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EDGE DETECTION OF DIGITISED HISTOPATHOLOGICAL SLIDE IMAGES USING DYNAMIC THRESHOLDING

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ABSTRACT

Malaria is one of the most common parasite transmitted disease of humans in the modern world. CAD (Computer Aided Design) which is relatively a young technology has been deemed highly impactful in recent times because of its cost effectiveness and accuracy. For the development of CAD to detect abnormalities in histopathological medical images, effective image segmentation of the image is required. For the image segmentation to be accurate it must be preceded by a robust edge detecting algorithm. In this paper we have introduced a newtree based approach, using statistical analysis and distance thresholding to provide a more efficient algorithm towards edge detection. The proposededge detection algorithm has provided a comparableresultwith other well-accepted methods.

KEYWORDS: Histogram, BMP, full and complete binary tree, Bin variance Calculation(BVC), Maximum distance Thresholding(MDT), Prominent Bins, Truncated Bins.

1. INTRODUCTION

Malaria is a parasite transmitted, infectious disease of humans. Malarial parasites belong to genus plasmodium with different species like Falciparum, Vivax etc. The life cycle of malarial parasites has distinct signature and pattern. This paper a new edge detection method is proposed to identify different features of types and stages of malarial parasites present in human blood.Interpretationof image by analysing the objects within the image is one of the main objectives of computer vision. The purpose of image segmentation is to partition an image into meaningful regions with respect to a particular perspective. There are mainlyfour techniques of image segmentationviz. threshold based techniques, edge based techniques, region based techniques and connectivity preserving relaxation techniques. Most widely used technique forimage segmentation is “edge detection”.For accurate segmentation of medical image an effective edge detection algorithm is required. Detecting edges is one of the most important aspects in image segmentation problem.It is an important requisite in digital image processing and is mainly used in the application of feature extraction. Edge detection is basically the process of detection of those regions in the image where there is an abrupt change in the intensity of the image.[5] It is a process of identifying and locating sharp discontinuities in an image. There are generally three types of edges viz. Horizontal edges, Vertical edges and Diagonal edges.

This paper proposes a robust digital slide image enhancement and edge detection algorithm that is equally effective with most medical images and yield excellent segmentation results in varied cases. In this paper we have developed a tree based algorithm for the edge detection of histopathological image. Furthermore a variance based dynamic thresholding technique has been used for the calculation of horizontal and vertical edges of the said image.

In the subsequent part of the paper, in section two we have discussed about the classical methods of edge detection. The third section contains the materials and methods that has been used for this citation. In the fourth section, the results of the proposed method are cited whereas the penultimate section represents the discussion. The final section contains the conclusion of our citation.

2. Literature Review

Segmentation methods are based on obtaining the regions, directly from abrupt changes in the intensity value. These methods are called Edge or Boundary based methods. Edge detection is the problem of fundamental importance in image analysis. Edge detection techniques are generally used for finding discontinuities in grey level images. There are three different types of discontinuities in the grey level namely like point, line and edges.

There are large numbers of edge detection operators available, each designed to be responsive to certain particular types of edges. The majority of different methods may be grouped into two categories.[1]

1. The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image,
2. The Laplacian method searches for zero crossings in the second order derivative of the image to find edges.

The Sobel operator is based on convolving the image with a small, separable, and integer valued filter. This is very alike to the Roberts Cross operator.[1][2] In Robert edge detection, the vertical and horizontal edges are obtained individually and then put together for resulting edge detected image. It performs a simple and quick approach to compute, 2-D spatial gradient measurement on an image.Prewitt operator[1][3] again is similar to the Sobel operator and is used for detecting vertical and horizontal edges in images. To estimate the magnitude and orientation of an edge, Prewitt operator is useful. Though Prewitt filter is a fast method for edge detection, it is only suitable for well contrasted noiseless images.

