Segmentation of vessel tree from cine-angiography images for intraoperative clinical evaluation.

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Abstract. The assessment of vascular complexity in the lower limbs provides relevant information about peripheral artery diseases, with a relevant impact on both therapeutic decisions and on prognostic estimation. Such evaluation is currently carried out by human operators via visual inspection of cine-angiograms, resulting in conflicting results and scorings that are largely operator-dependent, mostly because of the technical difficulties in the quantification of vascular network and its flow capability.

We propose a new method to automatically segment the vessel tree from cine-angiography video for intraoperative clinical evaluation, in order to improve the clinical interpretation of the complexity of vascular collaterals in Peripheral Arterial Occlusive Disease (PAOD) patients.

1 Introduction

The assessment of vascular complexity in the lower limbs provides relevant information about peripheral artery diseases; in fact, vascular collaterals act as a sort of natural bypass system, sustaining tissue perfusion downward of vascular occlusion [1]. Intuitively, they can exert a protective impact on limb ischemia, thus reducing symptoms and improving the outcome in patients with Peripheral Arterial Occlusive Disease (PAOD) [2].

In current clinical practice, cine-angiography is widely used to assess the vascular complexity in the lower limbs, in order to obtain relevant information about PAOD. Therapeutic decisions and prognostic forecasts, in fact, are based on visual inspection of such images. Despite its wide use, this technique remains a largely operator-dependent process, also prone to errors mostly due to misinterpretations. Indeed, besides the hard task of identifying the vessel tree, video images feature the presence of surgical instruments, tools, electrode cables, catheters, etc., that makes the correct automatic evaluation even more challenging. In this work we define a new methodology for automatic vessel tree identification from a set of images obtained subdividing cine-angiography videos in different frames, with the goal of fostering more reliable clinical assessments in the described scenario. In particular, we aim at making use of Convolutional Neural Networks (CNNs) for the segmentation of the vascular tree over a set of images extracted during the cine-angiography process.

Interestingly, to the best of our knowledge, this is one of the first attempts to segment vessels in the ilio-femoral district on a set of 2-D frames. In fact, the method presents several challenges: (*i*) non-trivial image pre-processing operations are needed in order to elaborate and extract a set of static image from the cine-angiography video; (*ii*) fine-tuning of CNN parameters in each layers, in order to reach a high segmentation accuracy as described in [3]; (*iii*) assemble the segmented images to create the original cine-angiography video for intraoperative application.

2 Proposed Approach

The main goal of this work is to provide a new approach for automatic vessel segmentation from cine-angiography videos. The workflow of the proposed framework, illustrated in Figure 1, can be divided into three steps: (*i*) pre-processing operations build a set of images from cine-angiography videos and increase vessel enhancement, (*ii*) a fully convolutional deep neural network architecture called "U-net" [4] used in [3] is used to segment the vascular tree from the video frames, and (*iii*) sequences of segmented static images are combined to reconstruct the cine-angiography videos for the intraoperative application. It is worth noting that we start from the approach of [3] in order to provide clinicians with a different tool for segmenting ilio-femoral district; indeed, differently from the cited work, the cine-angiography video is subdivided into different frames instead of a static reconstructed image. Then, U-net perform segmentation on different kind of dataset.

3 Pre-processing of ilio-femoral images

Ilio-femoral images show some lighting variations, poor contrast and noise. To reduce these imperfections and generate images more suitable for extracting blood vessels, we applied following preprocessing steps:

- **Contrast Limited Adaptive Histogram Equalization** [5]
- **Gamma correction** [6]
- **Background homogenization**

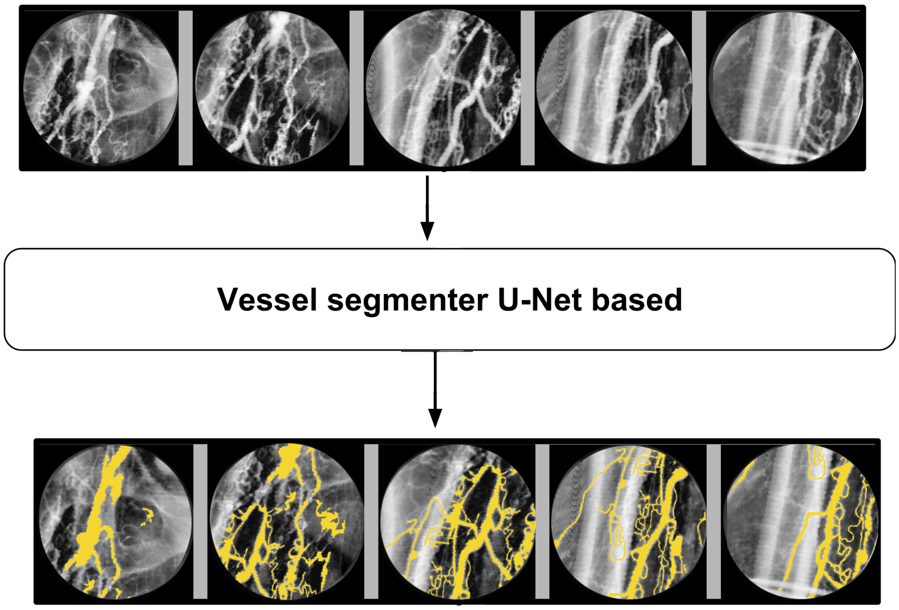

Fig. 1. Workflow of the proposed framework.

