Automatic Angiography Segmentation based on Improved Graph-cut

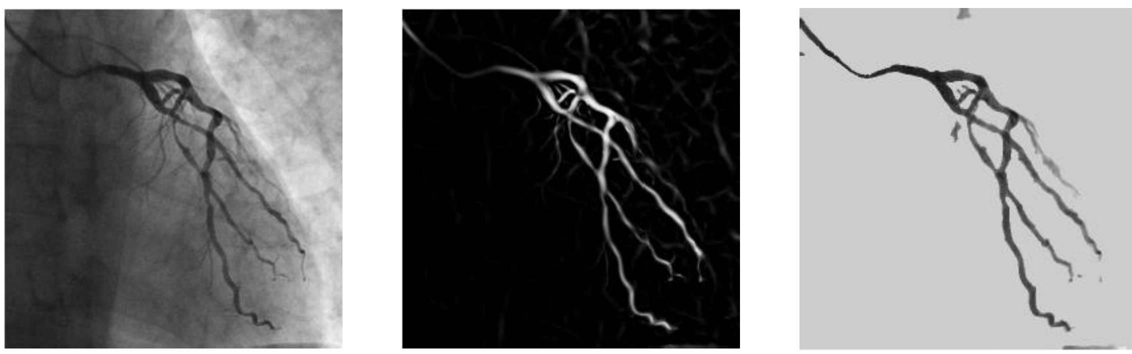
Chronic total occlusions (CTO) are obstructions of native coronary arteries with the presence of Thrombolysis In Myocardial Infarction (TIMI) flow grade 0 within the occluded segment with an estimated occlusion duration of more than three months. Recanalization of a CTO still remains a challenge for invasive cardiologists. 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 X-ray 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-.

Angiographic vessel image registration is a challenging problem due to the lack 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 improve this registration, we propose a prior automatic segmentation of the vessels in the images using graph-cuts [1]. In the graph cut framework, an energy function 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 criterion extracted from the neighborhood context. Furthermore, two additional nodes *T* and *S* called *Terminal nodes* are added to the graph, and connected to all the rest of nodes.

The energy function is divided in two weighted terms. The first term is called the *unary potential* and encodes likelihood information for each pixel. This potential gives values to the edges connecting each pixel node in the graph to the terminal nodes. The second term or *pairwise potential*, encodes 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 geodesic information of the image and a *vesselness* probability for the unary potential of our energy function. The vesselness probability is computed with the method in [2], which returns a vessel probability value for each pixel of the image. On the other hand, we use contrast information of the image -an improved version instead of just pixel differences as in the original graph-cuts algorithm- for the pairwise potential.

In order to validate our segmentation method we defined two different datasets. The first one is composed by 20 images acquired with a single plane Philips INTEGRIS Allura Flat Detector, of RCAs. Three experts have blindly annotated the centerlines with different labels: “vess” for the arteries that potentially can present a clinical interest (with a caliber of, at least, 1mm); “don’t care” for all other arteries in the image, and “cat” for the catheter guide. Each manual delineation required more than 5 minutes per image. The second dataset is formed by 31 images from 27 patients, acquired with a SIEMENS Artis zee, of 10 RCAs, 10 LADs, and 11 Cxs. In this case, two experts blindly segmented a total of 41 lesions (12 LADs, 13 Cxs and 16 RCAs) assisted by a semi-automatic method (QCA-CMS Version 6.0, MEVIS). The experts were asked to manually correct unsatisfactory segmentations, and the time required for the initialization and manual corrections resulted in 27.3 ± 15.6 seconds per image.

Figure 1 shows an example of vessel segmentation, including the original image, the vesselness probability map and the final segmentation mask.



(a) (b) (c)

Figure 1. (a) Original angiography image, (b) Vesselness probability map, and (c) Final segmentation

Moreover, we tested a multimodal registration of coronary trees with CTA data using our segmentation results in X-Ray images can improve the. As a basic registration method, we used the well known Free Form Deformation [5] (FFD), using Mutual Information. To quantify the improvement due to our segmentation method, we performed the registration using three different settings: (1) FFD applied on the images without any pre-processing (named [I2I-FFD]), (2) FFD applied on images using Vesselness as pre-processing (named [V2VFFD], and (3) FFD applied to the segmented images (named [S2S-FFD]). As we can see in Figure 2, in most of the test cases, our segmentation achieves the best registration performance. As a general trend, the direct I2I registration is totally ineffective, despite the FFD can handle different modalities due to the use of the Mutual Information; nonetheless the background in XRA images does not allow FFD to find an acceptable solution, even at large grid spacings.

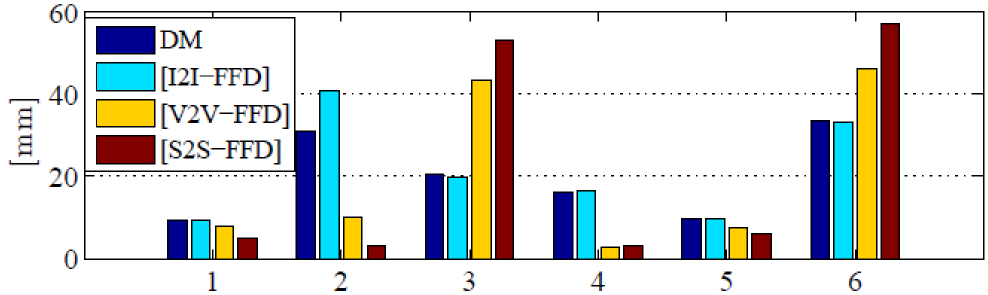


Figure 2. Results of non-rigid registration with different preprocessing methods applied on 6 different cases (The “DM” bars represent the average magnitude of the displacement between annotated landmark in XRA and CTA images).

References

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