POLITECNICO
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Extended Version

Deep Learning based Coronary Artery Centerline tracking aimed at Fractional Flow Reserve Prediction from CCTA images

Laurea Magistrale in Automation and Control Engineering -
Ingegneria del Controllo e dell'Automazione

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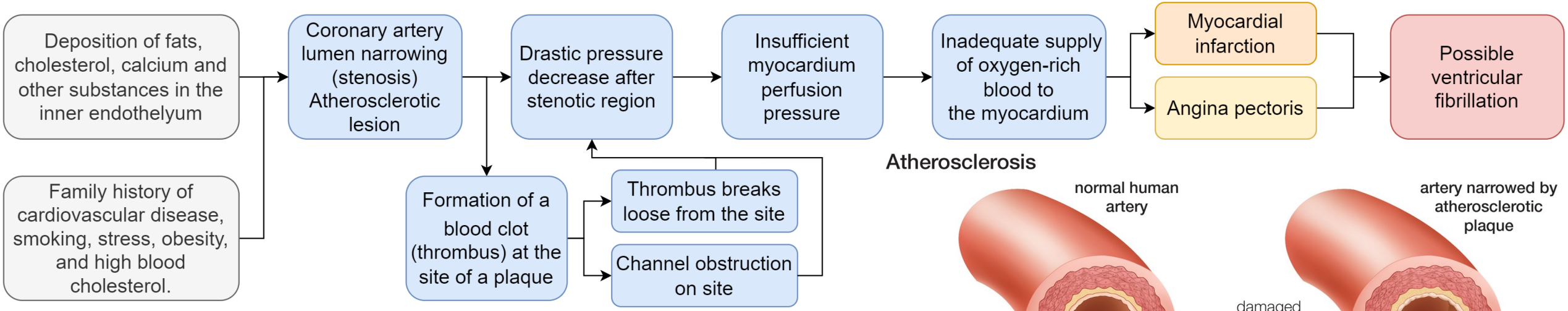
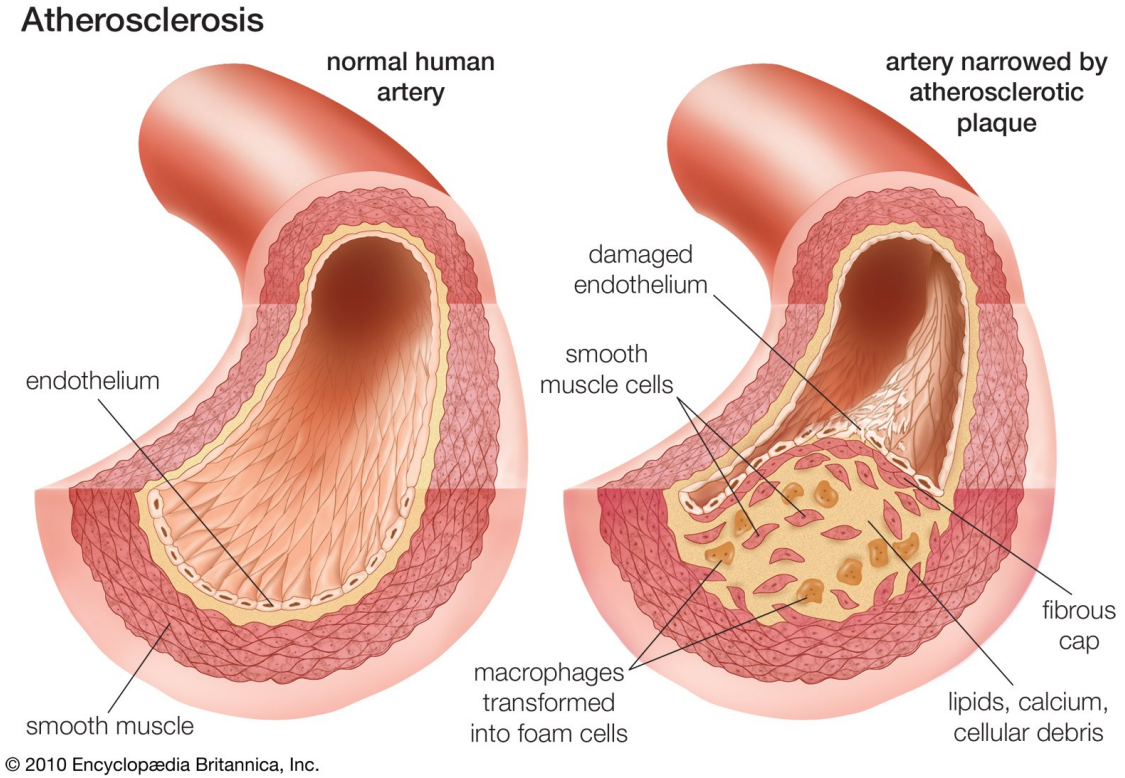
Academic year: **2021-22**

CORONARY ARTERY DISEASE

Leading cause of death in the world – WHO, AHA



Cardiovascular disease accounted for approximately 19.05 million global deaths in 2020.
Cardiovascular disease accounted for 874’613 deaths in the United States in 2019, 41.3% of which from Coronary Artery Disease (leading cause of death).



FRACTIONAL FLOW RESERVE INDEX (FFR)

Used for invasive, hemodynamically informative assessment of severity of coronary stenosis

Coronary angiography still used as standard stenoses evaluation method → Accuracy is very modest

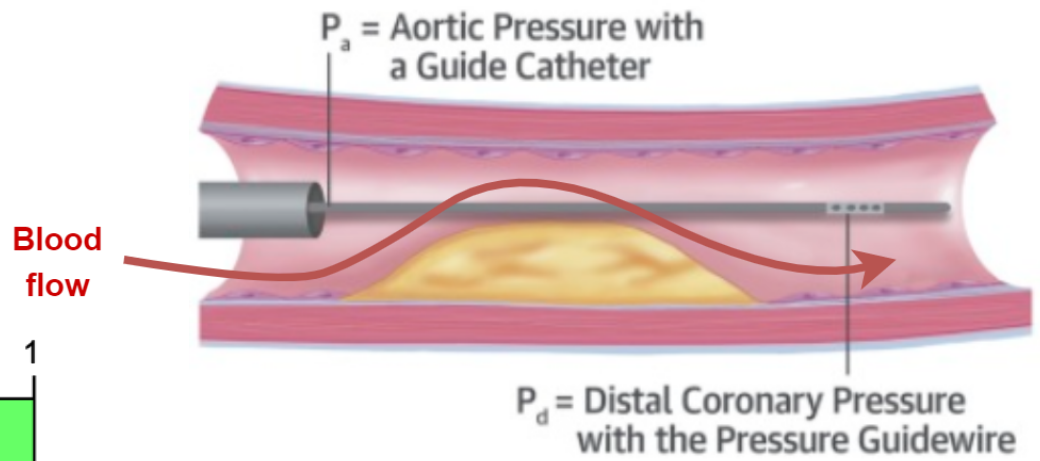
Intravascular ultrasound

Optical coherence tomography

→ No useful insight on coronary hemodynamics

Measures of **intracoronary pressure** provide information on the hemodynamic impact of single and multiple atherosclerotic lesions

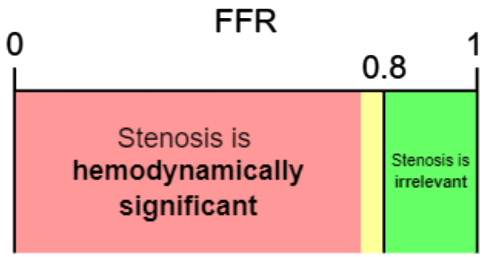
- P_a : aortic pressure, or pressure proximal to a stenosis
- P_d : pressure distal to -after- the stenosis



Fractional Flow Reserve (FFR)

$$FFR = P_d/P_a$$

(under hyperemia condition)



Coronary Computed Tomography Angiography (CCTA) images

Coronary Computed Tomography Angiography

Coronary Computed Tomography Angiography images are obtained from an X-ray CT scan.

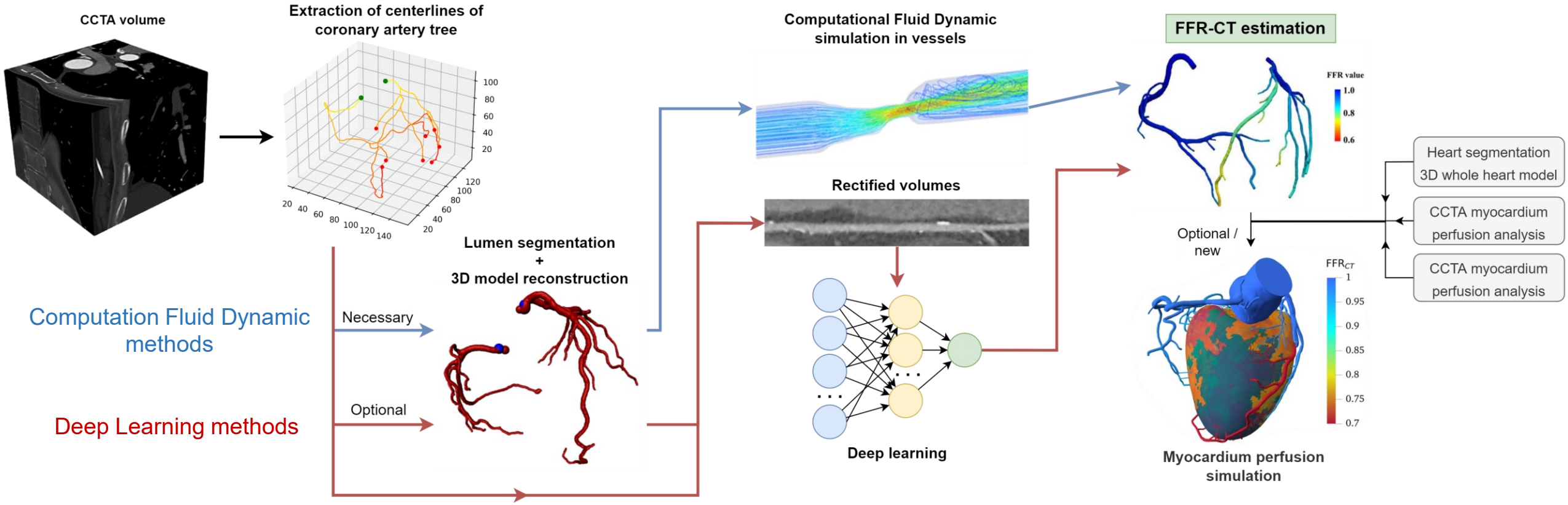
Coronary blood vessels are made visible by a **contrast liquid** injected in the arterial blood flow.

Adenosine is typically used to induce maximum **hyperemia condition** (maximum dilation of the blood vessels).

CCTA images are widely used to **assess the severity** and characteristics atherosclerotic plaque and lesions.

FFR DERIVED FROM CCTA IMAGES (FFR-CT)

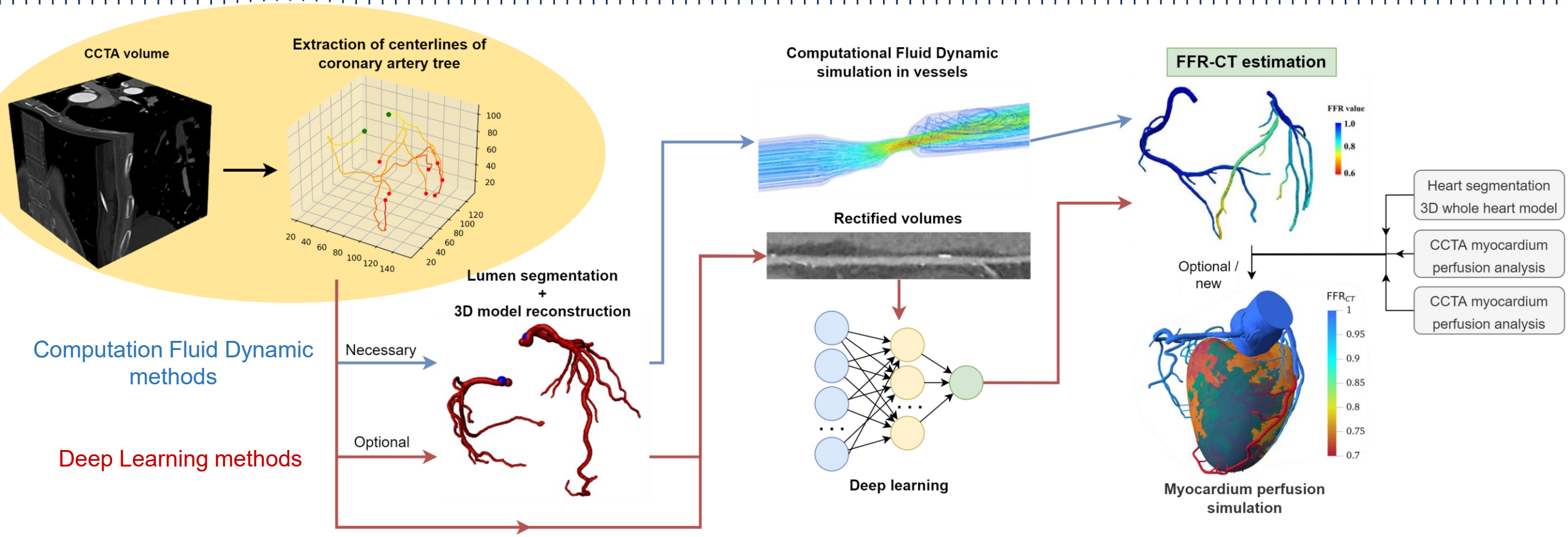
Fractional Flow Reserve index can be derived from Coronary Computed Tomography Angiography (CCTA) images



