AN UNSUPERVISED RETINAL VESSEL EXTRACTION AND SEGMENTATION METHOD BASED ON A TUBE MARKED POINT PROCESS MODEL

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- Introduction
- Vessel Extraction
- Vessel Segmentation
- Experimental Results
- Conclusion & Future Work

Introduction

- Retinal vessel extraction and segmentation is essential for supporting diagnosis of eye-related diseases

- Though deep learning methods are useful in vessel segmentation, it is still meaningful to do research on unsupervised methods for cases where labeled training data are not available

- We propose an unsupervised segmentation method based on our previous connected-tube marked point process (MPP) model

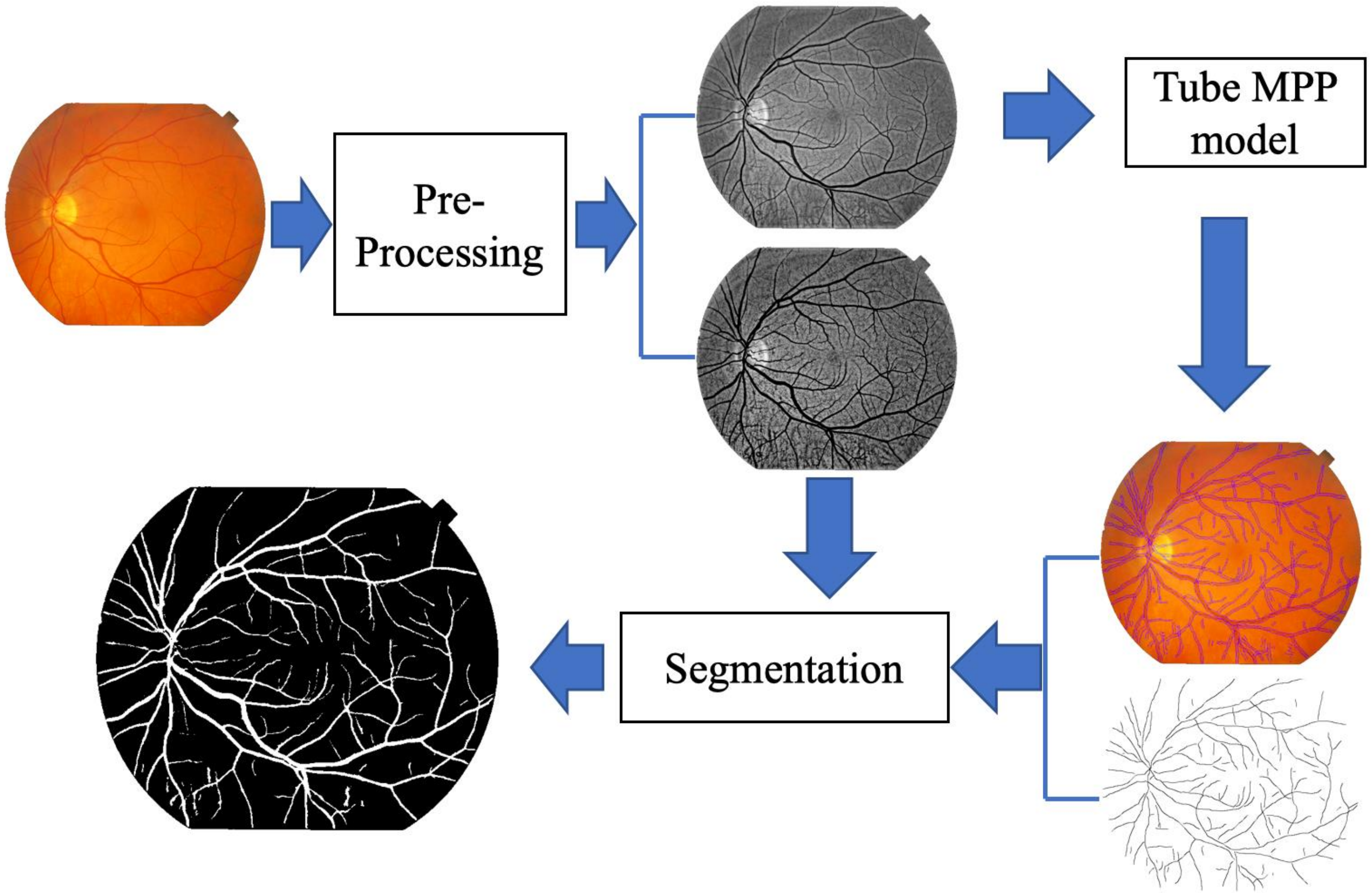


Fig 1. The framework of vessel detection method

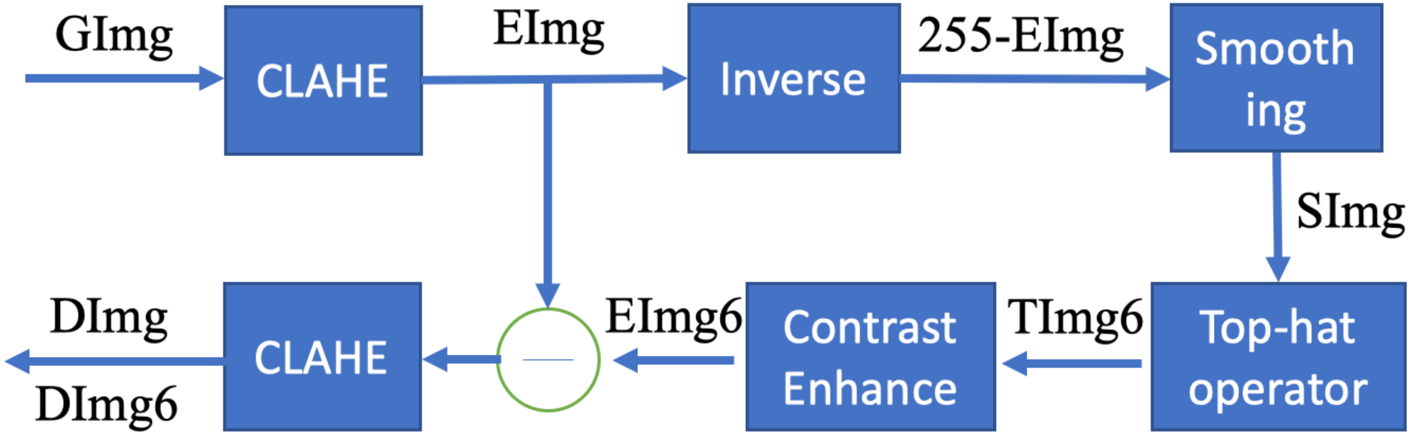
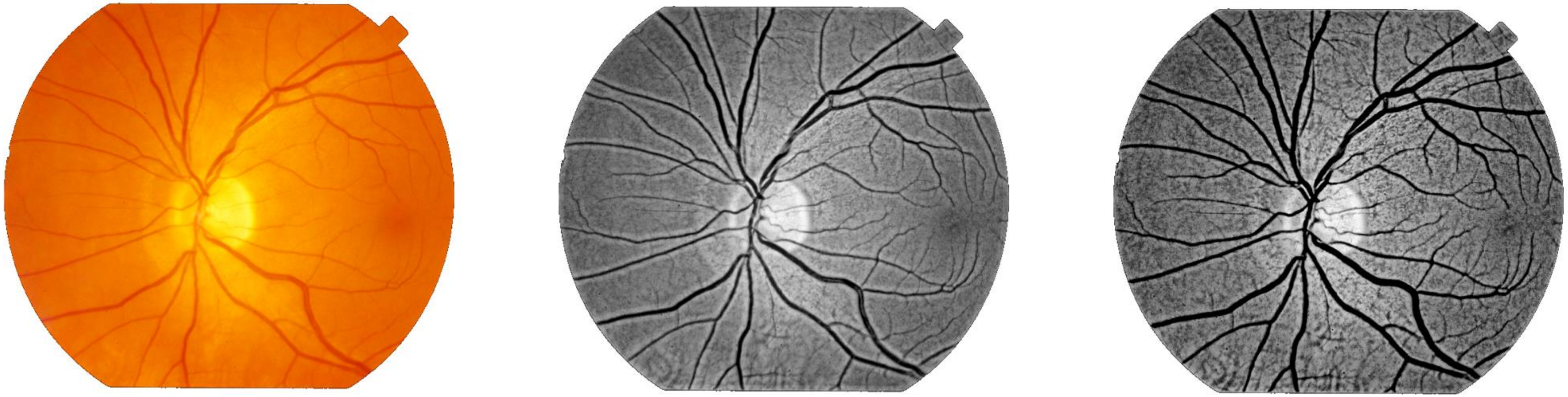


