Presentation script Matteo Leccardi – English

Title page

Good morning, I am Matteo Leccardi, form the Automation and Control Engineering master program, and my work concerns the automatic extraction of coronary artery centerlines from tomographic images of the heart.

Coronary artery disease

Coronary artery disease is characterized by the narrowing or blocking of a coronary artery. This narrowing, also called "stenosis", results in an insufficient supply of oxygen-rich blood to the heart muscles, which can cause infarction, the primarily cause of death in the world.

Fractional Flow Reserve index

The Fractional Flow Reserve index is based on invasive blood pressure measurements in the stenotic region. As of today, it is regarded as the main indicator to assess the severity of a coronary stenosis. However, it requires an invasive procedure, which has an intrinsic risk factor.

CCTA images

Recently, efforts have been made to use Computed Tomography images to automatically estimate the Fractional Flow Reserve index. These images, commonly called Coronary Computed Tomography Angiography, are the result of a radiographic exam in which a contrast liquid is injected in the arterial blood flow. From the x-ray scans a 3D image of the heart and its arterial system can be reconstructed.

FFR-CT

To estimate the Fractional Flow Reserve index from tomographic images, the state of the art is divided in two major categories.
One way is to use computational fluid dynamics to simulate blood flow in the arteries, while the other is to use machine learning to directly estimate the Fractional Flow Reserve index along the arterial tree.
Animation -> next slide.
Both these categories rely on the same preliminary step, which is to reconstruct the arterial tree by extracting the geometric center of the arterial vessels, simply called "centerlines" of the vessels.
This first step was the primary focus of my work.

Automatic coronary artery centerline estimation

Vessel centerlines extracted from tomographic images have many uses also in daily clinical practice. For this reason, many extraction methods have been proposed during the last decade. However, methods based on machine learning which iteratively track the artery centerline are currently the best-performing solutions.

Iterative centerline tracking (1 - seeds)
An iterative centerline tracker works by first placing a number of starting points, called "seeds", inside the vessels. This process can be both manual and automatic.
Animation -> next slide.
Then, a cubic portion of the tomographic image centered on one seed point is extracted and fed to a convolutional neural network.

Iterative centerline tracking (2 – tracker start)
The neural network interprets the image and performs predictions on where two centerline points are most likely to be. The two points should be placed at more or less opposite directions. The tracker then jumps to one of the two points and the process repeats for that point.

Iterative centerline tracking (3 – tracker full)
A direction is followed in a consistent way. When a termination criterion is met on the first branch, the second branch is explored starting again from the seed and following the other direction.
This process is performed for each seed point, and it is possible that some extracted centerlines are overlapping or very close to each other. At the end of the process, the estimated centerline points are stored as a point cloud.

Iterative centerline tracking (4 – tracker full)
The idea of a tracker with a neural network at its core was first proposed by Wolternik in 2018, and the general tracking procedure I just described follows his tracking algorithm.

Main contributions of this work
The main contributions presented in my work are four.
A comprehensive state of the art analysis regarding every step of the entire Fractional Flow Reserve index estimation procedure from tomographic images.
An improved neural network architecture with respect to the one proposed by Wolternik.
An improved, modular tracker which is capable of extracting the complete arterial tree starting from just two seed points.
And lastly, a new post-processing procedure based on graph algorithms.

Main contributions of this work : comprehensive state of the art analysis
A relevant part of my work focused on researching the latest state of the art regarding every aspect of the Fractional Flow Reserve estimation procedure. This analysis was part of a project in concert with Gruppo Multimedica, which showed interest in this particular task. However, due to time constraints, in this presentation I will skip to the other, more technical contributions.

Main contributions of this work : CNN
Now I will discuss the neural networks. To create the new neural network structure, I started from the one proposed by Wolternik and modified it in three different ways.

Baseline convolutional neural network
The neural network proposed by Wolternik is composed of 7 layers, 5 convolutional and 2 fully connected.
Each layer is composed of a three-dimensional convolution layer, a batch normalization layer and a rectified linear unit activation function.
The neural network estimates the position of two centerline points relative to the point under analysis. It does that by solving a classification problem over directions evenly distributed on a sphere, and by also solving a vessel radius regression problem, all in the same network.
The main issue is that all the weights are shared between the classification and regression tasks. This led me to think that this network might be undersized. In practice, I wanted to give each task more independence.

Intermediate convolutional neural network #1 (1 - without table)
To test the ground, I built a network composed of two identical networks working in parallel, one for just the direction classification task and the other for the radius regression task.