FFR-CT allows non-invasive assessment of the severity of stenoses and Coronary Artery Disease

FFR DERIVED FROM CCTA IMAGES (FFR-CT)

Fractional Flow Reserve index can be derived from Coronary Computed Tomography Angiography (CCTA) images

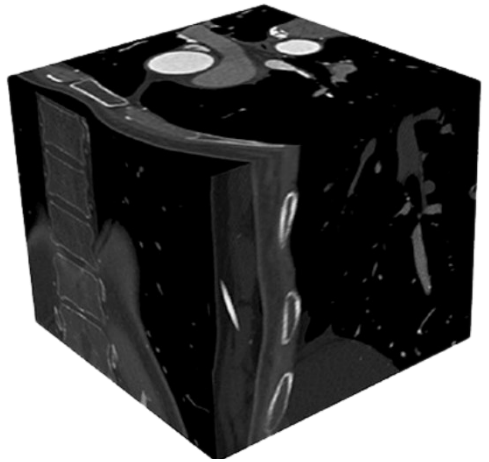


FFR-CT allows non-invasive assessment of the severity of stenoses and Coronary Artery Disease

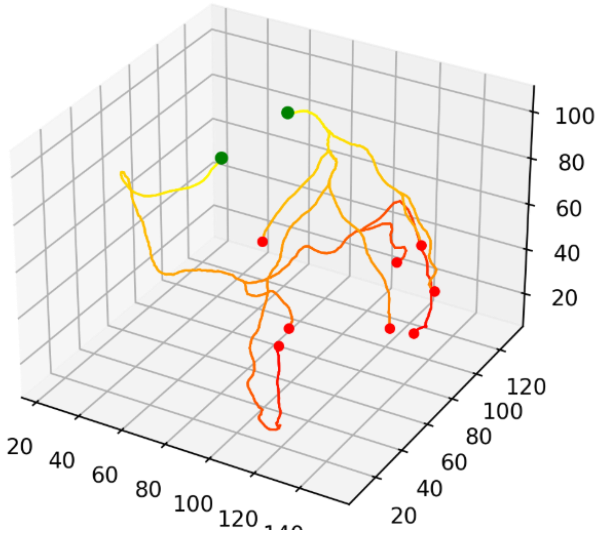
AUTOMATIC CORONARY ARTERY CENTERLINE ESTIMATION

Uses of CCTA extracted vessel centerlines include Multiplanar Reformatted Volume visualization and FFR-CT

CCTA volume



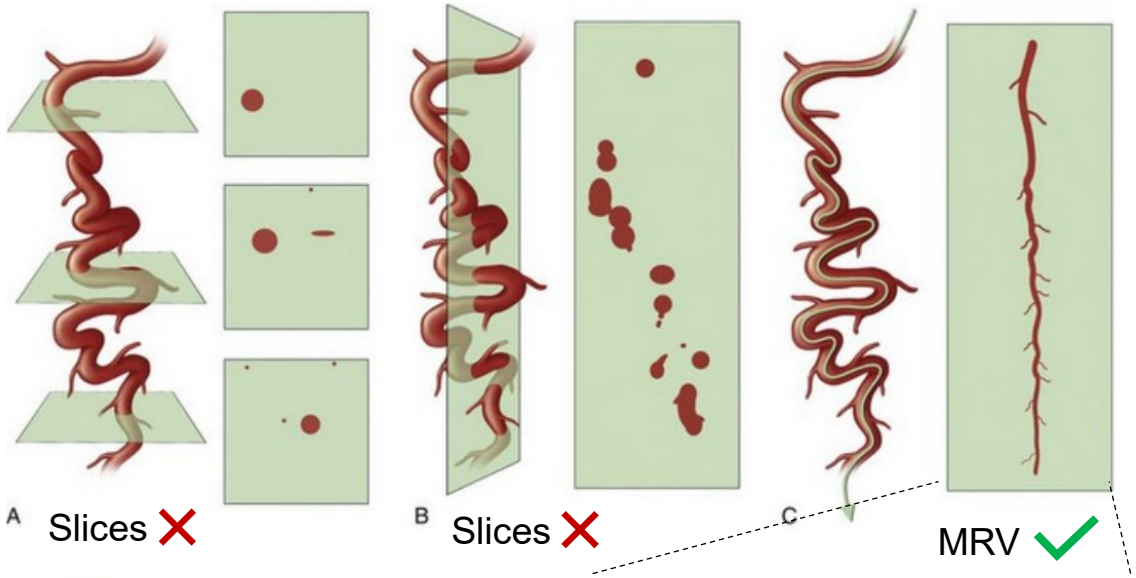
Extraction of centerlines of coronary artery tree

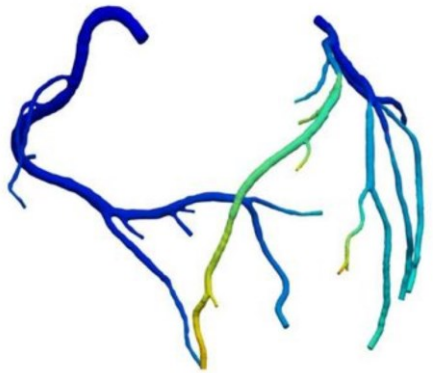


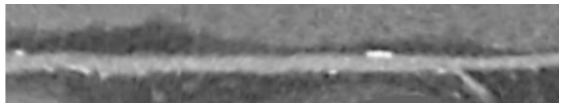
Classic application

New application

Multiplanar Reformatted Volume (MRV) visualization





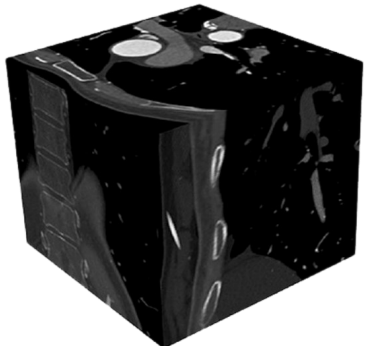


FFR-CT estimation in subsequent algorithms

AUTOMATIC CORONARY ARTERY CENTERLINE ESTIMATION

The current state-of-the-art methods are based on iterative trackers based on CNNs

CCTA volume



Minimal cost path methods

Short cuts

Centerline extraction after lumen segmentation

Whole volume analysis

Methods based on idealised tubular models, hand-crafted vesselness filters and shape priors

Suffer in stenosis / bifurcations areas

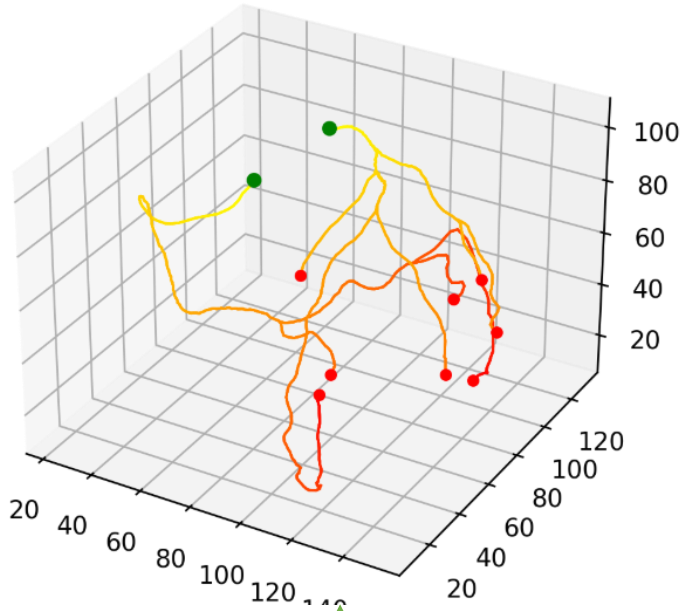
Machine learning methods relying on intermediate feature representations

Time consuming / Resource intensive

Iterative centerline tracker based on Deep Convolution Neural Networks

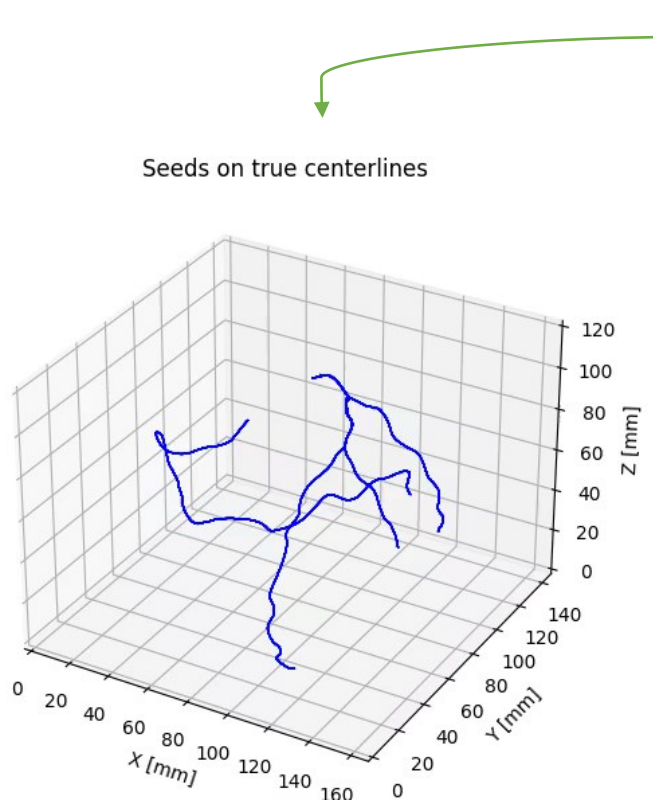
State of the art

Extraction of centerlines of coronary artery tree

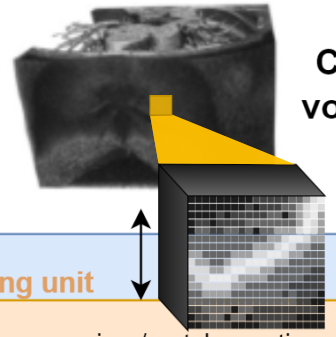


ITERATIVE CENTERLINE TRACKING

Pipeline representation



Seeds list
Seed 1 (x,y,z)
Seed 2 (x,y,z)
.....



CCTA volume

Modular Tracker

Sensing unit
Image sensing / patch creation
Path logger

Initialisator

Visual cortex
Input processing
CNN
Output interpretation

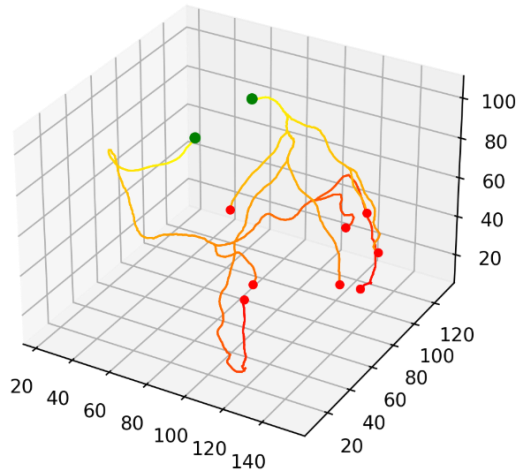
Movement logic
Jump actuator
Landing point computation
Termination logic

Path finaliser

Paths storage

Post-processing

Final result:
clean centerline tree



ITERATIVE CENTERLINE TRACKING

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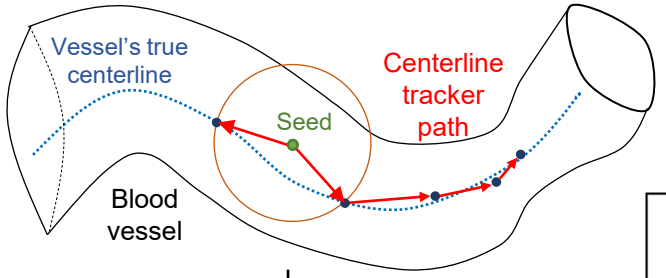
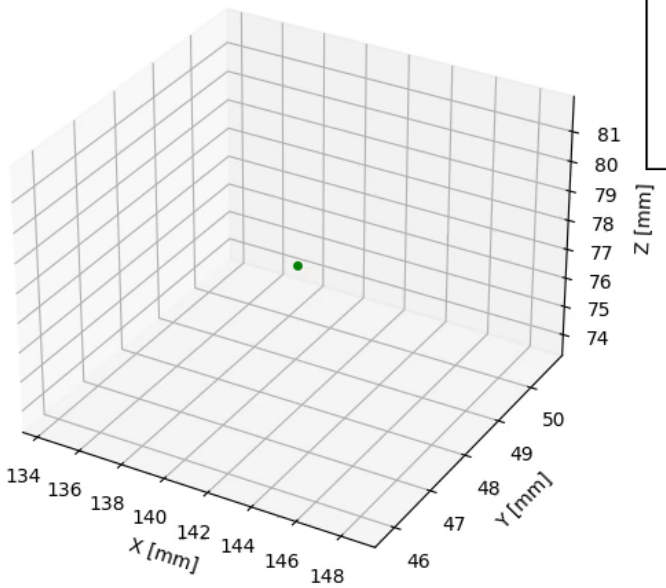


Centerline tracker in action



Seeds list
Seed 1 (x,y,z)
Seed 2 (x,y,z)
.....

