PROJECT REPORT

Iterative Vessel Segmentation of Fundus Images

Submitted by-

Palash Sethi

(2014B1A80260P)

To-

Dr. K K Gupta

In correspondence to the course:

DIGITAL IMAGE PROCESSING (EEE F435)

BITS-Pilani, Pilani

ABSTRACT:

This algorithm is based on the work of Nguyen et. Al. The idea behind this approach is that the blood vessel structures can be approximated as piecewise linear, so line detection on multiple scales can be used to separate the blood vessel structure from the background. By using lines of multiple lengths, vessels of different sizes and scales can be detected; problematic features, such as the small-scale vessel central light reflex have limited impact on the result at larger scales.

METHODOLOGY:

The part of the image containing the blood vessel normally has more intensity then the other portion. We have used these basic conditions to detect vessels in our code and the code goes through the following steps:

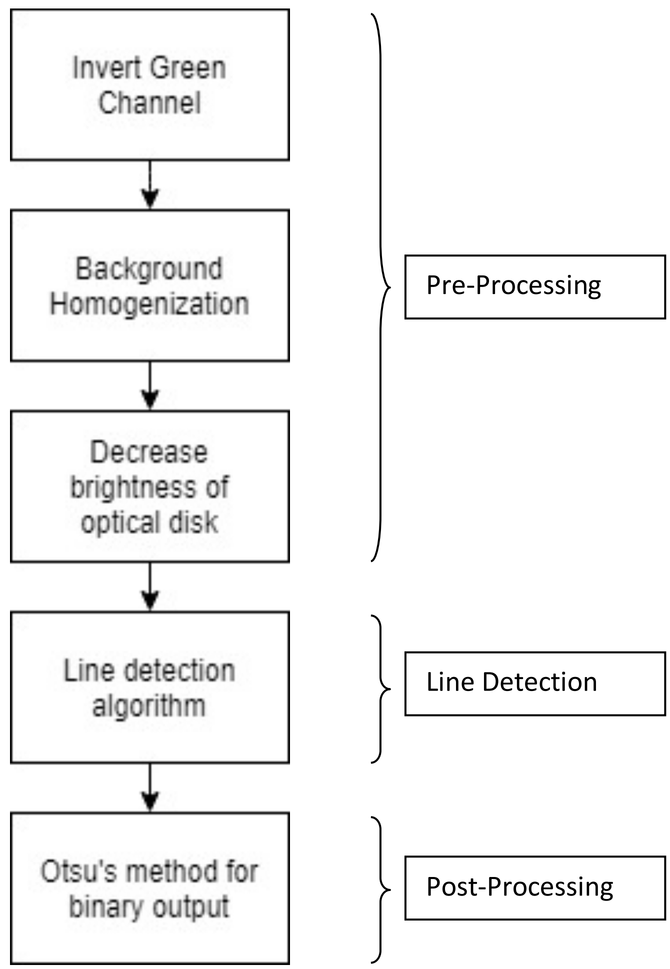
1. Pre-processing:
    - The inverted green channel of each RGB image was used.
    - Background homogenization without denoising was applied, which produces uniform background gray levels across the entire set of images. The local background gray level iscomputed by applying a 69*69 mean filter to the image. Thebackground is then subtracted and the resulting gray levels arescaled from 0 to 1. Finally, a constant is added to the imagegray levels so the mode gray level value in image is set to 0.5.
    - To limit the impact of the optical disk, bright regions (gray level values exceeding a fixed threshold) are replaced with a local average gray-level calculated with a 69*69 mean filter.

2. Processing:
    - A total of seven scales are used for line detection, with the line detectors of lengths 3,5,7…15. For each scale, the following procedure was carried out:
      a) For each pixel, the mean gray-level in a local 15*15window, $I_{avg}(x,y)$, is computed.
      b) For scale s, line detectionis performed by computing the weighted average of graylevelvalues along lines of length S for each of 18 differentangles, 0,10,…170. The largest response, $I_s(x,y)$ overall directions is calculated for each pixel. The line response forscale s is the difference between the maximum line detectionresponse and the average gray-level, $R_s = I_s - I_{avg}$.
      c) The line response is rescaled, R_s to have zero mean and unit variance.
    - The multi-scale line response is obtained by computing alinear combination of the line responses for each scale and theoriginal gray values in the image, I. The weighting used foreach line response is proportional to the scale of the response:

