Angiographic vessel segmentation for CT registration

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***Abstract*—Angiographic vessel image registration is a really challenging problem due to difficulties like the absence of some fragments of vessel and the non-rigid deformations they suffer caused by the breathing and heart beating of the subject. In order to make this registration easier, we propose a prior automatic segmentation of the vessels in the images using graph-cuts.**

I. Introduction

Chronic total occlusions (CTO) are obstructions of native coronary arteries with the presence of Thrombolysis In Myocardial Infarction (TIMI) flow grade 0 within the occluded segment with an estimated occlusion duration of more than three months. Recanalization of a CTO still remains a challenge for invasive cardiologists. New imaging technologies may help selecting those candidates with more chances to have successful recanalization and a higher likelihood to improve regional function after percutaneous coronary intervention (PCI). Recent studies try to implement new imaging techniques to improve the success rate of CTO recanalization.

Multislice Computed Tomography (MSCT) has emerged recently as a valuable technique for the non-invasive visualization of both the lumen and the features of the arterial wall of coronary vessels [3]. The importance of registration of CT to X-Ray images has been reported as a valuable tool to provide complete and high quality 3D information in addition to the poor data provided by Xray images [4]. Moreover, prior segmentation of the vessels is a typical step to apply before registration, since a lot of background noise is removed and the registration method can be simplified to work only with binary images -the segmentation masks obtained-.

In this paper, we present a segmentation method for angiographic vessels, based on the graph-cuts energy minimization framework. We define new unary graph-cuts potentials which fit the arterial structures present in X-ray images. The structure of the paper is as follows. The segmentation method is explained in section II. Images from the dataset and some qualitative results are shown in section III. Finally, section IV ends the paper with the conclusion.

II. Method

The vessel segmentation problem is posed as an energy minimization problem, solved by means of graph-cuts [1]. In this framework, an energy function $E(A)$ is designed such that the minimum value of this function corresponds to the optimal segmentation of the image. In order to minimize this energy function, a graph is constructed from the image in the following way: each pixel in the image is mapped to one node in the graph, and these nodes are interconnected following a neighbouring criterion. Furthermore, two additional nodes T and S called *Terminal nodes* are added to the graph, and connected to all the rest of nodes.

Considering the image as a vector of pixels $I = \{I_1, I_2, ...I_n\}$, the segmentation mask is defined as $A = \{A_i, A_2, ..., A_n\}$ where each A_i is either 0 or 1 classifying the corresponding pixel as background or foreground. The energy function is divided in two weighted terms:

$$E(A) = \lambda R_p(A) + B(A) \quad (1)$$

The first term $R_p(A)$ is called the *unary potential* and encodes information at the pixel level. This potential give values to the edges connecting each pixel node in the graph to the terminal nodes. The second term $B(A)$, or *pairwise potential*, encodes

(a) (b)

Fig. 1. Example from the dataset. (a): Original image, (b): Vesselness probabilities

information about the relations between pixels, assigning values to the edges interconnecting pixel nodes in the graph.

In our case, on one hand we join gray-level information of the image and a *vesselness* probability for the unary potential of our energy function. The vesselness probability is computed with the method of [2], which returns a probability value for each pixel of the image. On the other hand, we use contrast information of the image -pixel differences- for the pairwise potential. The $R_p(A)$ and $B(A)$ potentials for each pixel p within the graph are defined as follows:

$$\begin{aligned} R_p(p) &= \alpha V(p) + (1-\alpha) H_{gray}(p) \\ B(p,q) &= exp(-\frac{(I_p - I_q)^2}{2\sigma^2}) \cdot \frac{1}{dist(p,q)} \end{aligned} \quad (2)$$

where $V(p)$ are the vesselness probabilities and $H_{gray}(p)$ is a gray-level histogram of either the background or the foreground.

III. Results

In this section we present the dataset used for this work, and some qualitative results of the vessel segmentations. Quantitative results are yet to be computed, since for the moment we do not have any ground-truth.

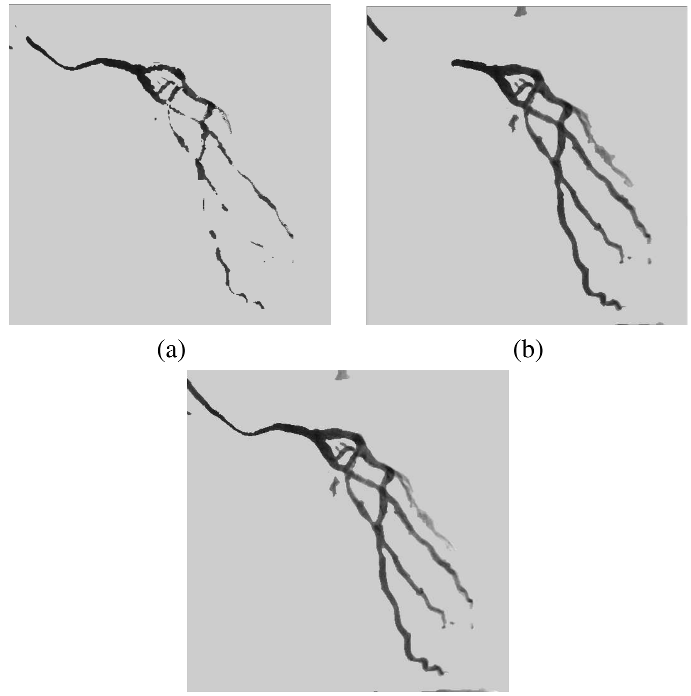
• *Data*: We have worked with a sequence of 512×512 angiographic images from the left coronary artery. Figure 1 shows one example.

• *Method*: The graph used for the energy minimization was built using a 8-neighbouring system.

Figure 2 shows different segmentations obtained when using partial information -only gray-scale or only vesselness)- in the unary potential. One can see that the segmentations are, in a way, complementary. The missing parts in one of the segmentations are correctly segmented in the other, and viceversa.

IV. Discussion

In this paper, we presented a method for segmenting vessels in angiographic images. Having a look at the results, we found that vesselness probabilities are not enough information to be included in the unary potential in order to correctly segment the whole coronary tree. On the other hand, using only gray-level information helped us to segment parts where the first experiment failed. Finally, when combining both informations in the correct way, we can reach a segmentation containing the correct segmented regions from the previous segmentations with partial information. Still, we plan to include geodesic paths computation in the unary potentials in order to favor the graph-cuts framework to segment long thin structures connecting all the parts of the coronary tree, while avoiding false positive segmentations.



(a) (b)

(c)

Fig. 2. Segmentations with partial and total information for the unary potential computation. (a): Gray-scale information, (b): Vesselness information, (c): Both informations

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