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# Segmentation of Vasculature from 2D Fundus Image

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**ABSTRACT**-Vessel segmentation in retinal fundus images is a primary step to clinical diagnosis for some eye diseases. The existing models mainly concentrate which will not be sufficient for the doctor to treat the diseases. By analyzing and detecting of vasculature structures in retinal images, we can early detect the diabetes in advanced stages by comparison of its states of retinal blood vessels. In this we present a method for both main and peripheral vessel segmentation. Here gray-voting is used to enhance the small vessels, while a two-dimensional Gabor wavelet is used to enhance the main vessels. We combine the gray-voting results with the 2D-Gabor filter results as pre-processing outcome. A Gaussian mixture model is then used to extract vessel clusters from the pre-processing outcome. These clusters are then sent into the complement method, At the last step, we eliminate the fragments that do not belong to the vessels based on the shape of the fragments. We evaluated the approach with two publicly available DRIVE and STARE datasets with manually segmented results. We also compare the results obtained from DRIVE and STARE datasets and we will also find their accuracies, specificities and sensitivities.

**KEYWORDS:** DRIVE Dataset, Gray vote, Gaussian Mixture Model, STARE Dataset.

## I. INTRODUCTION

Retinal fundus images are used to diagnose certain eye diseases and some systemic diseases. Blood vessels are one of the most important components in the retina, and abnormal vessels can indicate the presence of various diseases such as diabetes, glaucoma, retinopathy, obesity. Observing the morphological characters of vessels can help a physician to diagnose certain diseases. Manual vessel segmentation in retinal fundus images is a preliminary step to the clinical diagnosis of such diseases. However, manual segmentation is time-consuming and thus, segmentation results are highly dependent on the physician skill. Several algorithms are developed to accurately phase blood vessels from pictures with a spread of underlying pathologies and across a spread of ophthalmic imaging systems. However, small vessels play an important role in the clinical diagnosis and may be of great value in diagnosis of blood vessel related diseases in their early stages. The goal of this study is to extract small vessel fragments from retinal fundus images and use these fragments to complement the main vessel structure. This approach considers both main and peripheral small vessels during retinal image segmentation. We propose a gray-voting and Gaussian mixture model (GMM) method to segment the vessels in fundus retinal images. For this project we use the digital retinal pictures entry for testing.

## II. IDENTIFY, RESEARCH AND COLLECT IDEA

A common procedure during an examination is retinal imaging. An optical camera is used to see through the pupil of the eye to the rear inner surface of the eyeball. A picture is taken showing the optic nerve, fovea, surrounding vessels, and the retinal layer. The ophthalmologist can then reference this image while considering any observed findings. Our approach breaks the problem into two components. The first component concerns automatically processing a retinal image to denote the important findings. The second component concerns automatically reasoning about the findings to determine a diagnosis. Additional outputs include detailed measurements of the anatomical structures and lesions visible in the retinal image. These measurements useful for tracking disease severity and the evaluation of treatment progress over time. By collecting a database of measurements for a large number of people, the STARE project could support clinical population studies and intern training.

### III. STUDIES AND FINDINGS

A lot has been published on this project by many people; these are my two most

Relevant papers:

- Hoover, V. Kouznetsova and M. Goldbaum, "Locating Blood Vessels in Retinal Images by Piece-wise Threshold Probing of a Matched Filter Response", IEEE Transactions on Medical Imaging, vol. 19 no. 3, pp. 203-210, March 2000.
- This paper proposes a new supervised method for blood vessel segmentation using Zernike moment-based shape descriptors. The method implements a pixel wise classification by computing a 11-D feature vector comprising of both statistical (gray-level) features and shape-based (Zernike moment) features. Also the feature set contains optimal coefficients of the Zernike Moments which were derived based on the maximum differentiability between the blood vessel and background pixels. A manually selected training points obtained from the training set of the DRIVE dataset, covering all possible manifestations were used for training the ANN-based binary classifier. The method was evaluated on unknown test samples of DRIVE and STARE databases and returned accuracies of 0.945 and 0.9486 respectively, outperforming other existing supervised learning methods.
- Hoover and M. Goldbaum, "Locating the optic nerve in a retinal image using the fuzzy convergence of the blood vessels", IEEE Transactions on Medical Imaging, vol. 22 no. 8, pp. 951-958, August 2003.

### IV. PROPOSED METHODS

Our method mainly consists of 3 sections

- i. Pre-processing
- ii. Classifier
- iii. Post-processing

Every section has its own importance, In the first step that is in Pre-processing state there are red, blue and green channels in an RGB fundus retinal image. The green channel shows the best background/vessel contrast, and its signal noise ratio is higher than the other channels. In this study, the green channel of a fundus retinal image is used as the input to the subsequent step in the image preprocessing stage. However, an optic disk has a higher mean gray value than that of the entire image, whereas fovea has a lower mean gray value. The foreground is primarily considered to be a vessel that shows a different gray value in a different region of a retinal image. To extract the primary structure of a vessel, the original green channel of the image is passed through a 2D Gabor filter. The 2D Gabor filter uses a Gaussian kernel function modulated by a sinusoidal plane wave, which is very sensitive to a retinal vessel because changes in the gray level between the vessel and the background are shown as a Gaussian distribution. Although a 2D-Gabor filter can extract the main vessel structures in a retinal image, details, especially small vessels, are often lost. To obtain smaller vessel information from the green channel retinal image, we propose a gray-voting. The gray-voting method can enhance small vessels that have a similar gray level distribution to the background. In the first two sections of this chapter, we obtain the 2D-Gabor result and the gray-voting result by using a 2D Gabor filter and the proposed gray-voting algorithm. The 2D-Gabor result and the gray-voting result contain the main vessel structure and the small vessel information, respectively. To obtain an image with both the main vessel structure and the details, we fuse outcome of 2D-Gabor result and the gray-voting result.