CCTA volume

Modular Tracker

Sensing unit

Image sensing / patch creation

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Input processing → CNN → Output interpretation

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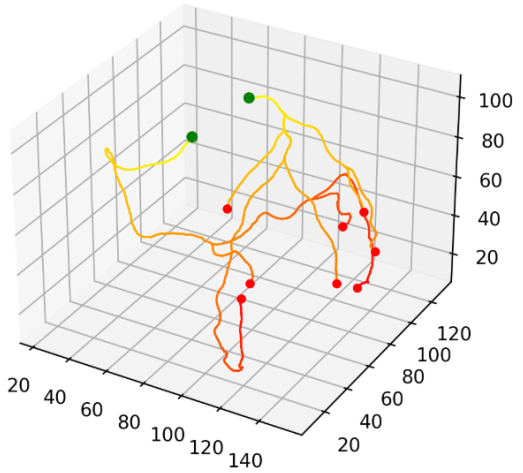
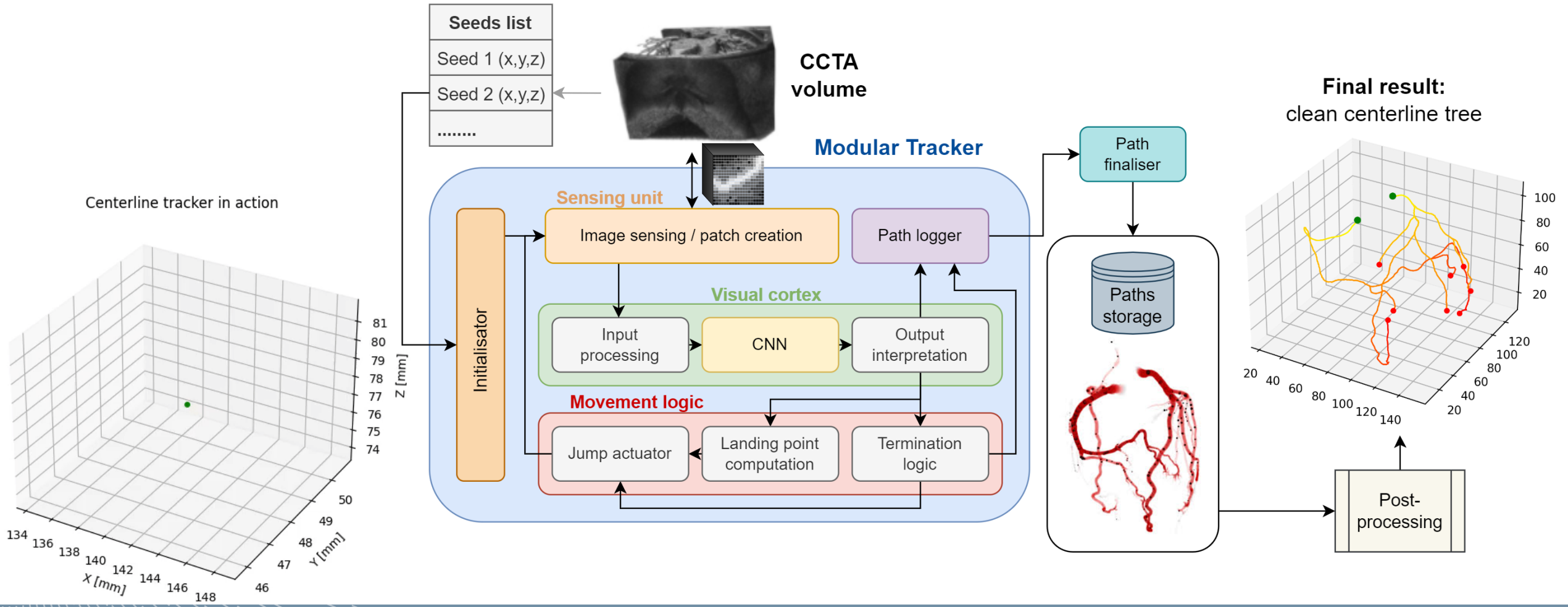


ITERATIVE CENTERLINE TRACKING

Pipeline representation



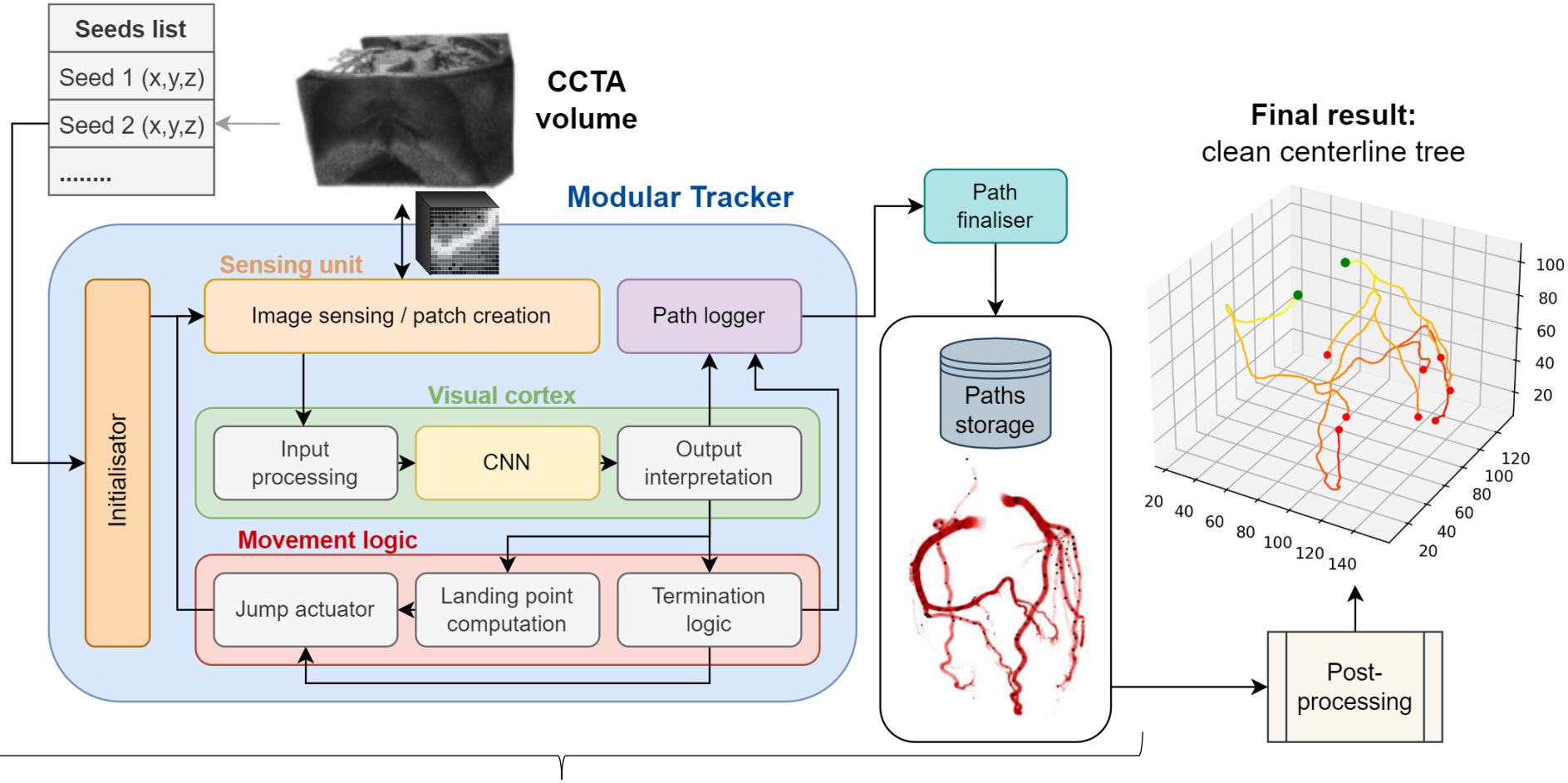
ITERATIVE CENTERLINE TRACKING

Pipeline representation

Wolternik et al.

"Coronary artery centerline extraction in cardiac CT angiography using a CNN-based orientation classifier"

Medical Image Analysis 51, pp. 46-60 2019



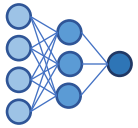
Wolternik et al.

MAIN CONTRIBUTIONS OF THIS WORK

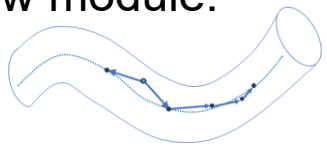
The contributions of this work are four-fold

1. Comprehensive **state of art** analysis.

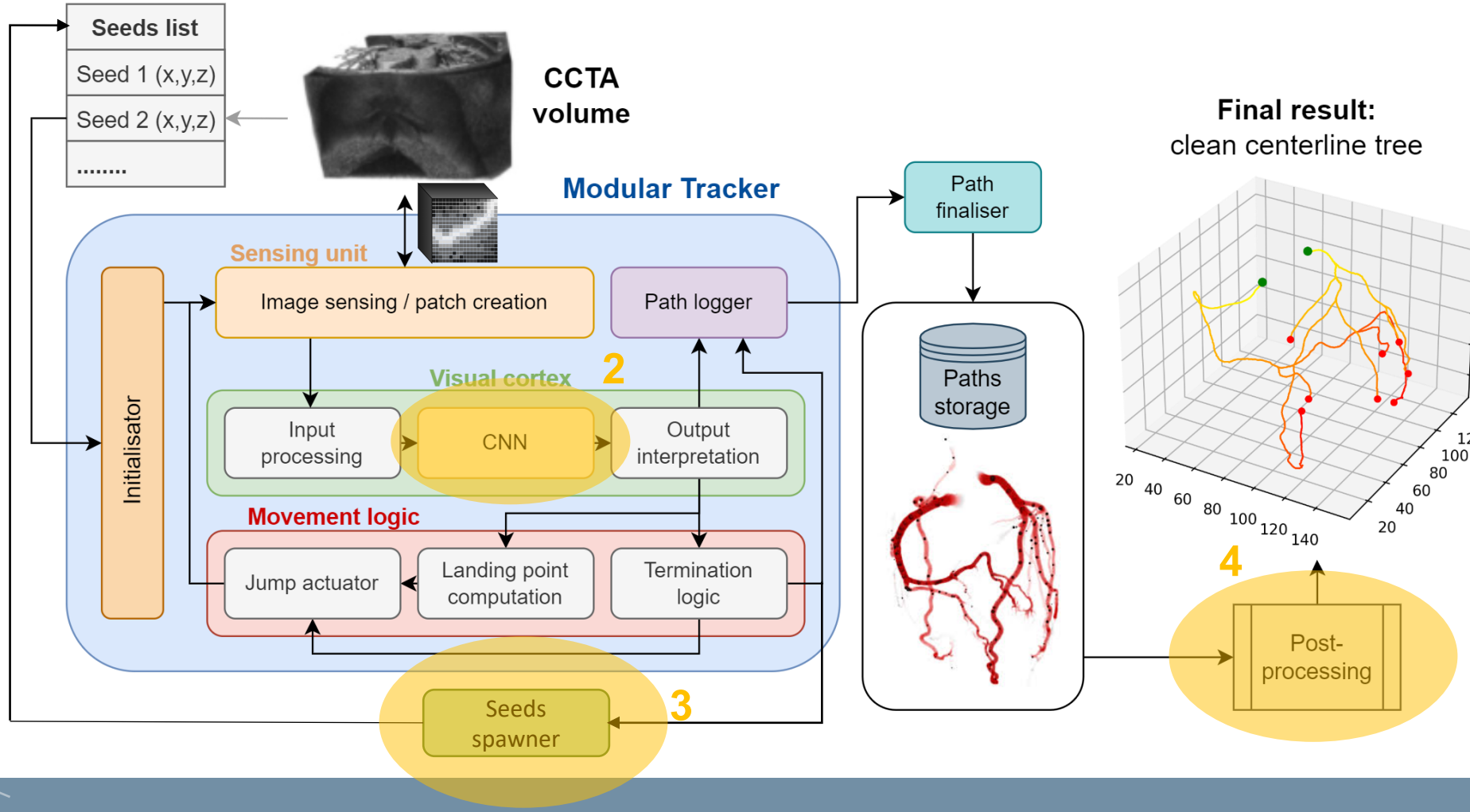
2. Improved **CNN** architecture.



