Université de Strasbourg

ICUBE

PhD Thesis proposal

Skeletonization of tubular objects by discrete normal accumulation

Supervision

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Founding

This thesis will be available in the fall of 2024.
Funding period: 3 years.

Candidate profile

Master's degree in Computer Science, Imaging or Applied Mathematics.
Experience in image processing and deep learning.
Python and C++ programming.

Application

Candidates must submit a file containing the following information:

— results and rankings for Master 1 and Master 2
— complete results of diplomas obtained before the Master
— curriculum vitæ
— cover letter.

Subject

Detecting the central line (or skeleton) of tubular objects is an important issue for many projects in a wide range of fields, from medical imaging to geometric modeling for animation, not forgetting forestry agronomy, industrial quality control and fluid flow simulation. In all these fields, the main problem lies in managing branching zones, whether this involves detecting, segmenting or modeling them. The challenge is even greater when the object is thin, or the underlying data incomplete, noisy or inhomogeneous.

Previous work has developed a method of centerline detection based on a point cloud and the estimation of normals at these points [1]. The main advantages of this approach lie in its robustness to incomplete data and in its genericity, theoretically allowing it to be applied to any type of object for which a field of normals can be estimated. The basic idea is to immerse the continuous object in a discrete space and then calculate a probability map based on the principle of accumulating surface normals. This method has been used, for example, to calculate the skeleton of vascular networks in 3D cerebral MRI angiography images (see Figure 1).

However, when used on discrete data such as an image, this method has two drawbacks. On the one hand, it requires a binary image for the estimation of normals. This binarization step can be based on a filtering and/or segmentation method, for example, and can be complex to implement. On the other hand, the accuracy of the skeleton obtained is linked to the image resolution: in the case of thin objects whose thickness is close to the resolution limit (small vessels, for example), the skeleton obtained may suffer from certain defects.

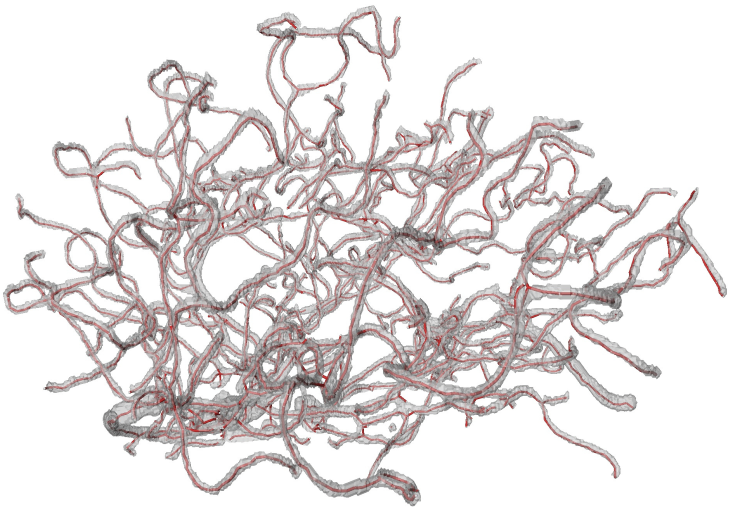

Figure 1: Detection of the centerline of a 3D MRI brain angiogram obtained by an approach based on the accumulation of normals.

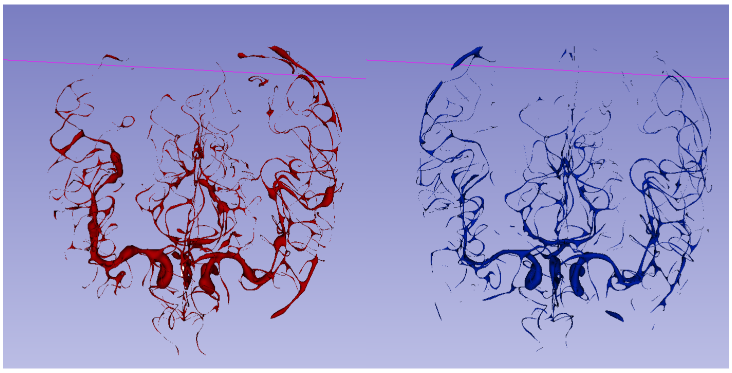

Figure 2: Segmentation of a cerebral vascular network in MRI imaging [11]. Left: automatic segmentation using convolutional neural networks. Right: ground truth. Automatic segmentation still suffers from certain shortcomings (disconnections, missing parts, etc.).

The first objective of this thesis is to develop a method for centerline detection of tubular objects that alleviates the two previous problems. To extend the method to the calculation of skeletons in grayscale images, a method for estimating normals dedicated to this type of data will be developed. In order to calculate a skeleton with an accuracy greater than the image resolution, super-resolution methods, based in particular on deep learning, could be considered [2]. This research could also draw on the work of Hespen *et al.* [3], which enables sub-pixel accuracy to be achieved in vessel wall thickness measurement.

Finally, this work will be integrated into a methodology for segmenting vascular networks in 3D cerebral MRI developed by the IMAGeS team.

In this context, the structures of interest present morphological (size, shape), spatial (positions, orientation) and topological (branching variability) properties, which make reliable image annotation particularly tricky, and induce significantly greater variations than for other structures. For such objects, deep learning approaches still suffer from a lack of robustness (see Figure 2).

With this in mind, several recent works propose methods for incorporating topological-type constraints into neural networks [4, 5, 6, 7, 8] or modeling shape *a priori* or anatomical constraints [9, 10].

The final aim of this work is to obtain, from a 3D MRI angiographic image, a model of the vessels based on the calculation of their central line (or skeleton) and associated radii. Deep learning approaches will be able to infer this information directly, without the need for prior segmentation.

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