Leukaemia's Cells Pattern Tracking Via Multi-phases Edge Detection Techniques

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***Abstract*—Edge detection involves identifying and tracing the sudden sharp discontinuities to extract meaningful information from an image. The purpose of this paper is to improve detecting the leukaemia edges in the blood cell image. Toward this end, two distinctive procedures are developed which are Ant Colony Optimization Algorithm and the gradient edge detectors (Sobel, Prewitt and Robert). The latter involves image filtering, binarization, kernel convolution filtering and image transformation. Meanwhile, ACO involves filtering, enhancement, detection and localisation of the edges. Finally, the performance of the edge detection methods ACO, Sobel, Prewitt and Robert is compared to determine the best edge detection method. The results revealed that the Prewitt edge detection method produced an optimal performance for detecting edges of leukaemia cells with a value of 107%. Meanwhile, the ACO, Sobel and Robert yielded performance results of 76%, 102% and 93% respectively. Overall findings indicated that the gradient edge detection methods are superior to the Ant Colony Optimization method.**

***Index Terms*—Leukemia Edge Detection; Medical Image Processing; Pattern recognition; Ant Colony Optimization.**

I. INTRODUCTION

Edge detection is an essential operation in numerous fields such as medical image processing, shape recognition, defect detection on mechanical parts and various industrial and machine vision applications [1]. Edge detection is used to identify and locate the sudden significant changes and discontinuities in digital images such as photometrical images, physical geometrical characteristics, leukaemia blood cells, etc. [2,3]. Generally, edges are significant local changes or sudden discontinuities which normally occur on the boundaries of two different regions in the digital images and often carries useful physical information [4]. The edges in an image indicate higher frequency information of an object, and hence they play an important role in image processing and pattern recognition.

Apart from this, an edge is defined as a group of connected pixels lying between boundaries of two regions in an image. In binary images, edges are the black pixels with one nearest white neighbour. Image edge detection is the process of detecting and extracting edges from digital images to retrieve essential details of image analysis. Therefore, detecting edges plays a crucial role in many applications in the field of image processing, computer vision and image segmentation [5].

Due to the importance of image edge detection for analysing the sudden changes and discontinuities in an image, various researchers have implemented edge detection methods in medical image processing such as[6-10]. According to [11], edge detection process involves four primary interrelated steps which are filtering, enhancement, detection and localisation. Filtering is an essential pre-processing operation that is used to suppress or reduce noises in an image [12]. Despite the importance of filtering process, selecting the appropriate filters is a crucial criterion in image processing field. Indeed, filtering may affect the strength and degrade the contents of the edges in an image. Thus, the primary concern in edge detection filed lies in the scale of the filters.

The edge detection is carried out with the strong edge contents which usually contain the information needed to describe the content of an image. Distinguishing strong edges among the weak ones is an essential criterion which determines the efficiency of the edge detection methods. For instance, thresholding can be employed for determining the true edge points in an image [13].

In fact, detecting the leukaemia in blood cells is still a major challenge and active research in medical image processing. It has become imperative to develop algorithms that can detect and trace the immature cancerous cells in the blood.

The rest of the paper is organised as follows. The related significant studies of detecting leukaemia edges are presented in Section "Related Studies". The methods employed in this study for detecting leukaemia edge detection are elaborated in Section "Methodology". The results of the of the proposed edge detection methods are demonstrated in Section "Results and Discussion", and Section "Conclusion" is dedicated to bringing about the summary of the paper.

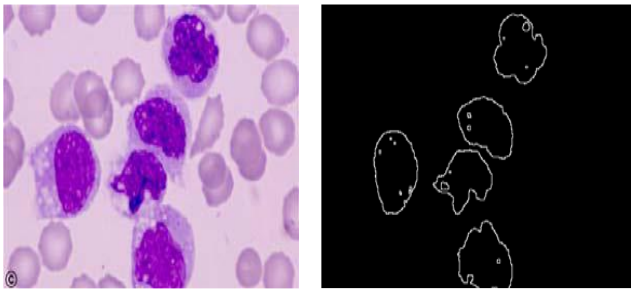
II. RELATED WORKS

Over the past decades, medical image processing has become an essential method to interpret and visualise medical images. As a result, researchers have developed multiple powerful methods for storing, detecting, transmitting, displaying and analysing medical images. However, the most challenging aspect of medical imaging lies in the development of an optimal algorithm that can detect cancerous cells with better accuracy and efficiency [14].