The Laplacian of Gaussian[1][3] is a 2-D measure of the 2nd order spatial derivative of an image. The rapidly changing regions are identified and hence they are useful for edge detection. The Laplacian is often applied to an image that is smoothed with a Gaussian Smoothing in order to reduce its sensitivity to noise.Canny edge detection[3] is a multistage algorithm to detect a wide range of edges in images. This detector finds edges by looking for local maxima of the gradient of f(x, y). The gradient is calculated using the derivative of a Gaussian filter. It has been observed from the present study that the performance of canny edge detection operator is much better[1] than others in respect to the image appearance and object boundary localization.

Apart from the filter based methods some commonly known methods for edge detection are Active Contour or Snake Model, Contextual based Hopfield Neural Network (CHNN), Morphological filters based methods, Bayesian Edge Detection and Fuzzy set based.

Active contour or Snake Model[6] which is basically contour locking models and have been used for medical imaging, shape modelling, edge detection, curve tracking etc. whereas Contextual based Hopfield[7] which is used to find the edges of CT and MRl images by incorporating pixels contextual information into a pixels labelling procedure which results the removal of noises. Morphological Filters[8] is used to remove noise by Morphological opening and closing operations with least loss of edge feature. Bayesian edge Detection[9] works on the clinical ultrasound B-scans image and results the binary set i.e. 0 and 1 with the probability of the presence of edges between two neighbouring pixels.Fuzzy Set Based.[10] partitions the image into two portions i.e. the edge portion and the non-edge portion and on the detection it removes the non-edge portion resulting the sub-edges of the sub-regions in the edge portion.

3. MATERIALS AND METHOD

We have used images from the DPDM platform of the CDC (Centre of Disease Control and Prevention) website. DPDM is an education resource which is designed for health professionals and laboratory scientists which aids the education of the laboratory technicians and also consists of diagnostic quizzes for the self-assessment of the skill of the technicians. DPDM consists of over 150 images of malarial parasites in blood smear (thick and thin). Using these images and converting them in pseudo-grayscale, we have tested our edge detection algorithms for all the images.

3.1. Generation of a Full and Complete Binary tree

In the previous work, ‘A Tree-based Approach towards Edge Detection of Medical Image using MDT’[1], a method was devised for the edge detection and enhancement of a 2^8 bit grayscale DICOM image. In this paper an alternative approach for2^8grayscale BMP images for edge detection of h-istopathological slides is proposed.

A full and complete binary tree T is created where each of the nodes of the structure contains three pointers viz. Frequency available in the image, colour intensity and balancing factor. Then comparison between frequency of intensity of the left child node f(L) and the right child node f(R) is performed, whichever being greater will be the intensity of the parent node. The frequency of the parent node will be the summation of f(L) and f(R) whereas the level(l) and the total number of colour intensity (C) are used to determine the balancing factor, the left node having the balancing factor of the (C-2^l) and the right node having the balancing factor of the parent node.[4][1]

Subsequently the level histograms of each level of the tree are generated with reduced number of colours i.e. half of the colours to the root in bottom-up mode obeying the following rules.

- It will work for all leaf nodes i.e. iNode (h) + 1 to tNode (h) where iNode is the internal node and tNode represents the total number of nodes.
- The frequency count of the Tree[i] is compared with its child nodes i.e.f (L) (Left child of the tree) and f(R) (right child of the tree). The larger intensity will become the parental intensity and the parental frequency will be the sumof the frequency count of the two children.
- The iteration will be terminated when the counter reaches the root node i.e. when the parent node and the root node overlap.

