Multi Algorithms for Improving Leukemia Images Edge Detection Technique

*Ahmad Kadri Junoh*a,1, Moath Ali Alshorman*a,2, Wan Zuki Azman Wan Muhamad*a,3, Mohd Hafiz Zakaria*a,4 and Afifi Md Desa*a,5

*A institute of engineering mathematics, Universiti Malaysia Perlis, Perlis, Malaysia.

**Corresponding Author

Abstract

Edge detection is an essential pre-processing operation in image processing and pattern recognition. It involves identifying and tracing the sharp sudden discontinuities to extract meaningful information from an image. Edge detection simplifies the analysis of an image by drastically reducing the amount of data to be processed and filtering out inadequate information, while at the same time preserving useful structural information about object boundaries in an image. The discontinuities signify the sudden changes in pixel intensity which describes boundaries of objects in a scene. The purpose of the present study is to detect the leukaemia edges in the white blood cell image. Toward this end, two distinctive procedures are implemented 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 localization of the edges. Finally, the performance of the edge detection methods ACO, Sobel, Prewitt and Robert is compared in order to determine the best edge detection method which yielded optimal true edges of leukaemia in the white blood cell image. The results revealed distinctive results whereby the Prewitt edge detection method produced 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.

Keywords: Image processing, edge detection, leukemia, blood cell, filtering.

INTRODUCTION

Edge detection is an essential operation in numerous fields such as medical imaging, shape recognition, defect detection on mechanical parts and various industrial and machine vision applications (Liu & Fang, 2015). Edge detection is used to identify and locate the sudden changes and discontinuities in digital images such as photometrical images, physical geometrical characteristics, leukaemia blood cells and etc. (Muthukrishnan & Radha, 2011; Pratt, 2001; Trujillo & Olague, 2006). 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 (Fan, Song, & Jutamulia, 2007). The edges in an image indicate higher frequency information of an object and hence they play important role in image processing and pattern recognition (Sherin & Mredhula, 2017). They characterize boundaries and thus have a wide range of useful applications including segmentation, pattern recognition and identification of objects in scenes. Indeed, edges signifies significant visual information of the object in an image because they relate to the major geometrical, physical, and photometrical variations in scene object in the digital images (Verma, Sharma, & Kumar, 2012).

An edge can be 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. Apart from this, image edge detection is the process of detecting and extracting edges from digital images to retrieve important details of image analysis. Therefore, detecting edges plays a crucial role in many applications in the field of image processing and computer vision. Indeed, edge detection is very important operation in image analysis applications such as image registration, scene’s object identification and image segmentation (Lu & Chen, 2008).

The principle of edge detection process involves four primary interrelated steps which are filtering, enhancement, detection and localization (Ramadevi, Sridevi, Poornima, & Kalyani, 2010). Filtering is essential pre-processing operation that is used to suppress or reduce noises in an image. Noise removal is intended to remove noises while maintaining the true edges of an image which improve the performance of edge detector with respect to noise (Poornima, Ramadevi, & Sridevi, 2011). Digital images are often corrupted by various noises which refer to the variations in the intensity of an image. Undoubtedly, the amount of noise in an image reduce the precision of edge detection operation.
Despite the importance of filtering process, selecting the appropriate filters is crucial criterion in image processing field. Indeed, filtering may affect the strength and degrade the contents of the edges in an image. Thus, the major concern in edge detection filed lies in the scale of the filters. For instance, the large-scaled filters provide robust noise removal but they may filter fine details of an image. Meanwhile, the small-scaled filters are not robust as they are susceptible to edge signals in an image. Hence, depending on the type of filter specific edge features are filtered in the images.

In fact, in order to facilitate accurate edge detection, it is essential to determine changes in intensity in the neighbourhood of a point. 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 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 (Rajeswari & Rajesh, 2011).

Besides filtering and enhancement processes, binarization is a crucial operation in edge detection process. It is the process used to convert the grey scale images into a black and white images which can be archived by the local of global thresholding (Verma et al., 2012). The importance of binarization arise from its crucial role to decrease the computational process of grey level image information in order to facilitate detection of edges in an image. Nonetheless, the localization process determines the true locations of an edge in digital images which often is required for some applications.

Despite the existence of various edge detection algorithms, edge detection remains one of the most challenging field in image processing. The major challenge in image edge detection is finding true edges. Edge detection is essential operation in image processing process because it involves filtering, enhancement, detection and localization operations. In fact, finding the optimal boundaries of an image in order to obtain specific information and features such as detecting leukaemia blood cells in the blood is a challenging criterion in medical image processing. Undoubtedly, the implementation of the conventional edge detection methods is not sufficient to extract the patterns of leukaemia cells from blood images.

Indeed, to mark up the true edges of leukaemia cells is phenomenon task in image processing. This is due to the complexity of recognizing the sharp intensity changes of the cancerous leukaemia cells with the blood cells especially at the early stages. In fact, employing the appropriate edge detection filters to extract the relevant information from the images while sustaining the essential attributes of the image is critical task in image processing. This is because distinct edges (boundaries) in medical images may not exist and are extremely difficult to be detected due to the similarity between the blood cells and the presence of noises. Moreover, due to the partial volume effects caused by the imaging device’s resolution, the boundaries of an image may be ambiguous and blurred. These obstacles make the segmentations of neighbouring structures in medical images as challenging tasks.

Apart from this, leukaemia is a cancerous disease of white blood cells that causes the infected immature white blood cells to increase uncontrollably. This process leads to the destruction of the immune system and death. More importantly, the current procedure for detecting leukaemia in the blood cells involves taking a sample of the blood and examining it by haematologists. However, this procedure is prone to human judgements and errors, time consuming and tedious and is incapable of detection immature leukaemia cells at early stages. Therefore, in spite of numerous proposed algorithms, more improvement and research is needed in this field.

