# Vessel Segmentation

Wenzhen Zhu WUSTL

## **Notation**

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Equation
My thoughts and explanations
book segment with an error or an error description
answer for the problem
question
assumption
intermediate answer

### Intro

ArchHacks 2016 https://archhacks.io/ 's theme is HealthTech.

I participate this hackathons and after building an app and talking to several medical students, I realized that I can actually apply what I learned from computer vision class and make some really world application to help patients who are suffering and to help doctors to be more efficient. That's why I choose to do this project.

Edge detection is an essential task in computer vision, and vessel segmentation is also an important task in clinical care and medical research.

First, doctor can diagnose many disease from small change of vessels, like diabetes. Second, some disease needs to remove vessels first in order to make further diagnosis.

## Helper function

## Related Work

## Morphology Operators

We define a 2D image whose range is  $[N_{\text{min}}, N_{\text{max}}]$  as a functional  $S : \mathbb{R}^2 \to [N_{\text{min}}, N_{\text{max}}]$  and a 2-D structuring element as a functional  $S : \mathbb{R}^2 \to [N_{\text{min}}, N_{\text{max}}]$  and a 2-D structuring element as a functional  $S : \mathbb{R}^2 \to [N_{\text{min}}, N_{\text{max}}]$  and a 2-D structuring element as a functional  $S : \mathbb{R}^2 \to [N_{\text{min}}, N_{\text{max}}]$  and a 2-D structuring element as a functional  $S : \mathbb{R}^2 \to [N_{\text{min}}, N_{\text{max}}]$  and a 2-D structuring element as a functional  $S : \mathbb{R}^2 \to [N_{\text{min}}, N_{\text{max}}]$  and a 2-D structuring element as a functional  $S : \mathbb{R}^2 \to [N_{\text{min}}, N_{\text{max}}]$  and a 2-D structuring element as a functional  $S : \mathbb{R}^2 \to [N_{\text{min}}, N_{\text{max}}]$  and a 2-D structuring element as a functional  $S : \mathbb{R}^2 \to [N_{\text{min}}, N_{\text{max}}]$  and a 2-D structuring element as a function  $S : \mathbb{R}^2 \to [N_{\text{min}}, N_{\text{max}}]$  and a 2-D structuring element as a function  $S : \mathbb{R}^2 \to [N_{\text{min}}, N_{\text{max}}]$  and  $S : \mathbb{R}^2 \to [N_{\text{min}}, N_{\text{min}}]$  and  $S : \mathbb{R}^2 \to [N_{\text{min}}, N_{\text{min}}]$ 

We define basic operators, with respect to the structuring element B with scaling factor e, image S and point  $M_0 \in \mathbb{R}^2$ 

Erosion

$$\epsilon_B^e$$
 (S) (M<sub>0</sub>) = Min<sub>M∈M<sub>0</sub>+∈B(M<sub>0</sub>)</sub>(S(M))

Dilation

$$\delta_{B}^{e}(S)(M_{0}) = \text{Max}_{M \in M_{0} + \epsilon B(M_{0})}(S(M))$$

Opening

$$\gamma_B^e(S)(M_0) = \delta_B^e(\epsilon_B^e(S))$$

Closing

$$\phi_B^e(S)(M_0) = \epsilon_B^e(\delta_B^e(S))$$

Top-hat

$$TH_B^e(S)(M_0) = S - \gamma_B^e(S)$$

Geodesic dilation

$$\begin{split} S^{1} &= \inf(\{\mathsf{Max}_{M \in M_{0} + c}(S_{m}(M))\}, \ S(M_{0})) \\ S^{d+1} &= \Delta_{S_{m}}^{d+1} \ (S) \ (M_{0}) = \Delta_{S_{m}}^{1} \left(S^{d}\right) (M_{0}) \end{split}$$

Geodesic closing

$$\phi_{S_m}^{\text{rec}}(S) = N_{\text{max}} - \gamma_{(N_{\text{max}} - S_m)}^{\text{rec}}(N_{\text{max}} - S)$$

## **Algorithms**

```
dir = NotebookDirectory[];
img = ColorConvert[
   Import[dir <> "DRIVE/training/images/21_training.tif"], "Grayscale"];
imgData = ImageData[img, "Byte"];
```

## Step 0: Construct Li

This paper is interesting because it used a linear structure element  $L_i$  which is 15-pixels long 1-pixel wide.

