Identification and Counting of Mouse Axons in a Retinal Scan

Evan Lewis

Department of Electrical Engineering and Computer Science,
Case Western Reserve University, Cleveland, OH, Email: egl6@cwru.edu

Abstract
This paper presents a method for detecting and counting the number of axons present on a retinal scan from a mouse. The algorithm used incorporates morphological transformations, including top hat, fill, and shrink transformations. The results from test cases indicate that the algorithm does indeed identify all of the axons, but has trouble filtering out the blank space in between axons.

KEYWORDS
Image Processing, Feature Detection, Retina Axons

INTRODUCTION

In the world of image processing, item detection is one area where humans have a great advantage. The gap becomes even more insurmountable when these items are not solid, vary in size and shape, fade in and out of the picture in no particular order, and blur together. One of the ways that people try to find objects is by matching them with a certain shape, such as finding cells with an ellipse detection algorithm [1]. This paper will discuss a method that uses details to identify separation in the objects to be detected.

DESIGN OF IDENTIFICATION ALGORITHM

For the design of this algorithm, the first objective was to separate all of the axons in the picture. The axons all have the same characteristic that they are dark around their edges, which gives an advantage already in terms of detecting boundaries. In order to amplify those boundaries a modified top hat algorithm was applied.

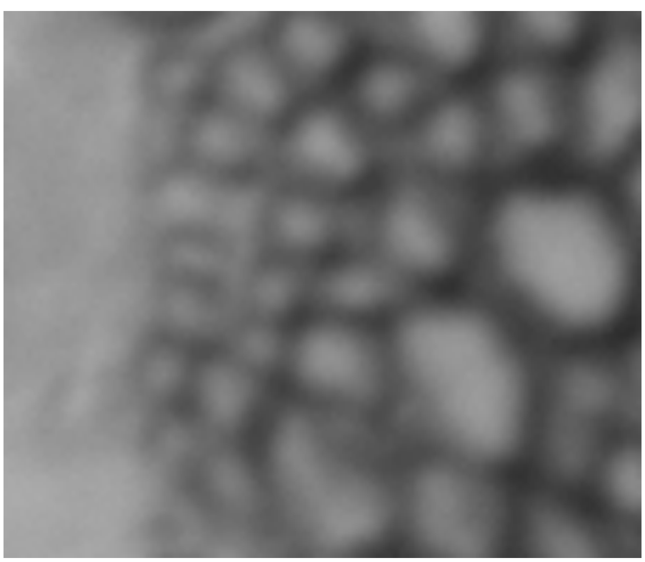

Figure 1. Original Image

First the image was inverted in order to place the edge details on the lighter end of the grayscale spectrum. Then an opening was taken from the image with a flat disk of radius 10 pixels. The radius was chosen to be small enough to get a proper background gradient, but large enough to completely remove all of the details of the axons from the image. This opening was then subtracted from the original image, creating a top hat filtered image. Then the top hat image was added to the inverted image, amplifying the boundaries while doing nothing to the background. This process was iterated 3 times in order to get fully amplified boundaries without great distortion of the image (Figure 2).

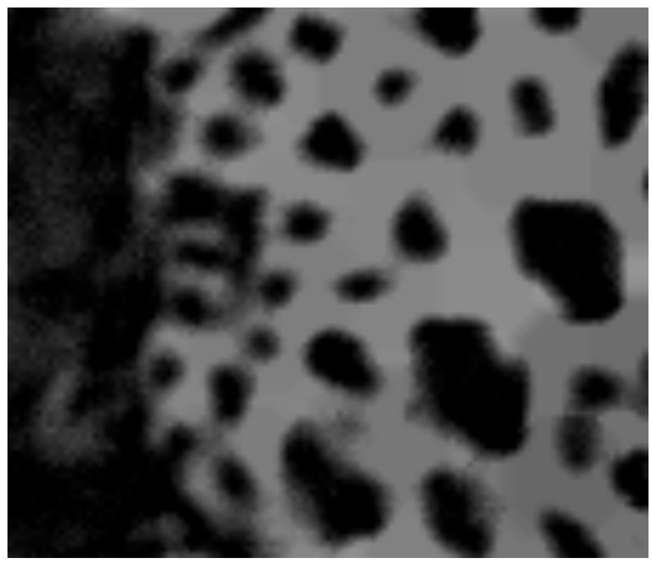

Figure 2. Top Hat Image

After the top hat algorithm a threshold was applied to the image to isolate the insides of the axons. From here, bridge and dilation filters were applied in order to get rid of noise in the image that belongs to one of the axons. Then, using a shrinking filter, all of the axons were shrunk down to 1 pixel. Then a hit-miss filter was applied to get rid of any other artifacts that don't belong.

Figure 3. Finished Algorithm

After this, all of the single pixels were located and counted up, resulting in the number and location of all the axons.

RESULTS AND DISCUSSION

In order to test this algorithm, six different images from a mouse retina were put through the algorithm. All images were grayscale 97x113 pixel TIF images. The results from the algorithm are shown in Table 1.

Table 1. Results of Algorithm on Six Images

Image Filename	Axons Correctly Detected	Axons Missed	Axons Incorrectly Detected	Processing Time (Sec) (Average of 3 Runs)
Sample_1_.tif	22	18	5	0.349
Sample_2_.tif	4	1	6	0.375
Sample_3_.tif	30	2	8	0.349
Sample_4.tif	34	2	4	0.336
Sample_5.tif	13	0	10	0.354
Sample_6.tif	30	3	0	0.358
Totals	173	27	33	0.354 (Average)

The reason for the excessive misses in the first sample was that there were too many small axons close together, so when the image was dilated they merged together to form one body. In all of the images, the cause of the incorrect detections was due to there not being a good means for separating out the background shapes from the axons. This is one of the greatest faults with this algorithm.

From the timing results, it appears that, with a bit of optimization, this algorithm could be put to use in near real time scenarios. One application might be to measure the flow of solid objects past a certain point, for example, traffic. There would, of course, need to be a large amount of post processing for that type of application to work. Overall, this algorithm could use some improvement, but it works to a reasonable extent and is a quick way to get some results.

SUMMARY

This paper presented a detection algorithm for finding and counting axons in a microscopic image. The algorithm employed a top hat and reduction routine to identify the individual axons. As seen in the results, this algorithm can be greatly improved with methods of separating out the background patches and keeping axons fully separated.

REFERENCES

[1] N. Kharma, H. Moghnieh, J. Yao, Y.P. Guo, A. Abu-Baker, J. Laganiere, G. Rouleau, M. Cheriet, " Automatic Segmentation of Cells From Microscopic Imagery Using Ellipse Detection," Image Processing, IET, Volume 1, Issue 1, March 2007 Page(s):39 - 47