The main objectives of this study are: (i) To detect the edges of leukaemia through the use of filtering, sorting process, kernel multiphase convolution, binarization and transformation techniques, (ii) To employ the gradient edge detection methods namely Sobel, Prewitt and Robert to recognize the pattern of the detected leukaemia cells in the white blood image, (iii) To utilize Ant Colony Optimization (ACO) algorithm to detect, extract and recognize the edge boundaries of the leukaemia cells from the white blood cell image, (iv) To compare the performance of the gradient edge detection methods (Sobel, Prewitt and Robert) with the ACO method to determine the optimal edge detection method which produced the optimal edges of the leukaemia cells, and (v) To describe the features of white and red blood cells based the detected edges through the visual comparison.

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 blood. In this regard, edge detection operation serves to reduce the analysis of medical image (white blood cells) by drastically simplifying the amount of data to be processed, while at the same time maintaining meaningful structural information about object (leukaemia) boundaries.

In the present study, various edge detection techniques including: Ant Colony Optimization algorithm, Sobel, Prewitt, Roberts are employed to extract the edges of leukaemia cancerous cells from blood image. Toward this end, the acquired blood cells are first pre-processed to suppress noises, to sharpen and to smoothen the white blood cells image. In this case, noise removal is carried out using linear (mean) filter. Mean filter is capable of removing noises while preserving important details of an image

The next stage involves sorting the leukaemia cells from the normal blood cells using the kernel single and multi-phases background elimination process. Furthermore, the binarization process is carried out to convert the leukaemia pixels into a binary image. The binary images are digital images which have only two possible values for each pixel which are black and
white colours. The colour used for the leukaemia in the image is the foreground colour while the rest of the image is the background colour. In order to capture the true edge colour image of the Leukaemia cells, the extracted leukaemia cell pixels are transformed to the original image using the transformation process.

The specific scope of this study is to detect, filter and extract the edge features of leukaemia cancerous cells in blood image. The leukaemia cancerous cells are a type of digital RGB images. Meanwhile, this study is limited to the coloured blood images of Red Blue Green (RGB) plane. It is not applicable for grey scale images.

Study Background

Edge detection is a crucial operation in image processing which aims to identify and locate edge points in an image. Digital image is an array of small integer numbers knowing as pixels. The pixels are the basic elements or units of the colours on an image which signifies the resolution of images. The importance of edge detection comes from its significant role at searching and extracting the true edges to provide useful information for further image analysis (Yeganeh et al., 2015). Over the past decades, medical image processing has become an essential method to interpret and visualize 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 (Mahaja, Golait, Meshram, & Jichlkan, 2014). Apart from this, 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 bloodstreams (Chin Neoh et al., 2015).

In the context of medical diagnosis, the existence of the leukaemia is identified when the blood samples are taken and examined by haematologists. Blood is the primary source of information which gives an indication of the sudden changes pertaining to leukaemia cells. These changes are detected based on the appearance or the number of the blood elements which indicate abnormal conditions (Reta et al., 2015). Image edge detection methods detect the leukaemia by producing a line drawing on the image, which highlights the sharp changes or discontinuities of the intensity (boundaries of the leukaemia) in the blood images. To exemplify, the boundaries of an object in an image refers to the sudden changes in the image intensity, for instance, different objects are usually different colours or hues which causes the image intensity to change while moving from one object to another in an image. In addition, different surfaces of an object receive different amounts of light, which again produces intensity changes (Poornima et al., 2011).

Furthermore, tracking and detecting diseases such as brain tumour, anatomical or structural tissues and blood diseases are active research topics in medical image processing (Chalana & Kim, 1997; X.-H. Han & Chen, 2011; X. H. Han & Chen, 2011). 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 artifacts. 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 recognized.

Edge Detection

Edge detection plays a significant role in various applications in image processing, object recognition and machine vision. The term edge detection is defined as the process used to identify and locate the sharp discontinuities in digital images such as the photometrical images, physical and geometrical segments or regions. The goal of edge detection is to recognize the existence of edges or boundaries in an image through localizing the pixels that indicates the sudden changes or discontinuities in the intensity of an image. It provides means of investigating and localizing the desired edge features to obtain meaningful information in the analysis of an image. Edges are a set of connected pixels that lie on the boundaries between an overlapping object and the background of the image (Babatunde, Folorunso, & Akinwale, 2010; Lei, Fan, & Wang, 2014; Maini & Aggarwal, 2009; Warade, Kale, & Thakare, 2015).

Edge detection works by drastically decreasing the amount of data to be processed while at the same time maintaining the structural meaningful information and properties for further analysis and image processing. For instance, in a grey level images, the edges are the local features with a neighbourhood separated regions in which each edge’s pixel is less uniform than other pixels on an image. Generally, image edge detection efficiency depends on the type of detection method and the amount of noise exist in an image. For example, in a noisy image, the process of detecting edges is difficult because both noise and edge contain high frequency contents which lead to indistinct and distorted results. In recent years, multiple edge detectors have been suggested to detect and extract edges in an image to obtain features for further image processing. The conventional edge detection methods are classified into two major categories: gradient and Laplacian methods as shown in Figure 2.1. The gradient methods include Canny, Log, Roberts, Prewitt and Sobel edge detectors (Canny, 1986; Maini & Sohal,
2006; Marr & Hildreth, 1980). These edge detectors work by finding the maximum and minimum gradient in the first derivative of an image. Alternatively, the Laplacian technique identifies edges through the search for the zero-crossings in the second derivatives of an image.

Since the conventional edge detection approaches are susceptible to noise and usually imply a huge space to search for edges in an image, alternative algorithms have been developed such as neuro-fuzzy, zero-frequency resonator and optimization algorithms such as Ant Colony Optimization algorithms and genetic algorithms (Fan et al., 2007; Sao & Yegnanarayana, 2012; Verma, Hanmandlu, Kumar, Chhabra, & Jindal, 2011; Yüksel, 2007). In fact, it is imperative to use the suitable edge detection method depending on the type of image. Because employing inappropriate edge detection method would blur edges while removing noises in the image and could sacrifice the location accuracy of the detected edges to a certain extent (Qiu, 2007). According to Neoh and Hazanchuk (2004), edge detection operators works by determining the variance levels between different pixels by a matrix gradient operations. This operation is calculated through the formation of a centred matrix on a chosen pixel in an image. The middle pixel in the formed matrix is categorized as an edge when the value of the matrix is above the given threshold. Meanwhile, (Ari, Ghosh and Mohanty (2014) defined edge detection as the operation of detecting edges in an image where there are sharp discontinuities or changes in the boundary of an image. The extracted edge points provide an insights into the significant details required in machine vision and image analysis (X. H. Han & Chen, 2011; Rajeswari & Rajesh, 2011).