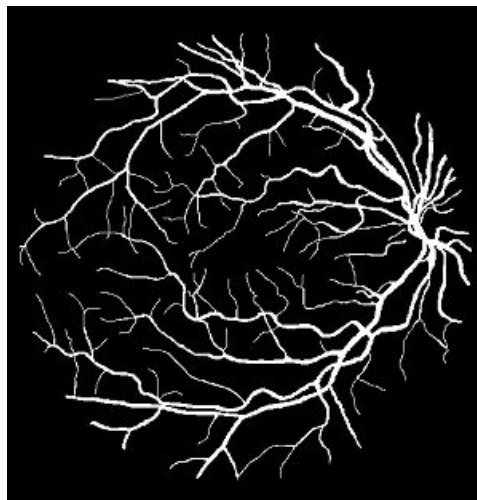
As shown the fused result may be composed of pixels of both vessels and noise. Because vessel pixels usually have higher gray-levels than noise, we use GMM to classify the pixels in the fused result. In this process, GMM is adopted to analyze the gray level distributions of the pixels in the fused result.

The post-processing of the vessel segmentation can mainly be divided into two parts. The first part complements the GMM classifier result using a gray-vote image that contains rich small vessel details. The second part eliminates the fragments that do not belong to the vessel using morphological characteristic. The vessel cluster IGMM contains the main vessel structure and some small vessel branches. However, some small vessel branches are broken into fragments.





RETINAL IMAGE



SEGMENTED IMAGE

#### IV. DATASETS

The two publicly available databases (S1 File), DRIVE (Staal et al., 2004) [16] and STARE (Hoover et al., 2000) [17] were used to test the proposed methods. The DRIVE dataset contains 40 images that were obtained from a diabetic retinopathy screening program in The Netherlands. In the database, 33 images do not show any sign of diabetic retinopathy, and 7 show signs of mild early diabetic retinopathy. These 40 images have been randomly selected from the screening population, which consists of 400 diabetic subjects between the ages of 25 and 90 reported by Staal et al. (2004). Each image consists of 584 x 565 pixels. The STARE dataset contains 20 retinal fundus images, which consist of 605 x 700 pixels. Both datasets contain manual segmentation results. For the STARE dataset, we used two sets of manual segmentation results to evaluate the proposed algorithm. In the first manual segmentation dataset, 10.4% of the pixels were marked as vessels; while 14.9% of the pixels were marked as vessels in the second manual segmentation dataset, which contains more small vessel details than the first one.

#### V. ALGORITHM EVALUATION

We evaluated the proposed algorithm's accuracy, sensitivity and specificity of segmentation results. These evaluation measures are widely used in the vessel segmentation field. The primary concept of the evaluation method is to count the number of pixels that are true positives (TP), which describes the number of pixels that the algorithm segmented as vessel correctly; false positives (FP), which describes the number of pixels that the algorithm segmented as vessels incorrectly; true negatives (TN), which describes the number of pixels that the algorithm segmented as background pixels correctly; and false negatives (FN), which describes the number of pixels that the algorithm segmented as

background incorrectly. These values can be obtained by comparing the algorithm’s segmentation results with the “gold-standard” manual segmentation results. The evaluation method is defined by the formulae.

$$\text{Accuracy} = \frac{TN}{(TP+FN+TN+FP)}$$

$$\text{Sensitivity} = \frac{TP}{(TP+FN)}$$

$$\text{Specificity} = \frac{TN}{(FP+TN)}$$

The evaluation results could be different according to different “gold-standard.” With the STARE dataset, there are two manually segmented results. The first manually segmented results, which are widely used for vessel segment evaluation, ignore many small vessels. Thus, because this approach contains significant amounts of small vessel information, the accuracy and specificity of the proposed method will be lower than the other vessel segment methods when using the first manually segmented result dataset to evaluate this approach.

METHOD	ACCURACY	SENSITIVITY	SPECIFICITY
DRIVE	0.9418	0.7359	0.9720
STARE	0.9364	0.7769	0.9550

## VI. CONCLUSION

Small retinal vessel segmentation plays an important role in clinical diagnosis; however, as mentioned above, small retinal vessel segmentation may lead to over-segmentation. Thus, new methods to solve this problem must be developed. Moreover, the evaluation algorithm using accuracy, sensitivity and specificity is based on the pixel, yet the overlap rate may not indicate the true topological structure which may be of more important than the pixel overlap rate. For example, if the vessels’ structures are all segmented perfectly in topological structures, but the vessels’ widths are all thinner than the manually segmented image, the evaluation methods used in this study cannot accurately reflect the real vessel segment affection. Compared with the other vessel segment methods, the proposed approach showed better segmentation results for both main and small vessels with relatively stable accuracies and high sensitivities.

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