Fully Automatic Segmentation of Coronary Vessel Structures in Poor Quality X-Ray Angiogram Images

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Abstract. In this paper a fully automatic method is presented for extracting blood vessel structures in poor quality coronary angiograms. The method extracts blood vessels by exploiting the spatial coherence in the image. Accurate sampling of a blood vessel requires a background elimination technique. A circular sampling technique is employed to exploit the coherence. This circular sampling technique is also applied to determine the distribution of intersection lengths between the circles and blood vessels at various threshold depths. After this sampling process, disconnected parts to the centered object are eliminated, and then the distribution of the intersection length is examined to make the decision about whether the point is on the blood vessel. To produce the final segmented image, mis-segmented noisy parts and discontinuous parts are eliminated by using angle couples and circular filtering techniques. The performance of the method is examined on various poor quality X-ray angiogram images.

1 Introduction

To exploit blood vessels of human body, several medical imaging techniques such as X-ray, Computed Tomography (CT), and Magnetic Resonance (MR) are used. Extraction of blood vessels in a medical image with lack of contrast pose, drift in image intensity and noisy signal is a significant challenge in medical imaging. Automated systems and high processing throughput are needed in computationally intensive tasks including visualization of coronary blood flow and three-dimensional reconstruction of vascular structure from biplane medical images [1], [2], [3], [4], [5]. Previously developed methods for blood vessel segmentation in medical images are limited by at least one of the following drawbacks. Firstly, these methods may be applicable for limited morphologies. Secondly, user involvement is needed to select the region of interest. Thirdly, lack of adaptive capabilities may result in poor quality of segmentation under varying image condition. Lastly, blood vessel segmentation process requires a large computational effort [6], [7], [8], [9], [10]. These blood vessel segmentation techniques may be classified under following titles; pattern recognition, model based, tracking and propagation, neural network, and artificial intelligent based techniques [11], [12], [13], [14], [15].

In this paper, a method is presented to segment coronary artiograms in a medical image. This proposed method generates a complete segmentation of vessels in a medical image without user intervention. The method can handle complex structures such

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as sharp curved, branched vessels, and vessels with varying length on a noisy and changing background. The method firstly fitters, and then extracts the background image of a medical image. Secondly, intersections between sampling circles and sampled blood vessel are determined to calculate the intersection distribution. The dominant intersections are checked to segment the vessel structure in the medical image. Finally, a circular filtering technique is used to remove small noisy fragments on the image. In Section 2, the proposed segmentation method is described. The performance of the method is examined on real images in various qualities. The results are given in Section 3 and finally the conclusions and future work are discussed in Section 4.

2 Description of the Segmentation Method

The proposed segmentation method exploits the spatial coherence existing in a medical image by considering neighboring pixels around the current one being processed. Therefore, the effect of local discontinuities and disorder are tolerated, and recognition of normal and distorted blood vessels in a noisy image is improved on fully automatic segmentation. The basic steps in automatic coronary segmentation are (1) filtering and extracting whole background image, (2) eliminating the pixel under the background threshold depth, applying the circular sampling to the pixels that are not eliminated in the previous step and applying proper Bezier spline to make more smoother samples along the scan-line in the circular sample, (3) eliminating the noisy and non-vessel parts by using angle couples at several levels over the threshold depth, (4) separating the disconnected parts from the sample, (5) determination of the blood vessel and circle intersections at several levels over the threshold depth, (6) calculating the intersection distributions and dominant intersection lengths, and then segmenting the image, and (7) finally circular filtering of whole image.

2.1 Eliminating the Background Effect

The background in a medical image affects the segmentation of the blood vessel in the image negatively. If the background is not eliminated correctly, the circular sampling technique will mis-sample the object. Therefore, a technique is needed to prevent this background effect. Here, the sampling circle gets larger so does the scan-lines then, mis-sampling occurs as illustrated in Fig. 1.a and b. Elimination of this effect is very important to produce a correctly segmented image. The elimination process is shown in Fig. 1.c and d. The background effect elimination approach described here uses an averaging technique that calculates the average intensity within the region of interests with a dimension of [(2N+1)x(2N+1)]. The centre point of this region is at current pixel point (m,n). The average $\overline{X}$ is given by Equation (1). The standard deviation of pixels in the region is given by Equation (2). Finally, threshold depth is calculated by using equation (3).