3. Improved **tracker** + new module.



4. New **post-processing** step for clean final centerlines



MAIN CONTRIBUTIONS OF THIS WORK : COMPREHENSIVE STATE OF THE ART ANALYSIS

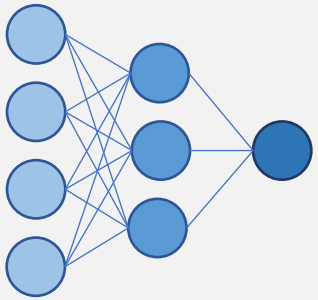
A relevant part of my work was focused on gathering and organizing knowledge about every step concerned with the whole FFR-CT estimation process, including *centerlines extraction, lumen segmentation*, *FFR-CT estimation* by means of CFD and NN methods and *myocardium perfusion estimation*.

Over 100 technical and medical papers and articles were considered, and the latest state of the art reviewed in a conjunct project with Gruppo MultiMedica.

Gruppo MultiMedica
Passione, ricerca e innovazione per la salute

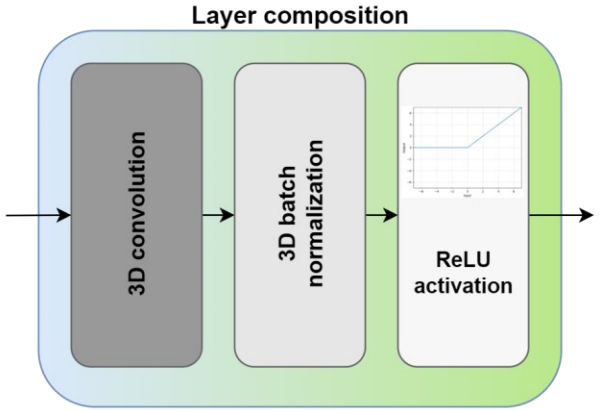
MAIN CONTRIBUTIONS OF THIS WORK : CNN

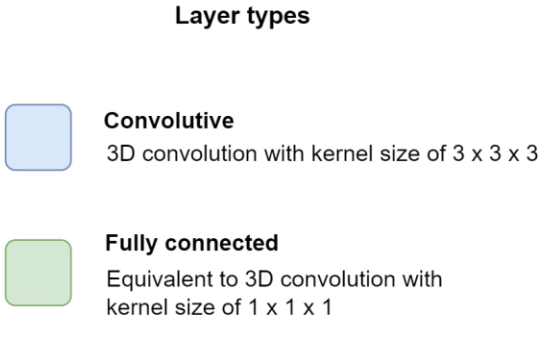
Improved CNN architecture

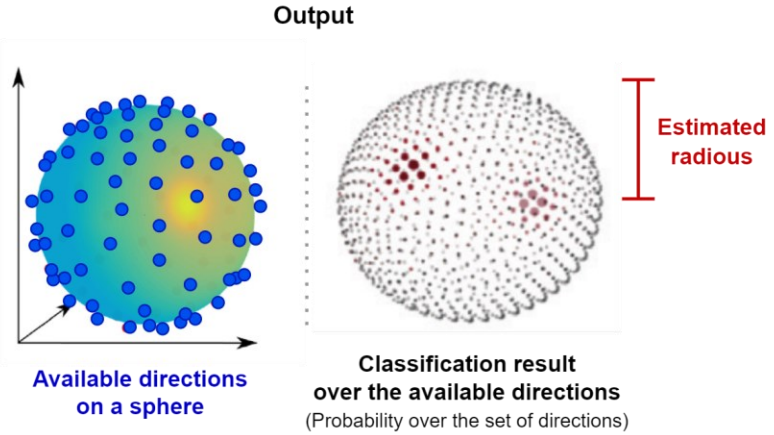


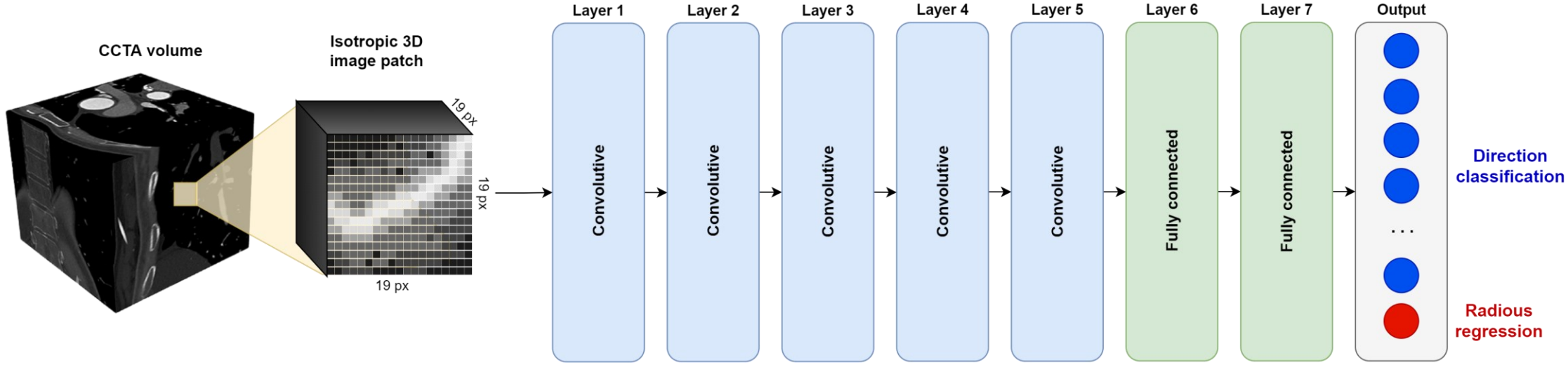
BASELINE CONVOLUTIONAL NEURAL NETWORK

Wolternik's network



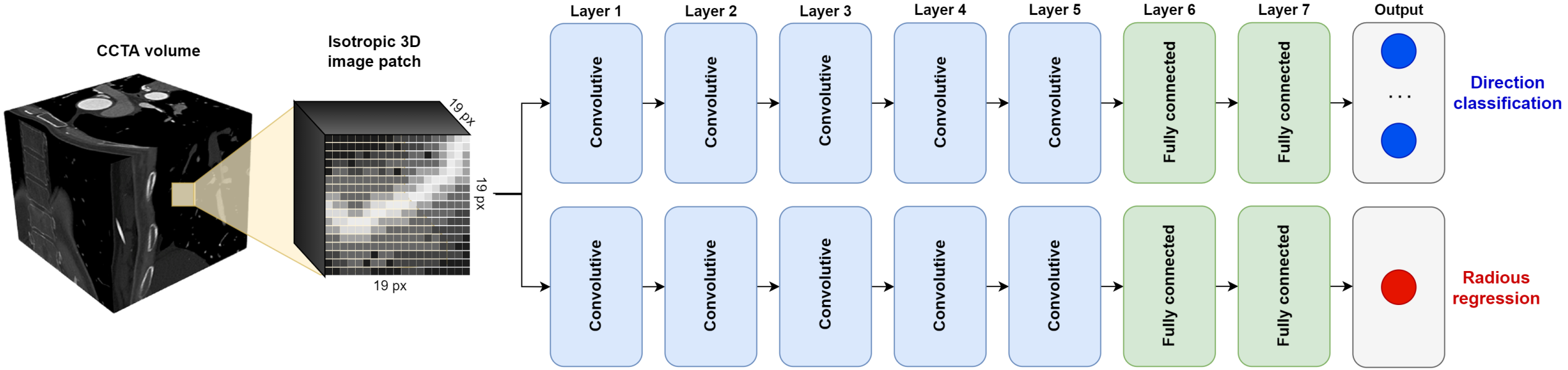






INTERMEDIATE CONVOLUTIONAL NEURAL NETWORK # 1

Double network ("input-layer-split")

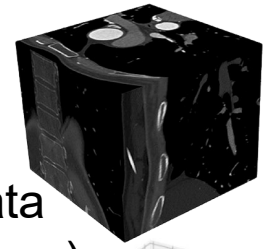


NEURAL NETWORKS TRAINING DATASET AND TEST SUITE

Images used for training and testing the CNNs were taken from the publicly available CAT08 challenge dataset

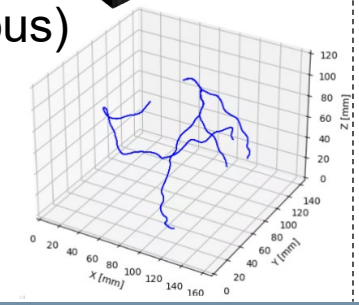
Dataset

All networks were trained in the same exact conditions (epochs, loss functions, training dataset, preprocessing) on 7 of the 8 images in the annotated training dataset from the *MICCAI 2008 Coronary Artery Tracking Challenge (**CAT08**)*, which is part of the *Rotterdam Coronary Artery Algorithm Evaluation Framework.*



Each training set image contains:

- CCTA image + pixel spacing metadata
- 4 annotated centerlines (x, y, z, radious)



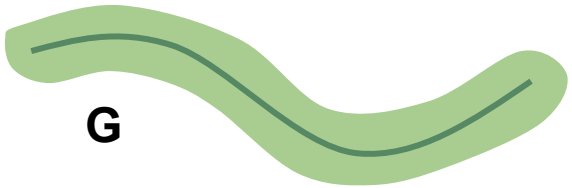
Test suite

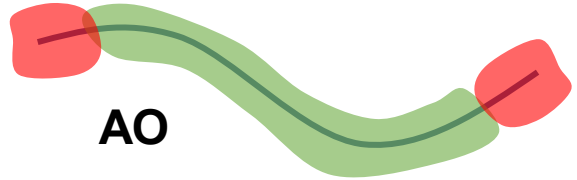
All networks were evaluated on the image left-out in training, in the same exact conditions.
The most relevant performance indicators are:

- ***mean($R_{err,abs}$)***: radious estimation absolute error.
- ***mean(α_{err})***: direction estimation angular error.
- ***mean($d(P_l,P_c)$)***: distance between the estimated landing point and the true centerline.
- ***mean($d(P_l,P_{c,opt})$)***: distance between the estimated landing point and the point used for training the CNN.

Each metric was computed considering:

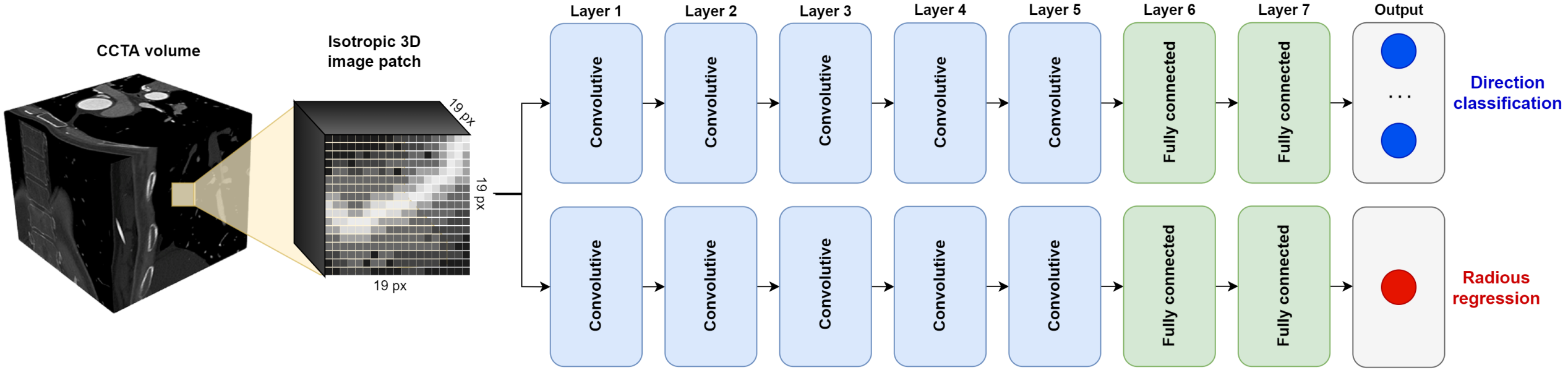
- **G**: all test points,
- **AO**: all tests points that are far enough from the endpoints of the true centerlines.