Fig 2. The pipeline of preprocessing

A similar preprocessing method as in [1] is used to enhance the contrast of retina images. Main operations include:

- Contrast limited adaptive histogram equalization (CLAHE)
- Gaussian smoothing
- Top-hat operator

[1] L. C. Neto et al., "An unsupervised coarse-to-fine algorithm for blood vessel segmentation in fundus images," Expert Systems with Applications, 2017.



(a) Original image (b) Enhanced image: DImg (c) Enhanced image: DImg6

Fig 3. An example of preprocessed images.

Two enhanced images are generated:

DImg = CLAHE(EImg – 0.22EImg6) is used for vessel extraction

DImg6 = CLAHE(EImg – EImg6) is used for vessel segmentation

Note: The vessels in DImg6 tend to be darker, but the noise in the background is also more significant

Vessel Extraction

To extract the skeleton of the vessels, we apply our previous connected tube marked point process (MPP) model [2] to the preprocessed image DImg

The vessels are modeled as connected tubes; each short tube has the shape in Fig 4, which is characterized by $[a, b, \theta]$; the blue and yellow region are the joint areas for connection

More details about the model are given in [2]

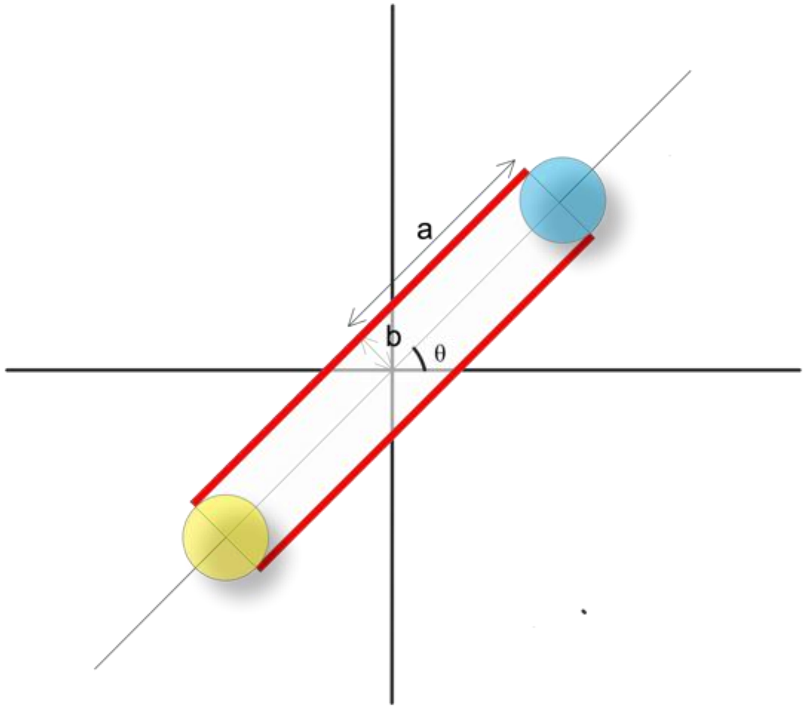


Fig 4. Shape model of a tube.

[2] T. Li, M. Comer, and J. Zerubia, "A Connected-Tube MPP Model for Object Detection with Application to Materials and Remotely-Sensed Images," in ICIP, 2018.

