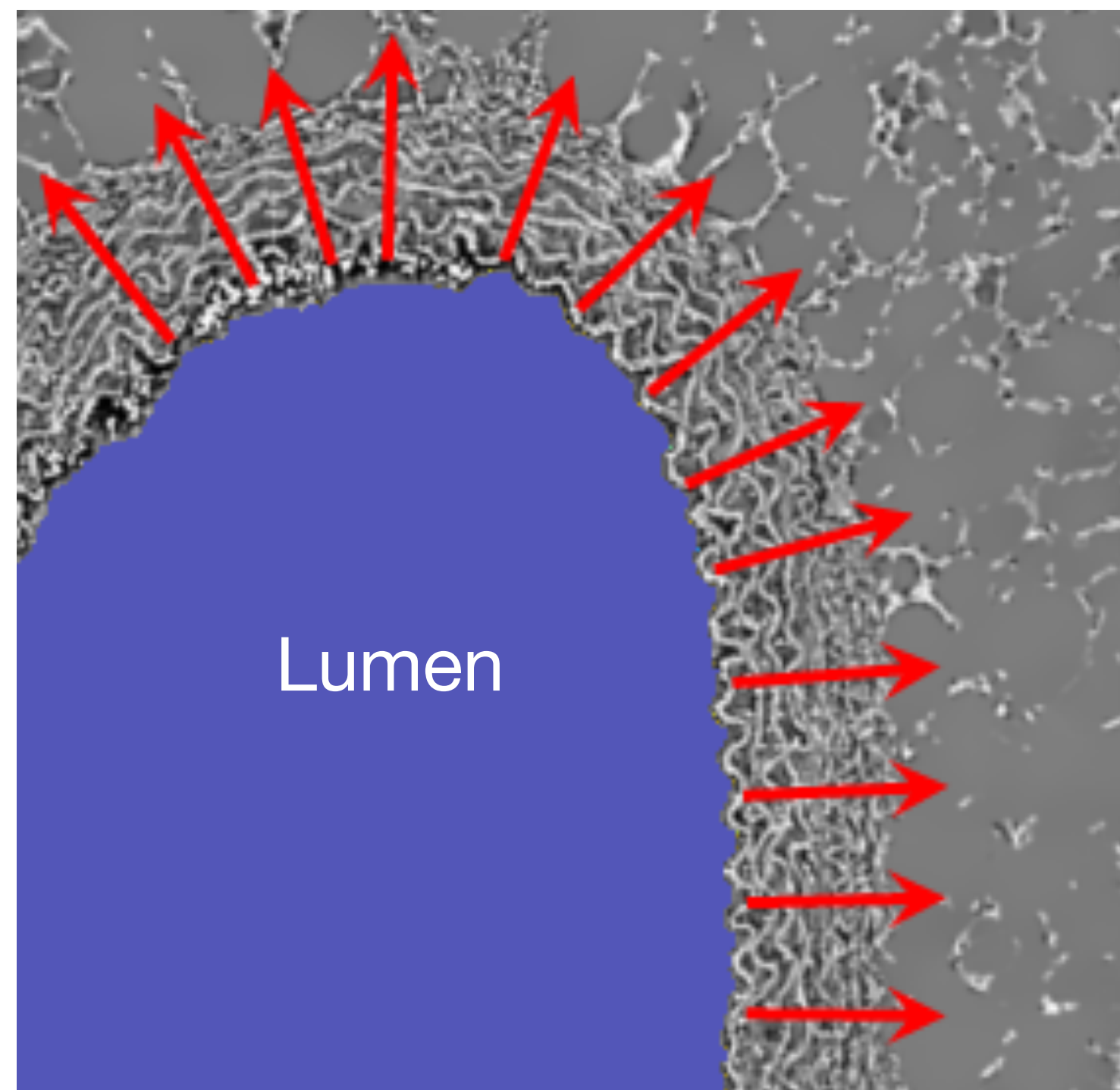
$$\vec{n}(x) = \frac{\sum_{y \in R \cap B(x, \rho_1)} \vec{n}(y)}{|\sum_{y \in R \cap B(x, \rho_1)} \vec{n}(y)|}$$



# Pipeline of the segmentation

## Distance map & Normal vector field

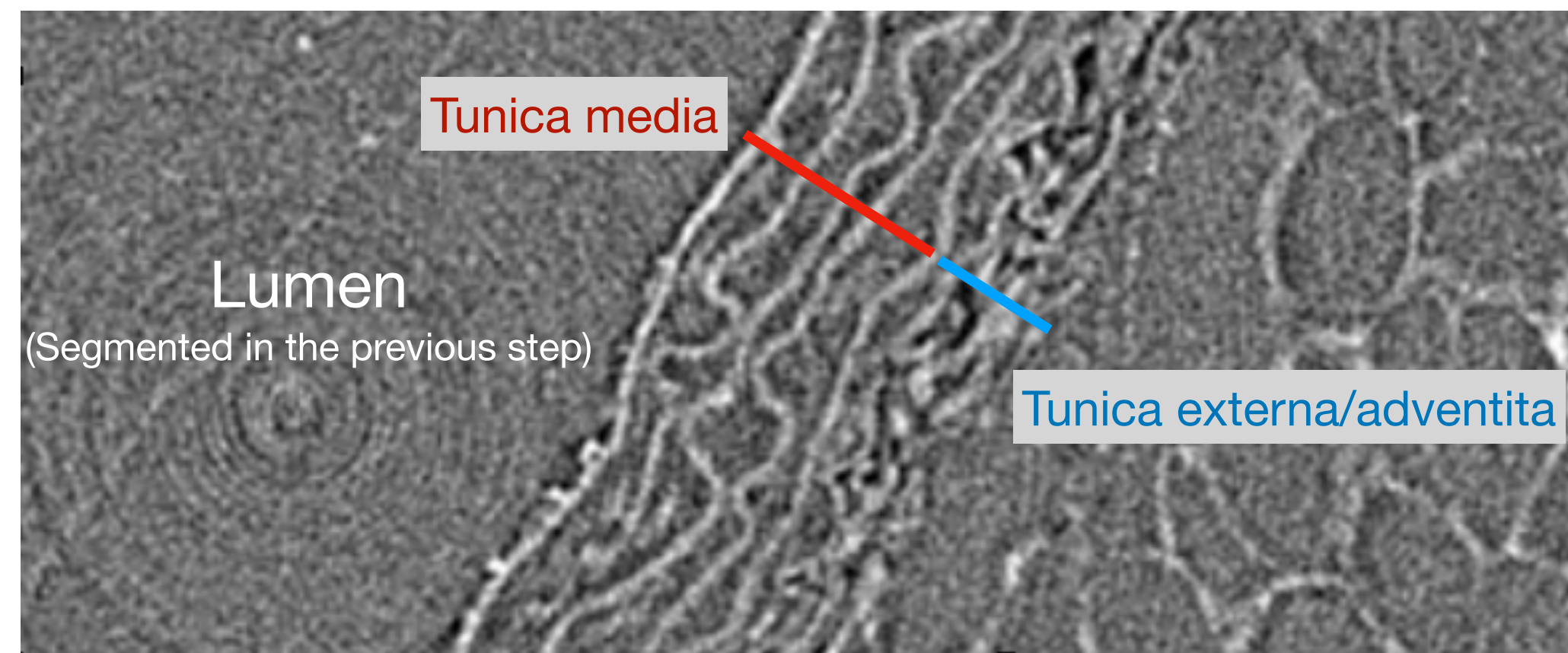
- It enables us to get normal vectors of any pixel at any distance