Apart from this, Verma and Sharma (2011) defined edge detection as a pre-processing stage for object recognition and features extraction. This definition suggested that edge detection is very useful in various applications in image processing and machine vision such as image classification, pattern and shape recognition, object identifications and detecting abnormal cancerous cells such as tumours, identifying defects in mechanical parts and 3D-reconstruction (Laligant, Truchetet, Miteran, & Gorria, 2005; Sun, Hou, Tan, & Li, 2014; Sun, Hou, Tan, Li, & Liu, 2014).

**Ant Colony Optimization**

Ant colony optimization (ACO) is a heuristic optimization algorithm that is inspired by the natural foraging behaviour of ant species to solve (Dorigo & Stuzle, 2004; Kirana, Ariffin, Khotimah, & Engineering, 2014; Lu & Chen, 2008). The first ACO approach, known as Ant System, was developed by Dorigo, Maniezzo and Coloni (Dorigo, Maniezzo, & Colorni, 1996). Since then, several ACO approaches have been developed such as Max-Min Ant System and Ant Colony System (Dorigo & Bimttari, 2006; Dorigo & Gambardella, 1997). Over the last decade, ACO has been utilized extensively to solve a wide variety of optimization problems particularly edge detection operation. In fact, ACO has won the interest of various researchers and was reported as an optimal edge detection algorithm in various studies such as (Ari et al., 2014; A. V. C. Baterina & Oppus, 2010; Benhamza, Merabti, & Seridi, 2013; Etemad & White, 2011; Gupta & Gupta, 2013; Jevti, Quintanilla-dominguez, Cortina-Januchs, & Andina, 2009; Lu & Chen, 2008; Nezamabadi-Pour, Saryazdi, & Rashedi, 2006; Tian, Yu, & Xie, 2008; Zhuang, 2004).

ACO-based approaches overcome the shortcomings of the conventional methods through the use of the inherent capability of parallelization. For detecting edges, the dispatch of ants on an image, establish a pheromone matrix which represent the edge information at each pixel on an image. In this scenario, the movements of ants over an image are caused by the local variations of the image intensity values. In ACO algorithm, the ants use the pheromones to move in an intelligent way from a destination to a food source in their colony (Benhamza et al., 2013). Figure 1 depicts the movement of ants from a their colony to a food source destination as reported in (Dorigo & Stuzle, 2004). In the context of image edge detection, ACO construct a solution using artificial ants which move from one state to a destination using local communication that is performed by movement to neighbour pixel. More specifically, with the help of a decision policy, ants aim to construct solution from the starting node. At the starting point, all nodes are initialized to a constant amount of pheromone. At every node, ants collect the local important information about that node including sensing the information on the outgoing arc and decision is made in a stochastic way. To illustrate this procedure, Figure 2 represents the movements of the ant while going from node i to nodes j,k and I with pheromone and heuristic information \( \tau, \eta \).

In addition, through the decision policy of ACO algorithm, the artificial ants seek to repeatedly change nodes until they actually reach the destination node. In this case, the time required for ants to reach the destination node usually varies from ant to ant depending on the decision policy or solution of the ACO algorithm. As soon as the ants reach the destination node, they tend to travel back by switching to the backward mode to eventually retraces the same path travelled in the forward mode to determine the shortest path. The shortest path usually is identified by the evaporation of the pheromones in which the shortest path indicates thicker pheromone and slow evaporation mode. In fact, pheromone trail evaporation is useful for the exploration mechanism which prevents the convergence of the algorithm towards a sub-optimal solution. Overall, the combination of the deposited pheromones, pheromones evaporation and ant’s movement as a complete cycle of ACO. Furthermore, in ACO based edge detection, the information heuristic is obtained by the local variations in the image intensity values which is less sensitive to detect the edges even in the presence of noise or in smooth edges. The edge detected in this case are indicated by the trapped ants in a local boundary in an image (Dorigo & Stuzle, 2004).
Singh and Vidyarthi (2013) proposed an enhanced ACO algorithm based on image edge detection method. In this study, the detection is basically done as per the natural phenomenon of the movement of ants for searching paths. And the edge boundaries are improved with respect to the visual impact of the images through the use of sharpening filters. This has facilitated the ACO based edge detection to successfully identify the important edges in the image. The proposed modified approach yields superior performance with suitable parameters. At the end, the study pointed out that future researches should focus on reducing the computational time and calculating the heuristic information. Figure 3 depicts the results of the proposed method in this study.

Reza-Alikhani, Naghsh, and Jalali-Varnamkhasti (2013) presented ACO-based edge detection approach, Fuzzy Inference System (FIS) and neural networks. The proposed algorithm uses ACO to assign a higher pheromone value for the probable edge pixels rather than other pixels so that ants movement toward edge pixels becomes faster. Another factor which influence the movement of ants is the heuristic information which was made proportional to the local change in the intensity of each pixel. Fuzzy system was used to detect the edges in four directions and to direct the movement of ants in ACO toward edges. Finally, the edges are extracted from the final pheromone matrix using the intelligent thresholding techniques. The results showed that the presented approach is capable of extracting high quality edges. Figure 4 shows the results of the proposed ACO based edge detection.
Gradient Edge Detectors

The gradient detectors refer to the process of detecting edges through the close observation of the minimum and maximum first derivatives of the pixels in an image. The important gradient edge detectors include Robert, Prewitt and Sobel which are known as the first order derivative edge detection methods. To illustrate the gradient methods, assume that $I(i, j)$ is the input image, then the gradient of the image is computed by Equation 1.

$$\nabla I(i, j) = l \frac{\partial I(i, j)}{\partial i} + l \frac{\partial I(i, j)}{\partial j}$$

(1)

Where, $\frac{\partial I(i, j)}{\partial i}$ is the gradient in the $i$ direction and $\frac{\partial I(i, j)}{\partial j}$ is the gradient in the $j$ direction.