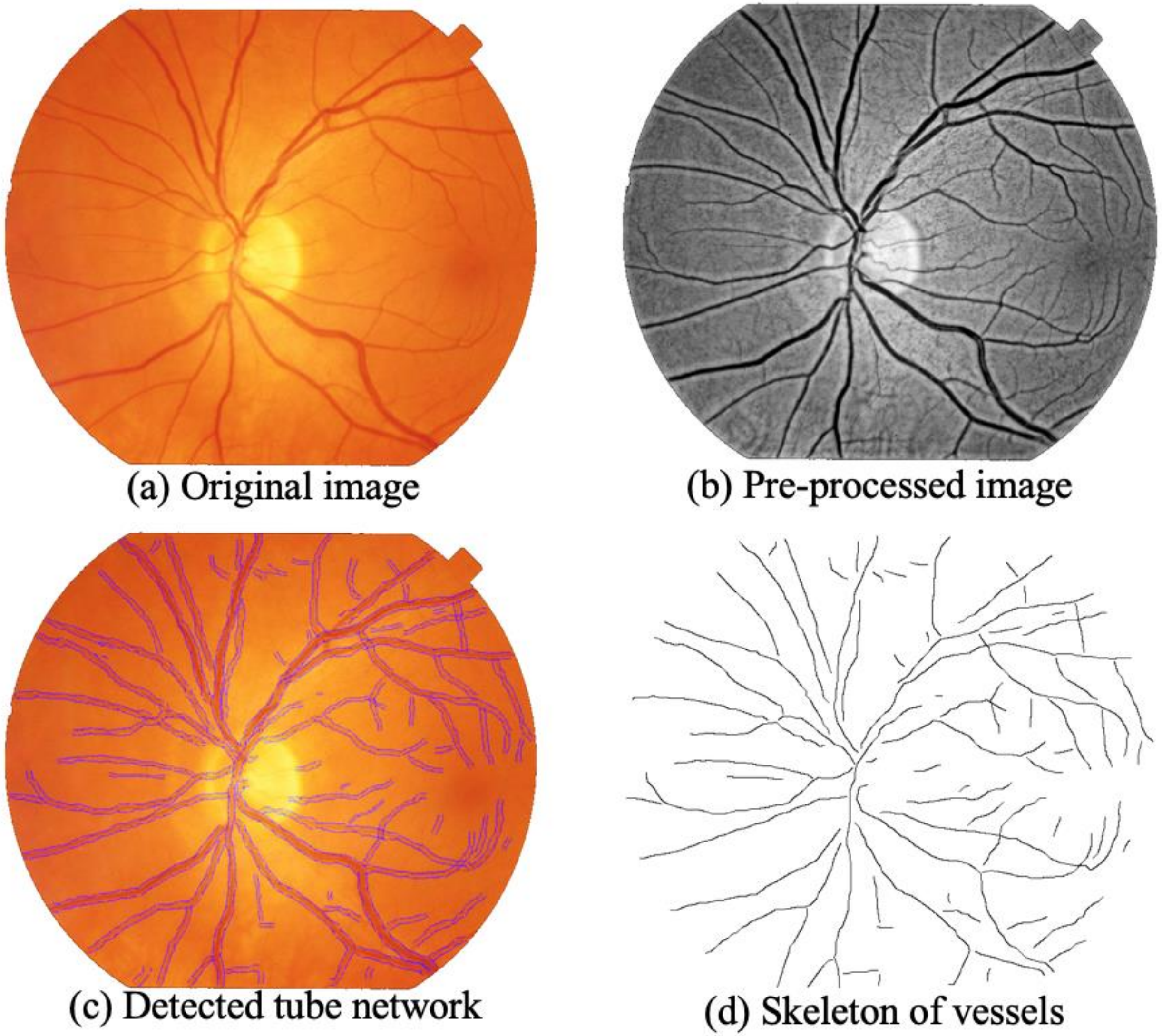


Fig 5. An example of retina network extraction

Fig 5 is an example of vessel extraction. (c) is the detected tube network from our MPP model. The skeleton in (d) is the centerline of the tubes in (c)

