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Blood Vessel Segmentation on Coronary Angiograms

Introduction

Miocardial infarction is the leading cause of death in developed countries and in emergency cases an immediate intervention is needed. Getting information on the state of the heart muscle is an important supporting information for the physicians.

One emerging technique to obtain this information is blood perfusion assessment in the heart muscles using densitometry on X-ray coronary angiography image sequences.

An automatic measurement system can provide a state of health assessment to the experts. On these images the coronary vessels are superimposed on the heart muscles. To get accurate results the coronary vessels should be excluded from the density measurements.

The patients have miocardial infarction and immediate intervention is essential. Since a common sequence containing hundreds of images has to be analyzed, the segmentation algorithm has to process the images very fast to give useful information to the experts before or during the intervention.

It has to segment the thick and dark vessels, which can change the density measurements. If the segmentation includes small parts of the heart muscles, then it will has no noticable effect on the measurements, but if a part of a thick vessel is not segmented correctly, then the density assessment can be misleading and show low blood perfusion.

In this paper we present a fully automatic fast vessel segmentation algorithm using Gaussian resolution hierarchy (Gaussian pyramid) and local operators using 3x3 neighborhood to mask the vessels.

Material and Methods

The proposed algorithm processes the following three main steps:

1. Preprocessing and generating the Gaussian pyramid
2. Vessel extraction and binarization
3. Fusion of the images and postprocessing

Since the digitally subtracted angiography (DSA) image sequences contain noise, the first step in preprocessing is denoising. It is performed in two steps:

1. Gaussian smoothing.
2. Bilateral filtering

The last three steps of the preprocessing is the following:

1. A thresholding using background value information excludes the pixels with higher value than the background from further analysis
2. A histogram stretching increases the contrast between the background and the vessels.
3. A threshold is applied for pixels with low value. If a pixel has a value lower than a given parameter it is labeled as vessel pixel. Pixels darker than this threshold are most probably a part of a thick and dark vessel or subtraction artifacts.

The Gaussian pyramid is generated from the preprocessed image sequence to speed up the vessel extraction. The pyramid contains four levels, including the original image resolution. The original images are the first level of the pyramid and all additional levels have halved width and height compared to the level before.

An example of generated pyramid can be seen in [Figure 1]. If no resolution hierarchy is used a larger neighborhood analysis is needed like 5x5, 11x11 or even 25x25 to extract the most thick vessels. These operations would be computationally expensive

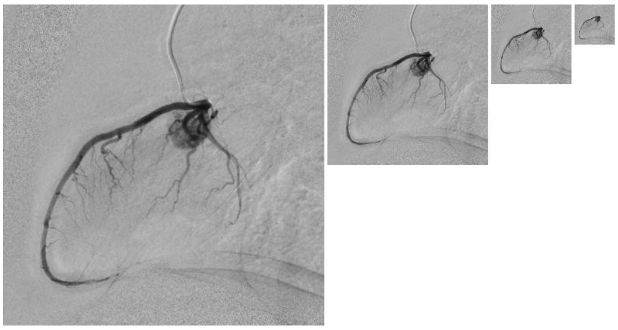


Figure 1: Example frame of an image sequence in different levels of a generated resolution pyramid. The halvening of image size with increasing level number is shown

A vessel extraction method is applied on each levels of the pyramid. A neighborhood analysis using operators searches for the thin dark lines in four different directions.

Due to the 3x3 sized operators it is able to detect only one pixel thin lines. Thicker lines and thus thicker vessels appear as one pixel thin lines on images with reduced resolution. Pixels labeled as vessel in a higher resolution level are excluded from the analysis of further levels.