# Pipeline of the segmentation

## Texture classification based on deep learning

- For finer segmentation

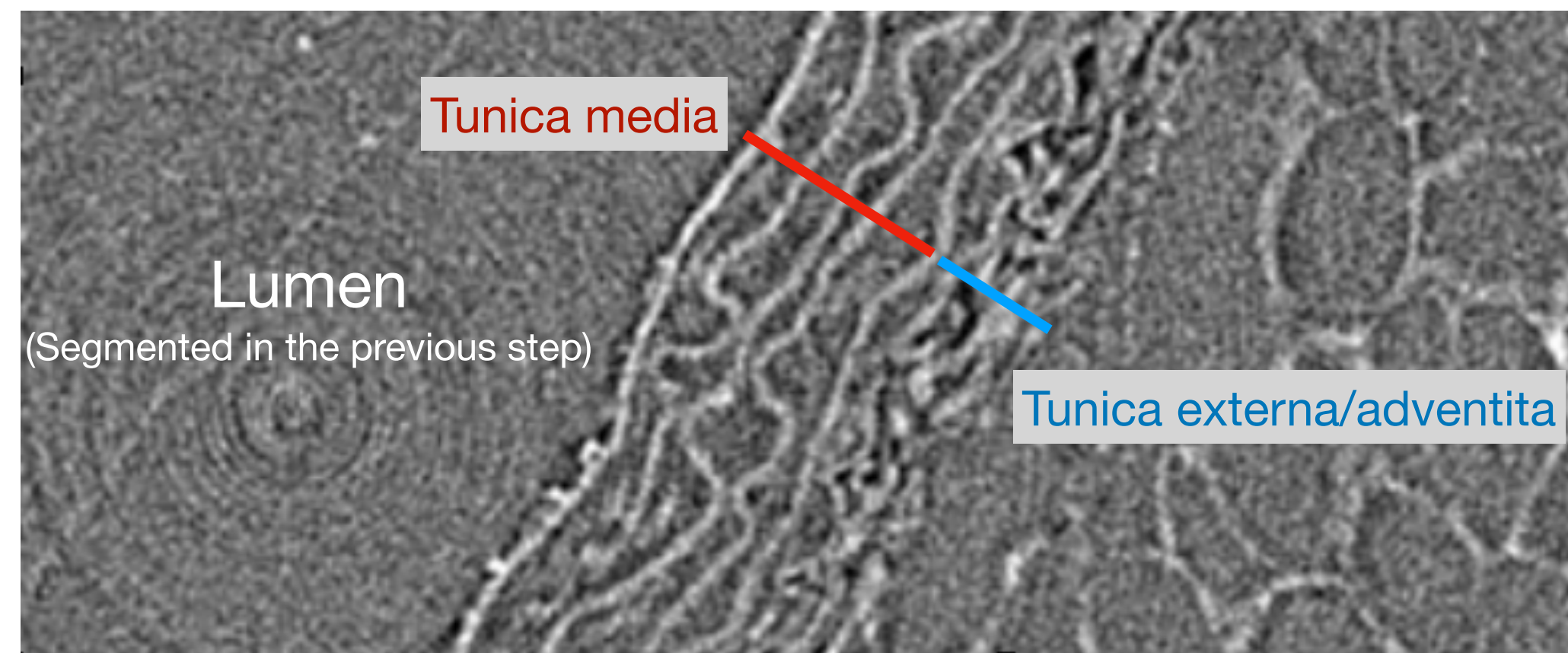




# Pipeline of the segmentation

## Texture classification based on deep learning

- For finer segmentation



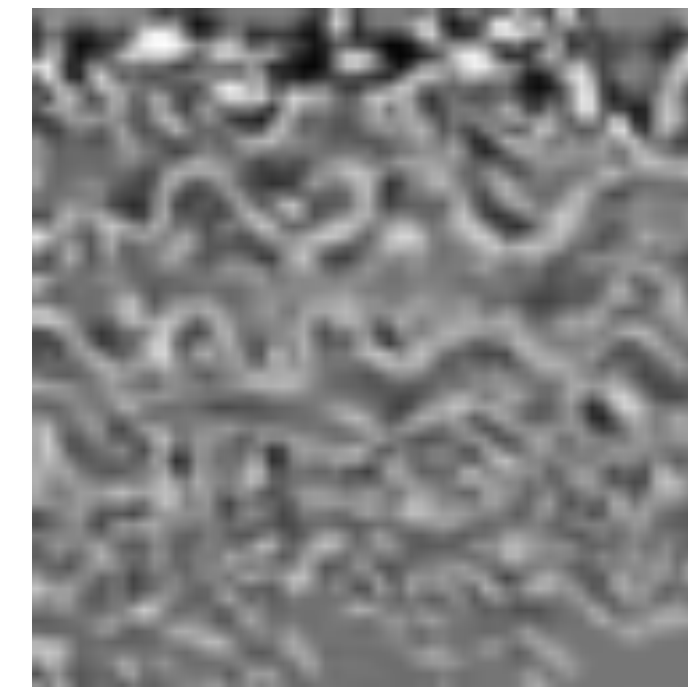
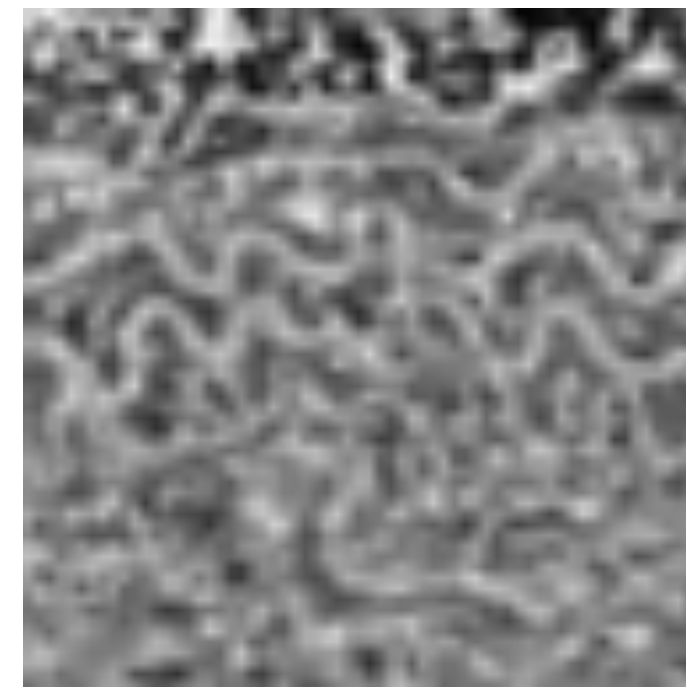
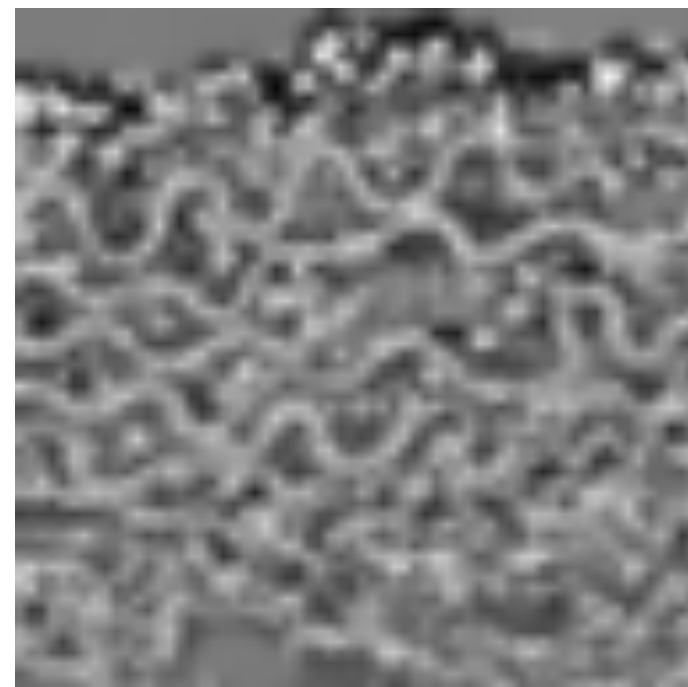
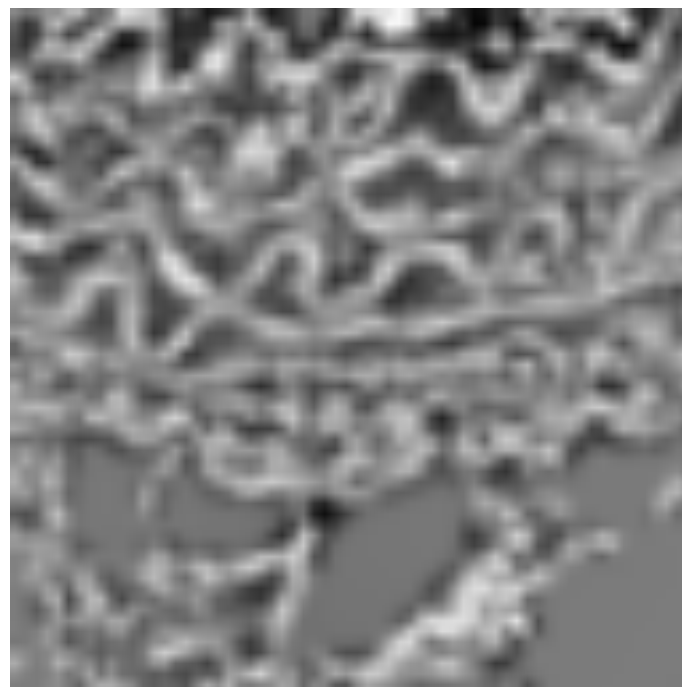
- Features of the images:

- No pixel-wise label
- The relative positions of different structures are known

# Pipeline of the segmentation

## Texture classification based on deep learning

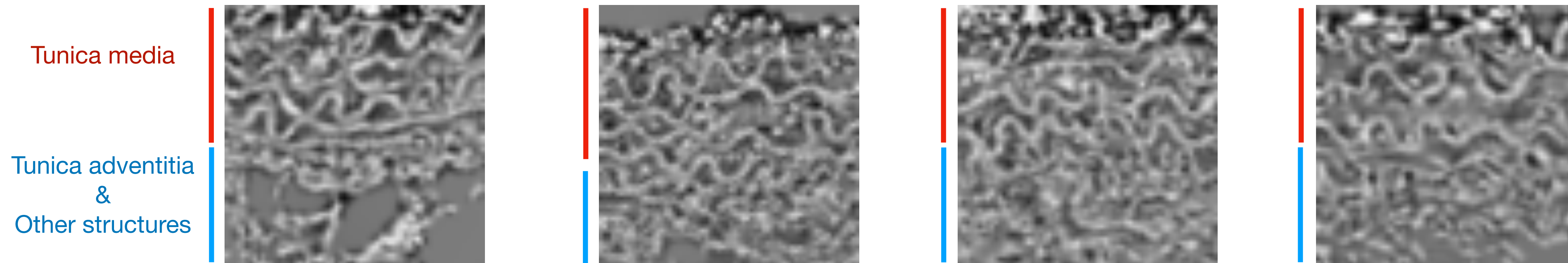
- Rotating and cutting patches with the help of the normal vector field



# Pipeline of the segmentation

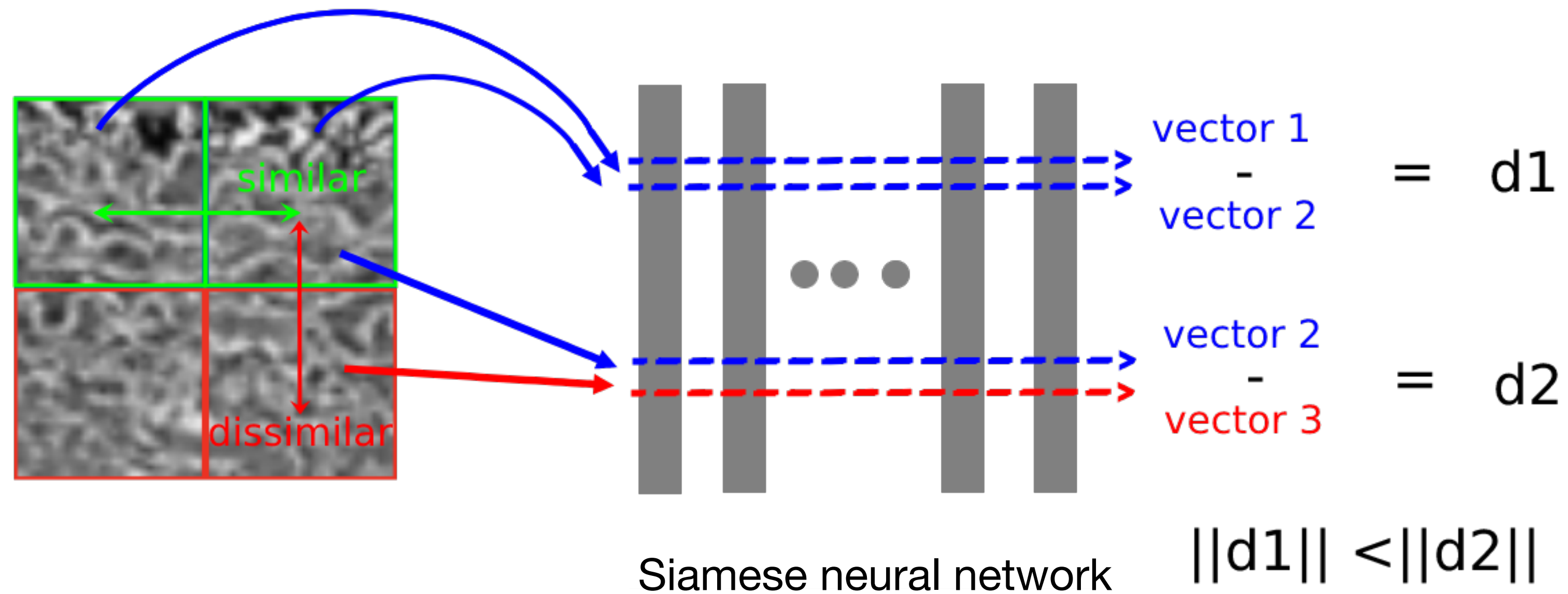
## Texture classification based on deep learning

