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Segmentation of Linear Structures from Medical Images

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Abstract

In this paper, an algorithm for the extraction of linear structures from medical images is implemented. Blood vessels in angiographic images have linear patterns. Hence, these features can be extracted easily using morphological operations. Blood vessels can be separated out as they have a specific Gaussian-like profile whose curvature varies smoothly along the vessel. In order to differentiate vessels from analogous background patterns, edge detection is performed and the application of linear filters like top-hat transformations can eliminate the background noise, thereby segmenting the entire blood vessels in the angiographic image. Such vessel extraction could help physicians in the computation of parameters related to blood flow.

Keywords: Blood vessels; edge detection; morphology; linear features

1. Introduction

Heart and vascular diseases are one of the main causes for the death of women and men in modern society. In clinical practice, angiographic images of the human cardiovascular system are acquired using a medical procedure called Cardiac catheterization. Segmentation of vessels from these images is crucial for diagnosis, treatment and surgical planning. The segmentation of vessels from 3-D medical images however is difficult and challenging. The main reasons are: 1) the width of vessels depends on the type of vessel, 2) the width typically varies along the vessel, 3) the images are noisy and the boundaries between the vessels and surrounding tissues are locally difficult to recognize, and 4) segmentation of linear structures from 3-D images is much more difficult. Former work [8] [10] on vessel segmentation from 3-D image data can be divided into two main classes of approaches, one based on differential measures and the other based on deformable models. Other 3-D approaches are based on level set methods. Segmentation of vessels using morphology gives better results when compared to the previous works [5] on the basis of edge detection. An edge is defined as a local change or discontinuity in image luminance [3]. There are two basic approaches to edge detection: the enhancement/ threshold method and the edge fitting method [1]. In the former method, the discontinuities in the image gray tone are enhanced by neighbourhood operators. The sobel operator involves the computation of local intensity gradients and the responses due to nonideal step edges are not good. A modification of that is the detection of second order zero crossings, and the corresponding edge operator is called the Laplacian [2]. Algorithms belonging to the second category, the edge fitting method, minimize the distance between the original noisy data and a predefined edge model in a finite dimensional space. Thus, the results of these algorithms are optimal for the chosen edge model and are less sensitive to noise and also involve more computations. In this paper, the use of gray scale morphology involving simple erosion and dilation operators eliminates the noise in the background. Tree like structure with a Gaussian like profile are very common in medical images. Hence an edge detector (Laplacian of Gaussian) is used for extracting the vessels from those images. The behaviour of this algorithm is studied on a set of angiographic images of normal patients. Finally, this algorithm is compared with other edge detection algorithms and a conclusion is presented.

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2. Morphological operators

Some of the basic definitions of morphological operators are given. More details can be found in [6]. A two dimensional image whose range is [N_{min}, N_{max}] defined as a functional S: $R^2 \longrightarrow$ [N_{min}, N_{max}] and a 2-D structuring element as a functional B: $R^2 \longrightarrow$ B where B is the set of the neighborhoods of the origin. In this approach it is considered only the structuring elements that are invariant by translation. Morphological erosion of image f by the structuring element B is defined as:

$$€(f,B)(s,t)=min\{f(s+x),t+y\}-B(x,y)/(s+x,t+y)ЄD_f;(x,y)ЄD_B\} \tag{1}$$

where D_f and D_B are the domains of *f* and *B* respectively. Morphological dilation is defined in a similar way for image f by the structuring element B as:

$$\S(f,B)(s,t)=max\{f(s-x),t-y\}-B(x,y)/(s-x,t-y)ЄD_f;(x,y)\ ЄD_B\} \tag{2}$$

Based on the combination of these operators, opening and closing are defined as:
Opening:

$$ß(f,B)=\ \S(€(f,B),B) \tag{3}$$

Closing:

$$Þ(f,B)=€\ (\ \S(f,B),B) \tag{4}$$

Top-Hat transformation is a technique used to extract brilliant or dark objects from a gray level image [10] and is defined as:

$$\text{Top-Hat: } ß(f,B)=f-ß\ (f,B) \tag{5}$$

Geodesic operators are defined with respect to a norm ‖.‖ or a connectivity graph in digitized mages (a neighbourhood C of unit radius) they depend on a marker image S_m and distance d. The geodesic reconstruction (or opening) is defined by

$$ß^{rec}_{Sm}(f) = \sup_{d\, Є\, N} (\Delta^{d}_{Sm}(f)) \tag{6}$$

3. Modelling of blood vessels and undesirable patterns

3.1. *Geometrical properties of vessels:*

Blood vessel is the only feature in the image that is completely described by the three following properties:

- It is piecewise linear.
- The shape of a cross-section looks like a Gaussian curve.
- It is connected, in a tree like way.

3.2. *Geometry of undesirable features:*

There are different kinds of undesirable features encountered when extracting the vessels from the angiographic image. They are classified into different cases as follows:
Case (1). Noise occurring during the digitization process.
Case (2). Background linear features that can be confused with vessels in some parts, but that do not meet all the requirements (they can be too thin or too close).
Case (3). Other kinds of patterns that is not linear.
Case (4). Low random-like signal along vessels due to a late diffusion time of the fluorescein dye.