$$R = \frac{1}{64}\left(\sum_{s} s\tilde{R}^{s} + I\right)$$

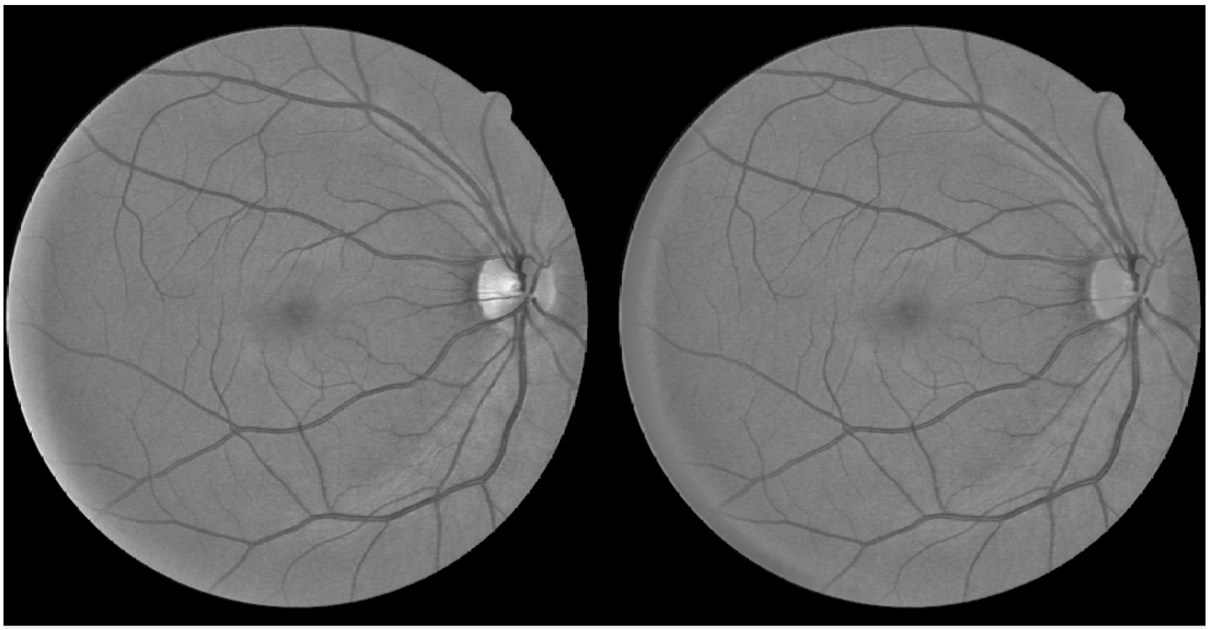
3.Post-Processing:

Otsu's method was used to obtain a threshold to binarize the multi-scale line response. The threshold returned by Otsu's method was reduced by 25% to retain finer features in the image. Finally, all connected components with an area below a fixed threshold of 100 pixels were eliminated.

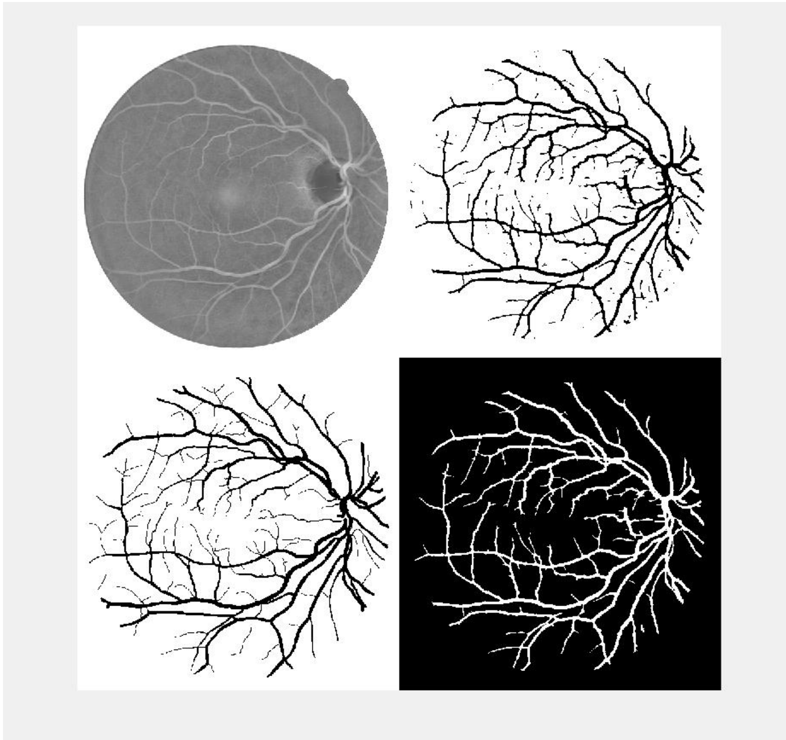


RESULTS/ OUTPUTS:

- Image after pre-processing step. As can be seen, the impact of bright optical disc has been reduced.



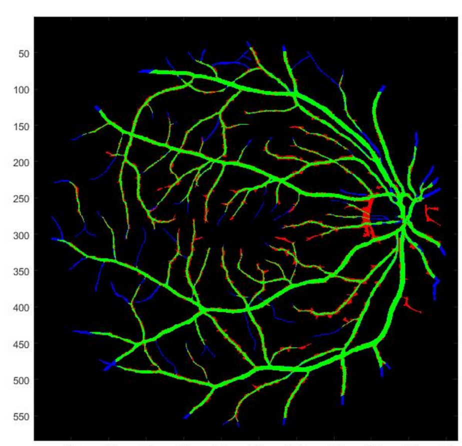
- Output after post-processing step.



a) Gray Value Input Image b) Output of Code
c) Supervised Output d) Binary Output

VALIDATION:

As the used dataset has supervised training data, we have calculated the difference between the output of the program and the intended result.



True positives (green), False positives (red),
False negatives (blue), True negatives (black).

REFERENCES:

- Test Image Source:
  The data available to us for analysis comes from the DRIVE database of retinal images,This database contains 40 images, 20 for training and 20 for testing. These images were manually segmented by trained researchers. These images can be used for training in supervised algorithms, and for measuring algorithm performance.
  (http://www.isi.uu.nl/Research/Databases/DRIVE/)