The line detection method uses the following operators:

$$\begin{bmatrix} A & A & A \\ B & B & B \\ C & C & C \end{bmatrix} \begin{bmatrix} A & A & B \\ A & B & C \\ B & C & C \end{bmatrix} \begin{bmatrix} A & B & C \\ A & B & C \\ A & B & C \end{bmatrix} \begin{bmatrix} B & C & C \\ A & B & C \\ A & A & B \end{bmatrix}$$

During the analysis, the algorithm fits all four operators to the neighborhood one by one. Our idea is to calculate the average pixel values under the areas labeled as “A”, “B”, “C” and compare them. The following code shows how an operator works:

```
if ( avg(A)  > avg(B)  ) && ( avg(C)  > avg(B)  ) then
  output =
    maximum( avg(A)-avg(B), avg(C)- avg(B) )
else
  output = 0
```

An example output of one operator can be seen in [Figure 3]. the outputs of the four operators are combined in a maximum image [Figure 4].

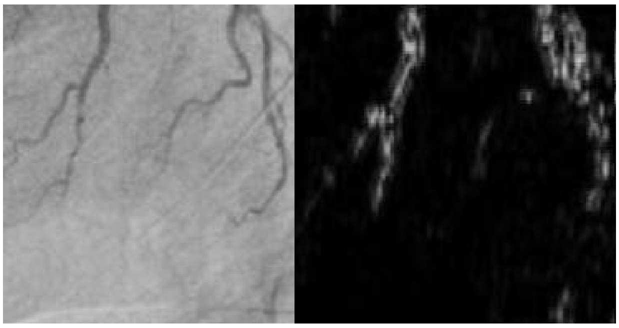


Figure 3: Part of an input image (left) and the output of the "vertical" operator (right) shows the highlighted vertical vessels

The output image series of the neighborhood analysis are rescaled to the resolution of the input image series and binarized by hysteresis threshold **[1]**. The two values of the hysteresis threshold are parameters of the algorithm and depend from the current X-ray device and image quality. [Figure 4] shows the result of this thresholding: light gray pixels are over the higher value, the dark gray are between the two given values and connected to a light one.

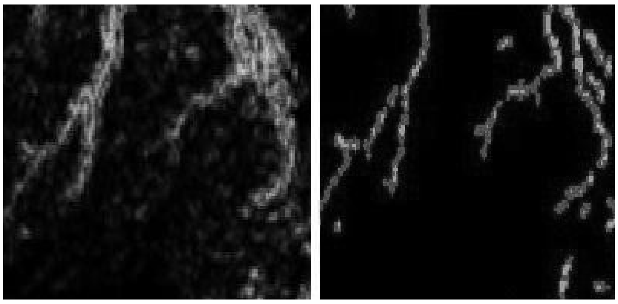


Figure 4: maximum values of the four vessel extraction operators (left) and the thresholded image (right)

The binary image series originated from the different levels of the resolution hierarchy are combined using a pixelwise OR operator.

To reduce the effects of rescaling the edges of the masked areas in the combined image series are fitted to the local gradient maximum in their neighborhood. This local gradient maximum is probably the real edge of the vessel in the input images.

To do this, a gradient magnitude map "G" is calculated from the input data. A map D is generated using the G. This D works like a distance map. If a pixel has a non-zero value in G, then the pixel value is expanded to the 10x10 neighborhood. The new values in D for these pixels are decreasing with the distance from the original pixel. The decreasing value reaches zero 5 pixels away from the center pixel.

An "intelligent dilate" method considers this D. The segmented objects are only dilated at a pixel if there is a pixel in its 3x3 neighborhood which is not labeled as vessel and has a higher value in D than the center pixel. This method dilates the segmented vessel to the local gradient magnitude maximum, which is most probably the edge of the vessel in the input image. As a last step, morphological close and open operators are used to smooth the edges.

Results

The proposed algorithm is evaluated using 30 randomly chosen 200x200 pixel sized ROIs from 10 series and two full image sequences.

All of the used image sequences contain 100 or more images with a resolution of 512x512. During the evaluation manually segmented images are used as gold standard. The manual segmentation is performed by experts and the first author.