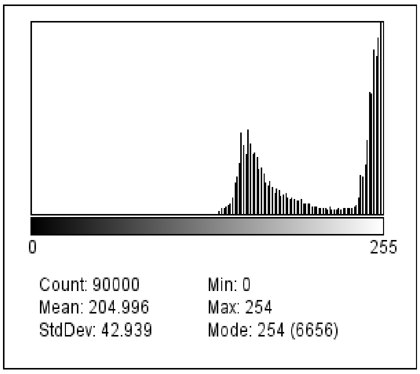

Fig: Grey-scale Histogram at level 6

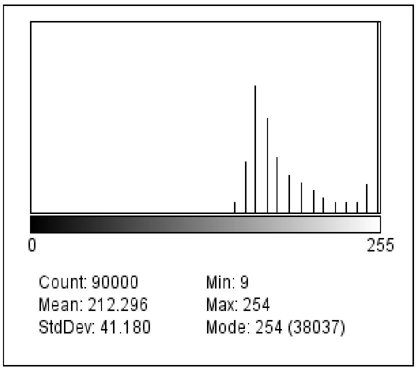

Fig: Homogeneity Histogram at level 6

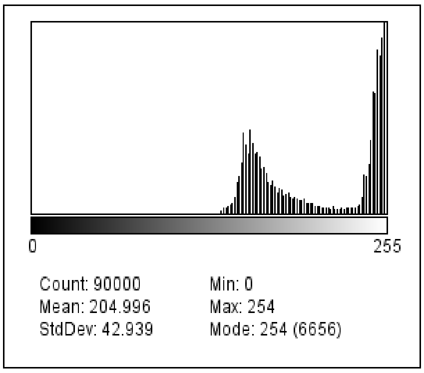

Fig: Grey-scale Histogram at level 7

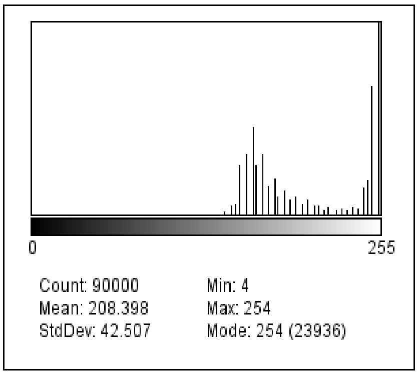

Fig: Homogeneity Histogram at level 7

3.2. Calculation of Adaptive Thresholding
BinVariance Calculation Method (BVC)

In each level of the tree, half of the intermediary bins are truncated as stated by the above condition. This will generate different bin distance in the histogram of the particular level of a tree. This method calculates the coefficient of variation of each of the bins i.e.

$$\textbf{BVC} = \frac{\sigma}{x} \qquad \text{………… (i)}$$

where σ =standard deviation of the bins,

x=no of bins.

$$\text{Again } \sigma^2 = \frac{\Sigma(Xi - \bar{X})^2}{N+1} \qquad \text{………… (ii)}$$

where X_i= different bin distances as i=0,1, 2…..n

$\bar{X}$ = mean of the bin distance

N = total number of bins.

Algorithm to calculate Bin Variance

avgBinDist ← totBinDist / totBin
Loop i ← intermedNode+1 to treeNode
Do binVar ← Tree[i, 1] - Tree[(i - 1), 1]
totBinVar ← $\sum_i((\text{binVar} - \text{avgBinDist})\text{^}2)$
End loop var ← totBinVar/(totBin+1)

Maximum Distance Thresholding Method (MDT)

In the precursory process the bin variance (BVC) for each level of the tree is calculated and here it is segregated it into two types viz. 1) The Prominent Bins and 2) The Truncated Bins. The Prominent bins are the points of the histogram having sharp measurable discontinuities whereas the truncated bins have insignificant discontinuities and are thereby discarded. The calculation of MDT is:

MDT ←totPrmBinDist / totPrmBin

3.3. Generation of Enhanced Image

With the help of this process an enhanced image is generated using the original image. The mapping from the original level histogram to the desired level histogram is also done. To map a particular intensity, it is at first selected and checked whether it is prominent or not. If it is prominent then it will proceed to the next image pixel. If it is not prominent then the next prominent intensity will be selected to propagate.