$$\overline{X}(m,n) = [\sum_{k=-N}^{N} \sum_{\ell=-N}^{N} I(i+k, j+\ell)]/(2N+1)^2 . \quad (1)$$

$$\sigma(m,n)=\sqrt{\left\{\left[\sum_{k=-N}^{N}\sum_{\ell=-N}^{N}\left(I(m+k,n+\ell)-\bar{X}(m,n)\right)^2\right]/(2N+1)^2\right\}}\ . \tag{2}$$

$$T = I_{Pxl(I,J)} - \{\bar{X}_{Pxl(I,J)} - \upsilon[\sigma(m-1,n)\alpha + (1.0-\alpha)\sigma(m,n)]\}\ . \tag{3}$$

Where T is the depth of background threshold and I(m,n) is the intensity value of the current pixel. The parameters υ and α in Equation (3) are experimentally determined as 0.25 and 0.75, respectively.

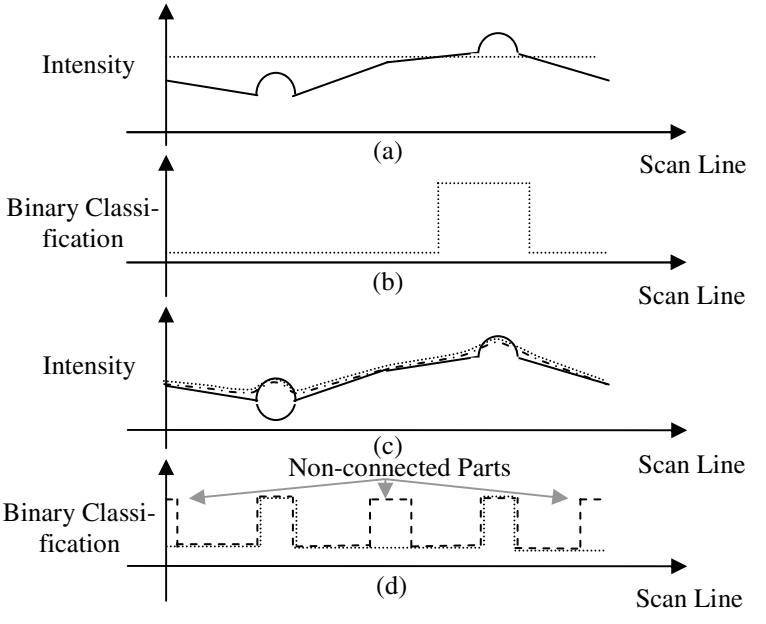

Fig. 1. Sampling along the circular scan-line (a) without (c) with background effect elimination, and corresponding binary classifications (b) and (d)

Accurate choice of the length of the averaging area is important. A large averaging area flattens the background whereas small averaging area does not cover enough background information. To eliminate most of the non-vessel-like structures, the background threshold depths are calculated at each pixel by Equation (3). This threshold depth is not used to produce final segmented image. It is used to make a preclassification to eliminate the pixels, which are not a part of a blood vessel.

2.2 Circular Sampling Technique and Eliminating Non-vessel and Nosily Areas

The circular sampling technique samples a structure around a sampling point by extending the sampling circles spatially. Thus, it enables the segmentation process to