INTERMEDIATE CONVOLUTIONAL NEURAL NETWORK # 1

Double network ("input-layer-split")



CNN name	Domain	mean($R_{err,abs}$) [mm]	mean(α_{err}) [deg]	mean($d(P_l, P_c)$) [mm]	mean($d(P_l, P_{c,opt})$) [mm]	Learnable params	Test exec. time [s]
Wolternik's	G	0.246	25.74	0.402	0.515	**176'533**	**110**
	AO	0.203	24.81	0.368	0.466		
Input-layer-split	G	0.197	25.18	0.380	0.472	353'066	168
	AO	0.152	24.56	0.346	0.422		

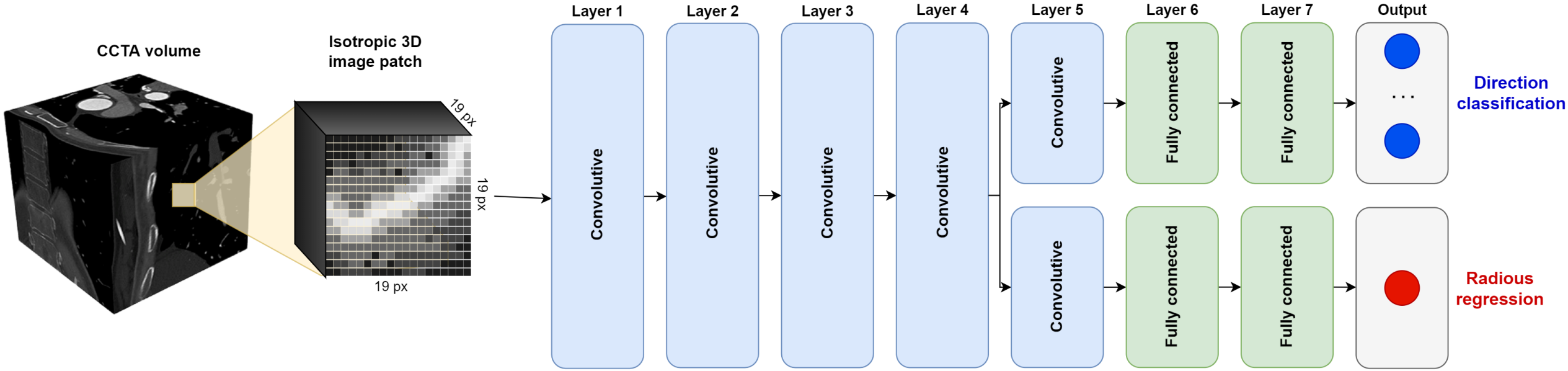
- 5.97%

Most important metric in tracking

How far the CNN "lands" from the true centerline

INTERMEDIATE CONVOLUTIONAL NEURAL NETWORK # 2

Network with common initial layers ("midsplit-4")



CNN name	Domain	mean($R_{err,abs}$) [mm]	mean(α_{err}) [deg]	mean($d(P_t, P_c)$) [mm]	mean($d(P_t, P_{c,opt})$) [mm]	Learnable params	Test exec. time [s]
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	AO	0.203	24.81	0.368	0.466		
Input-layer-split	G	0.197	25.18	0.380	0.472	353'066	168
	AO	0.152	24.56	0.346	0.422		
Midsplit-4	G	0.158	**24.04**	0.379	0.454	236'309	123
	AO	0.114	**23.70**	0.347	0.419		
[illegible]							

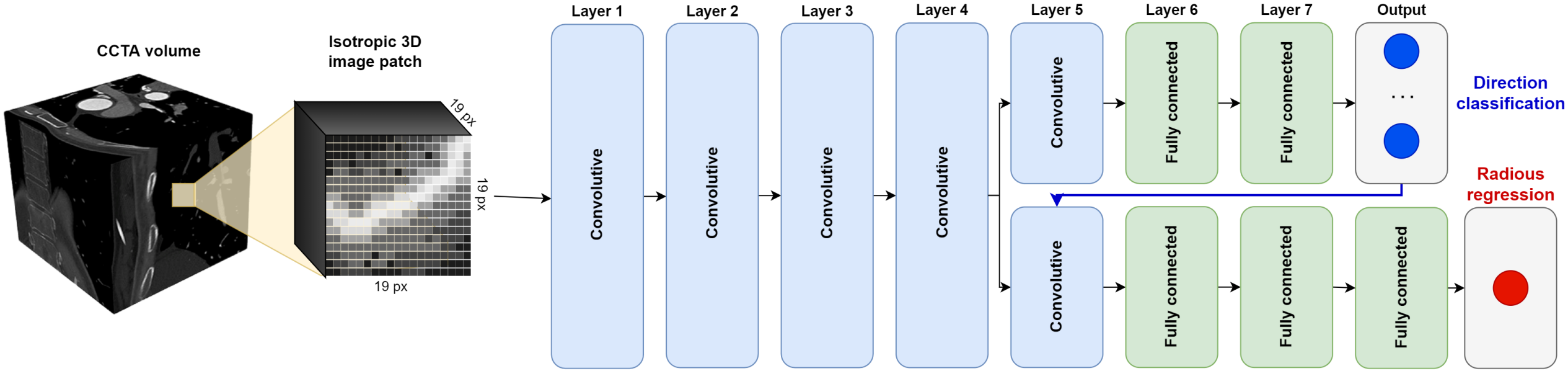
- 5.7%

Most important metric in tracking

How far the CNN "lands" from the true centerline

PROPOSED NEW CONVOLUTIONAL NEURAL NETWORK

Network with common initial layers + feedback on direction classification in radious regressor ("midsplit-4-FD")



CNN name	Domain	mean($R_{err,abs}$) [mm]	mean(α_{err}) [deg]	mean($d(P_t, P_c)$) [mm]	mean($d(P_t, P_{c,opt})$) [mm]	Learnable params	Test exec. time [s]
Wolternik's	G	0.246	25.74	0.402	0.515	**176'533**	**110**
	AO	0.203	24.81	0.368	0.466		
Input-layer-split	G	0.197	25.18	0.380	0.472	353'066	168
	AO	0.152	24.56	0.346	0.422		
Midsplit-4	G	0.158	**24.04**	0.379	0.454	236'309	123
	AO	0.114	**23.70**	0.347	0.419		
Midsplit-4-FD	G	**0.1399**	25.26	**0.3498**	**0.424**	270'357	133
	AO	**0.097**	24.58	**0.313**	**0.374**		

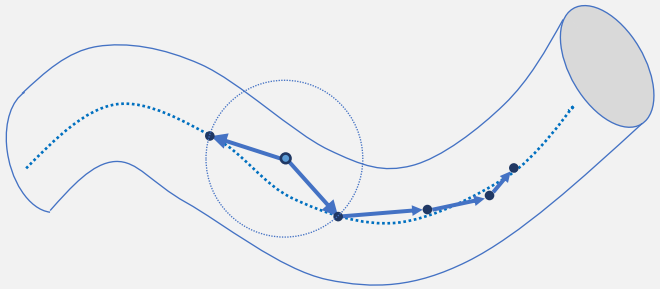
- 14.9%

Most important metric in tracking

How far the CNN "lands" from the true centerline

MAIN CONTRIBUTIONS OF THIS WORK : TRACKER

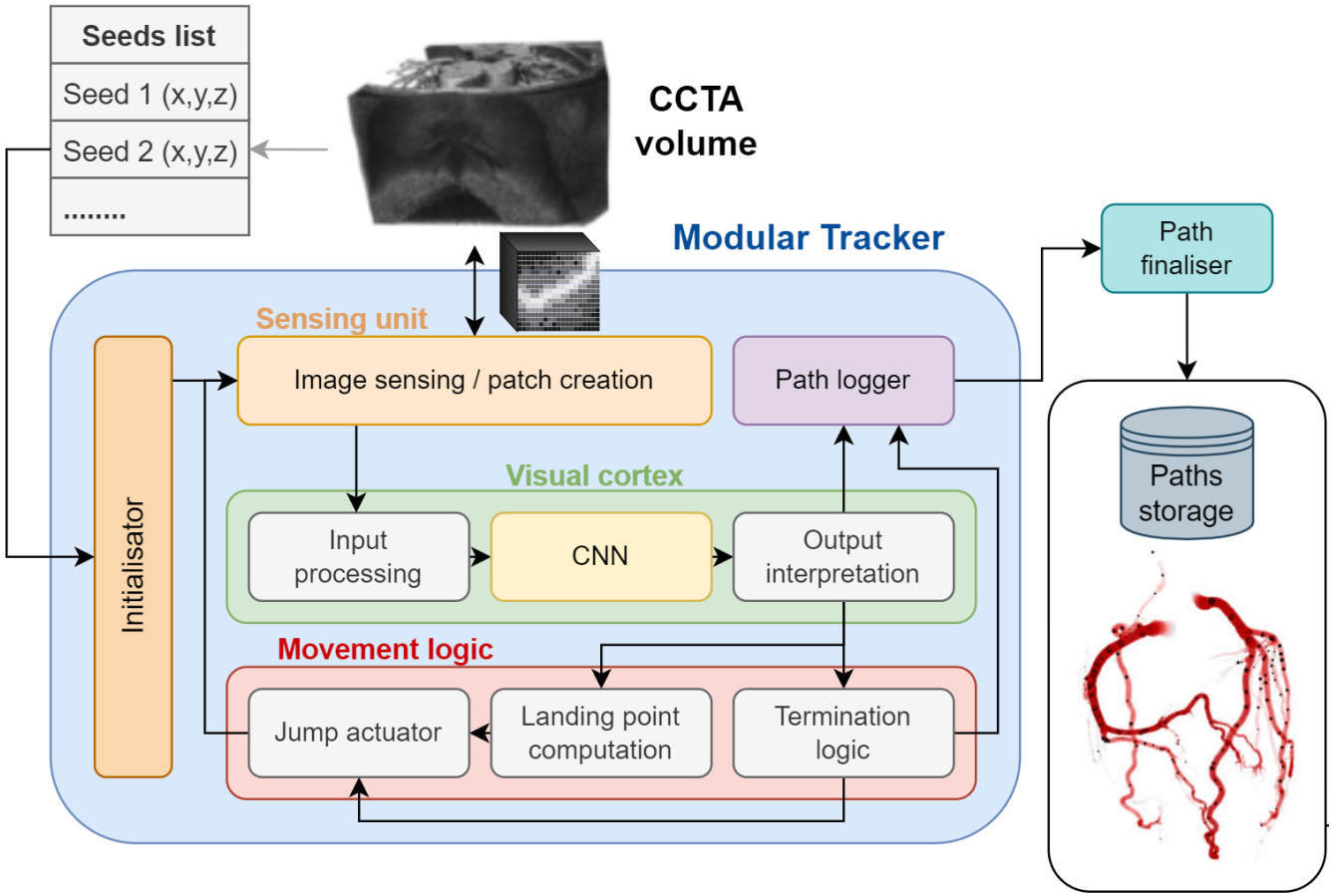
Improved tracker modularity
New tracker module



BASELINE TRACKER

Wolternik's tracker

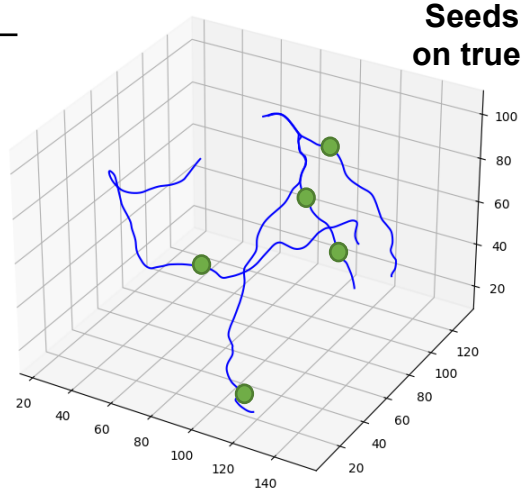
- Procedural algorithm.
- Strict directional constraints (new direction < 60° from previous direction).
- No bifurcation handling.
- Needs at least one seed per coronary artery.
- Static seeds list