- Rotating and cutting patches with the help of the normal vector field



# Pipeline of the segmentation

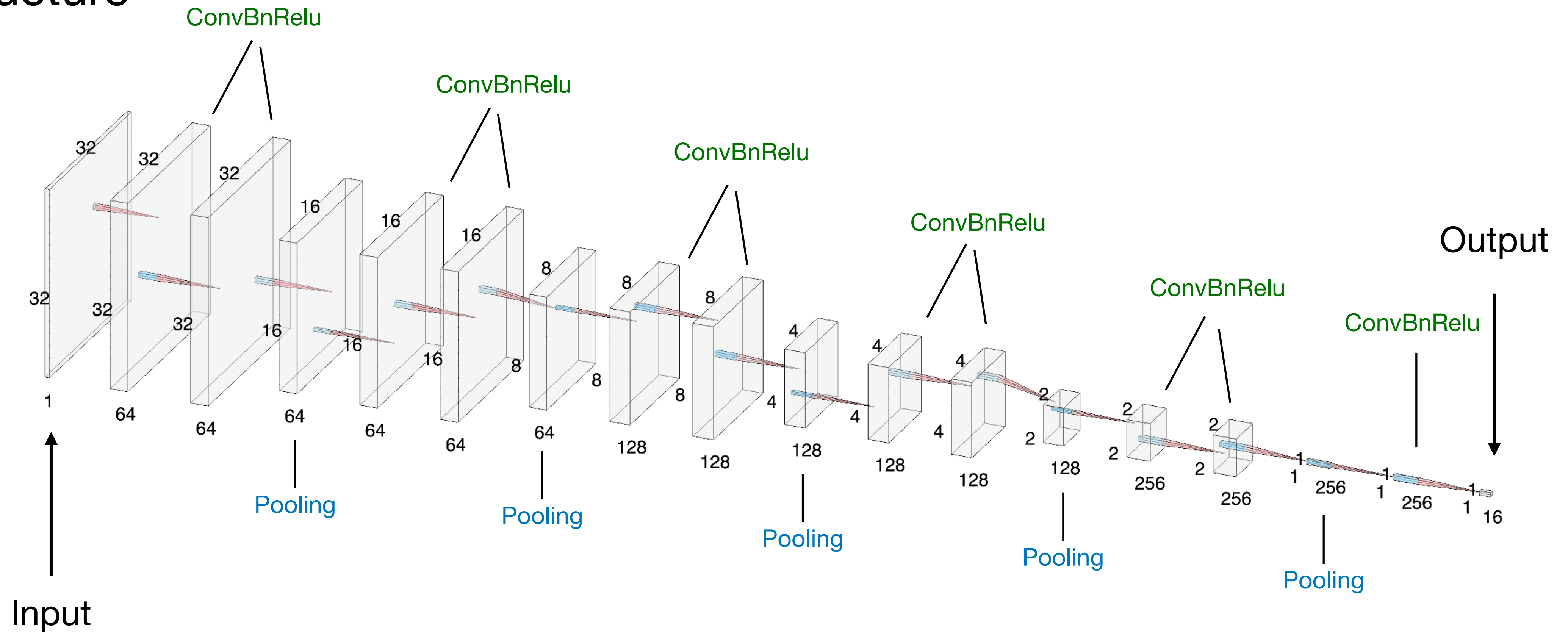
## Texture classification based on deep learning



# Pipeline of the segmentation

## Texture classification based on deep learning

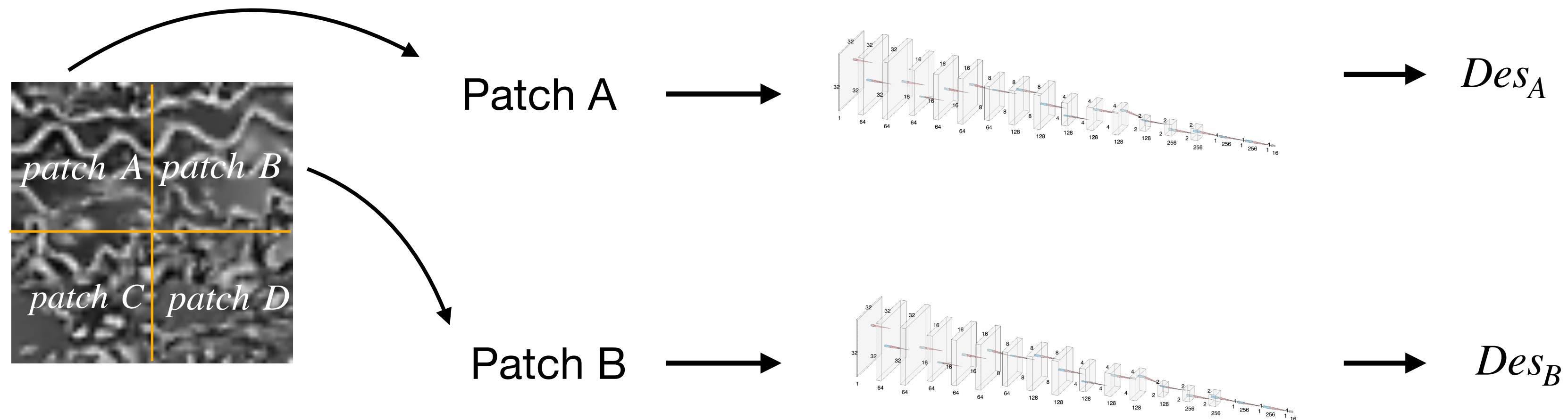
- Structure



# Pipeline of the segmentation

## Texture classification based on deep learning

- Loss function



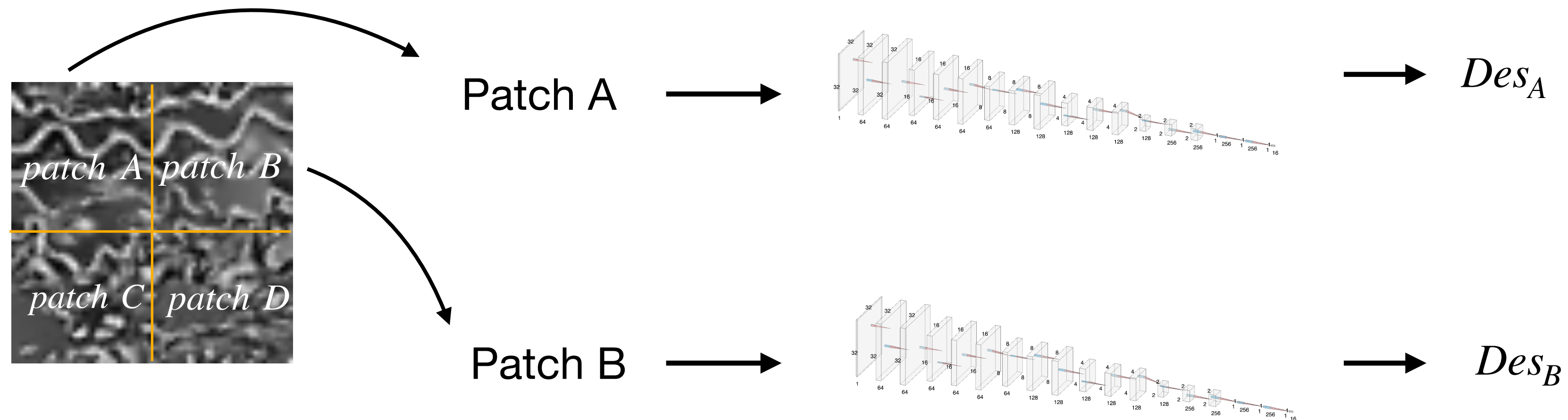
- $$\mathcal{L}(d_{ij}, d_{kl}) = \alpha \cdot \delta_{ik} \cdot \Delta^T \cdot \Delta + \beta \cdot (1 - \delta_{ik}) \cdot [\max\{0, m_p - (\Delta^T \cdot \Delta)^{1/2}\}]^2$$

Where  $\Delta = d_{ij} - d_{kl}$ ,  $\delta$  is the Kronecker symbol,  $\alpha = 2$ ,  $\beta = 1$ ,  $m_p = 2$

# Pipeline of the segmentation

## Texture classification based on deep learning

- Loss function



- $\mathcal{L}(d_{ij}, d_{kl}) = \alpha \cdot \delta_{ik} \cdot \Delta^T \cdot \Delta + \beta \cdot (1 - \delta_{ik}) \cdot [\max\{0, m_p - (\Delta^T \cdot \Delta)^{1/2}\}]^2$

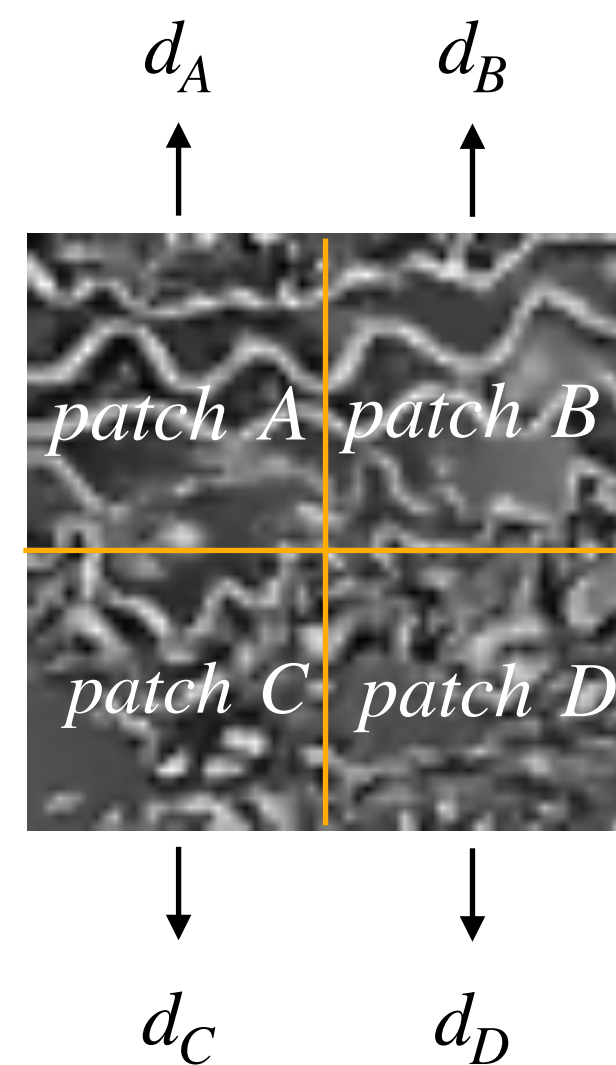
Where  $\Delta = d_{ij} - d_{kl}$ ,  $\delta$  is the Kronecker symbol,  $\alpha = 2$ ,  $\beta = 1$ ,  $m_p = 2$