In addition, the gradient magnitude can be computed by the following formula (Equation 2)

$$|G| = \sqrt{\left(\frac{\partial I}{\partial i}\right)^2 + \left(\frac{\partial I}{\partial j}\right)^2}$$

Similar to: $|G| = \sqrt{G_x^2 + G_y^2}$

(2)

Another equation to compute the gradient magnitude is $\theta = \arctan(G_y / G_x)$.

The aforementioned equations give the edges their strengths (magnitudes). Meanwhile the gradient direction is always perpendicular to the direction of edge. The following subsections illustrates the types of gradient edge detection methods which are employed in the present study.

Roberts Cross Operator

Robert operators are discrete differentiation edge detection methods which are used to compute an approximate gradient of an image through the sum of the squares in the adjacent pixels. The input images are convolved with the default operator kernels and then the direction and the gradient magnitude are computed.

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Figure 5: Two typical Roberts Cross Filters

Robert operator performs quick and simple computation of the spatial gradient on an image. It basically emphasizes regions of high spatial frequency which often correspond to edge boundaries in an image. The most common usage of this method is to input a greyscale image and output a binary image. Furthermore, this operator was 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 5. According to Equation (2.3) the $G_x$ represents the horizontal direction and $G_y$ is the vertical direction. In this case, the $G_x$ image yields diagonals that run from the top-left to the bottom-right of the matrix while the $G_y$ image yields diagonals that run from the top-right to the bottom-left. The gradient components in each dimension of $G_x$ and $G_y$ are measured separately by applying the masks separately to the image. Then the combination of the
two individual images $G_x$ and $G_y$ are used to find the total magnitude of the gradient at each point. The absolute magnitude of the gradient and the oriented angle of the edge that associates to the spatial gradient are calculated using Equation 3 and Equation 4 respectively.

$$|G| = |G_x| + |G_y|$$  \hspace{1cm} (3)  

$$\theta = \arctan \left( \frac{G_y}{G_x} \right) - 3\pi/4$$  \hspace{1cm} (4)

Since there are only four input pixels needed to compute the value of the output pixel, the calculation of the Robert operator is fast and limited to those of addition and subtraction. However, as Roberts Cross kernels are relatively small, it is very sensitive to the noise and is only good for images that have very sharp edges.

**Sobel Edge Detector**

Sobel operators are discrete differentiation operators used to compute an approximation of the gradient of image intensity function for edge detection. It was first introduced by Sobel in 1970 for segmenting images and edge detection through the use of the Sobel approximation to the derivative. 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. This procedure is used to determine the absolute estimated gradient magnitude of each point in an input grey scale images.

Sobel's algorithm is similar to Roberts's algorithm where both methods have the same basis of examining the two axes edges individually and then combine them for the resulting edge detection. For example, Roberts Cross kernels are used to find the edges that run along the vertical axis of 45 degrees and axis of 135 degrees, whereas Sobel's kernel tries to detect edges along the horizontal axis and vertical axis. However, Sobel operator has slower computation ability than Robert's operator but it has a large kernel which makes it less sensitive to noise as compared to Robert operator. Thus, Sobel operator has larger mask and thus errors due to effects of noise are reduced by local averaging within the neighbourhood of the mask in an image.

It convolves the input image with 3x3 two matrix as shown in Figure 6 and computes the gradient magnitude and direction (angle of orientation) using Equation 3 and Equation 5 respectively.

$$\theta = \arctan \left( \frac{G_y}{G_x} \right)$$  \hspace{1cm} (5)

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**Figure 6: Two typical Sobel Filters**

**Prewitt Operator**

Prewitt operators are discrete differentiation operators which used to compute the approximation gradient of the image intensity function. Prewitt edge detector was developed by Judith M.S Prewitt and is based on the convolution of the image with a small, separable and integer valued filter in the vertical and horizontal directions. Basically, this operator is similar to the Sobel operator in terms of detecting horizontal and vertical edges in an image. In Prewitt, the calculated edge is based on the difference between the corresponding pixel intensities of the image. More specifically, this operator calculates the gradient of the intensity of an image at each point and give the direction and the rate to the largest possible increase from light to dark on an image. The derivative that utilized in this edge detection method is shown in Figure 7. Prewitt edge operators give better performance than that of Sobel operators.

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Horizontal mask
As mentioned earlier in this chapter, leukaemia is a type of blood cancer occurs in white blood cells (WBCs) which disrupts the balance of the WBCs in the blood stream. 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 imitation of similar signs and the complex nature of blood images (Mohapatra, Patra, & Satpathy, 2011). The acute leukaemia classification and segmentation methods are based on four primary groups including boundary, threshold, region and hybrid. Most of the techniques combines boundary and region criteria (S. Agaian, Madhukar, & Chronopoulos, 2014; S. S. Agaian, Panetta, Nercessian, & Danahy, 2010; Mohapatra & Patra, 2010; Mohapatra, Patra, & Satpathi, 2011; Mohapatra, Patra, & Satpathi, 2011; Mohapatra, Samanta, Patra, & Satpathi, 2011; Pedreira, Macrini, Land, & Costa, 2009; Reta, Robles, Gonzalez, Diaz, & Guichard, 2010; Shitong, Chung, & Duan, 2007).

Besides the time consuming and tedious diagnostic procedure, microscopic cell images are prone to errors because of the complexity pertaining to the nature of the blood cells. Thus, this type of procedure to identify the immature leukaemia cells in the bloodstream is not sufficient. In fact, the premature and hasty identification of the leukaemia cells, can lead to proper treatment. A typical blood microscope image is plotted in Figure 8.