Leukaemia is a type of cancer disorder which affects the White Blood Cells (WBCs), whereby immature and abnormal WBCs are produced vigorously by the bone marrow into the bloodstreams [15]. The current methods to diagnose leukaemia are carried out by trained specialists in expensive laboratories. However, this procedure to determine leukaemia is not sufficient due to the imitation of similar signs and the complex nature of blood images [16]. The acute leukaemia

classification and segmentation methods are based on four primary groups including boundary, threshold, region and hybrid. Most of the techniques combine boundary and region criteria [17-19].

Various studies have been conducted on edge detection of leukaemia such as gradient-based watershed transform of segmentation method to separate the blast cells from the background. In another study, a segmentation method for counting white blood cells was presented [20]. The experimental results showed that the presented method is more influential as compared to traditional methods which use information of local context. The proposed method employed the gradient edge detectors for identifying the colour of leukaemia from blood image to introduce a new approach to detect leukaemia. The results of the proposed approach indicated excellent results regarding detecting of leukaemia blood cells as shown in Figure 1.



(a) Original blood image (b) Image with leukaemia

Figure 1: Leukaemia edge Image edge detection

Throughout the literature, we found that it is entirely challenging to obtain true edges which represent the leukaemia in blood cell image, especially at its early stages. Thus, the methods proposed for detecting the leukaemia edge detection should be investigated further.

III. METHODOLOGY

A. Blood Image Acquisition

The blood images are acquired from Universiti Sains Malaysia hospital through the use of a digital camera which was placed in the eye of the microscope. Throughout the process of image acquisition, the purpose was to acquire a less noisy image by restricting the movements of the digital camera or the microscope as well as the suitability of lightening conditions. Total of six blood images where acquired however due to the similarity between the acquired blood images, only one image is employed for the analysis in this study.

B. Image Preprocessing

Image pre-processing is necessary operation in image processing. The pre-processing operation in this study consist of blood cell image filtering, sorting of leukaemia and the normal blood cells using kernel single and multiphase operations, binarization and transformation to transform and enhance the resolution of the leukaemia cells. The pre-processing operations are elaborated in the following subsections.

1) Linear Filter

Mean filter is one of the most important and common noise removal methods in image pre-processing. Linear (mean) filter works by applying a mask over each pixel in the white blood cell image. Each pixel component that comes under the mask is then averaged together to form a single pixel which signifies the output of the mean filter. The mean filter is called the average filter because it takes the average of the values or components of each pixel under the filter mask. The averaging procedure of the mean filter helps at detecting the local variations caused by grain noise which can be reduced considerably by substituting it with an average value. Figure 2 depicts the 3x3 matrix linear (mean) filter employed in this study.

1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9

1/16	1/8	1/16
1/8	1/4	1/8
1/16	1/8	1/16

Figure 2: Linear filter employed for denoising of blood image

2) Image Kernel

It is sometimes called image convolution operation and is carried out to determine the most critical portions of the blood image. It is a vital tool which modifies specific portions that signify the existence of leukaemia cells. In this paper, both single and multi-kernel filtering operations are used to modify the spatial frequency characteristics of the leukaemia cells in the white blood cell image. Image 3x3 kernel is shown in Figure 3.

0	1	0
1	1	1
0	1	0

Figure 3: 3x3 kernel

3) Binarization

Binarization is important to image pre-processing operation that is employed to convert blood images into binary images. It involves separating the image into background and foreground and then assigning the pixel to either background or foreground objects by comparing their intensities to a predefined threshold. In this study, the binarization operation is achieved by computing the global thresholds on the input image (white blood cell). The resultant image consists of only values 0 and 255. The maximum value is 255, and the minimum value is 0.

4) Image Transformation

It is an essential operation which aims at transforming the filtered white blood cell to describe the original image (output image).It is the process that assists in determining the true colours of the cells which signify the existence of leukaemia in the blood image.

C. Gradient Edge Detection

In this study, Sobel, Prewitt and Robert gradient edge detectors are used to detect the edges of the leukaemia in the white blood cell image. At the start, the original white blood cell image is filtered, binarized and transformed as mentioned earlier in this chapter. The next stages involve calculating the gradient pixels of the leukaemia edges. The gradient edge

detectors are calculated based on computing the pixel's gradient and detecting the local maxima for localising the step edges. The following subsections elaborate the implementation of these methods to detect the cancerous leukaemia cells in the blood image.