- $Loss(Des_A, Des_B) = \alpha \cdot y \cdot D(Des_A, Des_B)^2 + \beta \cdot (1 - y) \cdot \max(0, m - D(Des_A, Des_B))^2$  20

# Pipeline of the segmentation

## Texture classification based on deep learning

- Training
  - 1457  $2D$  slices generate 47118 image patches of size  $64^2$
  - 80 % for training, 20 % for validation



A prediction is considered correct if:

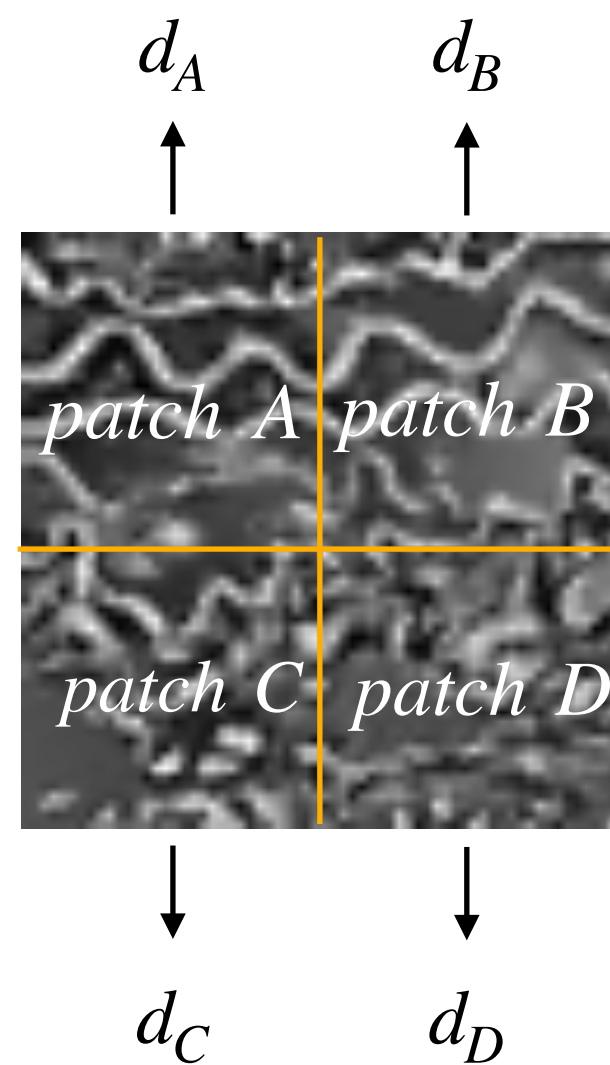
$$\|d_A - d_B\|_2 < \min\{\|d_A - d_C\|_2, \|d_A - d_D\|_2\}$$



# Pipeline of the segmentation

## Texture classification based on deep learning

- Training: 5 epochs, 164s
- Validation:



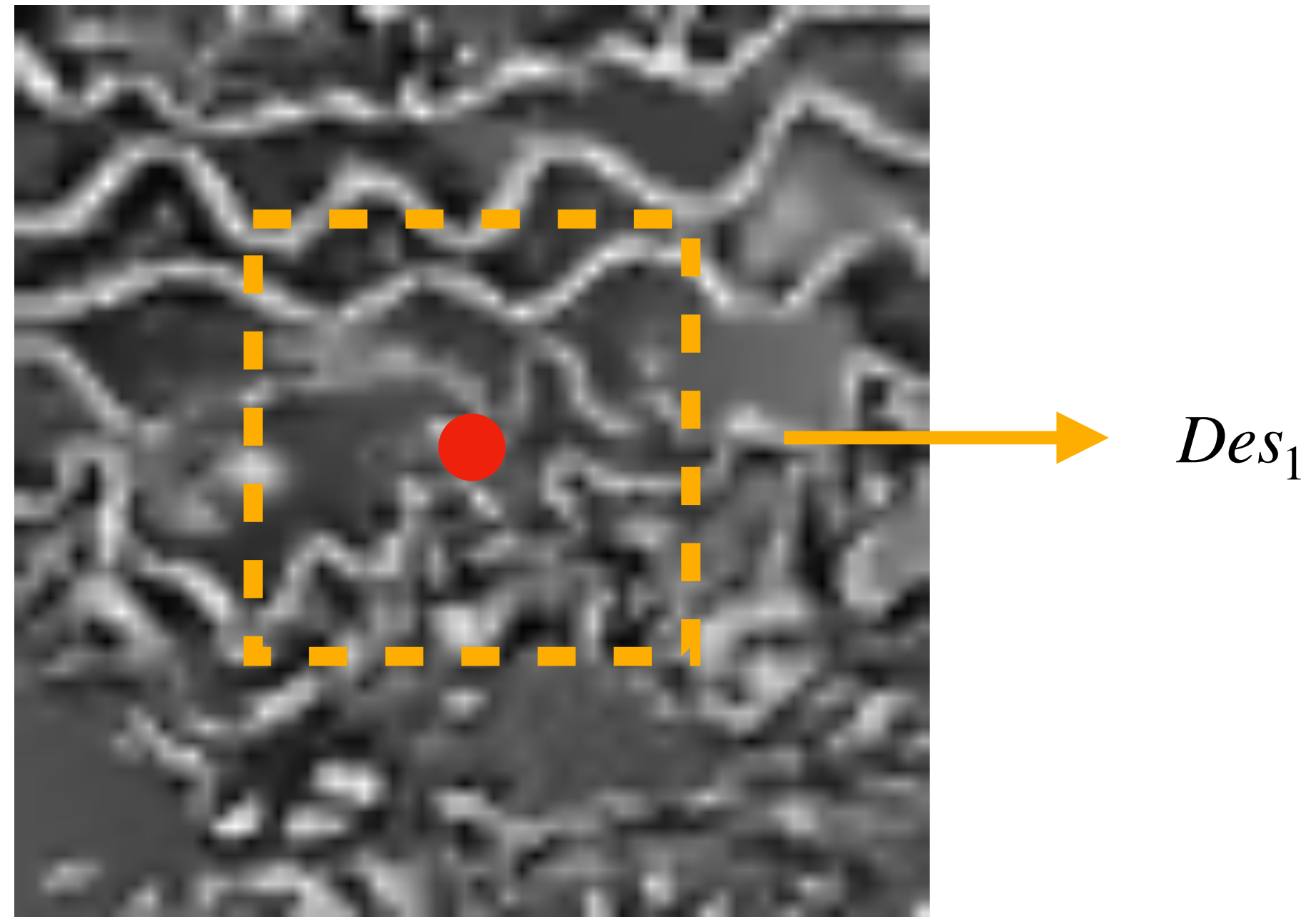
A prediction is considered correct if:

$$\|d_A - d_B\|_2 < \min\{\|d_A - d_C\|_2, \|d_A - d_D\|_2\}$$

Accuracy: 99.14 %

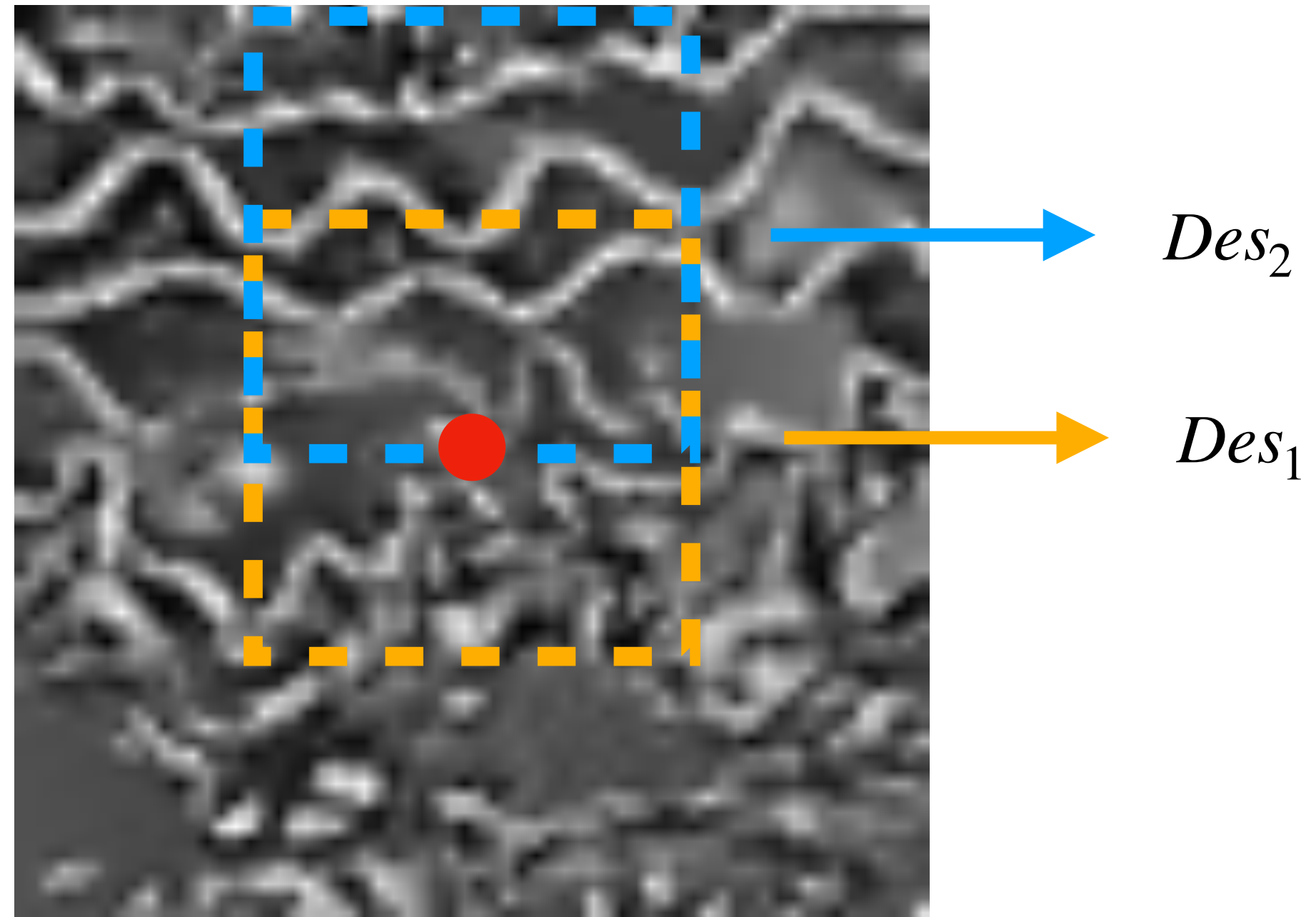
# Results

## Prediction of patches



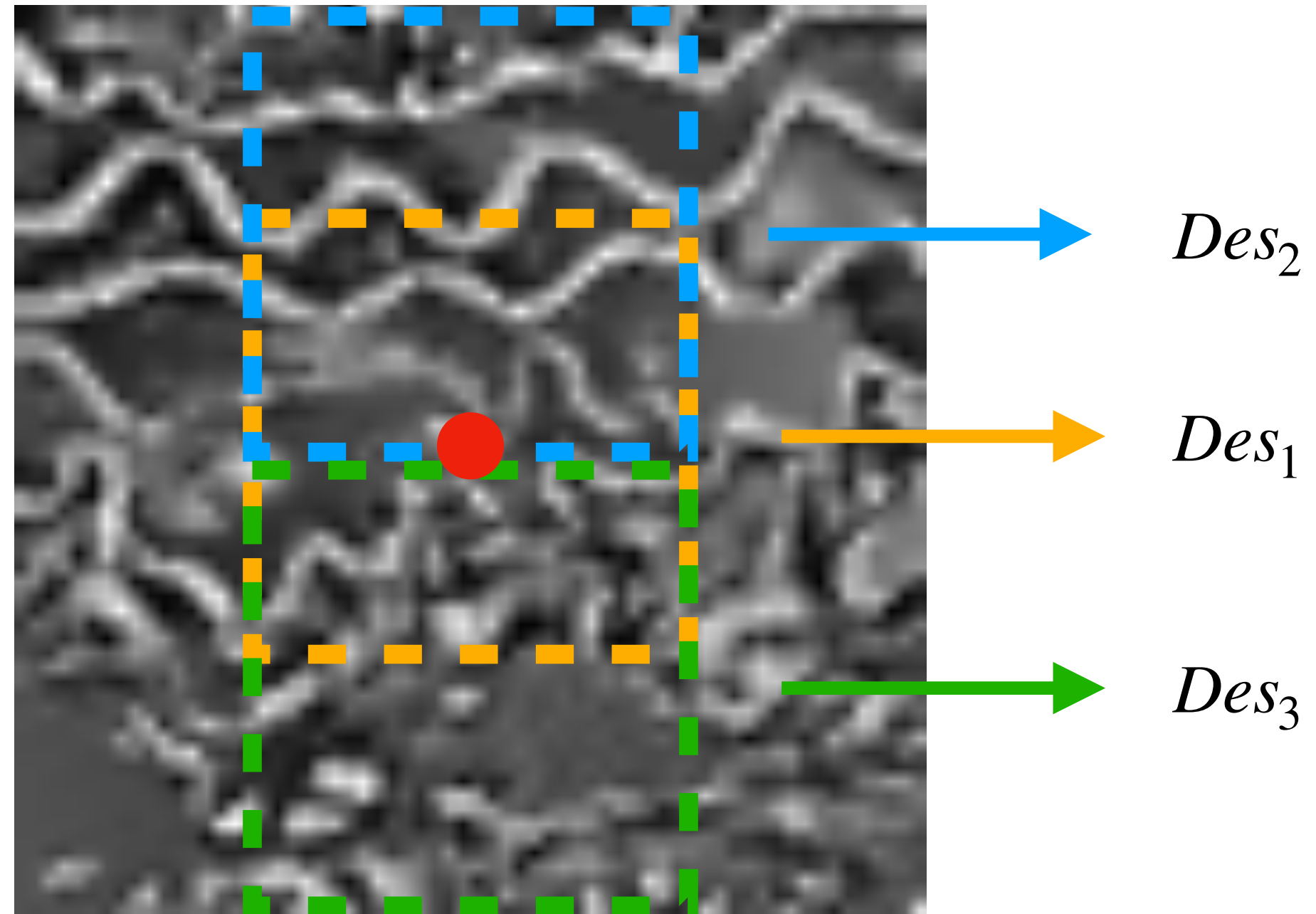
# Results

## Prediction of patches



# Results

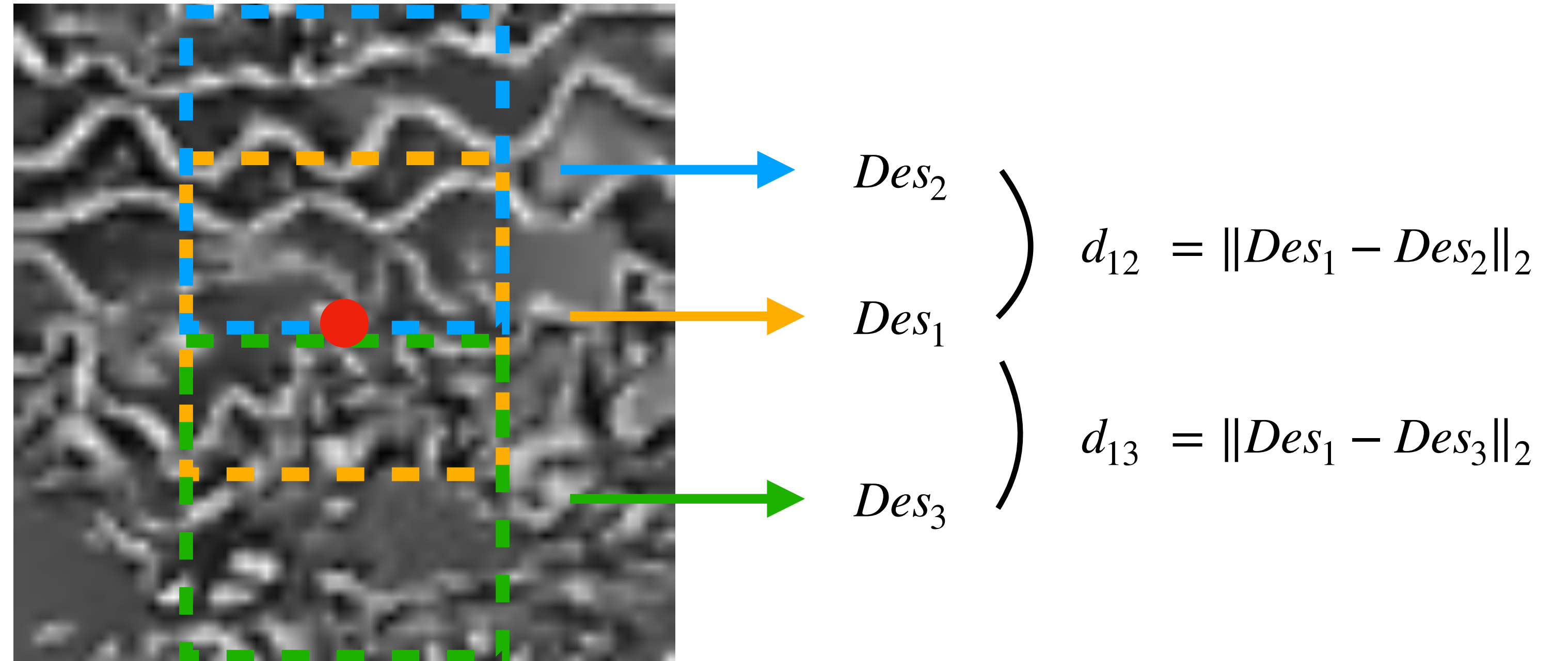
## Prediction of patches



# Results

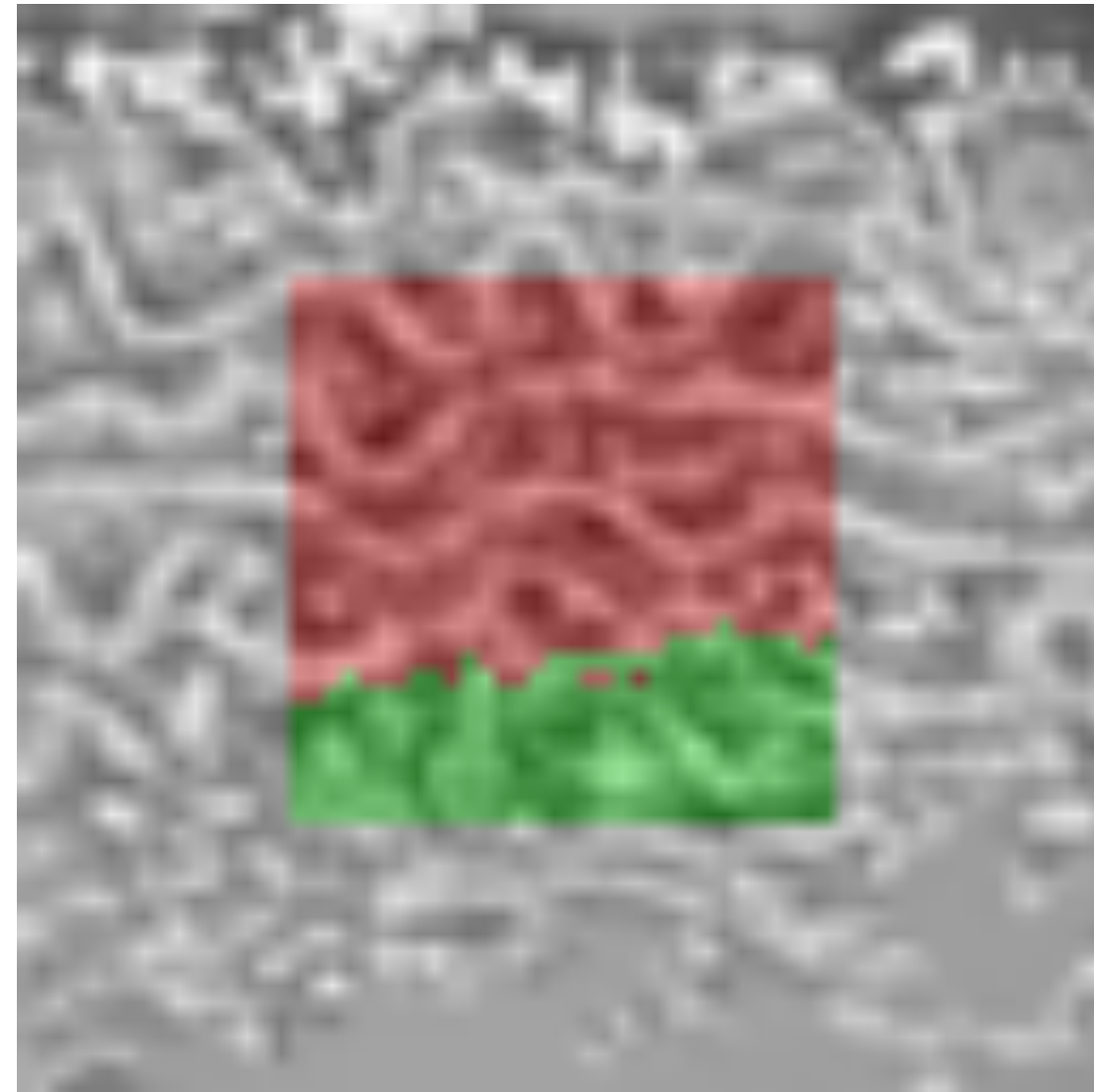