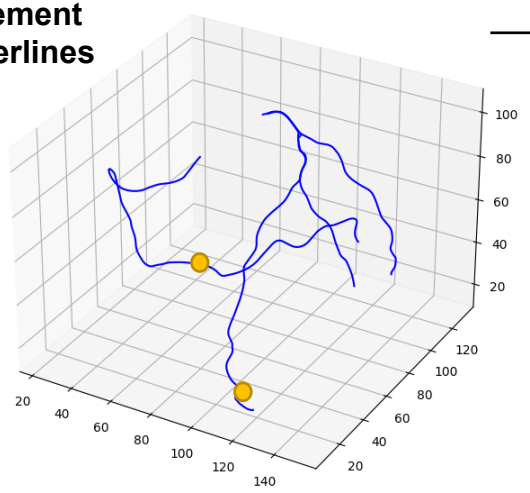


BASELINE TRACKER

Wolternik's tracker - performance

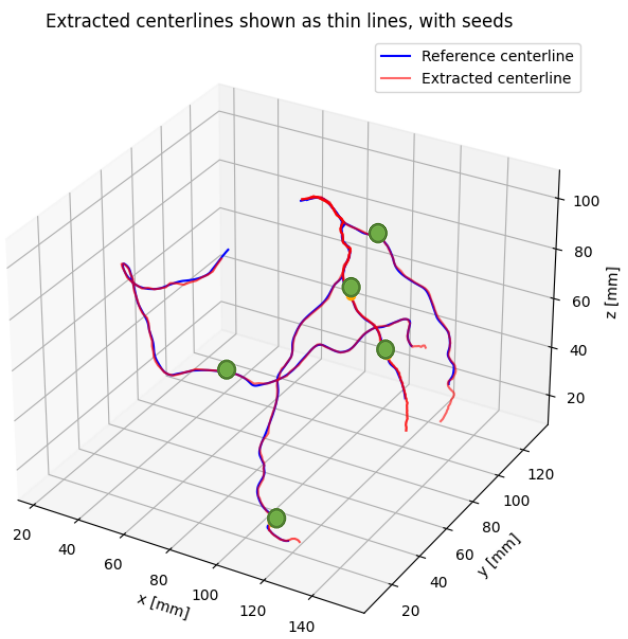
Seeds placement on true centerlines





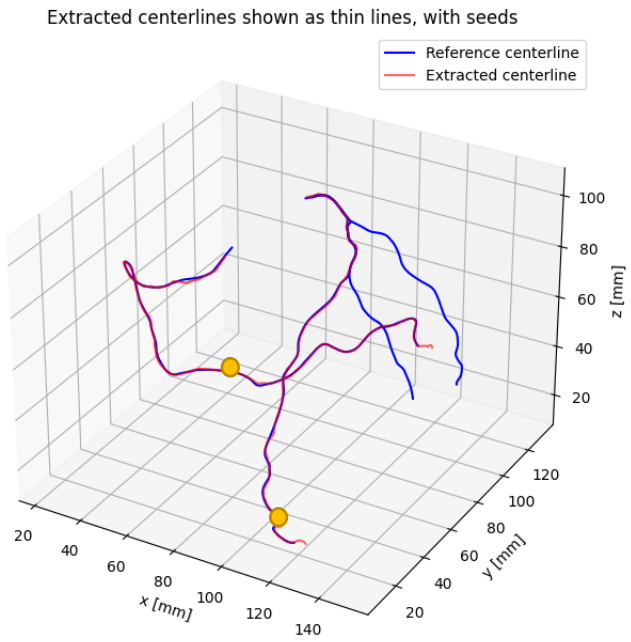
Easy situation
at least one seed per vessel

Difficult situation
just one seed per arterial tree



Arterial tree fully extracted

Full arterial tree extraction failed



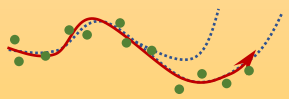
PROPOSED NEW TRACKER

Tracker with fine-tuned parameters + new module ("seedspawner" tracker)

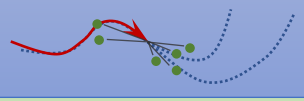
- **Modular**, object-oriented algorithm.
- **Looser directional constraints** (new direction < 90° from previous direction).
- **Iterative seeds generator** for **bifurcation handling** by part of the "seeds spawner" module (slower but more complete extraction).

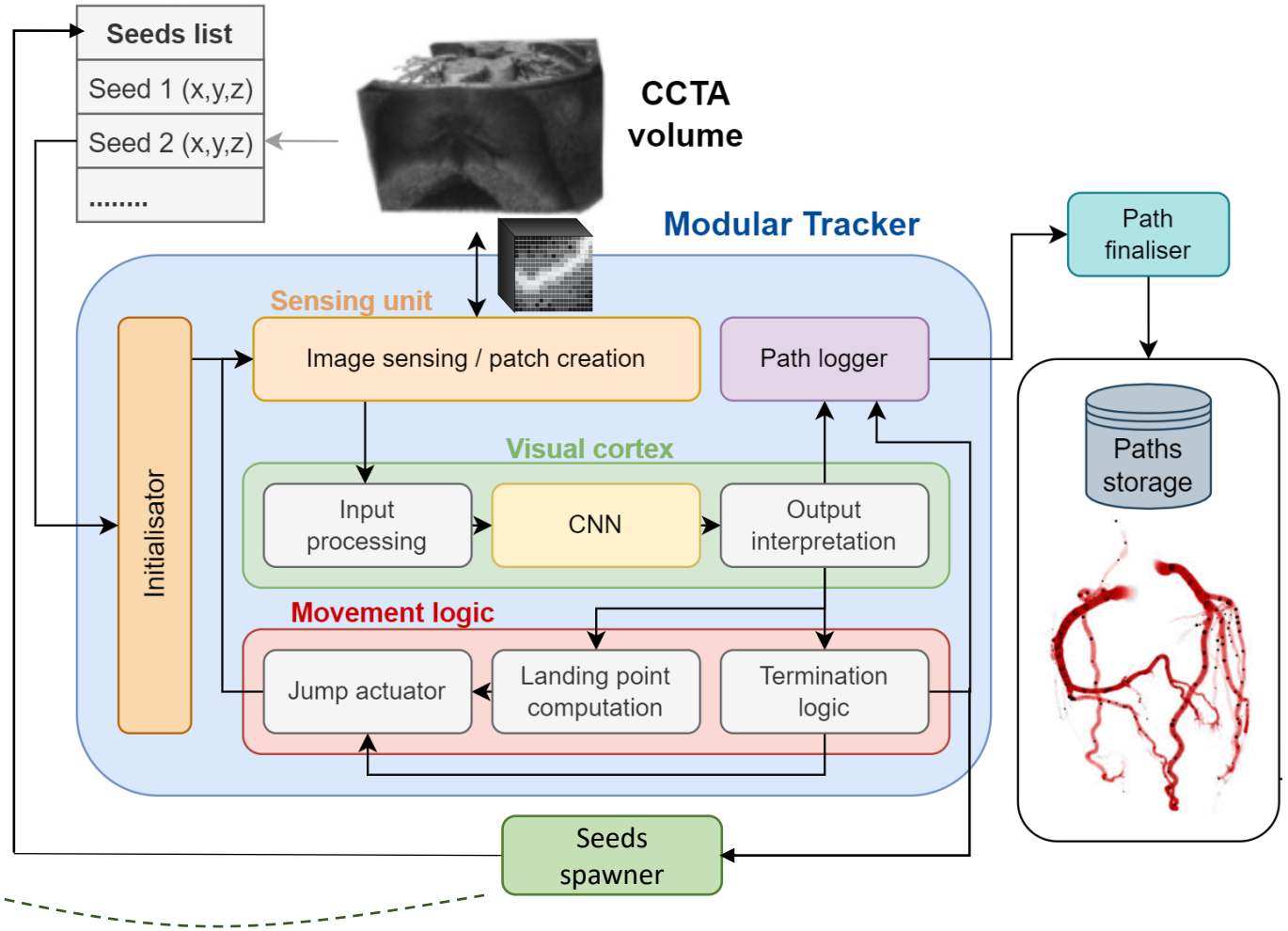
Seeds spawner module

Hansel and Gretel module
Plants seeds along the way while exploring the new centerline path



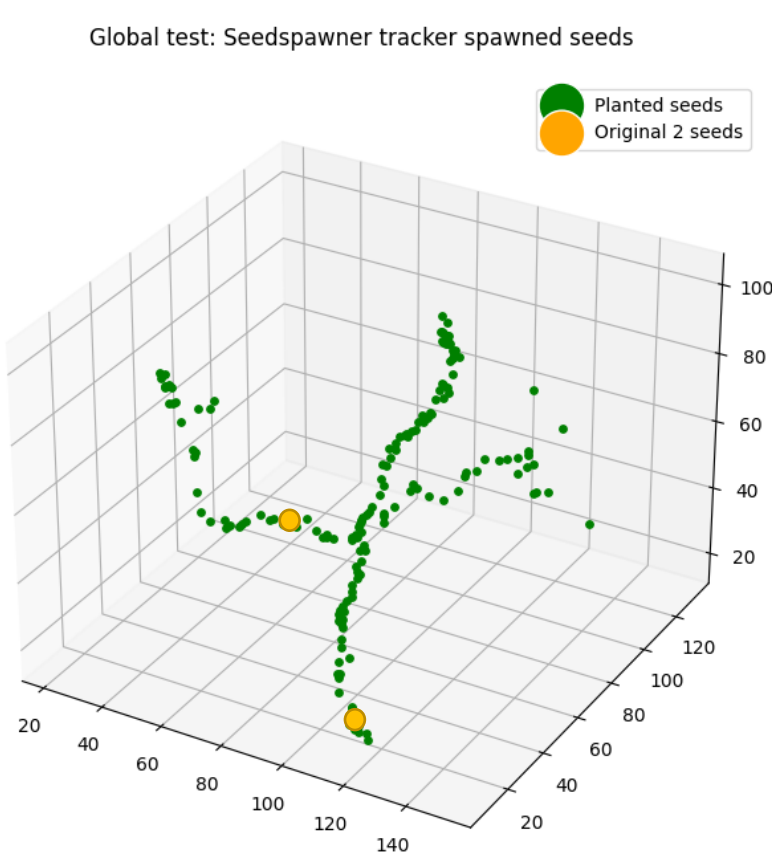
Directional seeding module
Plants seeds along the most likely directions as classified by the CNN