D. Sobel

Sobel edge detector works by computing the gradient's approximation of the white blood cell image intensity for edge detection analysis. It basically performs a 2-D spatial gradient quantity on an image and so indicates the regions where high spatial frequency occur which correspond the presence of edges (leukaemia). It convolves the input image with 3 x 3 two kernels as shown in Figure 4 and computes the gradient magnitude and direction (angle of orientation) using Equations (1) and (2) respectively.

+1	+2	+1
0	0	0
-1	-2	-1

+1	+2	+1
0	0	0
-1	-2	-1

Figure 4: Two typical Sobel kernels

$$|G| = |Gx| + |Gy| \tag{1}$$

$$\theta = \arctan t(Gy / Gx) \tag{2}$$

E. Prewitt

Prewitt edge detector computes the gradient of the intensity of an image at each point and gives the direction and the rate to the most significant possible increase from light to dark on an image. The changes of frequency distributions signify the regions where the sudden changes occur which indicates the existence of the edges in an image. The derivative utilised in this edge detection method is shown in Figure 5.

-1	0	+1
-2	0	+1
-1	0	+1

+1	+1	+1
0	0	0
-1	-1	-1

Figure 5: Two typical Prewitt kernels

F. Robert

Robert operator performs a quick and simple computation of the spatial gradient on an image. It basically emphasises regions of high spatial frequency which often correspond to edge boundaries in an image. It is one of the first basic operators used to detect edges in an image based on a pair of 2 x 2 convolution masks to compute a 2-dimensional spatial gradient on an incoming matrix as shown in Figure 6.

+1	0
0	-1

0	+1
-1	0

Figure 6: Two typical Roberts cross kernels

$$|G| = |Gx| + |Gy| \tag{3}$$

$$\theta = \arctan t(Gy / Gx) - 3\pi / 4 \tag{4}$$

G. Ant Colony Optimization (ACO)

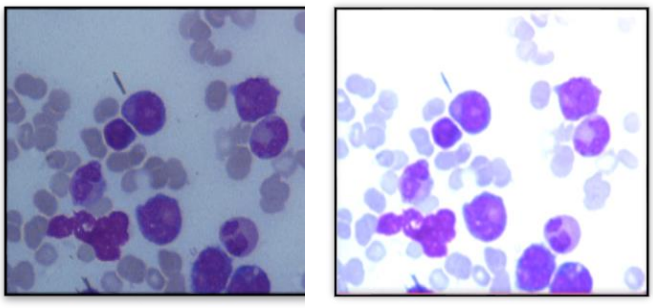
ACO is a very effective approach to optimise and detect leukaemia edge boundaries in digital images. It works by dispatching ants over the white blood cell image. In this case, ants made to move based on the heuristic information on 2-dimensional image from one pixel to another. This process helps at constructing the matrix of the pheromones. Each entry in the pheromone matrix represents an intensity change of the original blood image which is influenced by the edge locations. More specifically, the movements of ants are direct by the local change or discontinuities in an image.

The procedure of ACO-based edge detection is composed of four interrelated steps which are initialisation, construction, updating and decision phases which are described in the following subsection. The first step is the called the initialisation phase which is used to determine the solution space, pheromone parameters and pheromone matrix calculation. The second step is the construction stage which involves the movement of ants are from one pixel to another based on the probability transition rule. The third and fourth stages concern about updating and finding the positive edges of the ACO algorithm respectively. The updating operation is usually performed several times per one iteration to construct the final matrix of the pheromones which indicate the shortest and thus optimal path of the ACO. Meanwhile, finding the true edges operation involves identifying the true edges based on the final pheromone values.

IV. RESULTS AND DISCUSSION

A. Pre-processing and Filtering

The acquired image, as well as the filtered blood image, are shown in Figure 7. It can be observed that the linear filter produces clearer and smoother image.