## Prediction of patches

- Compare  $d_{12}$  and  $d_{13}$



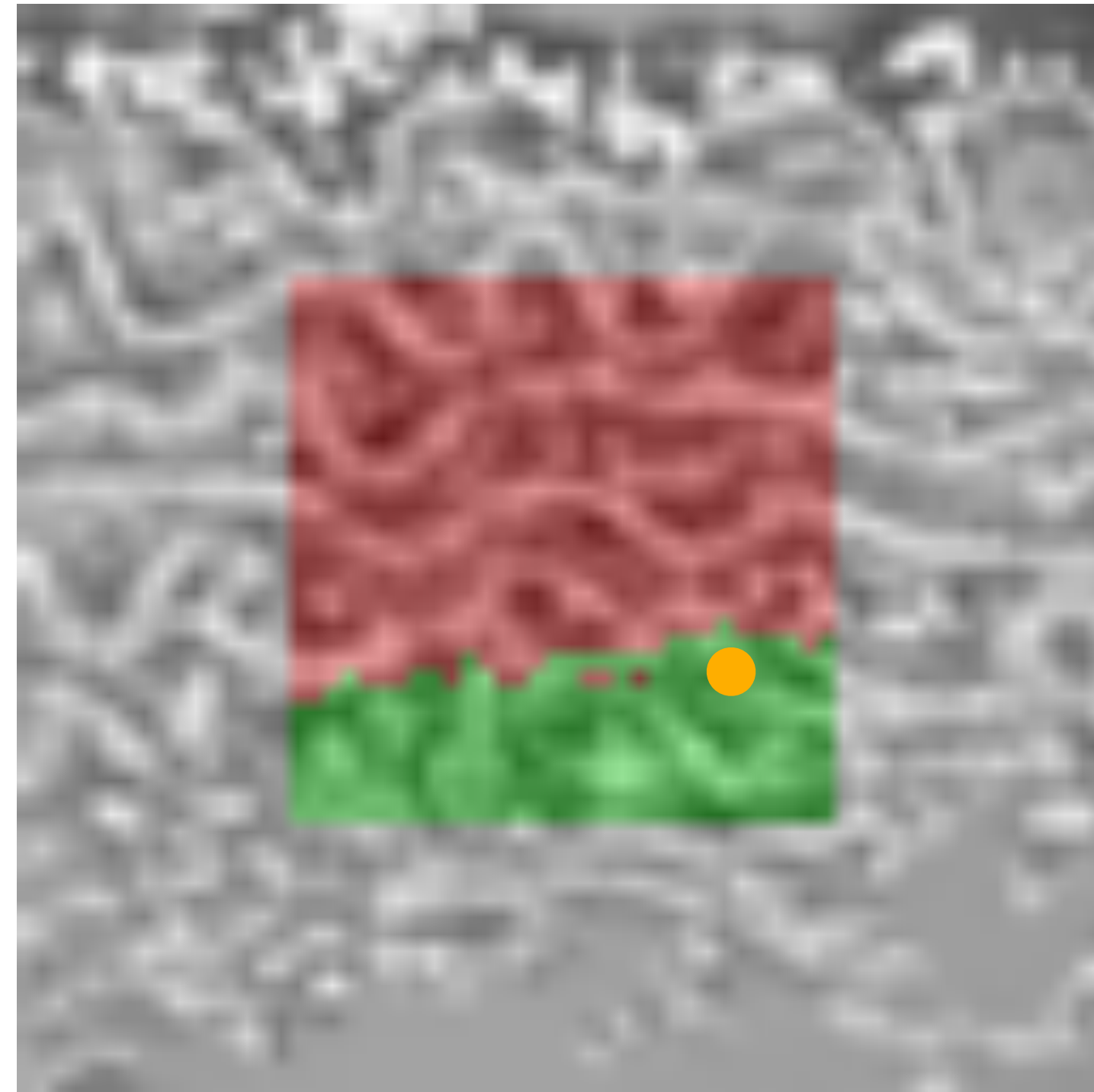
# Results

## Prediction of patches



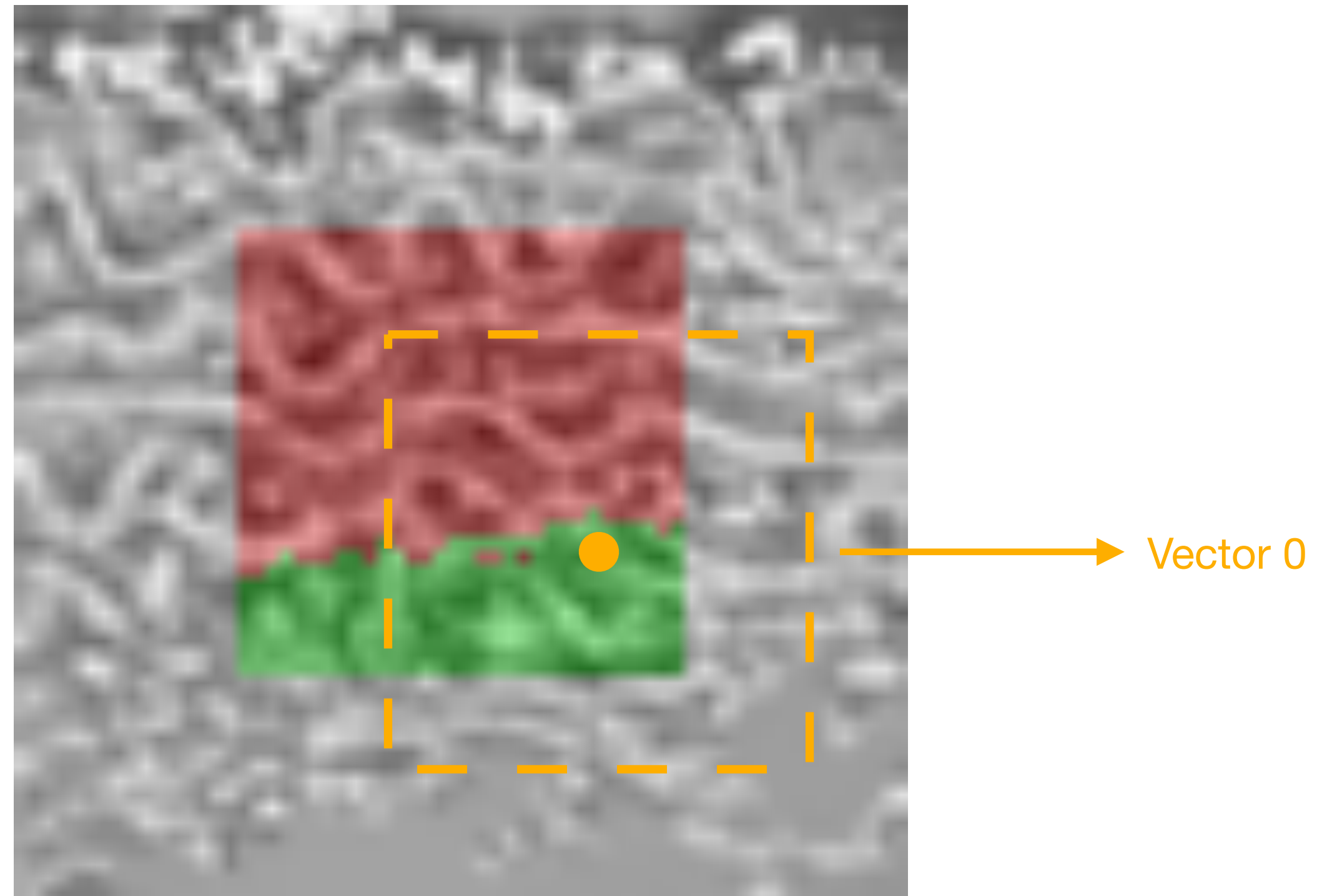
# Results

## Prediction of patches



# Results

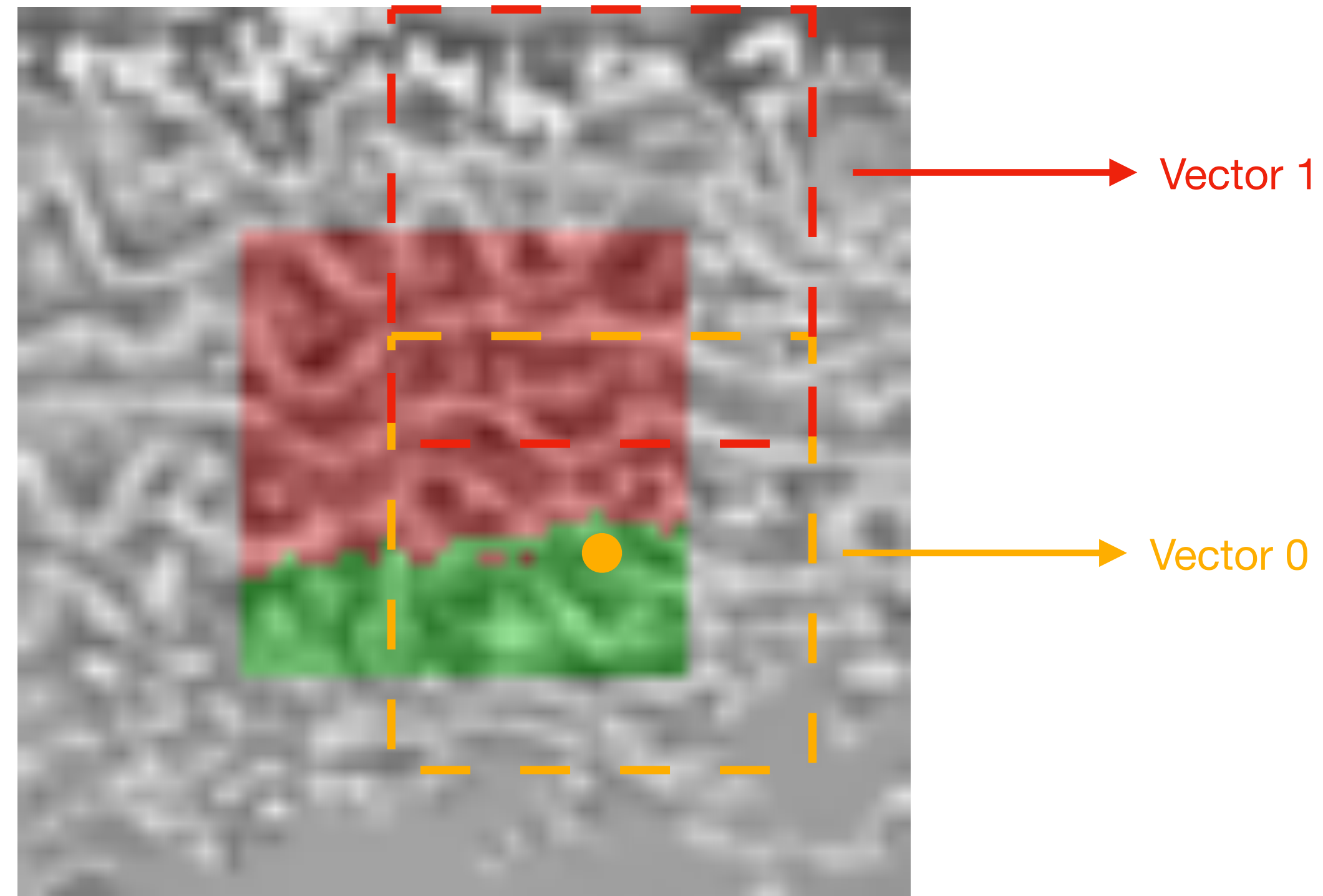