angles = Table [{Cos[t], Sin[t]}, {t, 0, 11 
$$\pi/12$$
,  $\pi/12$ }]   
  $\{\{1, 0\}, \{\frac{1+\sqrt{3}}{2\sqrt{2}}, \frac{-1+\sqrt{3}}{2\sqrt{2}}\}, \{\frac{\sqrt{3}}{2}, \frac{1}{2}\}, \{\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}\}, \{\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}\}, \{\frac{1}{2}, \frac{\sqrt{3}}{2}\}, \{\frac{-1+\sqrt{3}}{2\sqrt{2}}, \frac{1+\sqrt{3}}{2\sqrt{2}}\}, \{0, 1\}, \{-\frac{-1+\sqrt{3}}{2\sqrt{2}}, \frac{1+\sqrt{3}}{2\sqrt{2}}\}, \{-\frac{1}{2}, \frac{\sqrt{3}}{2}\}, \{-\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}\}, \{-\frac{\sqrt{3}}{2}, \frac{1}{2}\}, \{-\frac{1+\sqrt{3}}{2\sqrt{2}}, \frac{-1+\sqrt{3}}{2\sqrt{2}}\}\}$ 

For every  $\frac{\pi}{12}$ , there is an linear structure element.

Graphics[{Red, PointSize → Large, Point[angles]}]

linearStrut =

Table[Round[{Cos[t], Sin[t]} \* #] & /@ (Range[15] - 8), {t, 0, 
$$11\pi/12$$
,  $\pi/12$ }];

Here is a visualization of the structure element.

GraphicsRow[showBinaryImage[kernelFromStructure[#]] & /@ linearStrut]



kernels = kernelFromStructure[#] & /@ linearStrut

## Step I

## Calculating Sop

The first step is calculating  $S_{op}$ , which can be summarized in the followings:

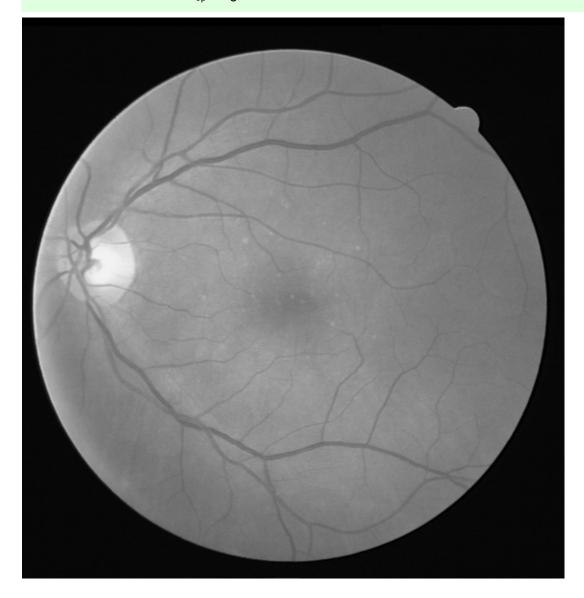
- 1. Opening with 12 structure element on  $S_0$  (original images)
- 2. Pick the maximum from these 12 images pixel-wise and form a maximum image
- 3. Do geodesic opening on the maximum image, the result will be our  $S_{op}$

$$S_{op} = \gamma_{S_0}^{rec} \text{ (Max}_{i=1,...,12} \{ \gamma_{L_i}(S_0) \} )$$

openingImageList = Opening[img, #] & /@kernels

AbsoluteTiming[openingDataList = ImageData[#] & /@ openingImageList] maxOpeningData = MapThread[Max, openingDataList, 2] maxOpeningImage = Image[maxOpeningData] markerImage = img; mask = maxOpeningImage; SopData = geodesicOpening[markerImage, mask] SopImage = Image[SopData]

Here is a visualized result  $S_{\text{op}}$  image.



## Step 2

## Calculating S<sub>sum</sub>

This transformation (a sum of top hats) reduces small bright noise and improves the contrast of all linear parts. Vessels could be manually segmented with a simple threshold on  $S_{sum}$ 

$$S_{sum} := \sum_{i=1}^{12} (S_{op} - \gamma_{L_i}(S_0))$$

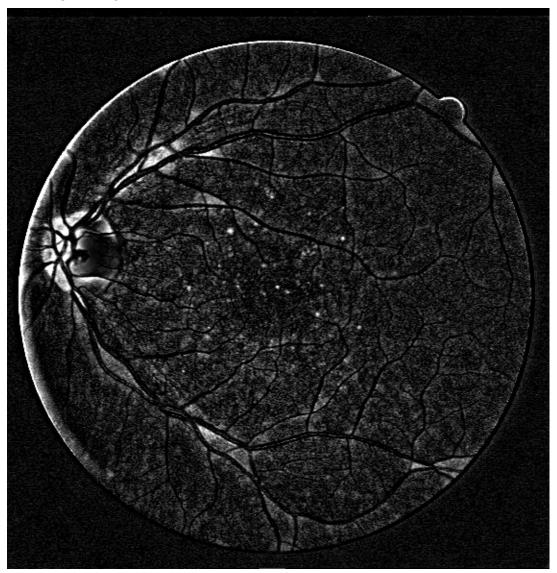
The second step is calculating  $S_{sum}$ , which can be summarized in the followings:

- 1. Opening with 12 structure element on  $S_0$  (original images).
- 2. Use  $S_{\text{op}}$  to minus the opening images pixel-wise.
- 3. Sum the 12 difference image up to get  $S_{\text{sum}}$  image

AbsoluteTiming[topHatData = (SopData - #) & /@openingDataList]

AbsoluteTiming[SsumData = Total[topHatData]]

#### SsumImage = Image[SsumData]



## Step 3

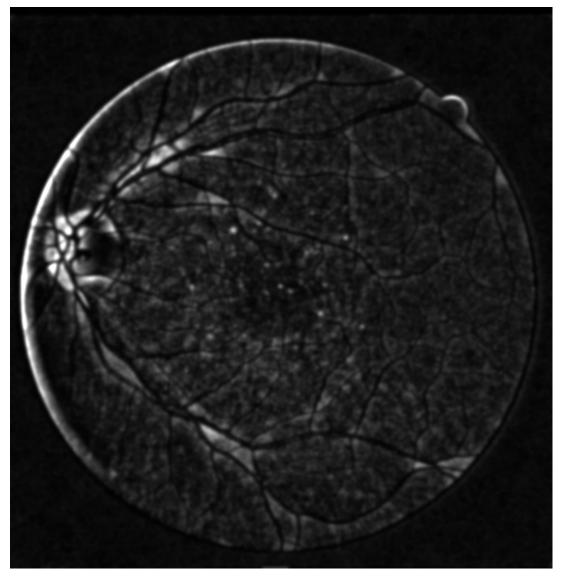
This step is very straight forward:

- 1. Apply Gaussian filter with r = 7 and  $\sigma = 7/4$
- 2. Apply Laplacian filter with r = 1.

$$S_{\mathsf{lap}} = \mathsf{Laplacian} \big( \mathsf{Gaussian}_{\sigma \,=\, 7/4}^{\mathsf{width} \,=\, 7\,\mathsf{px}} (S_{\mathsf{sum}}) \, \big)$$

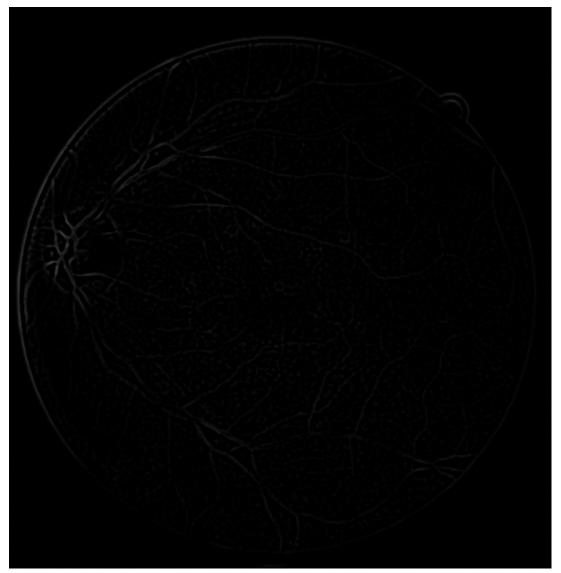
## Applying Gaussian filter

gaussianImage = GaussianFilter[SsumImage, {7, 7 / 4}]



## Applying Laplacian filter

SlapImage = LaplacianFilter[gaussianImage, 1]



## Step 4

## Calculating S<sub>1</sub>

This step can be summarized in the followings:

- 1. Opening with 12 structure element on  $S_{lap}$ (Laplacian applied image).
- 2. Pick the maximum from these 12 images pixel-wise and form a maximum image
- 3. Do geodesic opening on the maximum image, the result will be our  $S_1$

$$S_1 = \gamma_{S_{lap}}^{rec} \left( Max_{i=1,\dots 12} \left\{ \gamma_{L_i}(S_{lap}) \right\} \right)$$

AbsoluteTiming[openingOnSlapData = ImageData /@ (Opening[SlapImage, #] & /@kernels)] Pick the maximum