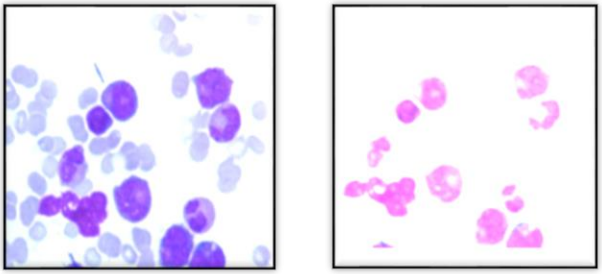


(a) Original blood image (b) Filtered blood image

Figure 7: The original blood image and the resultant of the linear filter

B. Image Multiphase Kernel

The results of the kernel filtering which involves first and second kernel phases are displayed in Figure 8.

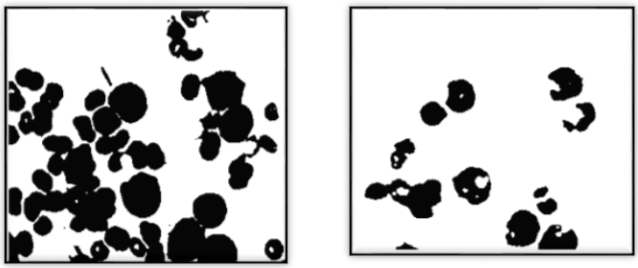


a) Kernel first phase blood image b) Kernel second phase blood image

Figure 8: The results of the multiphase kernel filtering of the blood image

C. Image Binarization

The results of the binarization operation which involves first and second binary phases are shown in Figure 9.

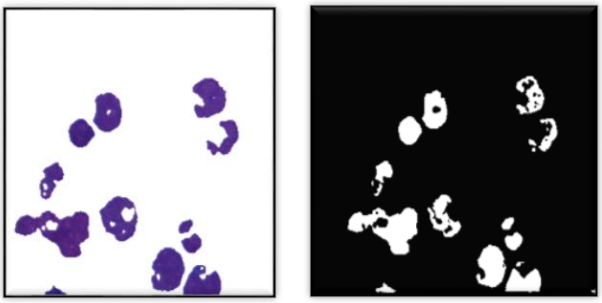


a) First phase binary image b) second phase binary image

Figure 9: The results of the multiphase binarization operations of the blood image

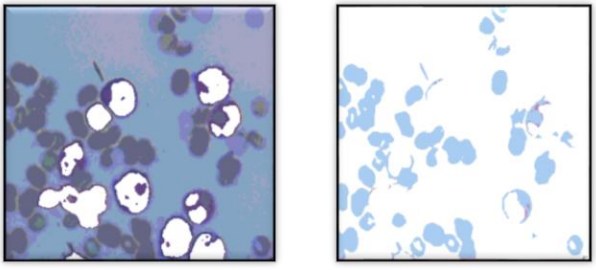
D. Image Transformation

The results of the transformation operation which involves first and second binary phases are shown in Figure 10.



a) First phase binary image b) second phase binary image

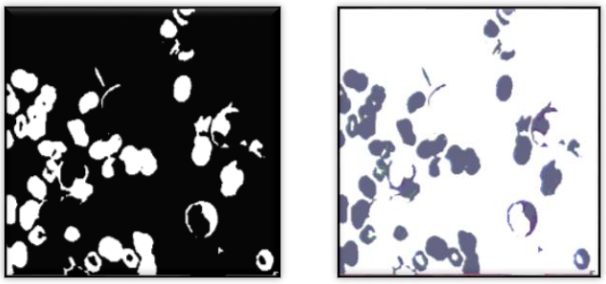
Figure 10: The results of the multiphase transformation operations of the blood image



a) Blood image with leukaemia b) The remaining red blood cells after removing leukaemia

Figure 11: The results of the part removal process which aims at localising the leukaemia cells

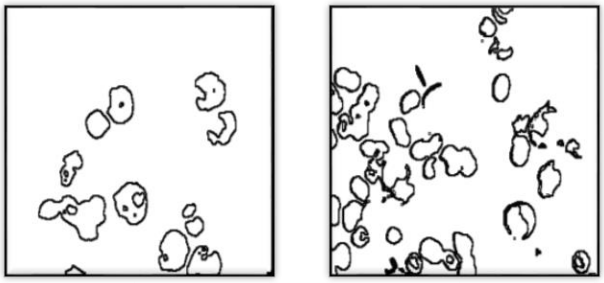
To further enhance the visibility of the part removal of the leukaemia and the red blood cells, Figure 12 shows the results of the binary transformed blood image with leukaemia and with red blood cell.