The detected tube network is next used for segmentation of vessels

Vessel Segmentation

Tube-based segmentation algorithm

- Expand the width of detected tubes by 4 pixels
- Each step takes 3 connected tubes for segmentation (Local processing less sensitive to non-uniform illumination)
- Cluster the pixels in segmentation area into 2 clusters:
  C_1 for vessel pixels;
  C_0 for background pixels
- The clustering process is similar to K-Means(K=2), but with our own defined distance measure

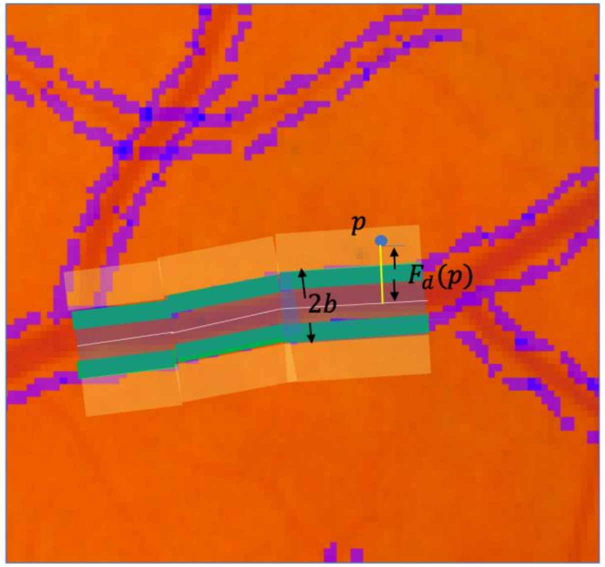


Fig 6. Illustration of a segmentation area

Distance between a pixel p and C_0 (resp. C_1) is given by:

$D_0(p) = \omega_g DistG_0(p) + \omega_d\left(1 - Rad(p)\right) + \omega_r F_r(p)$ (1)

$D_1(p) = \omega_g DistG_1(p) + \omega_d Rad(p) + \omega_r(1 - F_r(p))$ (2)

where $\omega_g, \omega_d, \omega_r$ are pre-set weights

Intensity distance to C_0: $DistG_0(p) = 1 - exp\left(\frac{-(F_g(p)-u_0)^2}{c_g\delta_0^2+1}\right)$ (3)

Intensity distance to C_1: $DistG_1(p) = 1 - exp\left(\frac{-(F_g(p)-u_1)^2}{c_g\delta_1^2+1}\right)$ (4)

where $F_g(p)$ is the gray value, u_0 and u_1 are the sample mean of C_0 and C_1 in the current iteration, respectively; $\delta_0$and δ_1 are the sample standard deviation of C_0 and C_1 in the current iteration respectively; $c_g$is a parameter

$Rad(p)$ measures the location distance between p and C_1:

$$Rad(p) = 1 - exp\left(\frac{-F_d(p)^2}{c_d R(p)^2 - 0.5}\right) \qquad (5)$$

where $F_d(p)$ is the Euclidean distance from p to the centerline of the closest tube object w_p, R(p) is the half-width of w_p, c_d is a parameter.

Neighboring distance $F_r(p)$ is the ratio of pixels belonging to C_1 among p 's 8 neighbor pixels

The clustering process:

- **Initialization**: label pixels in the expanded area as 0, and the pixels on the center line of tubes as 1, leave others unlabeled

- **Updating**: classify the pixels in the segmentation area into C_0 and C_1 according to (1) and (2), then update $F_r(p)$, u_0, u_1, δ_0, δ_1

- **Stop condition**: maximum iteration 20 is reached or both u_0 and u_1 are not changed between previous iteration and current iteration

Experimental Results

Test on **STARE** and **DRIVE** datasets

STARE contains 20 color images(700×605)