3.4. Generation of Edge Map

In the previous process, enhanced image is obtained at the desired histogram level. Now in this process the horizontal and the vertical edges are mapped and the image f(h) is obtained. The horizontal edge is mapped from leftmost pixel in the first row to the rightmost pixel in the last row in row major order and the horizontal edge map image f(h) is obtained. Then the MDT value is then compared with the corresponding pixel position. If the difference is greater than MDT then the pixel position will be set to 0 i.e. it will be black else it will be set to 255 i.e. white.

$$(h) = \sum_{i=0}^{r}\sum_{j=0}^{c} P_{i,j} = \begin{cases} 0 & |P_{i,j} - P_{i+k,j}| > MDT \\ 255 & |P_{i,j} - P_{i+k,j}| > MDT \end{cases} \qquad \text{………… (iii)}$$

Similarly the vertical edge map imagef(v) is also obtained where it sets pixels vertically i.e. in column major order rather than horizontally and the two edge map images i.e. the vertical and the horizontal image maps are superimposed using the logical OR operation. Our enhanced edge mapped image is obtained as the output which is discussed in detail in the 'Results' section of this research paper.

$$EdgeMap = f\,(h) \vee f(v) \qquad \text{…………. (iv)}$$

4. RESULTS

The proposed algorithm was implemented using MS C# and tested with various histopathological slide samples obtained from CDC (Centre of Disease Control and Prevention). The tests were carried out on images which were at first converted into grayscale by the pseudo-grayscale conversion technique[2] and then using theproposed edge detection technique, the following results are obtained.

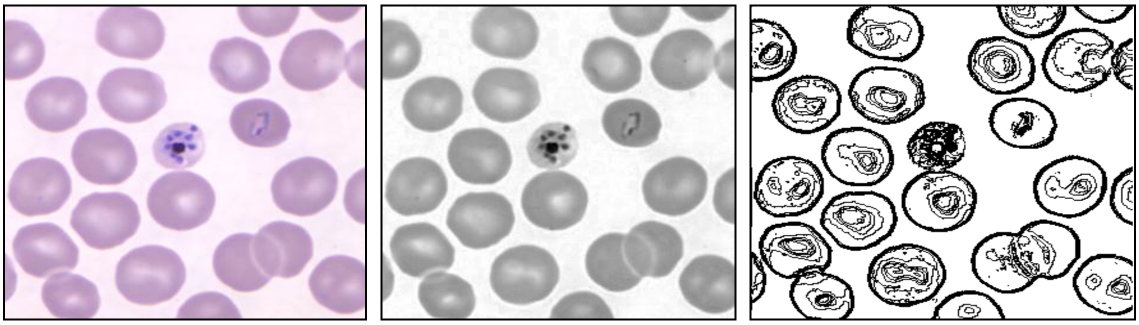

Fig: Mature schizont in a Giesma stained thin blood smear: (a) Original Colour Image, (b) Pseudo-Grey scaled Image and (c) Proposed Edge Map Image

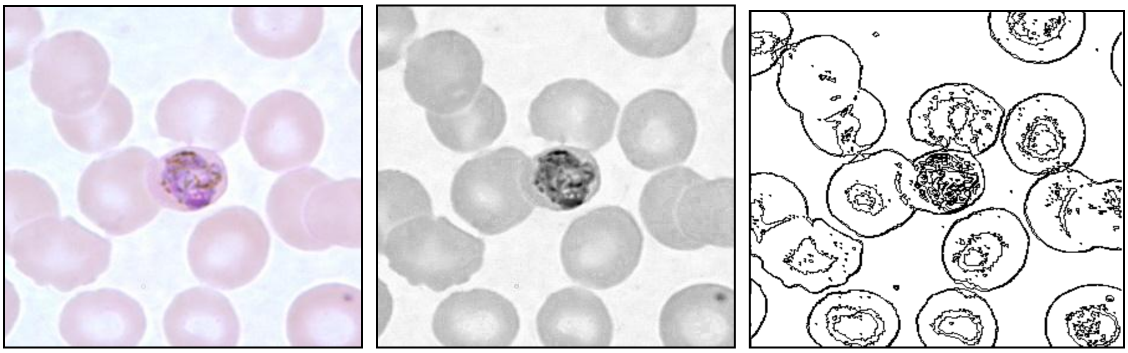

Fig: Developing gametocyte of P. malariae in a thin blood smear: (a) Original Colour Image, (b) Pseudo-Grey scaled Image and (c) Proposed Edge Map Image