Over the years, various medical image processing methods have been developed such as threshold based methods, contour based methods, image segmentation and edge detections. While the Ostu and histogram segment the white blood cells through the use of image intensity level, the contour method identifies the sharp boundaries of the white blood cells through the segmentation and filtering operations. Despite the existence of various methods to analysis blood cell images, edge detection technique provides useful information regarding the presence of leukaemia cells in blood images (Anoraganingrum, 1999).

In the following paragraphs, some of the empirical researches on blood cells which involve identifications and tracking of the movements of specific cells or inject substance are presented. Despite the large literature on image processing, the focus of this study is to review the relative studies on medical image edge detection, blood image segmentations, and identifications.

Wu, Berba and Gil (2000) presented an iterative thresholding algorithm for segmentation purpose specially from noisy images. The proposed algorithm overcomes the segmentation and extraction problems from heavy noisy cell images. In addition, it works over the adjusted threshold of an image iteratively providing robustness to image thresholding and detection. Starck, Candès and Donoho (2002) presented an explicit mathematical model for characterizing the cell nuclei shapes and sizes. They also proposed noise removal based wavelet filter combining the enhance and geometric distances and the intensity gradient. The proposed method showed the usefulness of localizing the acute leukaemia cells from the other blood cells.

Nee, Mashor and Hassan (2012) proposed gradient based watershed transform segmentation method to separate the blast cells from the background. In this method, the Red Green Blue (RGB) image is converted into Hue-Saturation Value (HSV) colour model and saturated component is extracted for further processing to find the gradient magnitude of the saturated component. This method is used for edge detection and extracting the white cells from the blood image, eliminating of the background and red cells and dilation or erosion. The results showed that, leukemic cells can be identified and this method gives very accurate results. In another study conducted by Chatap and Shibu (2014) a segmentation method for counting white blood cells was presented. The first step involved a simple thresholding approach is applied on blood images. The proposed approach uses the knowledge of the blood cell structure. The experimental results showed that, the presented method is more influential as compared to traditional methods which uses information of local context. Furthermore, it can perform accurate segmentation of white blood cells though the un-sharp boundaries.

Dhingra and Kaur (2014) developed watershed algorithm to detect white blood cells in the blood sample images. The initial step involved extracting the leukaemia cells from the blood sample images. Next the authors calculated the number of number of cells in the blood sample image to determine the

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**Vertical mask**

**Figure 7:** Two typical Prewitt Filters

**Edge Detection of Leukaemia White Blood Cells**

![Blood cell (Mahaja et al., 2014)](image)

**Figure 8:** Blood cell (Mahaja et al., 2014)
average parameters such as area, perimeter and radius of the blood cells. The next step includes calculating the compactness and time of the code execution. The experiments and simulation were conducted over a number of images. Moreover, authors employed segmentation methods including k-means clustering, hough transform to find the abnormal white blood cells which indicates leukaemia presences in the sample blood image. Alomari, Sheikh Abdullah, Zaharatul Azma and Omar (2014) proposed a method based on an iterative detection algorithms for segmenting and counting of white blood cells and red blood cells. The separation process was carried out by thresholding and pre-processing of each cell type. Meanwhile, the counting process was performed using the modified circle detection method which uses automatic counting procedure. The authors aim to detect irregular cells and to select the optimal cell from the detected circles. In addition, they intend to enhance the algorithm detection, to determine the number of iteration in a dynamic way and to improve running time. Laster they employ a quantitative such as Precision, F-measurement and Recall tests analysis methods to validate the accuracy of the proposed technique. The average accuracies of the proposed approach were 95.3% for RBCs and 98.4% for WBCs.

Suryani, Wiharto and Polvonov (2014) proposed fuzzy rule system based on the morphology of white blood cells to detect and identify the acute leukaemia (lymphocytic and myeloid leukaemia type M3). First, gradient edge detectors including thresholding, canny and colour identification methods were employed to detect and extract the leukaemia from blood image. The next step involved identifying the leukaemia from healthy blood cells using the fuzzy rule based system with Sugeno method. Experimental results showed 83.65% accuracy of the proposed method to detect leukaemia in the blood images. Figure 2.10 depicts the original blood image with the leukaemia identified image. Another study conducted by Viswanathan (2015) introduced a new approach to detect leukaemia. The proposed approach comprises of (1) contrasting enhancements to highlight the nuclei, (2) segmenting morphological contour and (3) detection of leukaemia using fuzzy c means. The enhancement and contrast were carried out by simple addition and subtraction operations. The segmentation concerned about segmenting normal white blood cells and detecting the edges of the nuclei cells. The final step involved using fuzzy c means to classify the detected leukaemia from the normal white blood cells. The results of the proposed approach indicated excellent results regarding detecting of leukaemia blood cells. It outperforms the visual diagnostic procedure by haematologists. Furthermore, it identified the leukaemia cells from the whole slide blood image and provided accurate detection of abnormal and normal white blood cells with less computation time and error rates. The result of the proposed method with respect to the original blood image is displayed in Figure 9.

Another study by Vaghela, Modi, Pandya and Potdar (2015) discussed various useful methods for detecting the edges of leukaemia in the blood cells. The purpose of the study is to detect and count the cancerous cells in the blood. The authors compared the performance of various edge detection methods such as histogram equalization, linear contrast stretching and morphological techniques like area closing and area opening. The results indicate that such methods produce nearly accurate edge detection of leukaemia cells. Figure 10 depicts the result of the proposed method in this study.
images. The proposed approach comprises of three stages which are pre-processing, segmentation, and post-processing. While the pre-processing stage concerns about colour correction and enhancement of the image, the segmentation and post-processing stages concern about employing Ostu threshold and watershed to extract image features and noise removal respectively. The test results showed an accuracy of 99.3% for both watershed and Ostu threshold techniques for segmenting white blood cells.