DRIVE contains 40 color images(565×584), 20 for training and 20 for testing

The parameters for tube-MPP model are set to: $T = 28, a_{min} = 3, a_{max} = 16, b_{min} = 1, b_{max} = 6, \alpha = 0.5$, $\beta = 0.12, \lambda = 0.38$

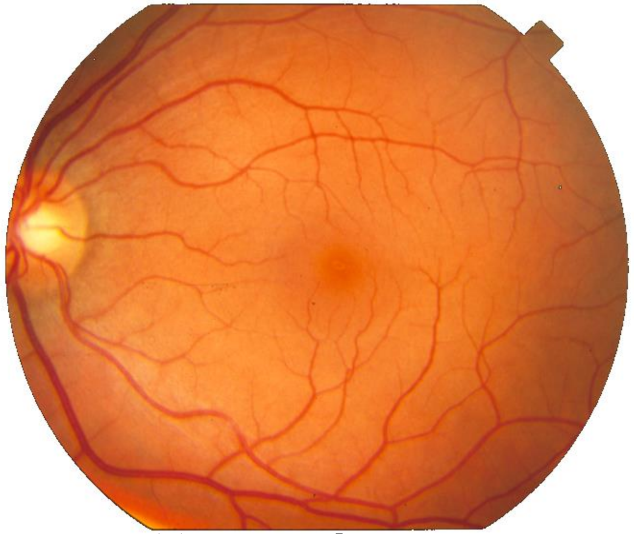
For the segmentation algorithm we set: ω_g =0.58, $\omega_d = 0.27, \omega_r = 0.15, c_g = 1.75, c_d = 1.63$

Measures include: $Se = \frac{TP}{TP+FN}, Sp = \frac{TN}{TN+FP}, Acc = \frac{TP+TN}{N}, G = \sqrt{Se \times Sp}$

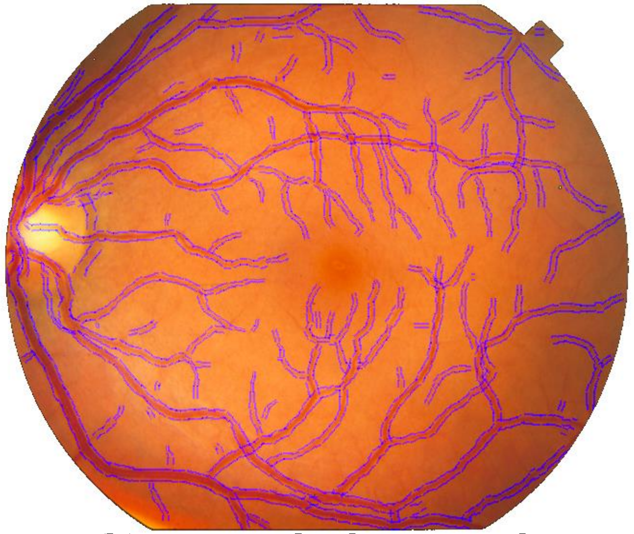
Se: sensitivity Sp: specificity Acc: accuracy G: G-score

TP : True Positive; TN : True Negative; FP: False Positive

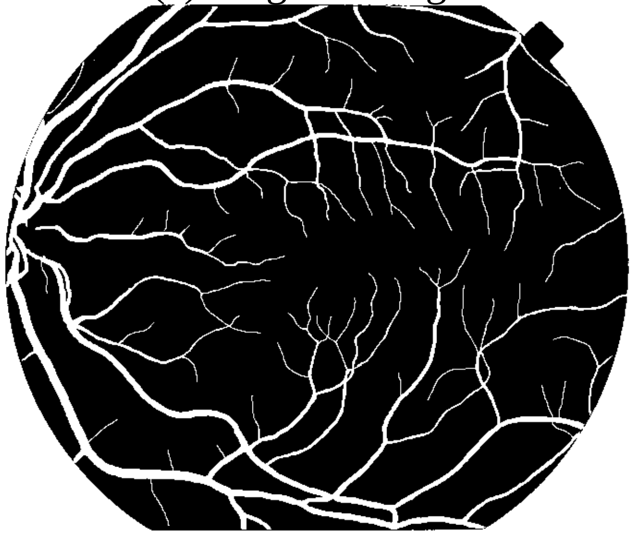
FN: False Negative; N: total number of pixels in FOV(Field of view)



