Region-Oriented Segmentation of Vascular Structures from DSA Images Using Mathematical Morphology and Binary Region Growing

Marco Donizelli

CRS4 (Center for Advanced Studies, Research and Development in Sardinia)
via Nazario Sauro 10, 09123 Cagliari (Italy)
Email: donza@crs4.it

Abstract. In this paper we describe a region-oriented segmentation algorithm suited for the detection and extraction of large blood vessels in angiographic images. The algorithm is based on the mathematical morphology top-hat operator followed by a binary region growing process. The combination of these two steps generates an image containing only the largest vessels regions, allowing a fully automatic segmentation without any manual interaction. We demonstrate the advantages of our approach comparing its results with those of other classical and morphological algorithms.

Keywords: DSA image processing, Blood vessel segmentation, Mathematical morphology

1 Introduction

Blood vessel delineation in angiograms forms an essential step in solving several practical applications, such as diagnosis of vascular diseases (e.g. stenosis or malformations), blood flow studies and three-dimensional reconstruction of vascular structures. Many authors have previously developed segmentation procedures to extract the regions corresponding to the blood vessels in DSA images [1-3]. Unfortunately, the results of these classical segmentation techniques are not optimal: noise, overlapping structures, variations in background, and variations in the structures themselves, all combine to make the use of such well-established techniques inadequate. This paper describes a region-oriented segmentation technique that overcomes all these problems, by employing the mathematical morphology top-hat operator followed by a binary region growing process. The combination of these two steps generates an image containing only the large vessels regions, devoid of shorter capillaries or background noise artefacts, allowing a fully automatic segmentation without any manual interaction. The results of our approach are compared with those of other classical and morphological region segmentation algorithms [1, 3, 4], using the two test images representing two different kinds of vascular structures shown in fig. 1.

Figure 1. The two angiographic images used to test the algorithms.

2 The Previous Approaches

Three previously developed region oriented segmentation techniques have been implemented in order to compare the results of our algorithm.

The first one is the *multiphase region analysis process* (MRAP) described in [1]. It starts with the creation of a binary image via a regional thresholding algorithm, followed by a second phase that picks out the connected components in the binary output of the first phase and eliminates the spurious noise points. The third region analysis phase then attempts to grow the regions detected by the previous two processes, in order to compensate for the gaps in the larger objects left as a result of the thresholding algorithm. The two leftmost images of fig. 2 and fig. 3 show the results of the application of the MRAP algorithm on the images of fig. 1.

The second technique is the *region splitting* approach based upon *bimodality analysis* (RSBA) developed in [3]. Here, the input image is subdivided successively into smaller and smaller regions according to a bimodality measure and a bimodality threshold. That is, if a region is labelled bimodal, it is subdivided into four subregions, otherwise the grey scale values of the pixels within the region are assigned to the mean of the region, and no further subdivision is made. In our implementation, at the end of the splitting process we interactive threshold the output in order to obtain a binary image. The two central images of fig. 2 and fig. 3 show the results of the application of the RSBA technique on the images of fig. 1.

The third technique is the *morphological-thresholding* (ROSE) algorithm described in [4]. In this approach, a first morphological step produces eight different images by applying eight separate *opening* operations to the input image using eight differently oriented linear structuring elements, and combines these eight images into one containing the maximum pixel values. A second step thresholds the output of the morphological step using a dual feature thresholding. In our implementation, instead of this methodology that doesn't perform well on our images, we simply use an interactive threshold. The two rightmost images of fig. 2 and fig. 3 show the results of the application of the ROSE algorithm on the images of fig. 1

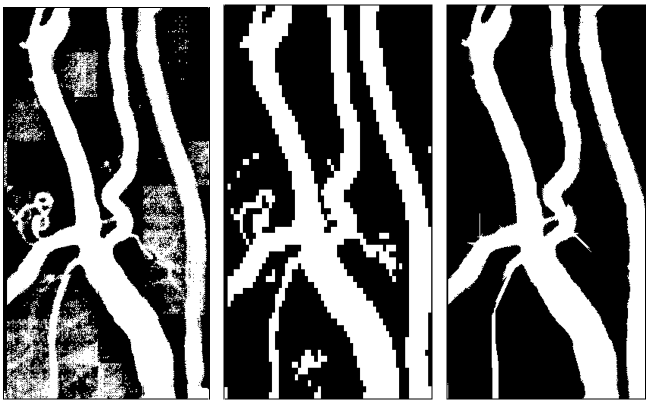

Figure 2. From left to right, respectively the result of the application of the MRAP, RSBA and ROSE techniques on the leftmost image of fig. 1.

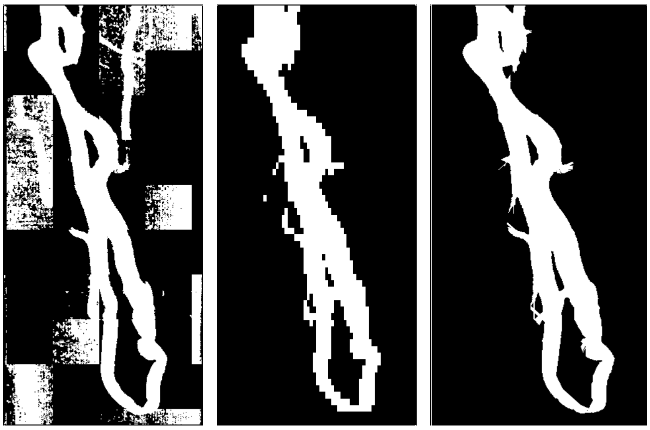

Figure 3. From left to right, respectively the result of the application of the MRAP, RSBA and ROSE techniques on the rightmost image of fig. 1.