METHODOLOGY

The methodology of this study concerns about detecting the edges of leukaemia in the white blood cell image. Toward this end, the acquired white blood cell image is pre-processed to suppress the noise and to smoothen the images for further analysis. The next step involves binarizing the blood to detect the existence of the leukaemia cells. Besides that, the edge detection methods such as Ant Colony Optimization (ACO) algorithm, Sobel, Prewitt and Robert gradient edge detection methods are utilized to extract the patterns of the leukaemia cells from blood image. This section comprises of introduction, methodology flowchart, image acquisition, pre-processing and edge detection methods. The pre-processing includes filtering operation to remove noise, binarization, image segmentation which composed of multi-phases kernel filtering (convolution) and transformation. The edge detection methods include Sobel, Prewitt, Robert and ACO.

Figure 11 depicts the methodology flowchart of this study. At start, the white blood cell is acquired as digital images. Then the acquired blood images are pre-processed to remove the artificats and to smoothen the images for further analysis. In this stage, the linear (mean) filter is employed to suppress the noise because it offers substantial features for removing noises while not affecting the contents of an image. The next stage involves binarization of the blood images to allow useful detection of the existence of the leukaemia cells. Besides that, the edge detection methods including Sobel, Prewitt, Robert and Ant Colony Optimization (ACO) algorithm are utilized to detect and recognize the patterns of the leukaemia in white blood cells image.
Image acquisition

The white blood images are acquired as a digital images of blood samples in either jpeg format. These images are in Red Green Blue (RGB) colour plane. The white blood cell images are acquired from Universiti Sains Malaysia hospital through the use of digital camera which was placed on the eye of the microscope. Throughout the process of image acquisition, the purpose was to acquire less noisy image by restricting the movements of the digital camera or the microscope as well as
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.

Pre-processing

Image pre-processing is vital operation in image processing. It is the initial process and it is useful for extracting the useful features accurately while suppressing the unnecessary ones. The captured blood images are usually affected by various noises such as noise due to movement of camera or respective patient in the time of image acquisition and unfavourable lighting condition. The acquired white blood cell images are pre-processed to suppress noises and to improve the quality of the image to make them suitable for the next step in image processing and analysis. Image pre-processing usually includes removing noise, contrast enhancing, sorting and isolating regions and use of different colour models grayscale image and image binarization. Image pre-processing is an essential stage to ensure the processed images contain the important information and details for further image analysis. Image denoising and enhancement are two crucial criteria of pre-processing operation. Despite the fact that noise removal is difficult process since it may affect the useful contents in the image. There are various types of filters in medical image processing however, mean filters are efficient noise removal and smoothing tools. 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.

Linear Filter (Mean Filter)

During the blood image acquisitions, images are usually corrupted by more than one noise such as salt and pepper noises in which the noisy pixels are denoted by the maximum and minimum grey values. The maximum value is 255 and the minimum value is 0. In addition, other noises include the movement of respective camera or microscope and due the effects of lightening conditions. Mean filter is one of the most important and common noise removal methods in image pre-processing. It basically involves suppressing the unnecessary information in an image which indicate artificats. The linear filters can remove certain types of noises and variations in the digital image. The application of mean filters is useful for eliminating the noises in the images.

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 in a considerable manner by substituting it with an average value. Figure 12 depicts the 3x3 matrix linear (mean) filter employed in this study.

Kernel Filtering

An image kernel is a small matrix used to apply effects to the filtered blood image, such as image smoothing, image sharpening, intensify and image enhancement. This pre-processing is sometimes called image convolution operation and is carried out to determine the most important portions of the blood image. It is a vital tool which modify specific portions that signify the existence of leukaemia cells. More specifically, the convolution kernel filtering is used to modify the spatial frequency characteristics of the white blood cell image which is comprised of integers (small matrix) and it works by determining the value of a central pixel by adding the weighted values of all neighbours together. In addition, different sized kernels usually contain different patterns and thus produce different results. In this study 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. The size of a kernel is arbitrary but 3x3 is often used as shown in Figure 13.
Binarization

Binarization is crucial image pre-processing operation that is employed to convert digital images into binary images. It involves separating the image into background and foreground and then assigning pixel to either background or foreground objects by comparing their intensities to predefined threshold. There are two ways to define or select the threshold which are local of global. As for the global threshold, the pixels below the threshold are set to black and those over the threshold are set to white. The global threshold can be selected through experimental calculations. 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 as shown in Figure 14. The maximum value is 255 and the minimum value is 0.

Image Transformation

Image transformation is vital pre-processing operation which aims at transforming the filtered white blood cell to describe the original image (output image). More specifically, the process of filtering, binarization and kernel convolution to produce an output image is called transformation process. It is the process that assist at determining the true colours of the cells which signify the existence of leukaemia in the blood image.

Gradient Edge Detection Methods

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. Figure 15 depicts the flowchart of the gradient edge detection methods. At 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 localizing the step edges. The following subsections elaborate the implementation of these methods to detect the leukaemia cancerous cells in the blood image.

Figure 14: Image binarization process
**Ant Colony Optimization (ACO)**

ACO is a very effective approach to optimize and detect edge boundaries in digital images. It is an operation that aims to identify points in the white blood image where sudden changes or discontinuities in the image’s intensity occur. These discontinuities signify the presence of the leukaemia cells in the blood image. It works by dispatching ants over the white blood cell image. In this case, ants move based on the heuristic information on 2-dimensional images from one pixel to another. The procedure of ACO-based edge detection is composed of four interrelated steps which are initialization, construction, updating, and decision phases which are elaborated in sections below and represented in details in Figure 16.