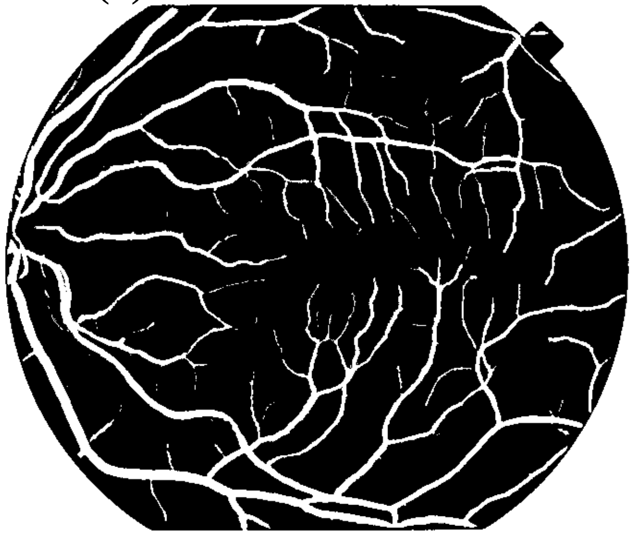
(a) Original image



(b) Detected tube network



(c) Ground truth

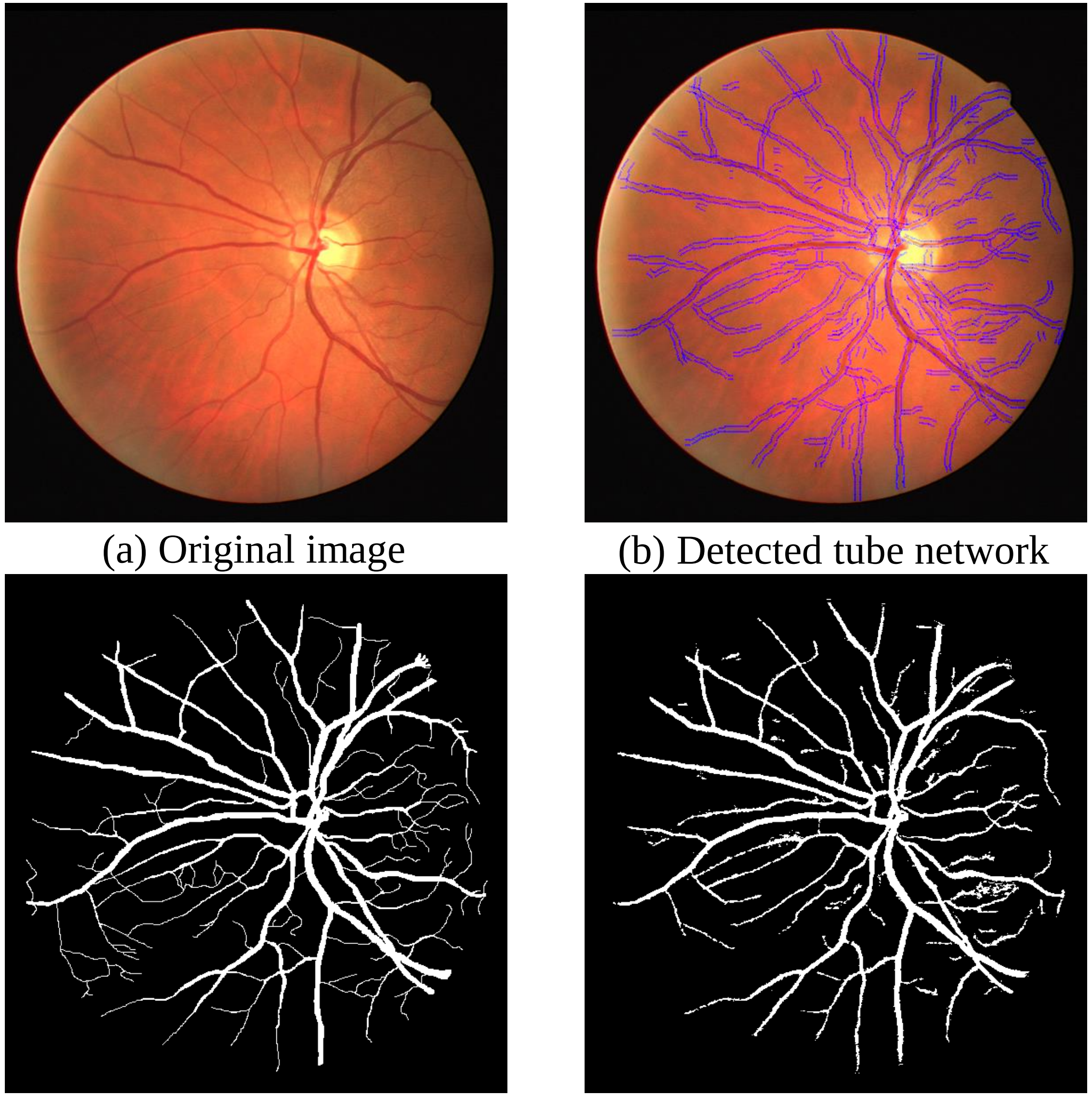


(d) Segmentation result

Fig 7. An example from STARE dataset

Se = 0.9220
Sp = 0.9549
Acc = 0.9514
G = 0.9383

- May not be continuous for thin vessels in segmentation due to the low contrast to their background.



(a) Original image (b) Detected tube network

(c) Ground truth (d) Segmentation result

Fig 8. An example from DRIVE dataset

Se = 0.7858

Sp = 0.9677

Acc = 0.9434

G = 0.8721

Table I. Quantitative results on **STARE** dataset

	Method	Se	Sp	Acc	G
	2nd observer	0.8956	0.9381	0.9346	0.9166
S	Fraz et al.(2012)	0.7548	0.9763	0.9534	0.8584
V	Orlando et al.(2017)	0.7680	0.9738	0.9515	0.8648
	Oliveira et al.(2018)	0.8315	**0.9858**	**0.9694**	**0.9053**
	Li et al.(2019)	0.8101	0.9795	-	0.8905
U	Zhang et al.(2016)	0.7791	0.9758	0.9554	0.8720
S	Neto et al.(2017)	0.8344	0.9443	-	0.8876
V	Proposed method	**0.8394**	0.9536	0.9422	0.8932

- Best G-score among unsupervised methods
- Best *Se* among all methods