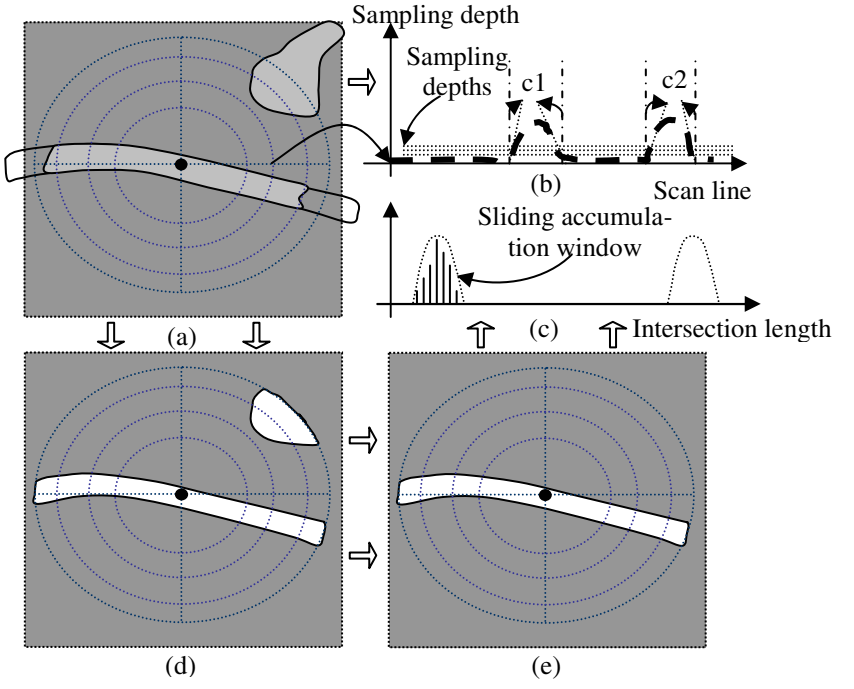

Fig. 2. (a) Circular sampling, (b) the intensity along a scan line of a circle, (c) distribution of intersection lengths of a circle and blood vessel, (d) circular sampling at a certain background threshold depth on a flat background and (e) removing the disconnected parts

exploit the spatial coherence that exists in the vessel structures on an angiogram. Here, the points around the sampling point on the image are sampled at a certain threshold depth related to the background level by using the circular sampler in Fig. 2. After the circular sampling, some noisy structures can be mis-segmented because random distribution of intersections could be concentrated at some lengths. Here, the Bezier spline is used to filter the samples along each scan line as illustrated in the Fig. 2.b. In order to reduce the number of the mis-segmentations, a technique illustrated in the figure, is employed. Here, these noisy structures are removed by counting the angle couples. The angle couples along the sampling circle's scan-line are calculated at the current pixel by accounting the several neighboring pixel intensities in the scan-line. Slope of each line producing the angle couples must be over a threshold degree (for example 45^0). These angle couples are calculated on each circular scan lines for each pixel after the agiogram is sampled, as illustrated in Fig. 2.a. A typical circular scan line with the angle couples is illustrated in Fig. 2.b. The number of angle couples is used to eliminate the noisy pixels. A pixel may be considered as non-vessel when the number of the angle couples for the current pixel is less than 4. If the number of the angle couples is far more than expected (such as 50), the pixel is classified as noisy.

2.3 Separating the Disconnected Parts from the Sample of Interest and Calculating the Distribution of Intersection Lengths

After a blood vessel on the image is sampled at various background depths, as illustrated in Fig. 2.d, the disconnected parts in the sampling scope are removed as shown in Fig. 2.e. Separating noisy or disconnected part from the sampled vessel slice is important because the parts may cause the generation of wrong segmentation results. The centre of each sampling point should be positioned on blood vessel so that enlarging sampling circles from the centre are used to eliminate the parts that are not a part of a blood vessel. Firstly each sample point along the scan-lines of the circles is pre-classified by using a binary classifier. If a sampling point along a scan-line of a circle is pre-classified as a part of a vessel that has no connection to the centre, the sample should be signed as background. This enables us to determine the circle and blood vessel intersection length distribution correctly. Therefore, only the considered blood vessel is accounted and other misclassified parts in the focused area are eliminated.

After the separation of the disconnected parts the circle blood vessel intersection lengths are accumulated according to the lengths. When a pixel is tested to determine whether it is on a blood vessel or not, it is expected that the accumulation distribution should be concentrated around a certain length. A sliding accumulation function is used to calculate this accumulation value. Width and weight parameters of the function vary according to the length of the blood vessels. If the blood vessel is narrow, the width of the function is narrow. When blood vessel's length gets larger, the circle-vessel intersection length distribution spreads as shown in Fig. 2.c. To produce the distribution of intersection lengths, the intersection lengths are accumulated by Equation (4).

$$\{D(l) = D(l) + 1\}_{I(m,n)}. \tag{4}$$

were, $D(l)$ represents the circles and blood vessel intersection accumulation distribution array, and $\{\}_{I(m,n)}$ represents the current depth and pixel. This accumulation process is done at several background threshold values depending on the deviation of the intensity around the current pixel.

This distribution function has also to be normalized according to the length of the intersection because more intersection occurs for narrow blood vessels than wide blood vessels. Finally, the measured length accumulation density value is over a certain threshold, the pixel is considered as blood vessel.

