A Leukocyte Detection System Using Scale Invariant Feature Transform Method

Lina Arlends Chris, Bagus Mulyawan, and Agus Budi Dharmawan

***Abstract*—This paper describes an automatic detection and recognition system of leukocytes on a given microscopic image. The developed system detects the locations of leukocytes from a blood cell image. After the automatic detection, the system classifies each leukocyte in one of the five categories (neutrophils, eosinophils, basophils, lymphocytes, and monocytes). The system processes an input image with the Scale Invariant Feature Transform (SIFT) algorithm for leukocyte detection. Meanwhile, two different recognition methods, i.e. the Euclidean distance and the Co-occurrence matrix methods are applied for automatic recognition. The combination of detection and recognition approaches provides the optimal recognition accuracies for almost all leukocyte types.**

***Index Terms*—Leukocyte detection, leukocyte recognition, microscopic image, scale invariant feature transform.**

I. Introduction

Blood is a bodily fluid that delivers nutrients and oxygen to cells. The analysis of blood cells can be used to detect blood disorder or to determine the presence of infectious diseases in human body. In order to identify the hematopoietic system disorders, hematologists need to perform the blood cells identification and counting for every blood elements, such as the erythrocytes (red cells), leukocytes (white cells), and platelets [1]. Since the task is very tedious and really time consuming, an automaticblood detection, recognition, and counting system is necessary and helpful.

Several researchers have proposed various methods todetect and recognize the blood cells, such as the work by Markiewicz using the Support Vector Machine method [2], Colunga with EMalgorithm [3], and Neural Network-based classifiers [4], [5]. However, the detection and recognition systems have not been tested for blood cells that were influenced by rotation or illumination effects after the segmentation process.

In this paper, an automatic leukocyte detection system that can detect the white blood cell locations from microscopic images is developed. The proposed system works based on the Scale Invariant Feature Transform (SIFT) method. First, the system detects the white blood cells locations using the SIFT method, then the system crops the images which contains the region of interest. After the automatic detection and cropping, the system will recognize the leukocyte type using two different recognition methods: 1) the distance based recognition system using the Euclidean distance method, and 2) the color based recognition system using the co-occurrence matrix method.

The remainder of this paper is organized as follows. In Section II, the proposed leukocyte detection system based on SIFT algorithmis explained. Section III presents the leukocyte recognition system, while Section IV describes the experimental setup and results. Finally, the conclusion is presented in Section V.

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II. Leukocyte Detection System

In the proposed system, the Scale Invariant Feature Transform (SIFT) method is applied to detect the leukocytes from the captured microscopic images. The SIFT algorithm, developed by Lowe [6]-[8] is an algorithm for image features generation which are invariant to image translation, scaling, rotation and partially invariant to illumination changes and affine projection [9]. The steps for defining the SIFT image features are as follows: 1) Scale space construction, 2) Keypoint localization, 3) Orientation assignment, 4) Keypoint descriptor.

First, the system creates a scale space from the input imagesby calculating the Difference of Gaussian (DoG) using the Gaussian kernel. This step is necessary as an input image may consist unncessary details for detection or recognition processes. Therefore it is important to identify locations and scales that contains only the region of interest from an image. The first step for detecting locations that are invariant to scale changes is by constructing a continuous function of scale, known as the scale space. The scale space of an image is defined as a function, $L(x, y, \sigma)$, that is produced from the convolution of a variable-scale Gaussian, $G(x, y, \sigma)$, with an input image $I(x, y)$

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (1)$$

where * is the convolution operation in x and y, and

$$G(x, y, \sigma) = (1/2\pi\sigma^2)e^{-(x^2+y^2)/2\sigma^2} \quad (2)$$

To build the DoG pyramid, the input image is convolved iteratively with the Gaussian kernel. The last convolved image is down-sampled in each image direction by factor of 2, and the convolving process is repeated [9]. Each collection of images of the same size are then build together the so-called Gaussian pyramid, which is represented by a 3D function defined in Eq. 1. The DoG pyramid is computed from the difference of each two nearby images in Gaussian pyramid. Fig. 1 shows the constructed scale space images.

