



Comparison of Thresholding Techniques for Segmentation of Blood vessels from Retinal Fundus Images

Hanna A. Hakkim¹, Tess Mathew²

PG Scholar, Department of Electronics & Communication, Rajadhani Institute of Engineering & Technology,
Trivandrum, India¹

Faculty Member, Department of Electronics & Communication, Rajadhani Institute of Engineering & Technology,
Trivandrum, India²

Abstract: Retinal fundus images are widely used by ophthalmologists for disease diagnostic purpose. These images include normal eye features such as optic nerve disk, fovea, and blood vessels. Among this identification of blood vessels has great relevance over disease diagnosis. Algorithms for vessel segmentation perform a binary classification in accordance of some threshold value and these algorithms are generally referred to as binarization methods. Global binarization methods try to find a single threshold value for whole image. Local thresholding methods compute thresholds for each pixel using information from local neighbourhood of the pixel. In this paper local thresholding method such as Niblack algorithm, Savoula algorithm and Adaptive Multi-level Thresholding are tried over retinal images to extract blood vessels.

Key words: Niblack algorithm, Savoula algorithm, Adaptive Multi-level Thresholding.

I. INTRODUCTION

For diseases like diabetic retinopathy and for other eye related disease diagnosis extraction of blood vessels is the prime step. So several methods had been put forward for this purpose. One of the methods is global thresholding-based binarization (global binarization). It tries to find a single threshold value for the whole image. Global binarization methods are very fast and they give good results for scanned text documents where background and foreground is uniformly different in the whole image. One of the global binarization methods is the Otsu method [1]. It is very fast and it use only one threshold value. But if we use a single threshold value for all images, we can lose very important information about blood vessels. Unfortunately, the Otsu method can give good result only for images where vascular tree is sharp in the whole image.

Local binarization methods on the other hand, try to overcome this problem by computing thresholds individually for each pixel using information from the local neighbourhood of the pixel. The computational speed of the local binarization methods depends on the number of analysed local neighbours of the pixel. Therefore, local binarization methods are slower than global binarization methods, but they are more exact. Here three algorithms named as Niblack algorithm and Sauvola algorithm and Adaptive Multi-level thresholding is tried over retinal images to extract blood vessels. First two methods are mainly used to convert the degraded document images to

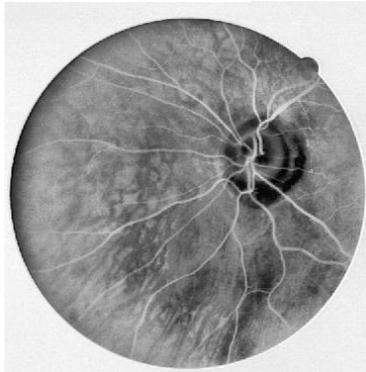
readable black and white images. Main aim of this paper is to analyse different methods of detecting blood vessels in retinal images using local binarization.

II. PRE-PROCESSING

Sometimes contrast of input image will be poor and as a result retinal features such as exudates and blood vessels cannot be easily distinguishable from background. So a contrast enhancement step will make this problem simple. In this work Contrast Limited Adaptive Histogram Equalisation (CLAHE) is used for image contrast enhancement [2].



(a)



(b)

Figure 1 (a) Input image (b) Image after CLAHE

CLAHE will divide the images in to contextual regions and after that histogram equalisation is applied to each portion. Histogram equalisation will provide a good method for modifying dynamic range and contrast of an image. It provide a non-linear monotonic mapping method which reassigns the intensity value of the input image so that output image contains a uniform distribution of intensity

III. NIBLACK METHOD

Niblack's algorithm is a local thresholding method based on the calculation of the local mean and of local standard deviation [3]. It calculates a pixel-wise threshold by sliding a rectangular window of the size $w \times w$ over each pixel position on the gray level image. The threshold is decided by the formula

$$T(x, y) = m(x, y) \cdot \left[1 + k \cdot \left(1 - \frac{s(x, y)}{R} \right) \right]$$

where $m(x, y)$ and $s(x, y)$ are the average of a local area and standard deviation values, respectively, k is the bias and R is the empirical constant. The size of the local region (window) is dependent on the application. The value of ' k ' is used to adjust the check the result of standard deviation due to object features and R is adjusted to reduce sensitivity to noise. The optimum selection of weight ' k ' is important. Advantage of Niblack algorithm is that it always identifies the regions correctly as foreground, but on the other hand it tends to produce a large amount of binarization noise.

IV. SAUVOLA METHOD

Noise that is presented in the background remains dominant in the final binary image of the Niblack method. Sauvola and Pietikainen [4] modified Niblack's method. They have proposed a method (it is named Sauvola's method) that solves this problem by adding a hypothesis on the gray values of image and background pixels. Similar to Niblack method, this algorithm is also a local

thresholding method. Sauvola's algorithm improves Niblack's method by computing the threshold using the dynamic range of image gray-value standard deviation which results in the following formula for the threshold:

$$T(x, y) = m(x, y) \cdot \left[1 + k \left(\frac{s(x, y)}{R} \right) \right]$$

Here also $m(x, y)$ and $s(x, y)$ are the average of local mean and standard deviation values, respectively, ' k ' is the bias and R is the maximum value of the standard deviation. The idea of both Niblack's and Sauvola's methods is to vary the threshold over the image, based on the parameters $m(x, y)$, $s(x, y)$, k and R for a window of fixed size $w \times w$. Here the window $w \times w$ is chosen large enough to include retinal structures and the background.