Neural network training dataset and test suite
Wolternik's network and the new networks were trained in the same exact conditions using seven images of the 2008 Coronary Artery Tracking Challenge training dataset.
The networks were then evaluated on the left-out image in a test program of my creation which guarantees the same identical testing conditions for every network. Many metrics are computed to assess the performance of the models. All metrics were computed both along the entire vessel, and also along the portion of vessel which is distant enough from its periphery.
The most important metric for tracking purposes is the one indicated in yellow, which indicates how far the neural network is able to place the estimated centerline points from the true centerline of the vessel.

Intermediate convolutional neural network #1 (2 - with table)
The performance metrics of the new double network got better with respect to Wolternik's, however the double network has the inconvenience of being double the size of the previous network.

Intermediate convolutional neural network #2
To mitigate this problem, a second network was built by keeping the first 4 layers of the network in common between the direction and radius estimation tasks. This is a quite common practice with deep convolutional neural networks, where the first layers would in any case perform the same low-level tasks.
This architecture showed a slight performance improvement with respect to the previous one, but it has the advantage of weighting about thirty percent less.

New convolutional neural network
This is the final shape of the proposed neural network. In this last network, the information about the estimated directions flows to the radius estimation branch. Also, another layer is added to the radius estimation branch to account for the new flow of information. By doing so, all the metrics got significantly better at the cost of having a slightly heavier network.

Main contributions of this work : Tracker
Now I will briefly discuss the centerline tracker.

Baseline tracker
Wolternik's tracker follows directions quite strictly with respect to the direction estimated in the previous step, which can compromise the exploration of new branches of the arteries. Moreover, it has no way of handling bifurcations, and the algorithm keeps a static list of seeds points.

Baseline tracker (2 - performance)
Here we can see that his tracker is able to extract the full arterial tree when at least one seed per vessel is supplied, however for this tracker it is impossible to extract all the vessels by placing just one seed per arterial tree.

New tracker
On the other hand, my tracker manages bifurcations by continuously placing new seeds to the original seeds list. This part of the job is taken care of by a new module, which has two ways for adding new seeds to the seeds list. The Hansel and Gretel module leaves a trail of seeds scattered in the proximity of the centerline, while the other one throws seeds towards the most likely directions to surpass stenotic regions, obstacles and bifurcations.

New tracker (2 – performance)
In the left image you can see the effect of the new seeds spawner module. The cloud of seeds allows my tracker to fully explore the arterial tree starting from the minimum number of seed points, while Wolternik's tracker fails in the same condition. The more complete extraction of the arterial tree has the cost of increasing the extraction time, however full tree extraction might justify a slower computation.

Main contributions of this work : post-processing
My last contribution is a new post processing step which, as far as I know, has no equivalent in the state of the art. The post-processing steps I will describe are completely automatic and do not require any human intervention.

New graphs-based post-processing (1)
Its purpose is to manage overlapping filaments in the final cloud of points and to create a data structure to store the arterial trees by using a connected graph. This allows to have a full map of the arterial tree.

New graphs-based post-processing (2)
The first step is to perform some pruning to get rid of filaments that are not long enough. After pruning, the centerlines point cloud is subdivided into two disjointed trees by means of an algorithm similar to the DBSCAN classification.

New graphs-based post-processing (3)
The second step is to detect the extrema of the centerlines. This is done by exploiting the property of peripheral points of having all the nearest neighbors focused in just one direction instead of two or more.

New graphs-based post-processing (4)
The third step is to classify each peripheral point to find the starting point, in green, and all the endpoints, in red. This is possible because the endpoints will all have an estimated vessel radius which is smaller than the radius of the artery at the beginning of the vessel.

New graphs-based post-processing (5)
The last step is to connect the starting point of the artery tree to all the endpoints. This is done by using the A-star shortest path algorithm. Once the oriented graph is built for each route, the graphs can be put together to create a single map of each arterial tree, two in total.

Conclusion
The final result is a monodirectional connected graph which models the centerlines of the left and right arterial trees in a very convenient way.
In conclusion, in my work I proposed a new neural network structure which, in the same conditions, performs better than the one proposed by Wolternik.
I also improved the tracker ability to extract the complete arterial tree starting by just two starting points.
Then, I proposed a new post processing step to manage overlapping portions of the extracted centerlines and create a convenient data structure to store the centerlines of the complete tree.

Final title page
Thank you.
Keep slide on for questions.