2.4 Decision Criteria and Threshold

The distribution of the intersection lengths, the peak values of the dominant intersections, and the relative values (to all intersections) of these dominant intersections are very important to determine a correct decision threshold value. Equation (5) is used to calculate the dominant or the maximum circle blood vessel intersections, where $M_k\{D(\ell)_{I(m,n)}\}$ represents the strength of the dominant intersection length along the intersection accumulation array, $a(\ell)$ is the weighting array used to calcu-

late the dominant intersections. Equation (6) is used to make decision about whether the current pixel is on a blood vessel or not. Then, the equation is used to segment the image and $S_{I(m,n)}$ represents the segmentation result. If the density is less than the bottom threshold T_b, the pixel is considered as background. If the density is above the upper threshold T_u, the pixel signed as artery. If the density is in between these two thresholds, then second decision rule is applied for the correct segmentation. We experimentally found that choosing T_b and T_u as 8.5 and 12, respectfully, yields satisfactory results.

$$M_k\{D(\ell)_{I(m,n)}\} = \{\sum_{\ell=-M}^{M} a(\ell)A(k+\ell)_{I(m,n)}\},\ \mathrm{M} \le \mathrm{k} < \mathrm{Max\_Length}. \tag{5}$$

$$S_{I(m,n)} = \begin{cases} \text{Background} & \text{if} \quad M_k\{D(\ell)_{I(m,n)}\} < \mathrm{T_b} \\ \text{Undecided} & \text{if} \quad \mathrm{T_b} \le M_k\{D(\ell)_{I(m,n)}\} \le \mathrm{T_u} \\ \text{Artery} & \text{if} \quad M_k\{D(\ell)_{I(m,n)}\} > \mathrm{T_u} \end{cases}. \tag{6}$$

The second decision rule checks the normalized second and third peak intersection in the distribution to make a more precise decision. If these peak intersections (relative to their intersection length) on the same branch of the vessel from the current centre are not evident and if the density is larger than a threshold value, the pixel signed as artery.

2.4 Circular Filtering

Generally, the vessels in a medical image are continuous and long structures. On the other hand, sometimes background and noisy structures could be detected as vessel structures even though they are more often discontinuous and short vessel like structures rather than long and continuous vessel structures. These mis-segmented parts are removed from the final image by using the circular filtering technique. Here, all pixels signed as blood at the previous stage are taken for further examination. The center of the circle is positioned at the current pixel to be examined, and then, the radius of the circle is increased to test whether the segmented structure is a small discontinuous part or not. If there was no pixel signed as a vessel along the enlarging circles' scan line, the pixel is considered as a non-blood vessel and set to background.

2.5 Fast Segmentation

Full resolution segmentation produces a better quality segmented images but it is more expensive than the half, quarter or fast segmentation. To accelerate the segmentation process, fewer pixels than full resolution calculation can be visited during the segmentation of images. Three approaches can be applied to speed-up the segmentation process. The first way (half segmentation) of doing this is that the image can be processed at every other pixel (or more) on vertical and horizontal lines. The second approach (quarter segmentation) processes every fourth pixel along the horizontal and

vertical scan lines. Then, neighboring pixels are signed by using a simple decision rule such as background threshold depth decision rule. Although this approach is quite fast, it produces poor quality segmentation results, especially for the thin blood vessels. The third way (fast segmentation) of speeding-up the segmentation process is to apply the whole decision processes to the neighboring pixels of a pixel segmented as blood vessel by using half segmentation approach.

3 Results

The performance of the method is tested on several real images with several difficulties. In the first experiment, the accuracy of the method on poor quality contrast angiogram image was evaluated. The Fig. 3.a show a low contrast image and

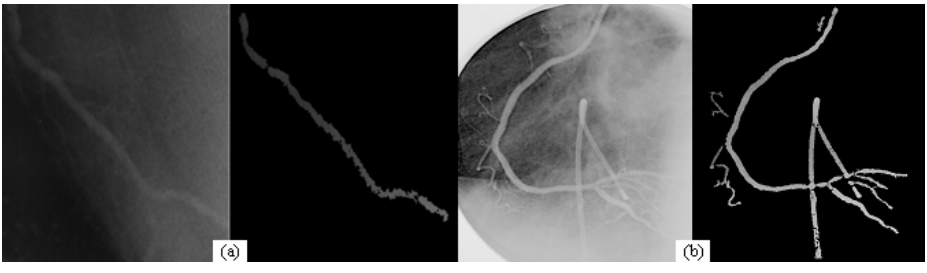

Fig. 3. (a) A poor quality angiogram and its segmented image, and (b) an angiogram image with many branches and its segmented image