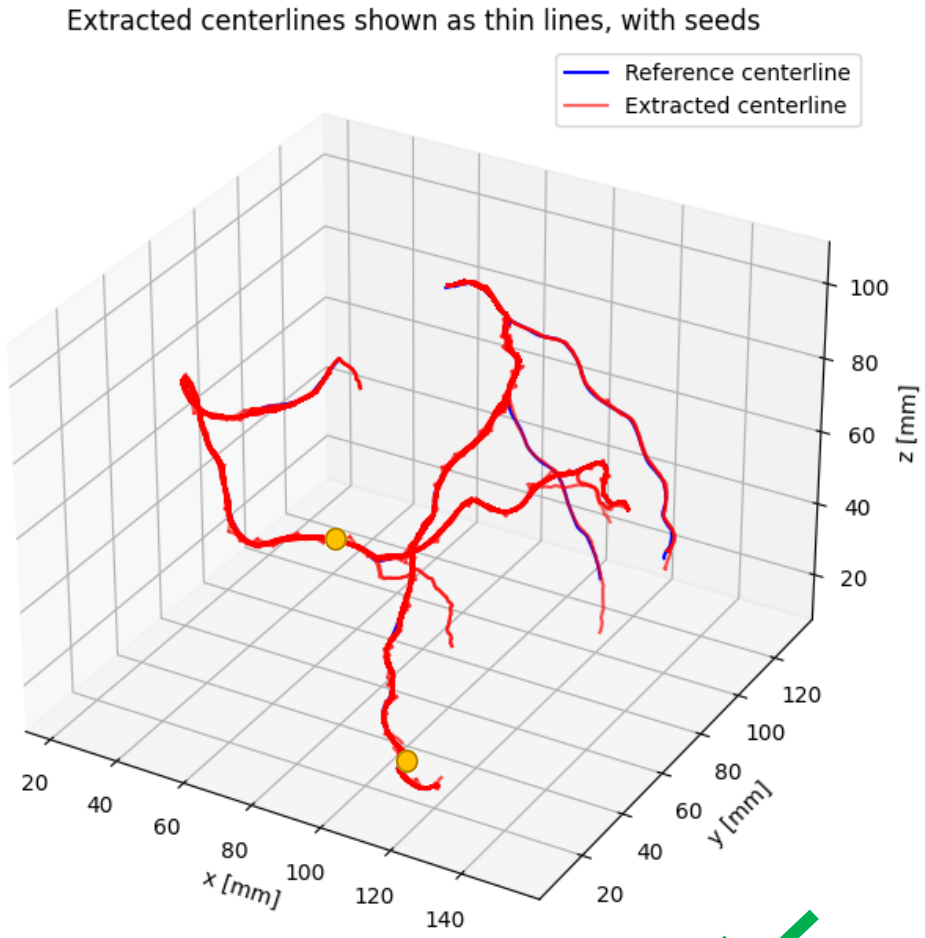


PROPOSED NEW TRACKER

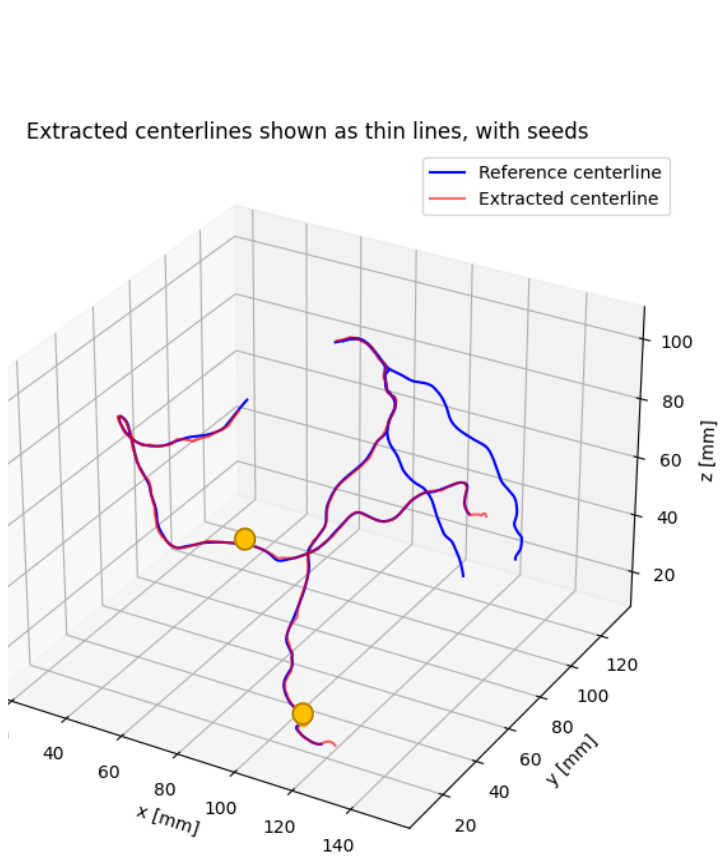
Seedspawner tracker performance against Wolternik's tracker



Effect of the seeds spawner module



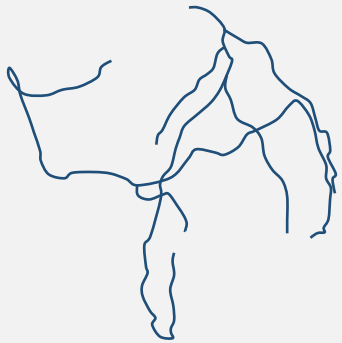
My "**seedspawner**" tracker ✓



Wolternik's tracker ✗

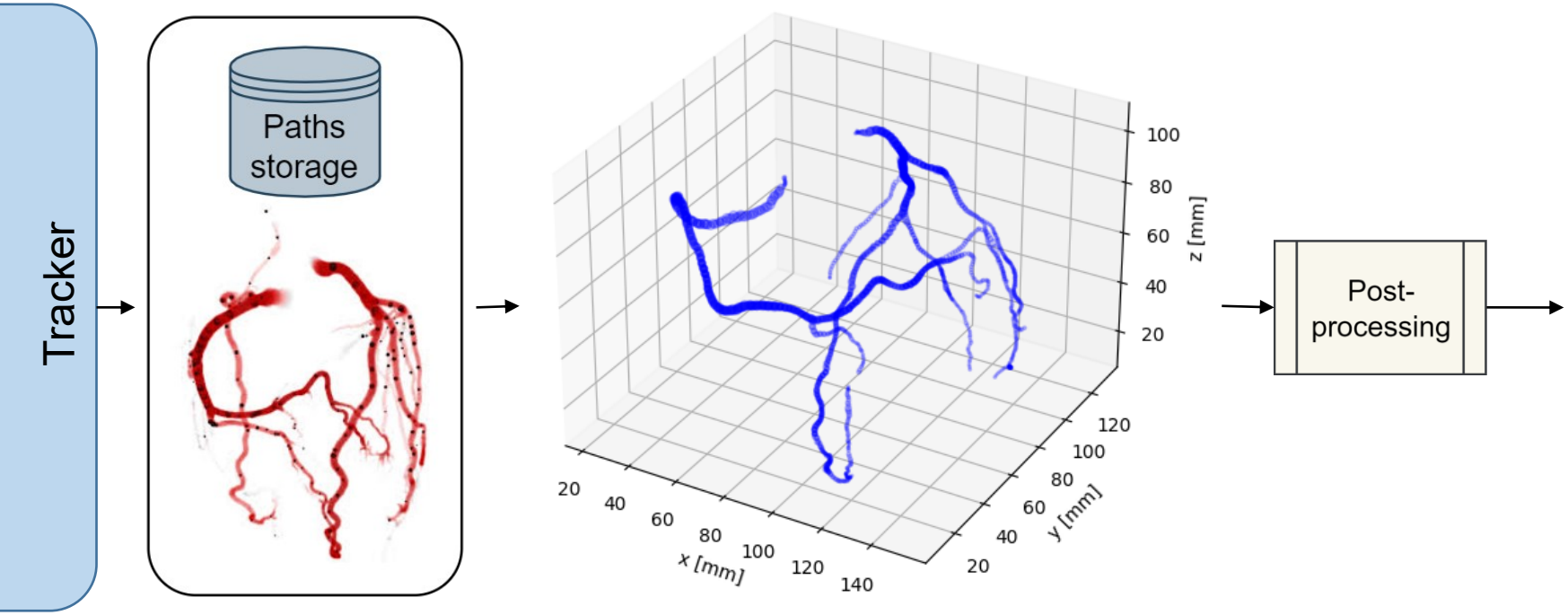
MAIN CONTRIBUTIONS OF THIS WORK : POST-PROCESSING

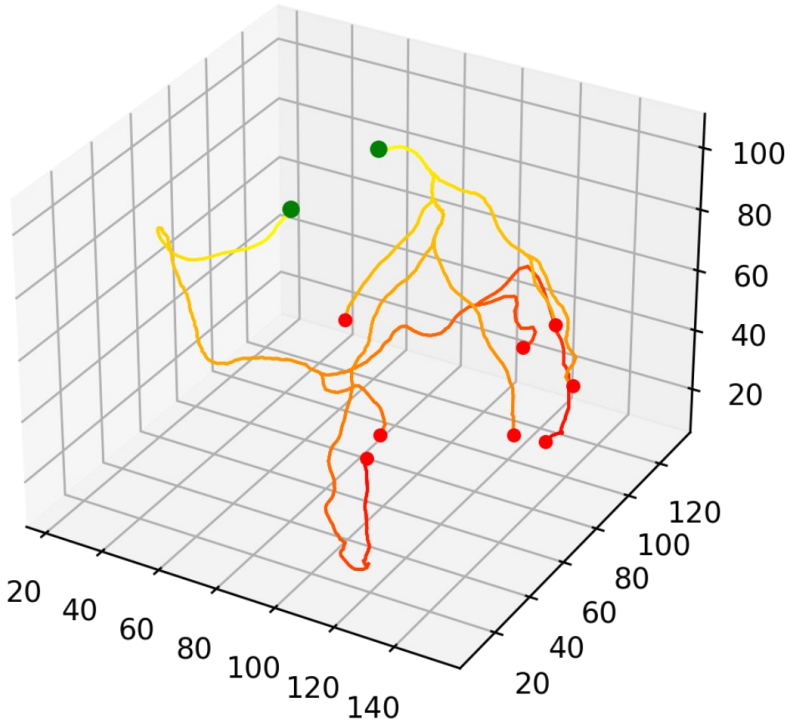
New post-processing based on graph algorithms



PROPOSED NEW GRAPHS-BASED POST-PROCESSING

Graphs allow to define and store the centerline tree topology in a consistent and easily accessible data structure





Unstructured cloud of points

Problems:

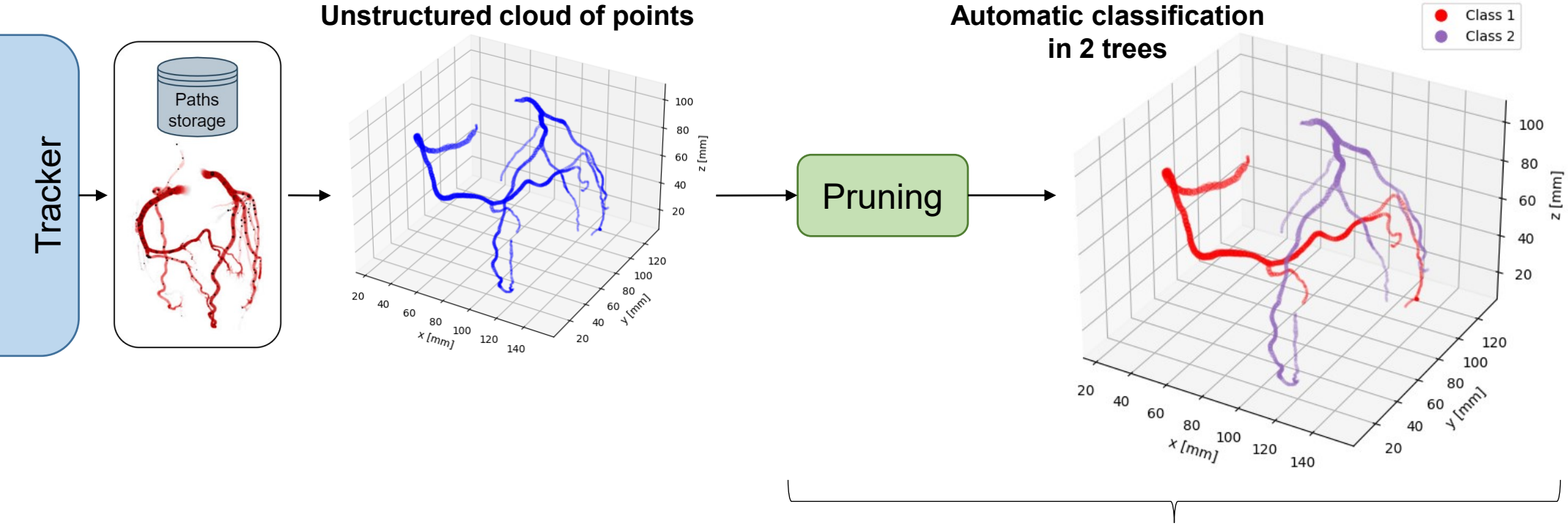
- To what arterial tree does each point belong (left or right)?
- What are the starting and ending points of the tree?
- How do I get a single path from a disordered cloud of points?
- What about overlapping paths?

Structured graph object

The proposed post-processing step have the **goal to create a structured graph object**, a **map** of every centerline point from the beginning (coronary ostium) to each end (endpoints).

PROPOSED NEW GRAPHS-BASED POST-PROCESSING

Step 1: pruning and automatic arterial tree classification



Step 1

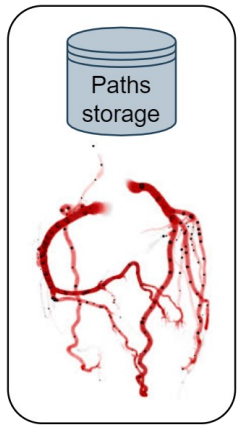
Pruning and **point cloud subdivision into 2 separate arterial trees**

Achieved through a DBSCAN-inspired algorithm

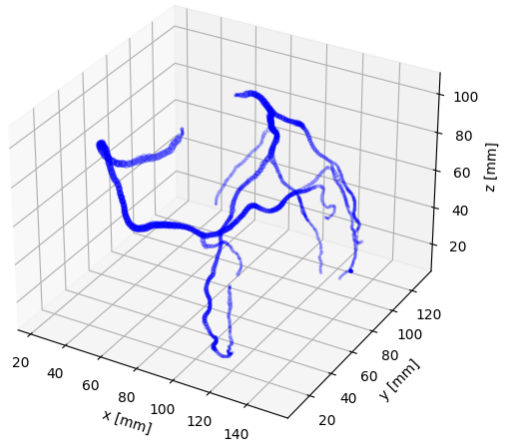
PROPOSED NEW GRAPHS-BASED POST-PROCESSING