## Prediction of patches





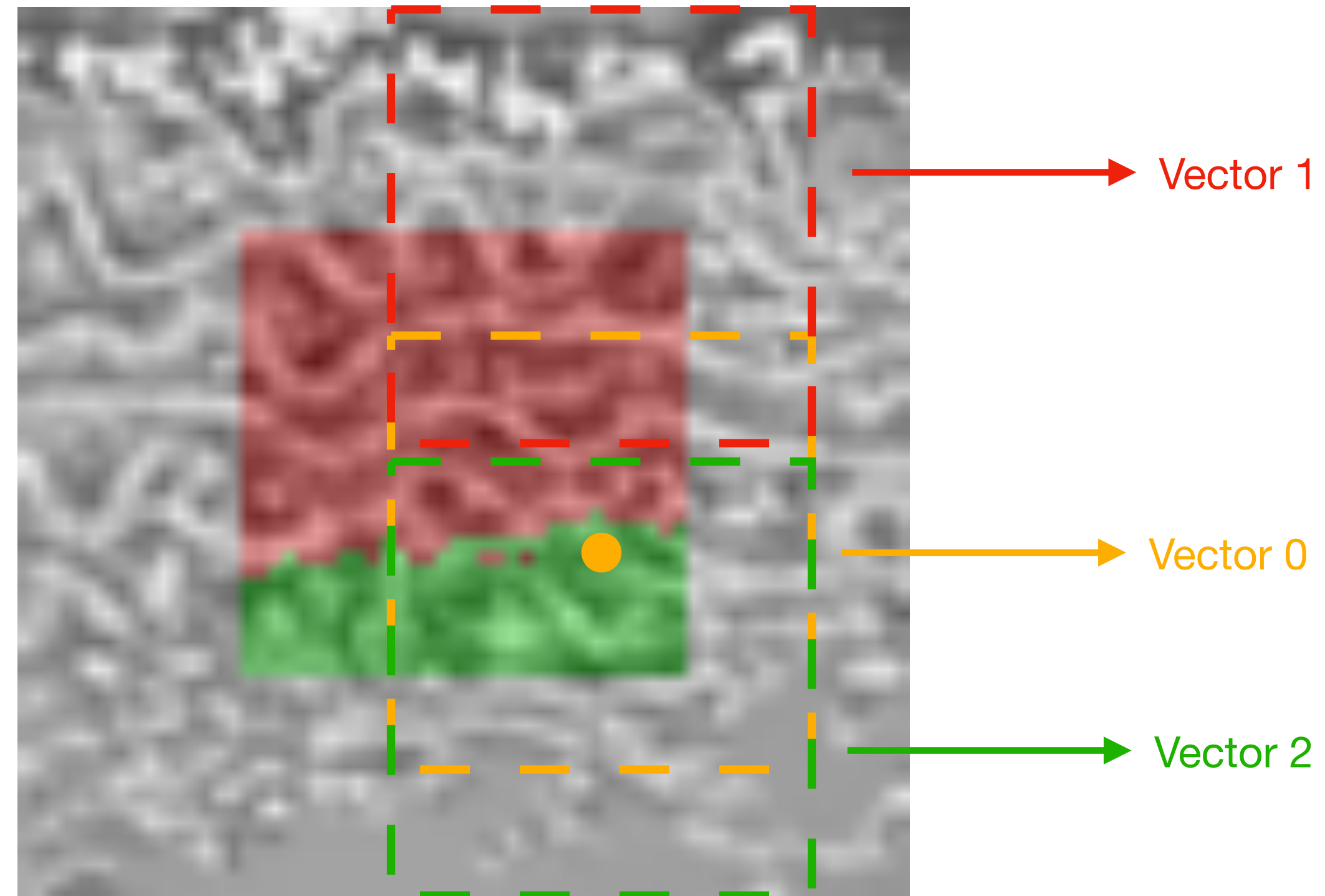
# Results

## Prediction of patches



# Results

## Prediction of patches



# Results

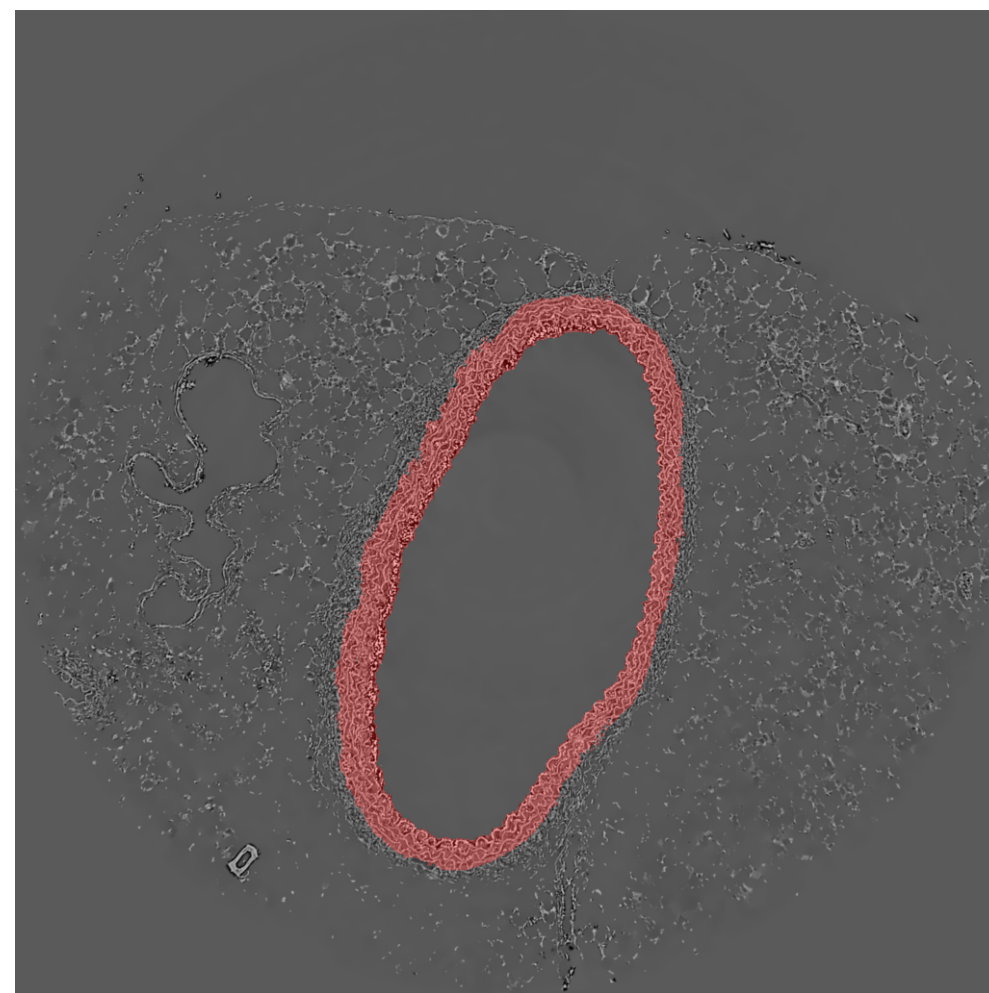
## Segmentation of whole *2D* images

- Manual annotation of *tunica media*  
= borders of the lumen & borders between *tunica media* and *tunica adventitia*