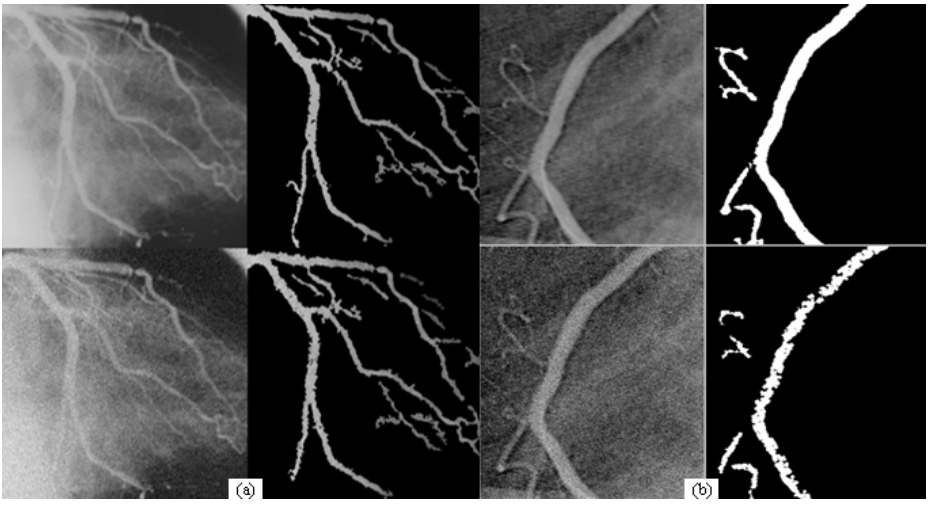

Fig. 4. (a) Noise added complex angiogram images and their segmented images and (b) Two other noise added complex angiogram images and their segmented images

corresponding segmented image, respectively. The performance of this method at the side of the blood vessel is slightly low but whole blood vessel is successfully extracted and tracked.

In the second experiment, the ability of the method was tested to extract branching arteries in a complex angiogram. Fig. 3.b shows an artery with many branches on varying background. The corresponding segmented images are also shown in Fig. 3.b. As seen from the result, the method successfully follows the branched arteries. The aim of the final experiment is to test accuracy of the method for several noise levels. For this purpose, two different images were selected. Fig. 4.a and Fig. 4.b (first and third images on the first and second lines) show noise added real images. Here, selected noise levels are 5, 20, 5, and 30 grey levels, respectively. Fig. 4.a and Fig. 4.b (second and fourth images on the first and second lines) show the corresponding segmented images. The method results in slightly noisy vessel edges but the whole blood vessel is successfully extracted and tracked. The results indicate that the proposed method yields accurate results even in complex and too noisy images.

4 Conclusion and Discussion

In this work a blood vessel segmentation technique is applied to extract the structure of the blood vessels in two-dimensional medical images. The technique exploits the spatial coherency that exists in two-dimensional medical image and works on each pixel on the image for extracting the structure of blood vessel. This fully automatic technique is robust to noise, low contrast and varying background, and able to extract vascular structures without human intervention. To eliminate small noisy parts and fragments at the final image, a circular filtering technique is used and quality of segmentation is improved. An elliptical filter may be considered as a future work to get further improvement.

When these segmentation results are compared to the results of the other methods such as the model based approach, this proposed method is quite successful in exploiting the whole vessel structure in a medical image except the branching areas and some long vessel like structures. Thus, the proposed method may not be very successful around the branching vessel area where the intersection length distribution gets more complicated. On the other hand, long vessel like structure in medical image may easily be excluded in other user intervened methods but the proposed method may not be that successful.

The segmentation method was run on P4-3.2 GHz PC. The segmentation durations for the poor quality image (300x220 pixels) is given in Fig. 3.a are about 73.2, 18.9, 10.1, and 34.5 seconds for full, half, quarter, fast resolution segmentation respectively. Typical durations for an image with dimension of 600x700 pixels (Fig. 3.b) is about 169.6, 43.4, 22.1 and 78.7 seconds for full, half, quarter and fast resolution segmentation, respectively. The durations were computed for noise added real images. The segmentation durations of noisy images (550x330 pixels) shown in Fig. 4.b are162.0 and 51.6 seconds, respectively, whereas those of the corresponding original images are 148.3 and 45.3 seconds.

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