# Multiscale Blood Vessel Segmentation in Retinal Fundus Images

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**Abstract.** Retinal fundus imaging is widely used for eye examinations. The acquired images provide a unique view on the eye vasculature. The analysis of the vasculature has a high importance especially for detecting cardiovascular diseases. We present a multiscale algorithm for automatic retinal blood vessel segmentation, which is considered as a requirement for the diagnosis of vascular diseases. The algorithm uses a Gaussian resolution hierarchy to decrease computational needs, and allows to use of the same methods to detect vessels of different diameters. The algorithm is tested on two public databases using a common notebook. The algorithm segmented each image in less than 20 seconds with a competitive accuracy over 93% in both cases. This proves the applicability for medical applications.

## 1 Introduction

The images of the eye background provide the unique opportunity to in vivo examine the human vasculature. The sight of the vessel structure facilitates the detection of substantial vascular abnormalities e.g. aneurysms, artery/vein ratio [1]. Most of the automatic and semi-automatic methods to analyse the vessel structure rely on a vessel segmentation.

Segmentation of blood vessels is a research area since years, the current algorithms usually use some kind of vessel enhancement or feature extraction before the thresholding, or vessel tracking [2]. The methods with the highest accuracy also have high computational needs if thick vessels are present. The use of the proposed resolution hierarchy makes it possible to detect these vessels faster, while preserving a high accuracy.

We present a fast and accurate multiscale vessel segmentation algorithm to segment the vessels for further analysis. The segmentation algorithm is evaluated using two public databases [3][4].

# 2 Materials and Methods

In general, our method works as follows:

- A Gaussian pyramid is generated.
- An efficient neighbourhood analysis applied on each level of the pyramid to enhance vessels of different diameter.
- The results of different levels are binarized and fused to obtain a final segmentation.

## 2.1 Gaussian Resolution Hierarchy

A Gaussian resolution hierarchy (Gaussian pyramid) is generated from the green channel of the fundus image, as it provides a reasonable contrast between the vessels and the background. The hierarchy consists of three levels (0-2). The original image has the highest resolution (level 0), and each further level has a halved width and height.

Due to the downscaling this hierarchy increases the speed of the segmentation, and allows the usage of the same $3 \times 3$ neighbourhood analysis to extract vessels with different diameters (Fig. 1). The neighbourhood analysis is applied on each level of the pyramid. This provides three grayscale images, whose pixels encode the probability, that the given pixel belongs to a vessel.

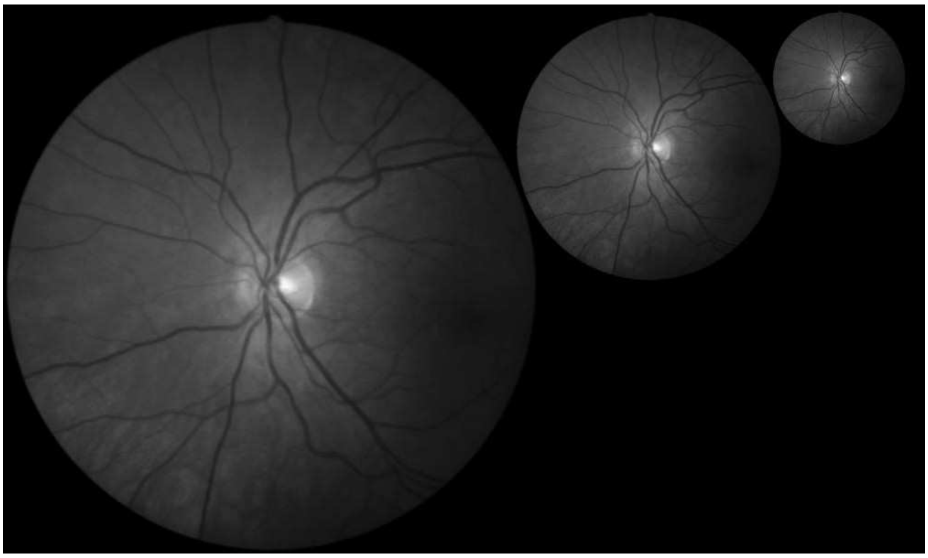

**Fig. 1.** The Gaussian resolution hierarchy generated from the green channel by decreasing resolution.

### 2.2 Neighbourhood Analysis

The Hessian matrix of the $3 \times 3$ neighbourhood for each pixel of the image are calculated. Since our images are two-dimensional, The hessian matrix will be a $2 \times 2$ matrix containing the second order derivatives shown in the following equation:

$$H(f) = \begin{pmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial x \partial y} \\ \frac{\partial^2 f}{\partial x \partial y} & \frac{\partial^2 f}{\partial y^2} \end{pmatrix} \tag{1}$$

The two eigenvalues of the matrix are calculated. They are reflecting the scale of the lowest curvature and the highest one in the neighbourhood. The value of the center pixel in the output layer is calculated from the ratio of these two eigenvalues using the following formula:

$$P_{vessel} = 1 - a_l/a_h \tag{2}$$

Where $P_{vessel}$ is the result value for the given pixel, $a_l$ is the lower, and $a_h$ is the higher eigenvalue. In case of a vessel pixel the two eigenvalues representing the curvature are highly diverse and result in a ratio unlike one. In homogeneous regions the two eigenvalues are similar and result values close to one. This will cause a higher pixel value in the enhanced images if a vessel is present compared to the homogeneous regions [5]. This analysis is applied in each level of the pyramid. In Fig. 2 we show one of the three images of the enhanced vessels.

### 2.3 Image Fusion

All of the vessel-extracted images are now upscaled to the original image size to have a standard resolution. All images are binarized applying a hysteresis threshold, where the two thresholds are set to 85% and 93%. The final vessel segmented image is achieved by merging. The binary images are merged by a pixel-wise OR operator (Fig. 3).

## 3 Results

The algorithm is evaluated using two public databases with gold standard manual segmentations. Both databases contain 20 retinal fundus images. The STARE database[3] contains only the input and goldstandard images with a resolution of $700 \times 605$. The DRIVE database [4] contains $565 \times 584$ resolution images and additionally provides manual segmentations, which are done by a trained independent human observer and accuracy measurements of published algorithms. The test hardware was a notebook with a 2.0 GHz processor and 2.0 GB SDRAM. Table 1 schows the comparison of the proposed method to the human obsewrver and the best published method of the DRIVE database.