V. ADAPTIVE MULTI-LEVEL THRESHOLDING

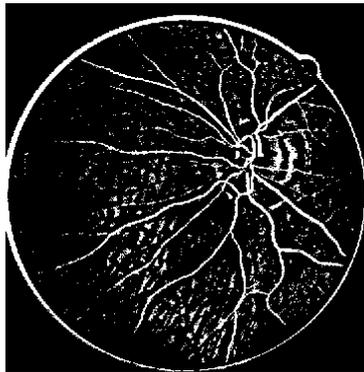
Multi level adaptive thresholding technique is a multilayered thresholding technique that applies different threshold values iteratively to generate gray level image [5]. At the initial step, first threshold value T_{MAX} is calculated from the histogram of image in such a way that it only keeps those pixels in first segmented image which is greater than T_{MAX} . Then morphological thinning operator is used to skeletonise I_{THIN} , the segmented image I_{SEG} which results in vessels which are only one pixel wide. Now edge image I_{EDGE} which highlights the edge pixels of all vessels is identified using equation below. For every pixel p in I_{THIN}

$$Edge(p) = \frac{1}{2} \sum_{i=1}^8 \left| I_{THIN}(p_{i \bmod 8}) - I_{THIN}(p_{i-1}) \right|$$

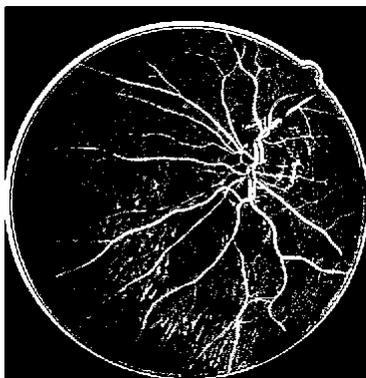
where p_0 to p_7 represents the pixels belonging to an clockwise ordered sequence of pixels defining the 8-neighborhood of p and $I_{THIN}(p)$ is the pixel value. $I_{THIN}(p) = 1$ for vessel pixels and zero for all the other conditions. $Edge(p) = 1$ and $Edge(p) = 2$ for vessel edge point and intermediate vessel respectively. Then reduce the threshold value by 1 and calculate I_{SEG} for next iteration and all the above steps are done iteratively until $T_{MAX}-1$ is zero.

VI. RESULTS

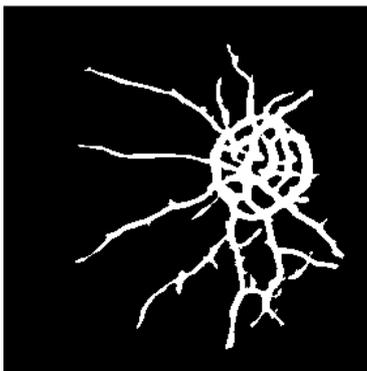
The described three algorithms are applied to the publicly available images available from DRIVE database containing 40 color images divided into two sets for testing and training. The database also contains two manually segmented vessels for each image from two different observers called as ground truth image. The result of proposed algorithm is compared with ground truth image and the different performance metrics are calculated. Results of three algorithms are shown in Figure 2.



(a)



(b)



(c)

Figure 2 Output of (a) Niblack Thresholding (b) Sauvola Thresholding (c) Adaptive Multi-level Thresholding

VII. PERFORMANCE MEASURES

Performance of each algorithm was evaluated for selecting the better algorithm. Performance was measured using four performance measures such as accuracy, sensitivity or True Positive Rate (TPR), specificity or False Positive Rate (FPR) and precision or Positive Precision Value (PPV). These measures follows from the definitions of parameters like true positive (TP): number of blood vessel pixels correctly detected as blood vessels, true negative (TN): number of background pixels correctly detected as non blood vessels, false positive (FP): number of background pixels wrongly detected as blood vessels and

false negative (FN): number of vessel pixels wrongly identified as blood vessels.

$$TPR = \frac{TP}{TP+FN}$$

$$FPR = \frac{FN}{TP+FN}$$

$$PPV = \frac{TP}{TP+FP}$$

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

Table 1. Comparison results

METHOD	TPR	FPR	PPV	Accuracy
Niblack thresholding	.6123	.1139	.2565	.8696
Sauvola thresholding	.6739	.1145	.2741	.8727
Multi-level Thresholding	.4574	.0431	.6057	.9038

VIII. CONCLUSION

This paper presents a comparative analysis of three local thresholding methods such as Niblack algorithm, Sauvola algorithm and Adaptive Multilevel Thresholding for blood vessels segmentation from retinal fundus images. These algorithms were tried over images publicly available from DRIVE database. Out of the three methods Adaptive multilevel Thresholding is found to have more accuracy when compared to other two methods. It has accuracy of 90% where as Niblack algorithm has accuracy of about 86% and Sauvola algorithm of about 87%.

ACKNOWLEDGEMENT

Authors would like to thank authorities of DRIVE database for providing images which provided good result for proposed algorithm and also like to thank our institution for their constant encouragement and support

REFERENCES

- [1] N. Otsu (1979) A threshold selection method form gray-level histograms. Proceedings of the 1986 IEEE Transactions Systems, Man and Cybernetics, Vol.9, No. 1, 62-66.
- [2] Vijay K., Singh Y.: "Enhancement of images using histogram processing techniques" Int.J. Comput. Technol. Appl., 2011, 2, (2), pp. 309313.
- [3] Niblack (1986), An Introduction to Digital Image Processing, pp. 115 - 116, Prentice Hall.
- [4] J. Sauvola and M. Pietika Kinen (2000). Adaptive document image binarization. Pattern Recognition. Vol. 33 (2000), 225 – 236.
- [5] Rais R.N.B, Anif M.S, Taj I.A. "Adaptive thresholding technique for document image analysis" Proc. Eighth IEEE Int. Multi-topic Conf. (INMIC), Lahore, Pakistan, December, 2004.