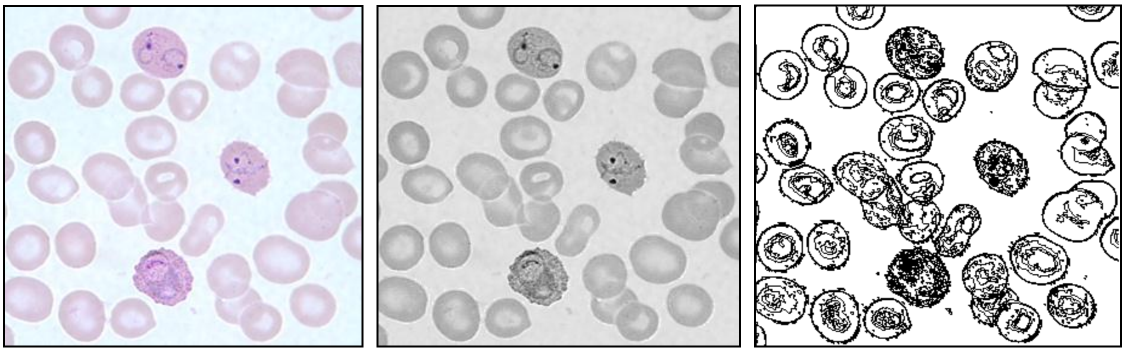

Fig: Infected RBC's showing developing (lower) and ring-form (upper two) trophozoites of P.ovale in a thin blood smear: (a) Original Colour Image, (b) Pseudo-Grey scaled Image and (c) Proposed Edge Map Image

The images are obtained from various blood samples containing P. vivax parasites. The edge detection by the proposed method results more accurate than any other classical methods. If there are any abnormalities in the blood sample then this method detects those more prominently as shown in fig above.

Table 1: Average of Relative Frequency (RF) of Detected Edge Pixels

	Roberts	Sobel	Prewitt	Kirsch	LoG	Proposed Algorithm
Roberts	1	1.7795	2.6155	2.1712	1.5101	1.5548
Sobel	0.5619	1	1.4697	1.2201	0.8486	0.8737
Prewitt	0.3823	0.6803	1	0.8301	0.5773	0.5944
Kirsch	0.4605	0.8195	1.2046	1	0.6955	0.7160
LoG	0.6621	1.1783	1.7319	1.4377	1	1.0295
Proposed Algorithm	0.6431	1.1445	1.6822	1.3965	0.9713	1

These derived values are analysed using one sample two tail T-Test where Alpha is 0.05. A t-test is used in statistical hypothesis testing for checking whether the null hypothesis can be supported. It is used to determine if two sets of data are significantly different from each other. The ratio of edge map pixels between each other as shown in the table 2 is used to perform the one sample two tail t-test to show their relative acceptance.

Table 2: One Sample Two Tail T-Test Result where α is 0.05

	Roberts	Sobel	Prewitt	Kirsch	LoG	Proposed Algorithm
Mean (μ)	0.542033	1.120484	1.740825	1.411166	0.920608	0.953713
SD (s)	0.119584	0.425011	0.531425	0.488054	0.361876	0.373833
Std Err	0.05348	0.190071	0.237661	0.218264	0.161836	0.167183
t-Stat	10.13529	5.895093	7.324839	6.465401	5.688533	5.704597
p-value	0.000267	0.002071	0.000924	0.001474	0.002358	0.002334
Significant Difference	Yes	Yes	Yes	Yes	Yes	Ys

Table 2 summarizes the t-test performed on the relative frequency for every method with other methods described. The result obtained show that there is no significant difference among Sobel, LoG and the proposed algorithm. The t statistics value of the proposed algorithm is very close to Sobel and LoG methods. It may be inferred that the edge map obtained from newly proposed method is acceptable.