3 The Proposed Algorithm

Within an angiographic image, large vessels have well-defined structural properties: continuous, connected line-like structures with slowly changing thickness, orientation and intensity, except for stenosis or other malformations [5]. The idea underlying our approach is to exploit these properties using operators defined in the field of mathematical morphology [6]. In particular, we use the *top-hat* operator described in [7], a morphological filter well-suited to identify and extract line-like patterns of a certain size and contrast, and then optimised to produce a binary image predominantly containing the regions corresponding to the large vessels. The implementation of the top-hat operator involves three steps. First, the morphological *closing* of the original image is obtained using a flat circular structuring element of size r (the width of the top-hat operator. Then, the original image is subtracted from the output of the first step. Finally, the image produced by the second step is thresholded according to a value h, which defines the height of the top-hat operator. The thickness, and consequently the typology, of the outlined vessels depend on r and h, related respectively to the size and to the contrast characterising the vessels regions. The two leftmost images of fig. 4 show the results of the application of the top-hat operator on the images of fig. 1.

Since the binary output of the top-hat operator contains also some residual shorter capillaries or background noise artefacts, the second phase of the proposed algorithm consists in a *binary region growing* process. In this phase we first compute the areas of all the regions of the binary image and then delete the regions smaller than a threshold area value (chosen by the user). The region growing process considers any object point (e.g., those with value of 255) in the binary output of the top-hat operator, and extracts the 8-connected region containing it. Then, if the area (e.g., the number of pixels) of the region is greater then the threshold, the region is outlined in the final image, otherwise it is not. The two rightmost images of fig. 4 show the results of the binary region growing run on the two leftmost images of the same figure, and represent the final result of our region segmentation technique.

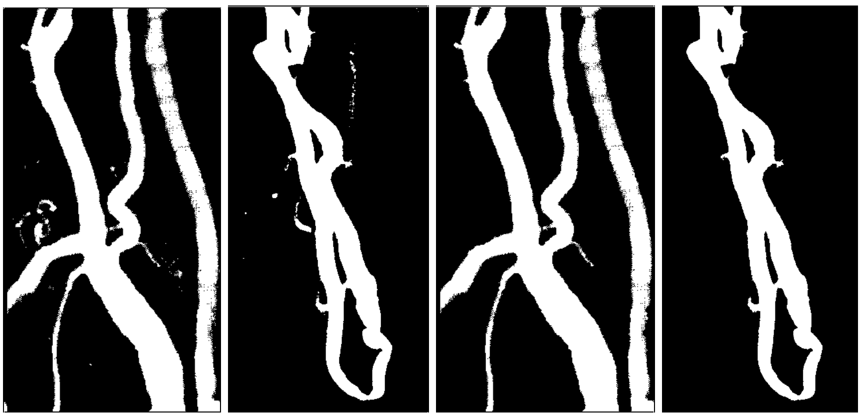

Figure 4. The two leftmost images show the result of the top-hat operator applied on the images of fig. 1, while the two rightmost images represent the final results of the proposed segmentation procedure, after the binary region growing process run on the leftmost ones.

4 Comparison of Segmentation Results

We have compared the results of the four region segmentation techniques considering the number of shorter capillaries or background noise artefacts present in the output images and the shape of the extracted large vessel.

Regarding the first aspect, the worse result is produced by the MRAP technique while both the morphological based operators give optimal outputs because of their capability to exploit not only the pictorial properties of the object to segment, but also their structural characteristics. The structuring element that is used in the morphological operation is constructed so that its shape matches the shape of the objects to be retained. For the ROSE operator, the use of linear structuring elements long enough to fit into the large vessels but not the more tortuous capillaries yields to an image which predominantly includes the large vessels, as happens for the top-hat operator. This operator, however, filters the undesired objects using mostly its height *h* rather than its width *s*. Being in fact correlated to the contrast of the region to be segmented, an appropriate high value of *h* assures that the top-hat operator selectively extracts only the regions characterised by an higher contrast, as the large vessels. This selective distinction carried out by the top-hat operator makes very simple for the binary region growing process to delete the few residual artefacts due to smaller vessels or background variations, and thus to produce the final image containing only the large vessels. We cannot obtain the same optimal result applying the region growing process on the outputs of the MRAP algorithm.

Concerning the shape of the segmented vessels, the RSBA technique gives unsatisfying results due the methodology itself. The output can be improved increasing the value of the bimodality threshold, but this leads to a very time-consuming segmentation process. The MRAP performs better on the first image than on the smoother second one, where the effects of the initial regional thresholding are more evident. The ROSE operator, employing linear non-isotropic structuring elements, leaves some artefacts in the outlined vessels, unlike the top-hat operator, which uses an isotropic structuring element. In addition, the top-hat operator is also superior to the ROSE operator from a computationally point of view, requiring only one closing operations instead of eight openings.

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