4. Morphological treatment for the recognition of geometric features

4.1. *Recognition of linear parts:*

Linear bright shapes can easily be identified using mathematical morphology [4]. An opening using a linear structuring element will remove a vessel when both the structuring element and the vessel have orthogonal directions. Conversely, when the structuring element and the vessel have parallel directions, the vessel will stay nearly unchanged. If we consider the openings along a class of linear structuring elements, a sum of top-hats along each direction will brighten the vessels regardless of their directions. However, this operation requires the length of the structuring elements to be large enough to remove big vessels; hence a lot of noise can be recovered in the sum of top hats. In order to deal with this problem, an image pre-processing is done using the connectivity property.

4.2. *Using the connectivity property:*

Noise is removed while preserving most of the capillaries using a geodesic reconstruction of the opened images into the original image f:

$$Sup_{op} = \beta^{rec}{}_{f}\,(MAX_{\,i=1\ldots12}\,\{\,\beta_{\,Li}\,(f)\}). \tag{7}$$

Each structuring element L_i (every 15) is 15 pixels long. Its size is approximately the range of the diameter of the biggest vessels for 512*512*8 images of cardial angiographies. In the image *Sop*, every isolated round and bright zone whose diameter is less than 15 pixels has been removed. Being a supremum of openings by reconstruction this operation is an opening, called linear opening by reconstruction of size 15. Removed elements include white noise (case1) and some abnormalities (case 3). The sum of top hats on the filtered image *Sop* will enhance all blood vessels whatever their direction, including small or tortuous vessels, even in the low signal (case 4). The large homogeneous pathological areas (case 3) will be set to zero , since they are unchanged by $ß_{Li}$, however the *Sop* image contains a lot of details corresponding to (case 2) that are also enhanced by the difference.

4.3. *Using differential properties as a separating tool:*

Any nonzero point in the picture has a dominant direction, and that can be considered as part of some lengthened pattern. After computing a Laplacian, a good estimation of the edge detection can be obtained. Laplacian images are highlighted around zero (fig.1(b)). Then a linear filtering removes patterns corresponding to case3, and in most cases patterns corresponding to case2. The filter sizes were chosen for typical 512*512*8 angiographic images of the heart. Values should be adjusted to the size of the blood vessel. Failing to adjust those parameters can lead to the removal of some apparently interesting features. The algorithm was designed to segment the main vessels and remove all possible false detection under various kinds of noise.

Fig.1. (a) Initial image; (b) Edge detection

5. Algorithm

The algorithm can be summarized as follows:

$$Sup_{op} = \beta^{rec}{}_{f}\,(MAX_{\,i=1\ldots12}\,\{\,\beta_{Li}\,(f)\}) \tag{8}$$

$$S_{sh} = \sum_{i=1}^{12} (Sup_{op} - \beta_{Li}\,(f)) \tag{9}$$

This transformation (a sum of top hats) reduces small bright noise and improves the contrast of all linear parts. Blood vessels could be manually segmented with a simple threshold on *Ssh*. However, most images contain noisy data requiring further treatment.

Hence, the computation of the edges is done using LOG operator.

$$S_{lap}= Laplacian\ (\ Gaussian\ (S_{sh}\ )) \tag{10}$$

Then the linear morphological filter, leads to the final result

$$S_1 = ß^{\,rec}{}_{S_{tap}}\,(MAX\ i_{\,=1\ldots12}\ \{\ ß_{\ Li}\,(S_{th}\,)\}). \tag{11}$$

$$S_2 = Þ^{\,rec}{}_{\,S1}\,(MIN\ i_{\,=1\ldots12}\ \{\ Þ_{\ Li}\,(S_1)\}). \tag{12}$$

$$S_{rec} = (MAX\ i_{\,=1\ldots12}\ \{\ ß^{\ 2}{}_{Li}\,(S_2)\}\ ). \tag{13}$$

A PC Pentium III 455 MHZ with 128 MB of memory runs this algorithm on a 512*512*8 image in less than one minute. Matlab version 6.5 is used as the working environment.

6. Results

The algorithm has been tested on a set of angiographic images of normal patients and it works well in most of the cases. However, we have encountered some false detection in the following cases:

- some features that looks linear;
- round linear bright structures are mistaken for vessels, and appear as white isolated circles.

and the first case should be avoided using black feature extraction. The complete segmented blood vessel is shown in fig.2.

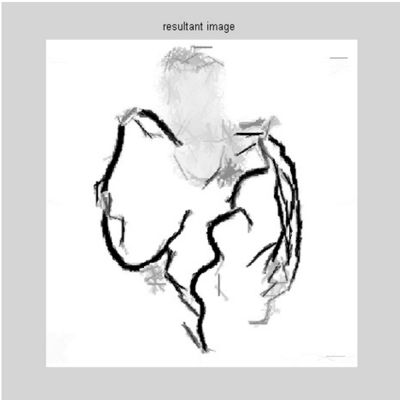

Fig.2. Segmented image

7. Conclusion

Thus an algorithm for extraction of linear structures (blood vessels) from medical images has been presented. Its strength lies in the combination of mathematical morphology and differential operators: algebraic based algorithms are used for basic feature extraction and removal of undesirable patterns, whereas linear operators are intended to compute shape properties in order to differentiate elements.

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