Note: SV means supervised methods, which use **labeled** training samples; USV means unsupervised methods, which do not use **labeled** training samples

Table II. Quantitative results on **DRIVE** dataset

	Method	Se	Sp	Acc	G
	2nd observer	0.7760	0.9725	0.9473	0.8687
S	Fraz et al.(2012)	0.7406	**0.9807**	0.9480	0.8522
V	Orlando et al.(2017)	0.7897	0.9684	0.9454	0.8745
	Oliveira et al.(2018)	0.8039	0.9804	**0.9576**	**0.8878**
	Li et al.(2019)	0.7969	0.9799	-	0.8837
U	Zhang et al.(2016)	0.7743	0.9725	0.9476	0.8678
S	Neto et al.(2017)	0.7806	0.9629	-	0.8670
V	Proposed method	**0.8063**	0.9529	0.9339	0.8761

- Best G-score among unsupervised methods
- Best Se among all methods
- Trade-off between Se and Sp

Conclusions

- In this work, a tube based segmentation algorithm for retinal vessel segmentation is proposed and tested on STARE and DRIVE datasets

- We get high sensitivity but relatively low accuracy and specificity

- In future work, we expect to improve accuracy and specificity by analyzing the structure of the extracted tube networks and the contrast quality for each tube

Thank you!