a) Blood image with leukaemia b) The remaining red blood cells after removing leukaemia

Figure 12: The results of the part removal process which aims at localising the leukaemia cells

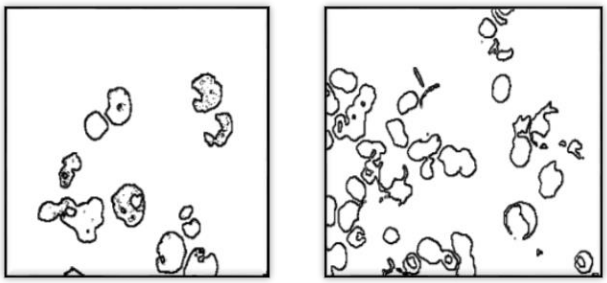
E. Sobel Edge Detection



a) Leukaemia edges b) Red blood cells edges

Figure 13: The results of Sobel edge detection method

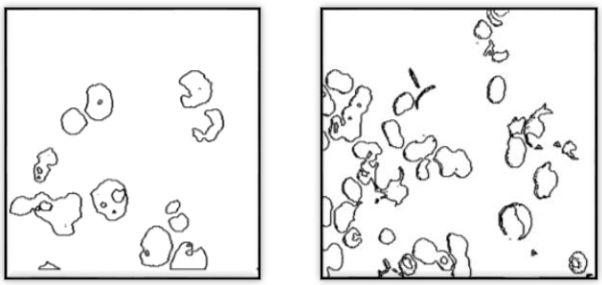
F. Prewitt



a) Leukaemia edges b) Red blood cells edges

Figure 14: The results of Sobel edge detection method

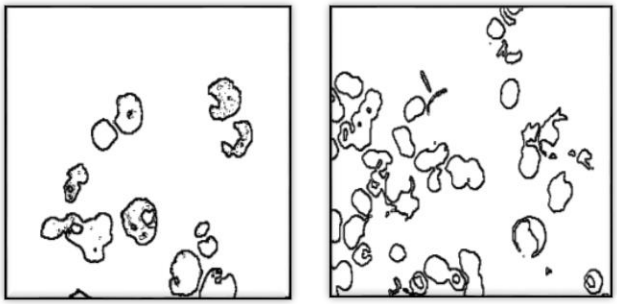
G. Robert



a) Leukaemia edges b) Red blood cells edges

Figure 15: The results of Robert edge detection method of the blood image

H. ACO



a) Leukaemia edges b) Red blood cells edges

Figure 16: The results of the ACO

I. Comparison

The performance of the edge detection methods employed in this study is compared through the obtained results. More specifically, the performance comparison was carried out based on the edges of each edge detection method. It can be clearly observed that the finest edge detection method which produced the optimal edges of the leukaemia in blood cell image is the Prewitt edge detection method. In line with this statement are the results presented in Table 1which also indicates that frequency's distributions of the edge detection methods. The results of the frequency distributions are obtained using Equation (5).

$$Frequency\ distribution = \frac{First\ Filter\ Output_A}{First\ Filter\ Output_B} \quad (5)$$

Table 1
Frequency Distribution

	Roberts	Prewitt	Sobel	ACO
Roberts		1.07	1.025	0.76
Prewitt	0.93		0.96	0.79
Sobel	0.98	1.04		0.78
ACO	1.09	1.12	1.19	

V. CONCLUSION

Leukaemia is a cancer disorder which affects the white blood cells (WBCs), whereby immature and abnormal WBCs are produced vigorously by the bone marrow into the bloodstream. Image edge detection detects the leukaemia presence by producing a line drawing of an image, which highlights the sharp changes or discontinuities of the intensity (boundaries of leukaemia) in the blood images. However, edge detection in medical images is extremely challenging aspect because distinct boundaries may not exist because of the neighbouring similarity between the organ structures and the presence of artefacts. Moreover, due to partial volume effects caused by the finite resolution of medical imaging devices, the boundaries of an image may be ambiguous and blurred and thus hard to be distinguished and recognised. Also, the performance of the edge detection methods; Sobel, Prewitt, Robert and ACO was compared in order to identify the significant method which produced optimal edges of the leukaemia cells. The finding of this comparison indicated that the Prewitt method produced positive, clear edges of the leukaemia cells.

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