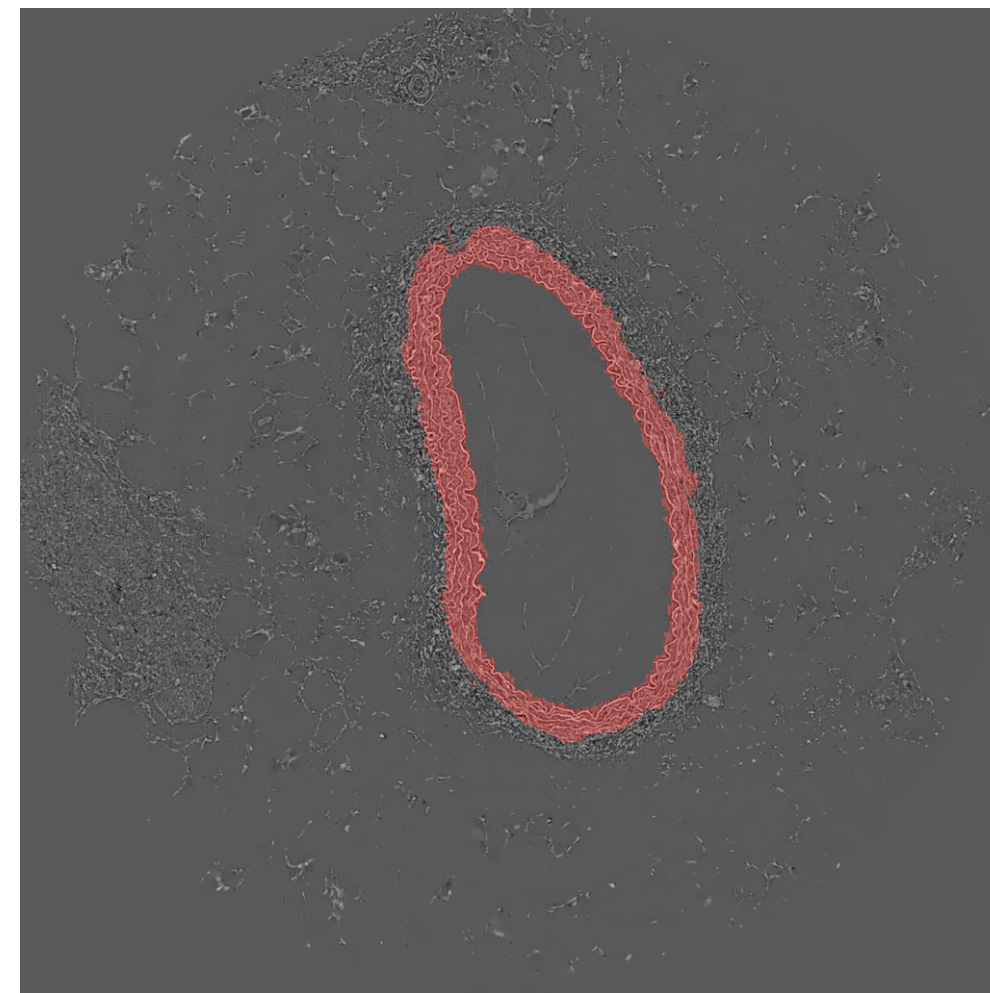
# Results

## Segmentation of whole *2D* images

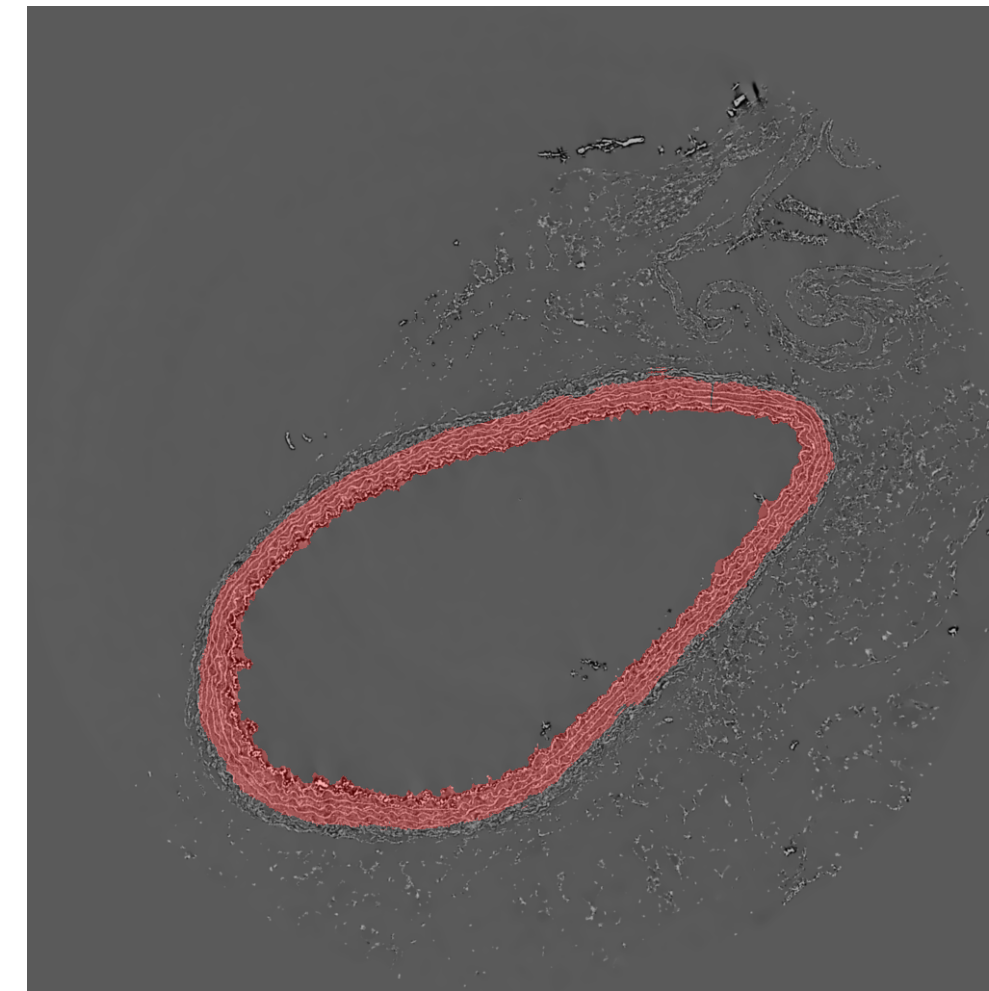
- Manual annotation of *tunica media*  
= borders of the lumen & borders between *tunica media* and *tunica adventitia*
- Results



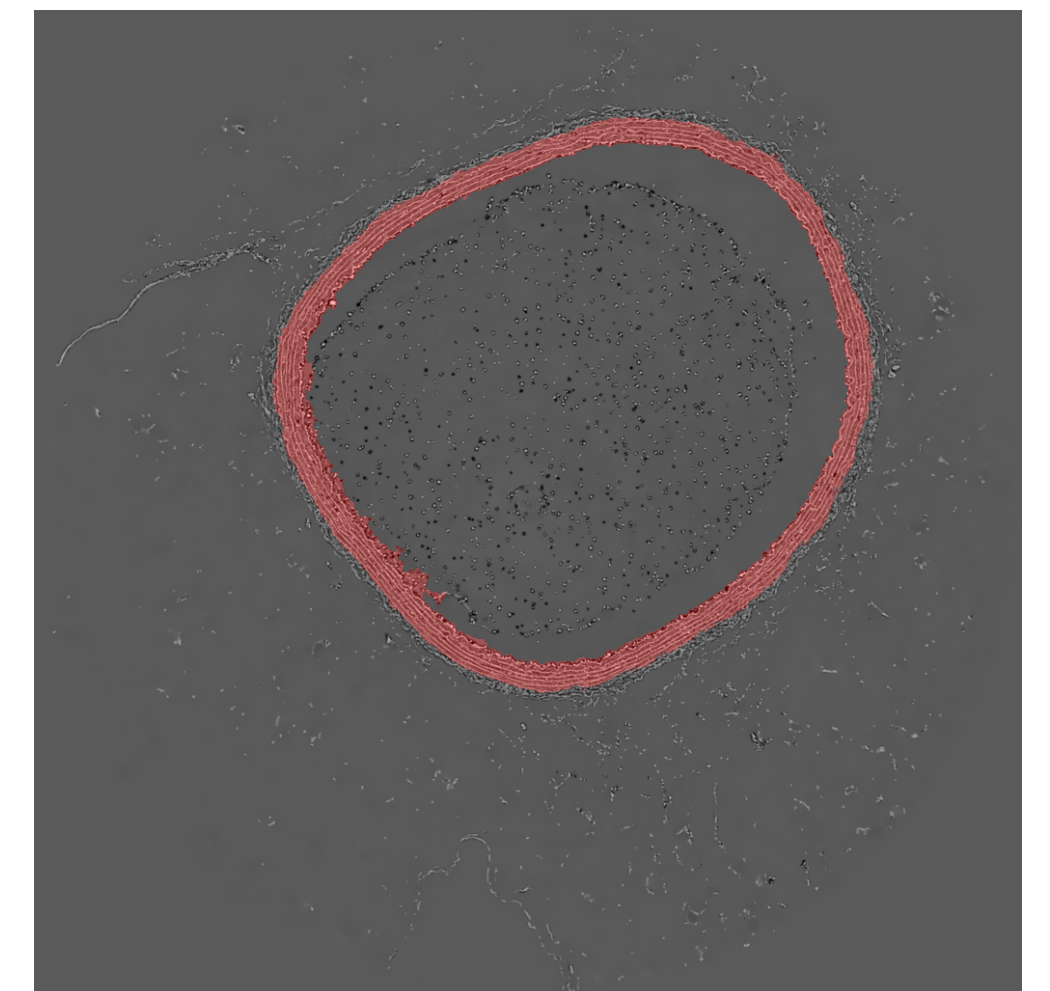
Dice score: 0.926



0.921



0.933

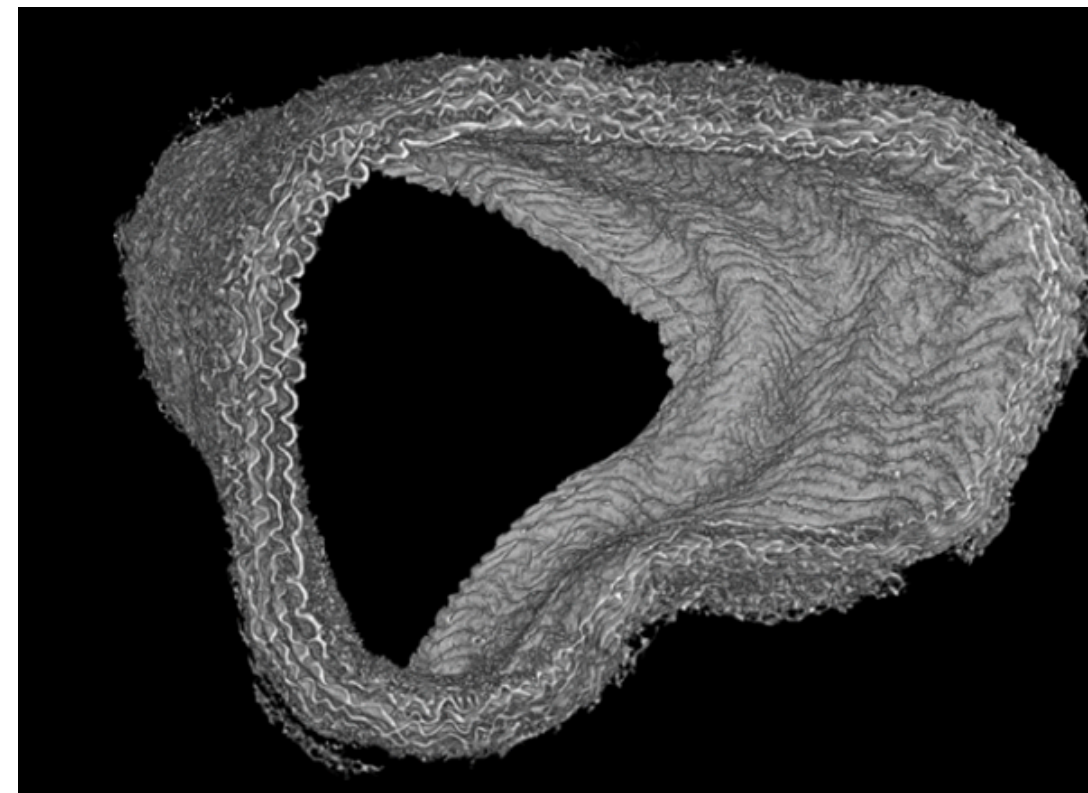


0.917

# Conclusion and perspectives

- The proposed segmentation pipeline is a first step towards the goal of analyzing vascular modifications in order to predict the arrival of related diseases.
  - It mixes conventional image processing and deep learning paradigms, and provides promising results.
- 

- The next steps of that work will consist of
  - exploring more thoroughly the deep learning part of the process
  - 3D implementation.



Reconstructed 3D volume

**Thank you!**