Step 2: automatic search of filament's extrema

Tracker

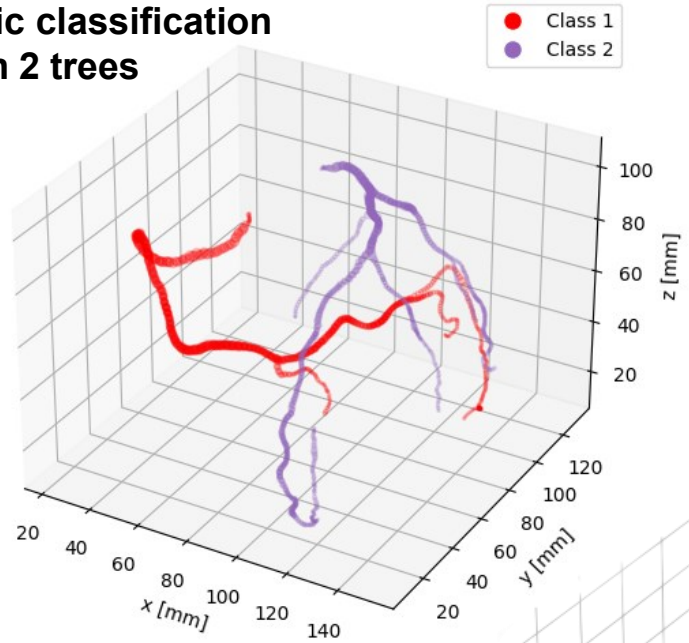


Unstructured cloud of points

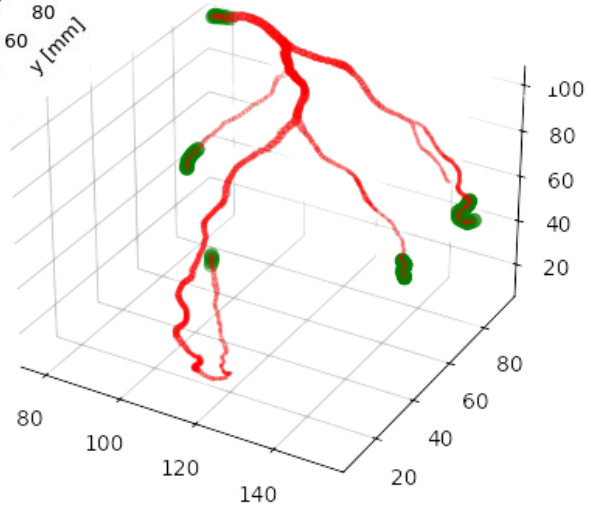


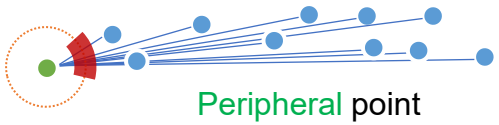
Pruning

Automatic classification in 2 trees

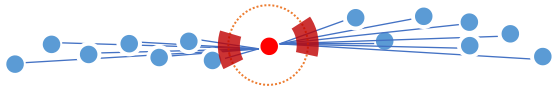


Automatic filaments' extrema classification





Peripheral point



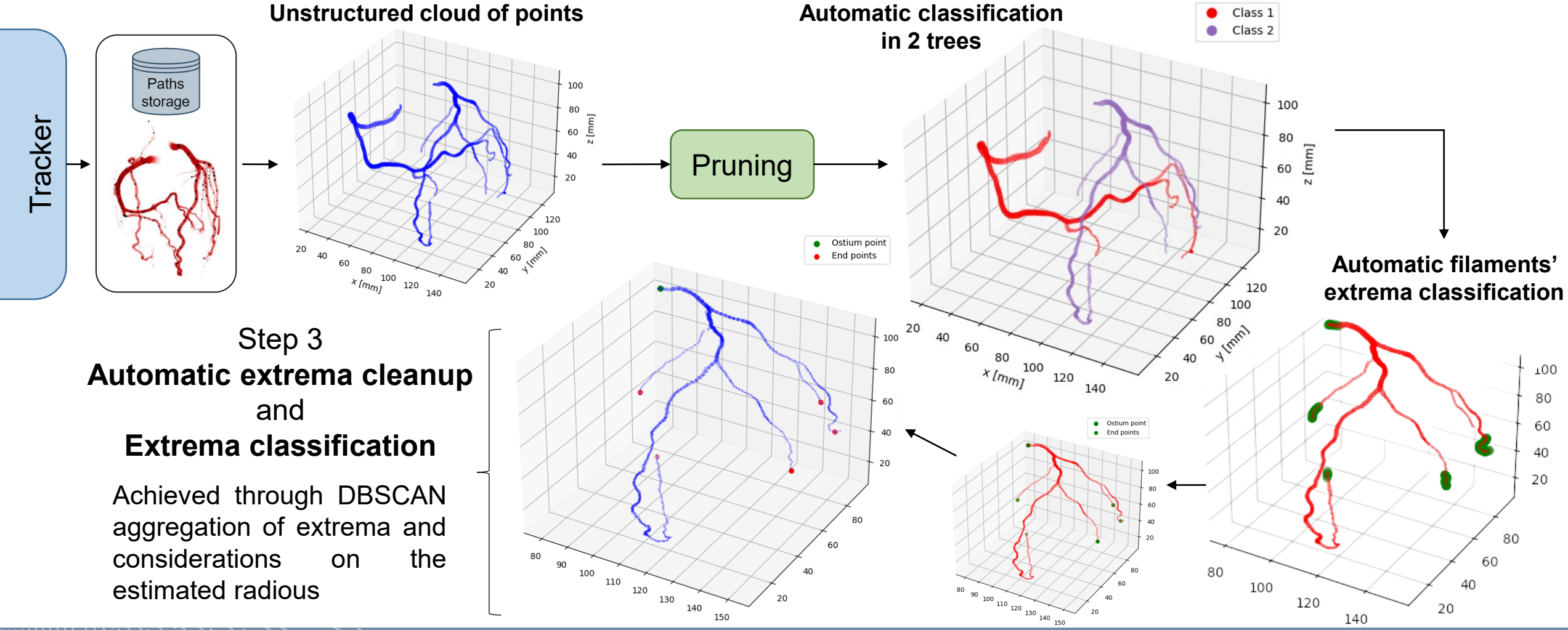
Non-peripheral point

Achieved through DBSCAN classification of versors towards each point's nearest neighbours

Step 2
Automatic extrema classification to detect all peripheral points in the filaments

PROPOSED NEW GRAPHS-BASED POST-PROCESSING

Step 3: automatic extrema classification into either "ostium" ● or "endpoint" ● classes



Step 3

Automatic extrema cleanup

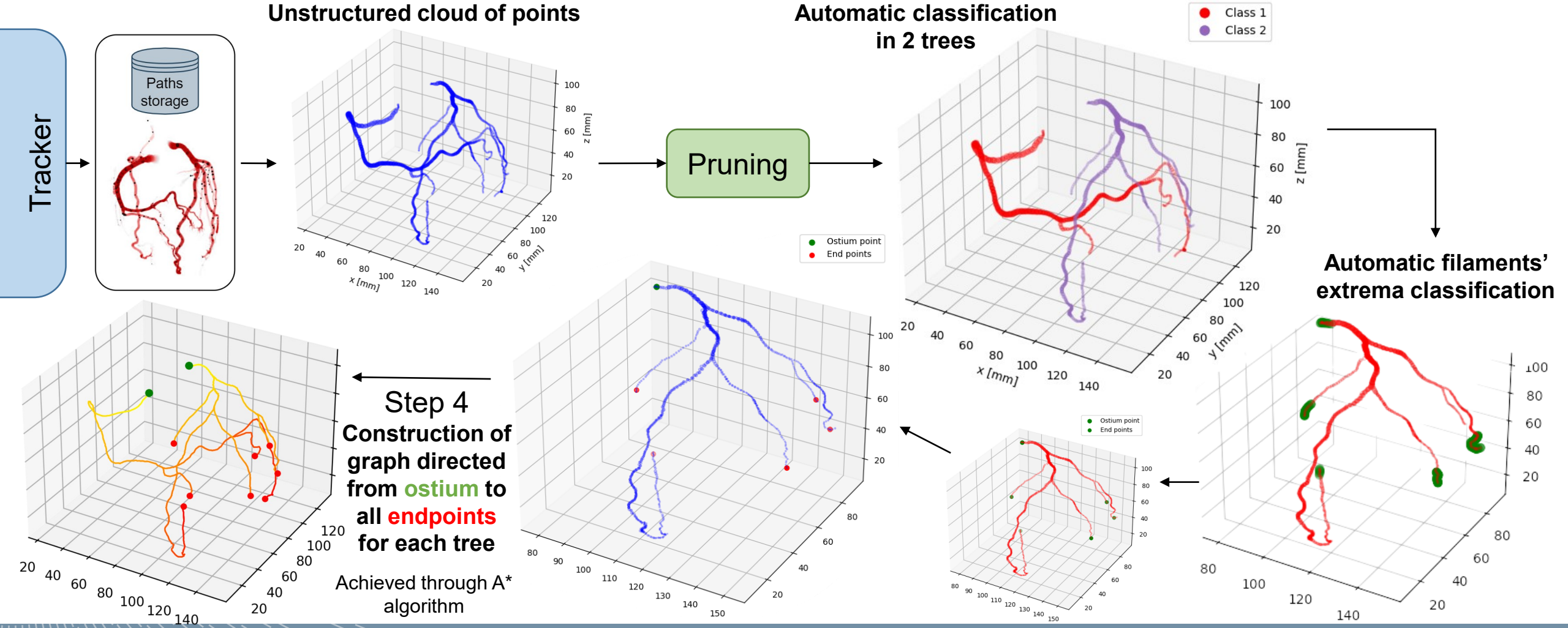
and

Extrema classification

Achieved through DBSCAN aggregation of extrema and considerations on the estimated radious

PROPOSED NEW GRAPHS-BASED POST-PROCESSING

Step 4: Connecting the ostium point ● to all endpoints ● through an oriented graph

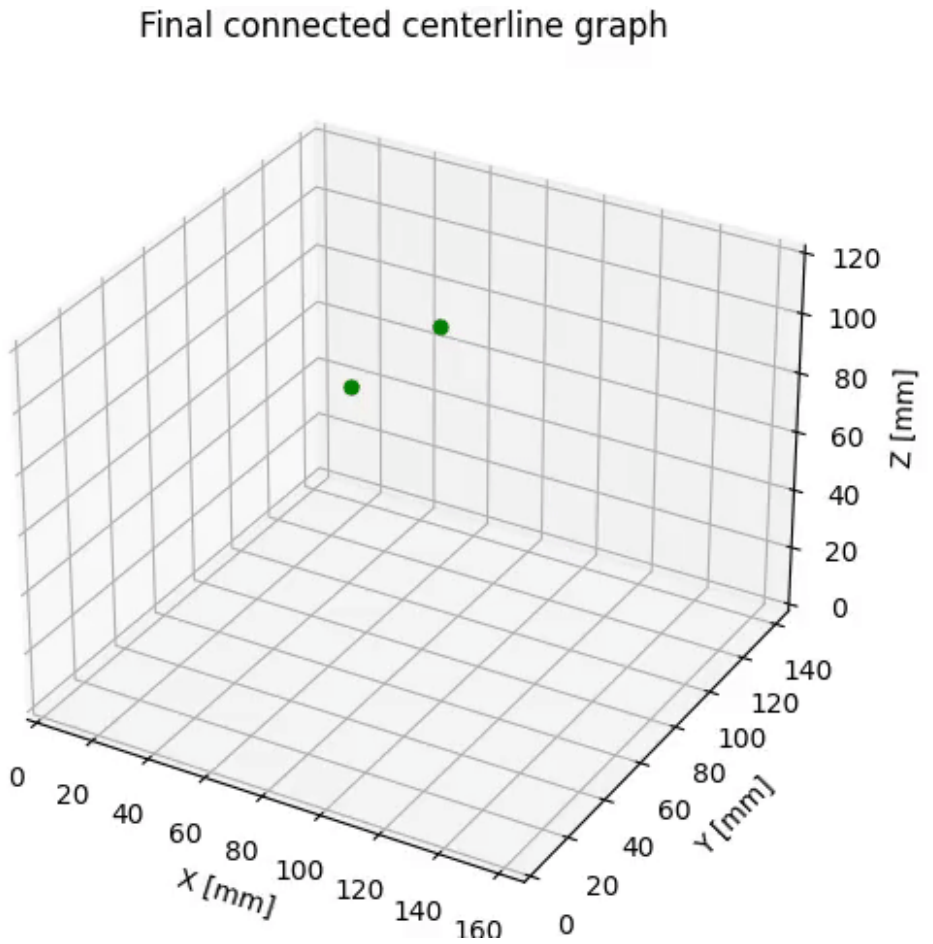


CONCLUSION

New CNN + new tracker + post-processing

Coronary Computed Tomography Angiography

- **Improved CNN architecture**
- **Improved tracker**
- **New post-processing step**



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Deep Learning based Coronary Artery Centerline tracking aimed at Fractional Flow Reserve Prediction from CCTA images

Laurea Magistrale in Automation and Control Engineering -
Ingegneria del Controllo e dell'Automazione

Matteo Leccardi