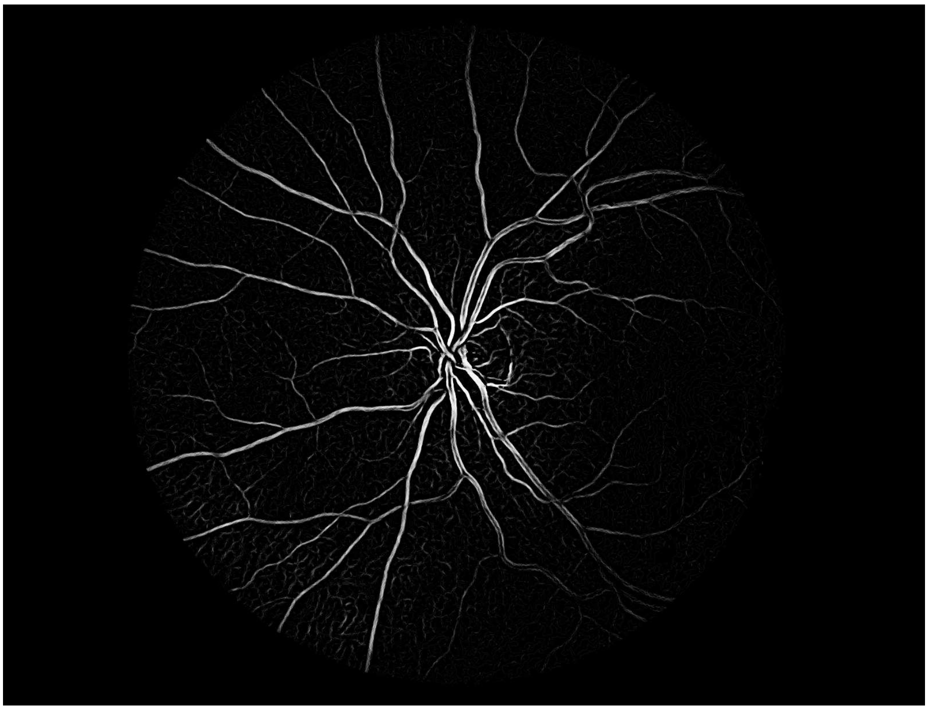

**Fig. 2.** A vessel enhanced image generated from the highest resolution level of the Gaussian hierarchy. The result was computed using the introduced neighbourhood analysis.

**Table 1.** Evaluation using the two public databases

| Algorithm | Accuracy | Specificity | Sensitivity | Calculation time |
|---|---|---|---|---|
| Proposed method(STARE) | 93.8% | 97.5% | 65.1% | 16 sec |
| Proposed method(DRIVE) | 94.9% | 96.8% | 75.9% | 11 sec |
| Best published(DRIVE) | 94.4% | - | - | - |
| Observer(DRIVE) | 94.7% | - | - | - |

## 4 Discussion

Based on the images of the mentioned public databases, we achieved a competitive accuracy compared to the other segmentation techniques or a human observer, while the applied resolution hierarchy decreases the computational needs. Our evaluations confirmed that the method offers a fast and reliable blood vessel segmentation applicable for quantitative analysis of vascular diseases.

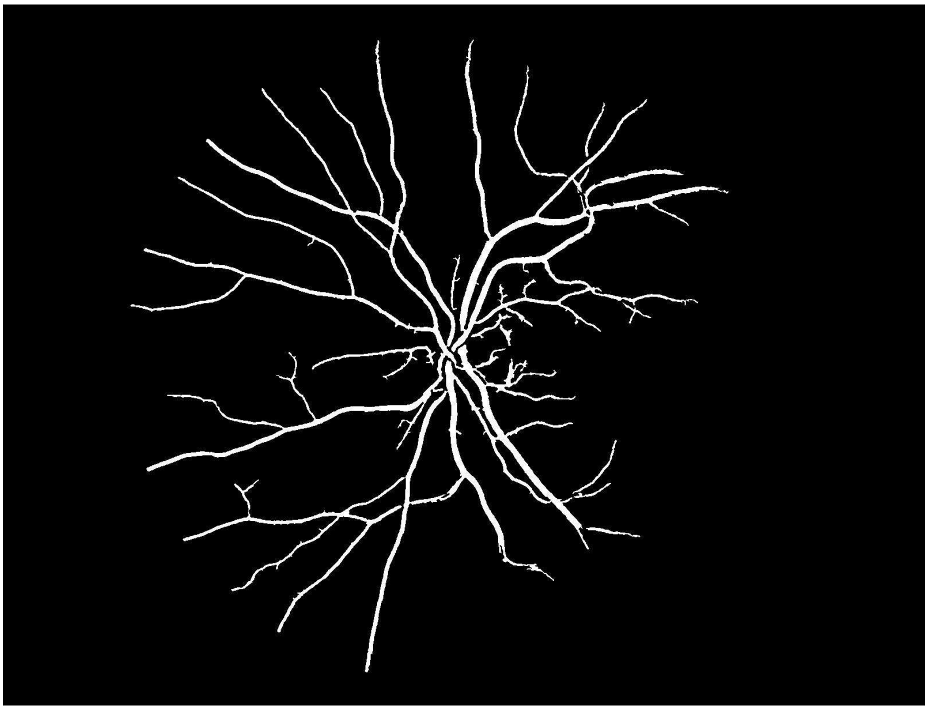

**Fig. 3.** The finally segmented image generated by binarizing and fusing the three vessel enhanced images.

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