---

**Figure 15**: Flowchart of the gradient edge detectors

1. **Start**
2. Reading image, pre-processing and filtering
3. Choosing operator’s gradient mask in (i) axis to convolve the resultant filtered image
4. Choosing operator’s gradient mask in (j) axis to convolve the resultant filtered image
5. Setting a threshold values, T.
6. For a pixel M (I,j).
   - Is G>T?
     - Yes: Mark pixel as an “edge”
     - No: Consider next pixel
7. **End**
Figure 16: ACO-edge detection procedure

i. Initialization phase

The initialization phase of ACO works by taking an input image as a solution space and dispatching ants over it. In this study, the white blood cell image $I$ of dimensions $M_1 \times M_2$ is considered as an input image and is assumed as a solution space for the ants. Considering $K$ as the number of ants that will move over the whole blood cell image ($I$) whereby each pixel of the this image is covered with an ant. The next step includes establishing the dimension of the pheromone matrix $\tau^{(0)}$ which must be similar to the taken white blood image dimension ($M_1 \times M_2$). This matrix is then initialized by a
small constant value $\tau_{init}$ ($\tau_{init} = 0.0001$). The reason behind selecting the initial value as small as possible is to avoid the stagnation of the movements of ant. The next initialization stage involves calculating the heuristic matrix information $(n_{i,j})$, at regions $(i,j)$ using Equation 6.

$$n_{i,j} = \frac{V_c(I_{i,j})}{Z}$$

(6)

where, $Z$ denotes the normalization factor and $V_c(I_{i,j})$ denotes the function of local group of pixels at $c$ that is called clique.

**ii. Construction phase**

This step involves with the movements of ants on two-dimensional image based on the pheromone trail and the heuristic information. Ants construct the pheromone matrix through their movements from one pixel to another based on the local variations or changes in an image. Figure 17 shows the movements of ants from the source node to destination node. This movement helps at construing the solutions by determining the optimal shortest path. During this process ants deposit some pheromone content over every path they moved on. If the ants deposited $\Delta \tau$ of pheromones, then the ants move from node $i$ to $j$ the time $t$ of the movement is computed by Equation 7:

$$\tau_{ij}(t) \leftarrow \tau_{ij}(t) + \Delta \tau$$

(7)

![Figure 17: Ants building path from sources to destination](image)

Ants construct the pheromone matrix of the leukaemia cells based on the local variations in the white blood cell image intensity values. The probabilistic transition rule that is used by the ants when constructing the pheromone matrix is calculated using Equation 8.

$$P^{(n)}_{ij} = \frac{(\tau_{ij}^{(n-1)})^\beta(n_{ij})^\alpha}{\sum_j \Omega_j (\tau_{ij}^{(n-1)})^\beta(n_{ij})^\alpha}, \text{ if } j \in \Omega$$

(8)

Where $\tau_{ij}^{(n-1)}$ is the pheromone matrix value at pixel $(i,j)$ within $n^{th}$ constructions step, $\Omega_{i,m}$ is the neighbourhood of pixel $(i,m)$ and $n_{ij}$ signifies the heuristic matrix value at pixel $(i,j)$. The $\beta$ and $\alpha$ influence the heuristic matrix and pheromone matrix respectively. In addition, the $(i,j)$ refers to the pixel location in the 8 neighbourhoods as indicated by Figure 18. In this case, the ant at location $(i,j)$ can move in any of the 8 directions (N, NE, NW, E, W, SW, SE and S).

![Figure 18: 8-connectivity neighbourhood of pixel $(i,j)$](image)

**i. Update phase**

This step involves updating the pheromone matrix which includes two updates. The first update is usually conducted by one ant and it is called offline update and is calculated by Equation 10. The second update is carried out by all ants and it is called the local update which is calculated by Equation 9. It is usually conducted after each construction step which aims to broaden the search for the ants with subsequent path. second update (local update) is carried out by all the ants after each construction step is achieved. This allows the subsequent to provide the necessary solution and makes the repetition lesser in the same iteration.

$$\tau_{ij}^{(n)} = (1-\varphi)\tau_{ij}^{(n)} + \varphi \tau_{ij}^{(0)}$$

(9)

Where $\tau_{ij}^{(n)}$ is the value of pheromone at edge $(i,j)$ upon completing the $n^{th}$ construction step of all ants, $\varphi \in (0,1)$ represent the decay coefficient of the pheromone and $\tau_{ij}^{(0)}$ is the pheromone’s initial value.

$$\tau_{ij}^{(n)} = \begin{cases} (1-\rho)\tau_{ij}^{(n-1)} + \rho \Delta \tau_j^{(k)} & \text{belongs to the best tour;} \\ \tau_{ij}^{(n-1)} & \text{else} \end{cases}$$

(10)
Where \( \rho \) is the rate of pheromone evaporation and \( \Delta_{ij}^{(k)} \) is the amount of pheromone laid on edge \((i, j)\) by \( k \)th ant. Pheromone evaporation causes ants to search for some new paths and offers a chance of discovering a new shorter path in the unexplored area which is called as the exploration path. The exploration path helps at avoiding the system a quick convergence towards the suboptimal path.

ii. Decision phase

In this phase, the threshold is calculated and applied on the last pheromone matrix to clarify each pixel either as an edge or a non-edge. Practically, the ants are made to deposit additional pheromones on best solution pheromone matrix which is determined by the threshold values.

RESULT AND DISCUSSION

The pre-processing results include the linear filter results, kernel filtering, binarization and image transformation results for the original image (Figure 19). The results of the pre-processing are essential for further image analysis and edge detection of leukaemia using the gradient edge detectors. In addition, filtering operation was carried out to denoise the original blood cell image using mean filter. The pre-processing process was carried out carefully because the necessary details of leukaemia edges might be filtered. Thus, the mean filter was employed to suppress noises and smoothen the white blood cell image. The following subsections demonstrate the results of the pre-processing and sorting operations. The results of the linear filter of the white blood cell are displayed in Figures 20. By comparing the original and filtered white blood cell image, it can be clearly observed that the obtained blood cell image through the use of linear filter reveals clearer and smoother image. This is can be argued to the efficient and suitability of using mean filter to suppress and to smooth the white blood cell image.