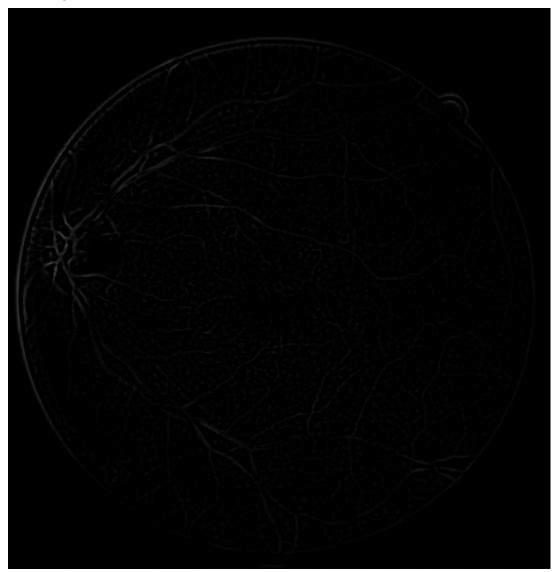
maxOpeningOnSlapData = MapThread[Max, openingOnSlapData, 2];

maxOpeningOnSlapImage = Image[maxOpeningOnSlapData]

Apply Geodesic opening on the maximum

S1Data = geodesicOpening[SlapImage, maxOpeningOnSlapImage]

S1 = Image[S1Data]



## Calculating S<sub>2</sub>

This step can be summarized in the followings:

- 1. Closing with 12 structure element on  $S_1$ .
- 2. Pick the minimum from these 12 images pixel-wise and form an image.

3. Do geodesic closing with marker being  $S_1$ , mask being the minimum image.

$$S_2 = \phi_{S_1}^{\text{rec}} \left( \text{Min}_{i=1,...,12} \left\{ \phi_{L_i}(S_1) \right\} \right)$$

```
AbsoluteTiming[closingImageList = Closing[S1, #] & /@kernels]
AbsoluteTiming[closingDataList = ImageData /@closingImageList]
minClosingData = MapThread[Min, closingDataList, 2];
minClosingImage = Image[minClosingData]
S2Data = geodesicClosing[S1, minClosingImage]
S2 = GeodesicClosing[S1, 1]
```

#### Calculating S<sub>res</sub>

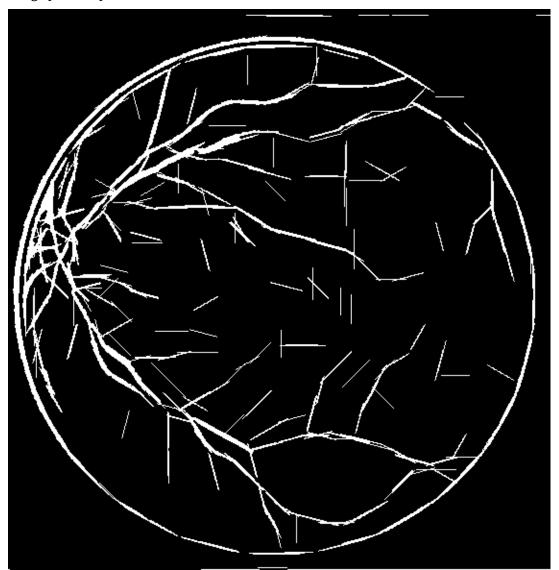
This step can be summarized in the followings:

- 1. Opening with 12 structure, r = 2 indicates the structure element 29 pixels long, 1 pixel wide on S<sub>1</sub>.
- 2. Pick the maximum from these 12 images pixel-wise and form an image.
- 3. If the pixel value  $\geq 1$ , assign 1 on that pixel, otherwise assign 0.

$$S_{res} = (Max_{i=1..} \ _{12} \{ \gamma_{L_i}^2(S_2) \} \ge 1)$$

```
openingOnS2 = Opening[S2, #] & /@ kernels2
openingOnS2Data = ImageData /@openingOnS2
SresData = MapThread[Max, openingOnS2Data, 2];
sres = Image[SresData]
sresByte = ImageData[sres, "Byte"]
convertToBinary[x_1] := If[x \ge 2, 1, 0]
result = (convertToBinary /@sresByte[[#]]) & /@Range[Length[sresByte]]
```

#### Image[result]



## **Future Direction**

In[23]:= Hyperlink["http://research.google.com/teams/brain/healthcare/"]

Out[23]= http://research.google.com/teams/brain/healthcare/

- 1. For glaucoma detection, there is one approach from a paper which extract the optic disk first, then replace vessels, because vessels are regarded as noises. I will implement this paper as
- 2. Google is working on similar things http://research.google.com/teams/brain/healthcare/
- 3. I think the most important thing is what theory I learned from this paper. I built an App this semester doing segmentation on Corneal Ulcer eyes. But the algorithm I developed is to the binarize on a threshold first and do morphology operations on binary images. Which works

well for the fluorescent images but not working well on images under natural lights. I want to try using the morphology I learned from this paper to solve the natural light problem. There are three medical school students promised me to give me images for testing.