Our algorithm has a fixed number of 4 hierarchy levels and uses fixed parameters for the preprocessing and 3 main parameters:

1. A threshold value for dark pixels to label them as mask pixels during the preprocessing
2. a lower threshold value,
3. and a higher threshold value for hysteresis threshold.

For comparison two other algorithms are validated: an algorithm which uses a Hessian matrix based vessel extraction without the resolution hierarchy but a different multiscale method **[2]**, and a hybrid version of the two algorithms, which uses both the resolution hierarchy and the Hessian matrix vessel extraction. For testing a common notebook was used (Core2Duo 2.0GHz processor and 2 GB RAM). None of the algorithms was parallelized.

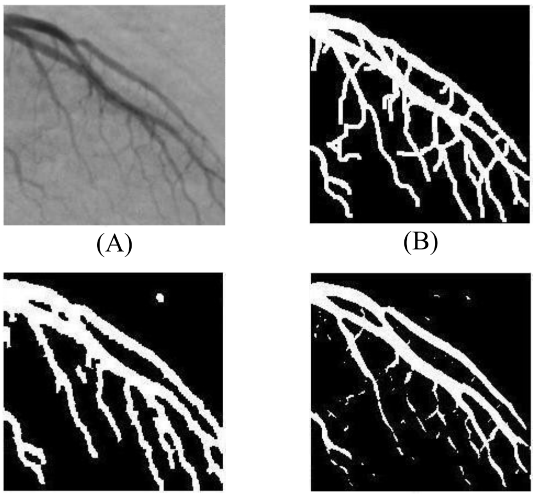
	Average Sensitivity	***Average accuracy***	***Average calculation time per frame***
Proposed method	0.7880	0.8918	0.7 s
Frangi	0.6685	0.8913	21.1 s
Hybrid	0.7043	0.8647	2.5 s

Table 1: Comparison of the three methods using the 30 ROIs show a significant difference in the calculation time

200x200 pixel sized ROIs in 30 frames of 10 image sequences are used to measure sensitivity and accuracy, while the calculation time was measured for the whole image sequences. The proposed method and the method presented by Frangi have similar accuracy but different sensitivity. The proposed method has higher sensitivity. It is developed to mask vessels, not to segment vessels with the highest accuracy.

The main difference between the two algorithms is the calculation time. The last column of the table shows the proposed algorithm is more than 30 times faster. Since the hybrid methods calculation time is almost 10 times faster than the method published by Frangi, it is clear, that most of this gain comes from the used resolution hierarchy.

A visual comparison of the algorithms can be seen in [Figure 5].



(A) (B) (C) (D)

Figure 5: Comparison of the three segmentation methods showing the input image (A), the gold standard (B), and the result of proposed method (C), and the result of method published in [2]. The proposed method segments the rough structures, while the other one is able to segment fine details.

	Average Sensitivity	***Average accuracy***
Series 1	0.8925	0.8921
Series 2	0.8715	0.7566

Table 3: Results of proposed algorithm using the two full length sequences

[Table 3] shows the statistics of the proposed method calculated using two full length sequences with a gold standard. In both cases the algorithm reached a sensitivity over 87%.

In the case of the second series the accuracy is lower because the algorithm segmented a lot salt and pepper noise and subtraction artifacts at the margin of the images. This noise had a strong influence on the averages calculated at the neighborhood analysis.

Discussion

In this paper we presented a fast and reliable algorithm to segment vessels in digitally subtracted coronary X-ray angiogram image series. The algorithm uses a resolution hierarchy to speed up the segmentation process and extracts the vessels using local operators. The algorithm was evaluated using various image sequences and reached high accuracy with low computational requirements. It is shown this algorithm is well applicable in angiography and the usage of the resolution hierarchy speeds up the process by the factor of eight. This speed up makes it more useful for applications before or during interventions.

Literature

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