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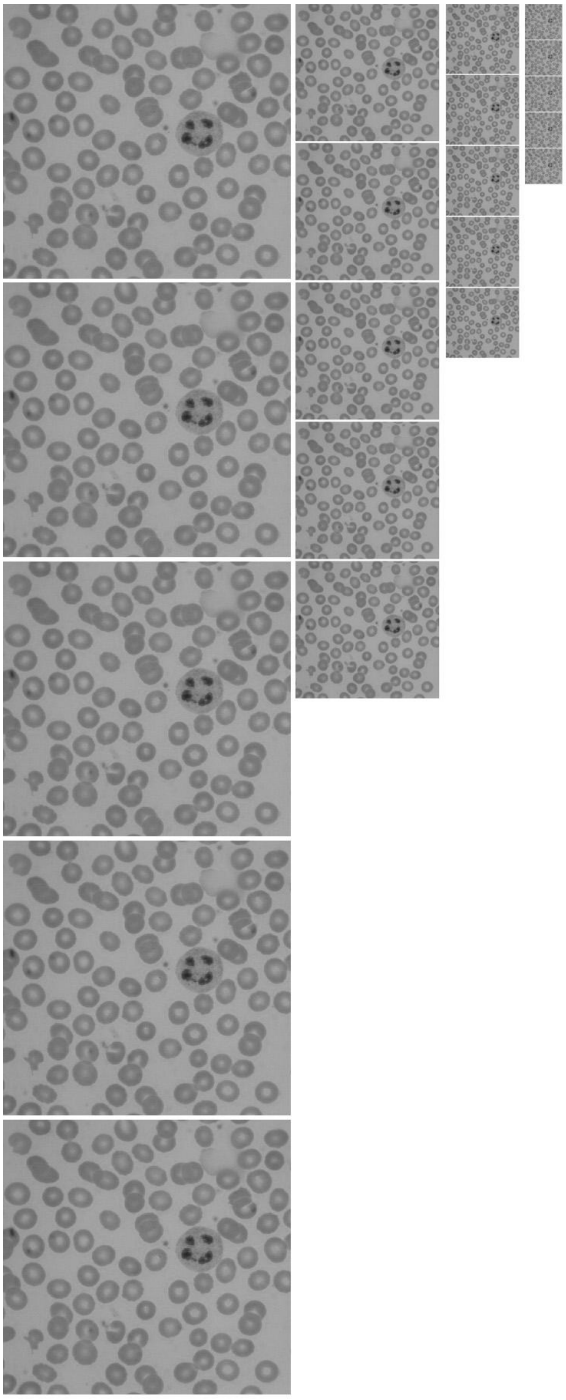

Fig. 1. The scale space images for leukocyte detection system.

The next step is to define keypoints. Keypoints are pixels from an image which have constant values for scaling, rotation, blurring, and illumination changes. Keypoint construction is done by finding the local extrema (maxima or minima) of DoG function. The local extrema are detected by comparing each pixel with its neighbors in the scale space. If the pixel value is higher or lower than the maxima or minima, then the pixel becomes the candidate for being a keypoint. The DoG function will have a strong response along edges, even if the location along the edge is poorly determined and therefore unstable to small amounts of noise.

The next step is to localize keypoints. In keypoint localization, a threshold cutting is applied on simple contrast value for each keypoint. The low contrast feature points are generally less reliable than high contrast feature points. The keypoints are selected only if they are larger than all of these neighbors or smaller than all of them. To improve the stability of matching, the points that have low contrast or are poorly localized along an edge are rejected.

After the thresholding step, the system performs the corner detection process. Harris corner detection algorithm is realized by calculating each pixel's gradient [10]. If the absolute gradient values in two directions are both great, then judge the pixel as a corner. Harris corner detector is defined as follows [11]:

$$R = detM - k(traceM)^2 \tag{3}$$

$$M(x,y) = \begin{bmatrix} I_u^2(x,y) & I_{uv}(x,y) \\ I_{uv}(x,y) & I_v^2(x,y) \end{bmatrix} \tag{4}$$

$$\begin{aligned} I_u^2(x,y) &= X^2 \otimes \omega(x,y) \\ I_v^2(x,y) &= Y^2 \otimes \omega(x,y) \\ I_{uv}(x,y) &= XY \otimes \omega(x,y) \end{aligned} \tag{5}$$

$$\omega(x,y) = \frac{1}{2\pi} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{6}$$

where k is an empirical value; $\omega(x,y)$ is a Gaussian function; $I_u(x,y)$ and $I_v(x,y)$ are the partial derivatives of the gray scale in direction u and v at point $\otimes$, and $I_{uv}(x,y)$ is the second-order mixed partial derivative; X and Y are the first-order directional differentials, which can be approximately calculated by convolving the gray scale and difference operators in direction u and v; $\otimes$ refers to convolution. If R exceeds certain threshold, then the point is determined as a corner.