The edge map obtained by the proposed algorithm is though similar to Sobel and LoGstatistically but significantly better than them, as it forms a single pixel connected edge map rather than discrete edge pixels. This is extremely important for the image segmentation in medical image analysis. So, the occurrence of edge pixels that are connected with least sensitivity to noise is a remarkable achievement for the algorithm proposed in this research paper. The generalized comparative analysis of all the methods described in this paper, is summarized in table 3.

Table 3: Comparison of the classical methods with the proposed method based on important parameters

Edge Operators	**Convolution**	**Sensitivity to Noise**	**Single Pixel edge**	**Edge Continuity**	**Algorithm**	**Computational Time**
Sobel	Yes	Yes	No	No	Simple	Slow
Roberts	Yes	Yes	No	No	Simple	Slow
Kirsch	Yes	Yes	No	No	Simple	Slow
Prewitt	Yes	Yes	No	No	Simple	Slow
LoG	Yes	No	No	No	Complex	Slow
Proposed Algorithm	No	No	Yes	Yes	Simple	Fast

5. DISCUSSION

The resultsthat are obtained by the application of our proposed algorithm are comparable with the results obtained from the fiveprominent classical methods namely, Roberts, Sobel, Prewitt, Kirsch and LoG. Table 1 shows the average relative frequencies (RF) of the detected edge pixels using the edge detection algorithms for the entire dataset. The ratio of edge pixels with respect to each other provides a definitive comparative statistics for the occurrence of edges.

6. CONCLUSION

In this research paper we have devised an efficient edge detection algorithm for the detection of different types of features and stages of malarial parasites in blood stream. This is a pre-processing step for image segmentation which is used in feature extraction and in detecting abnormalities. Creating a full and complete binary tree and using the variance of the bin distance (BVC) and maximum distance thresholding we have implemented this algorithm. One of its major advantage is that the abstraction of the edge depends on the level of the tree. From the statistical analysis it is evident that our algorithm is comparable with the prominent classical methods such as Robert, Sobel, Prewitt, Kirsch, LoG but is also significantly better than them because of less sensitivity towards noise, faster computation and single pixel continuous edge map which is very necessary for medical images.

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REFERENCES

1. Maitra et al, "A Tree-based Approach Towards Edge Detection of Medical Image using MDT", International Journal of Computer Graphics, SERSC Publication, 2015; 6(1): 37-56.
2. Muthukrishnan et al, "Edge Detection Techniques for image Segmentation", International Journal of Computer Science & Information Technology, 2011; 3(6): 259-267.
3. Acharjya et al, "Study and Comparison of Different Edge Detectors for Image Segmentation", Global Journal of Computer Science and Technology Graphics and Vision, 2012; 12(13): 29-32.
4. Maitra et al, “Adaptive Edge Detection Technique towards Features Extraction from Mammogram Images” Journal of Cancer Research Updates, Life Science Global Publication, 2016; 5(2): 47-58.
5. Mukherjee et al, “Grayscale Conversion of Histopathological Slide Images as a Pre-processing Step for Image Segmentation”, International Journal of Software Engineering and Its Applications, SERSC Publication, 2016; 10(1): 15-26.
6. Michael Kass et al, “Snakes: Active contour models”, International Journal of Computer Vision, Kluwer Academic Publishers, 1988; 1(4): 321-331
7. Chuan Yu Chang, “A Contextual-based Hopfield Neural Network for Medical Image Edge Detection”, IEEE International Conference on Multimedia and Expo (ICME), 2004.
8. Peng et al, "Morphological filters and edge detection application to medical imaging", Proceedings of the Annual Conference on Engineering in Medicine and Biology, 1991; 13(1): 251-252.
9. Chien-Min Kao et al, “A Bayesian Approach for Edge Detection in Medical Ultrasound Images”, IEEE Transactions on Nuclear Science, 1998; 45(6): 3089 – 3096.
10. Zeng et al, "Fuzzy-Set Based Fast Edge Detection of Medical Image", Fuzzy Systems and Knowledge Discovery, 2008; 3: 42 – 46.