As shown in Fig. 2, the resulting image shows an improvement of the lighting variations and the contrast between background and vessels. These preprocessing steps are necessary to remove noise and artifacts from the image in order to improve segmentation accuracy and detection of blood vessels.

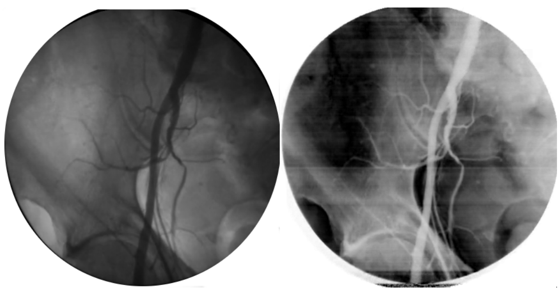

Fig. 2. Example of ilio-femoral image before (left) and after pre-processing operations (right)

4 Network Description

The U-net model is a fully convolutional network with symmetrical structure, composed of a contracting and an up-sampling part. The contracting path consists of the repeated application of two 3×3 convolutions and a 2×2 maxpooling operation with stride 2 for downsampling. The expansive path consists of an up-sampling of the feature map followed by a two 3×3 convolutions. In the final layer, a 1×1 convolution is used to map all 64 component feature vectors to the desired number of classes [4]. All layers use Rectified Linear Unit (ReLU) [7], except for the last layer, where Softmax [8] is used in order to select the best scoring category; hence, for each pixel it returns the probability to be part of a vessel or not. The U-net architecture adapted by [3] is showed in Figure 3.

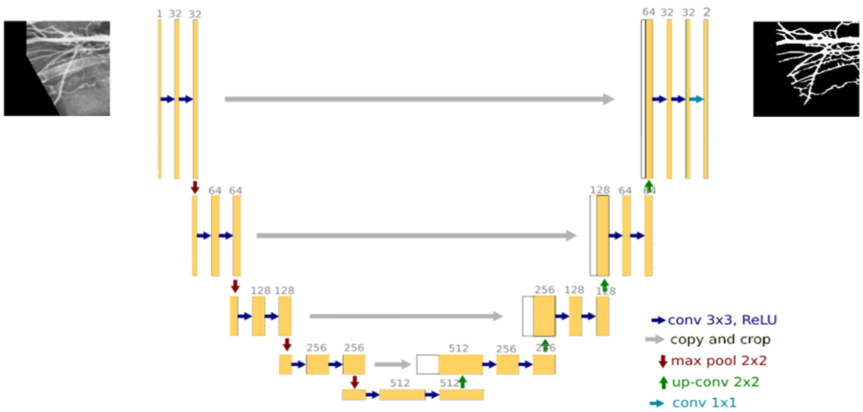

Fig. 3. U-net architecture adapted by [3]

5 Experimental Setting and Results

The U-net [4] was trained on 30, 600 tiles extracted from cine-angiographies. The ground truth used to accomplish the supervised learning was represented by a manual segmentation executed by an expert clinician. Data acquisition, as well as, data annotation, was executed the Interventional Cardiology Units of Magna Graecia University Hospital (Catanzaro, Italy) and at Federico II University Hospital (Naples, Italy).

For the real daily usage, once a `DICOM` file has been read, automatic segmentation of a 60 seconds cine-angiography (357 frames) takes, on the average, 90 seconds with an AUC mean value of 0.988 ± 0.006. As a result, original images with the highlited vessel tree is shown to the clinicians.

6 Conclusion

Considering that the cineangiography is an invasive procedure, the time available for collecting all data and defining a correct prognosis is usually quite short. Hence, a shorter timescale is needed for improving the clinical interpretation of the complexity of vascular collaterals in PAOD patients. Our proposed method features an intraoperative application to identify vascular abnormalities, thanks to a robust segmentation process of the cine-angiography video during the surgery.

By looking to this enhanced cine-angiography, operators can better visualize the vessels and evaluate condition of patients more easily. Structures that are not of interest (such as catheters and cables) are correctly recognized as “non vessel” and excluded from the final segmentation. Finally, given that the process result to be efficient enough to grant the generation of such enriched images also on ordinary hardware, the proposed workflow is already applicable into any typical intraoperative scenario.

Further efforts will be spent to both improve the segmentation accuracy and speed-up the process in order to obtain a more accurate and fast, up to real-time, segmentation workflow.

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