![Figure 19: Original blood cell and the brightness distribution](image-url)

![Figure 20: The filtered blood image brightness distribution](image-url)

Kernel Filter

The result of kernel filtering is divided into two parts which are kernel 1\(^{st}\) phase and kernel 2\(^{nd}\) phase results. The results of the kernel 1\(^{st}\) phase for the filtered blood cell image are presented in Figure 21. Meanwhile, Figure 22 demonstrates the results of the 2\(^{nd}\) phase kernel filtering for the filtered blood cell image.
It can be observed that there is substantial difference between kernel 1st phase and the 2nd kernel filtering operations. The 1st kernel phase results include both leukaemia cells and the red blood cells. In addition, it can be clearly observed that the 2nd kernel phase present better boundaries of the leukaemia cells in the blood cell image. Apart from this, the results of the 2nd kernel filtering indicated red pixels which is due to the effects of the kernel filtering.

**Figure 21**: The results of the kernel (1st phase) filter for the blood cell image

**Figure 22**: The results of the kernel (2nd phase) filter for blood image

**Binarization Results**

The results of the binarization operation for the 1st kernel phase and 2nd phase of the blood cell are presented in Figures 23 and 24 respectively. The binarization result of 2nd kernel phase shows clearly the leukaemia in the white blood cells. As for the binarization results of kernel filtering 1st phase, both the white blood cells and the leukaemia cells are shown without any indications regarding the edges of the leukaemia cells.

**Figure 25**: The results of the kernel 2nd phase binary transformation for the blood cell image in RGB form

**Figure 26**: The results of the kernel 2nd phase binary for the leukaemia cells of the blood cell image in RGB form

**Figure 27**: The results of the part removal process which aims at localizing the leukaemia cells
Gradient Edge Detection methods

This section aims at elaborating the results of the gradient edge detection methods (Sobel, Prewitt and Robert). The results of edge detection include the leukaemia edges and red blood cell edges. The result of Sobel edge detection method of the leukaemia and red blood cells are presented in Figure 31 (a) and (b) respectively. It can be observed that there is significant difference between the size, shape, number and the locations of the leukaemia cells as well as the red blood cells. The results of Prewitt edge detection method of the leukaemia and the red blood cells are presented in Figure 32 (a) and (b) respectively. It can be observed that there is significant difference between the size, shape, number and the locations of the leukaemia cells as well as the red blood cells. Meanwhile, the results of Robert edge detection method of the leukaemia and the red blood cells are presented in Figure 33 (a) and (b) respectively. It can be observed that there is significant difference between the size, shape, number and the locations of the leukaemia cells as well as the red blood cells.

Figure 28: The locations of the removed leukaemia cells, the remaining cells indicate the red blood cells

Figure 29: The results of the binarization operation to illustrate the locations of the removed leukaemia cells as well as the remaining cells indicate the red blood cells

Figure 30: The results of the transformation operation to illustrate the binarized locations of the removed leukaemia cells as well as the remaining cells indicate the red blood cells

Figure 31: The results of Sobel edge detection method
Ant Colony Optimization (ACO) Algorithm

The result of Ant Colony Optimization (ACO) edge detection method of the leukaemia and the red blood cells are displayed in Figure 34 (a) and (b) respectively. It can be observed that there is significant difference between the size, shape, number and the locations of the leukaemia cells as well as the red blood cells.

Performance 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 4.1 which also indicates that frequency’s distributions of the edge detection methods. The results of the frequency distributions are obtained using Equation 11.

\[
\text{Frequency distribution} = \frac{\text{FirstFilterOutput}_A}{\text{FirstFilterOutput}_B}
\]  

Where $A$ and $B$ are active cells that include the information of the edge (1). Inactive pixels are assumed as (0). Based on Table 1, it can be seen that the highest frequency’s distributions are obtained for Prewitt edge detection methods. Overall comparison revealed that the edge detection performance of the gradient methods is superior to that of ACO.
TABLE 1: Frequency’s distributions of the edge detection methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Roberts</th>
<th>Prewitt</th>
<th>Sobel</th>
<th>ACO</th>
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</thead>
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<tr>
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<tr>
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<tr>
<td>ACO</td>
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<td>1.19</td>
<td>0.78</td>
</tr>
</tbody>
</table>

CONCLUSION

Edge detection plays a significant role in image processing, object recognition and image segmentations. The term edge detection refers to the process used to identify and locate the sharp discontinuities in digital images such as the photometrical images, physical and geometrical segments or regions. The goal of edge detection is to determine the existence of edges or boundaries in an image through localizing the pixels which signifies the sudden changes or discontinuities in the intensity of an image. In this study the edges are a set of connected pixels that lie on the boundaries between an overlapping object and the background.

To recap, the objectives of the present study are: To conduct image pre-processing to suppress the noises, to sharpen and to enhance the white blood cell image. The pre-processing operation is vital operation in image processing. The mean filter was used to suppress noise in the white blood image.

The kernel single and multi-phase were also successfully employed in order to detect the edges of leukaemia cells of the filtered white blood cell image. Later the binarization and transformation pre-processing operations successfully used to enhance the edges of the leukaemia cells of the blood images. Meanwhile to utilize the Ant Colony Optimization (ACO) Algorithm to detect and recognize the leukaemia cells in the white blood image, the existence of the edge boundaries of the leukaemia in the white blood cell image was successfully detected.

In addition, the performance of the edge detection methods between Sobel, Prewitt, Robert and Ant Colony Optimization techniques were compared in order to identify the most significant method that can produce optimal edges of the leukaemia cells. The comparison result shows that the Prewitt method produced positive clear edges of the leukaemia cells better than other techniques.

Overall conclusion, we may conclude that medical image processing is an essential process which offers substantial accuracy at identifying, extracting and detecting various diseases in human. One of the most important applications of medical image processing is edge detection. Edge detection operation is vital operation which is employed to detect the edges of the leukaemia cells in the white blood at early stages. 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. The principle of edge detection process involves four primary interrelated steps which are filtering, enhancement, detection and localization. Pre-processing and filtering are essential operations used to suppress noises, enhance, detect and transform edges in an image. Noise removal is intended to remove noises while maintaining the true edges of an image which improve the performance of edge detector with respect to noise.

ACKNOWLEDGEMENT

Special thanks to Universiti Malaysia Perlis for supporting this research under Short Term Grant Scheme.

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