Once the SIFT feature location is determined, a main orientation is assigned to each feature based on local image gradients. For each pixel of the region around the feature location the gradient magnitude and orientation are computed respectively as [9]:

$$m(x,y) = \sqrt{(L(x+1,y,\sigma) - L(x-1,y,\sigma))^2 + (L(x,y+1,\sigma) - L(x,y-1,\sigma))^2} \tag{7}$$

$$\theta(x,y) = \arctan\left((L(x,y+1,\sigma) - L(x,y-1,\sigma))/(L(x+1,y,\sigma) - L(x-1,y,\sigma))\right) \tag{8}$$

Finally, the region around a keypoint is divided into 4×4 boxes. The gradient magnitudes and orientations within each box are computed and weighted by appropriate Gaussian window, and the coordinate of each pixel and its gradient orientation are rotated relative to the keypoints orientation. Then, for each box an 8 bins orientation histogram is established. From the 16 obtained orientation histograms, a 128 dimensional vector (SIFT-descriptor) is built.

III. Leukocyte Recognition System

For the recognition system, two methods are applied to the system: 1) the distance based recognition system using the

Euclidean distance method, and 2) the color based recognition system using the co-occurrence matrix method.
In the Euclidean distance based recognition system, the dissimilarities between the testing and training feature vectors are calculated using the Euclidean distance measurement [12], [13]:

$$r = \| \mathbf{x} - \mathbf{w} \| \quad (7)$$

With r is the Euclidean distance between $\mathbf{x}$ as the testing feature vector and $\mathbf{w}$ as the training feature vector. A small r value indicates a high similarity of two images.

Meanwhile, in the color based recognition system using the co-occurrence matrix method, the co-occurrence matrix is constructed by clustering the gray-scale values of an image. Such matrix is derived from the angular relationship between the neighboring pixels as well as the distances between them. The higher the color intensity of an image, the larger size of co-occurrence matrix can be obtained. First, the probability value $p(i, j)$ of the color frequency $f(i, j)$ of index pair i and j is calculated by [12], [13]:

$$p(i, j) = \frac{1}{\sum f(i, j)} \times \begin{bmatrix} f(i, j) & f(i, j) & ..... \\ f(i, j) & f(i, j) & ..... \\ ..... & ..... & ..... \end{bmatrix} \quad (8)$$

Next, obtainthe Haralick features by processing the probability values of the co-occurrence matrix. Five characteristic features are processed in the proposed system, i.e. entropy, contrast, homogeneity, energy, and correlation. Entropy is used to measure the randomness of intensity distributions. The entropy value is calculated by:

$$Entropy = -\sum_{i=0}^{I} \sum_{j=0}^{J} p(i, j) \log p(i, j) \quad (9)$$

For taking into account the power of intensity differences in an image, the contrast characteristic is evaluated. The contrast value is calculated by:

$$Contrast = \sum_{i=0}^{I} \sum_{j=0}^{J} (i - j)^2 p(i, j) \quad (10)$$

The homogeneity which calculates the uniformity of intensity variations in an image, is the contrary of the image contrast. Below is the equation for calculating the homogeneity:

$$Homogeneity = \sum_{i=0}^{I} \sum_{j=0}^{J} \frac{p(i, j)}{1 + |i - j|} \quad (11)$$

Next, energy, as the fourth features, is used to measure the texture uniformity. The energy value is calculated by:

$$Energy = \sum_{i=0}^{I} \sum_{j=0}^{J} (P(i, j))^2 \quad (12)$$

Finally, the correlation value is used to describe the relations between each pixel value with its neighbors. The correlation value is calculated by:

$$Correlation = \frac{\sum_{i=0}^{i} \sum_{j=0}^{j} [(ij) p(i, j)] - \mu x \mu y}{\sigma x \sigma y} \quad (13)$$

IV. Experiments

This section describes the experiments conducted for the proposed leukocyte detection and recognition system using the Scale Invariant Feature Transform method. We developed our own database, called the FTI-Untar blood cells database. The FTI-Untar blood cells database consists of a total of 183 blood cell images with 112 neutrophils images, 37 lymphocytes images, 21 monocytes images, 10eosinophils images, and 3 basophils images. The images were taken using a digital camera with 1600×1200 pixels that was attached to a microscope. Fig. 2 shows the sample of a blood cell image that is used in the experiment, whileFig. 3 shows the samples of blood cell images, the cropped leukocyte images, the cropped leukocyte images with 10% darken lighting effects, and the cropped leukocyte images with 10% brighten lighting effects.

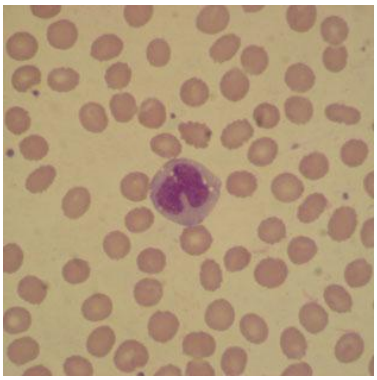

Fig. 2. The sample of a blood cell image for leukocyte detection system.

We have conducted various experiments with various targets for the proposed leukocyte detection and recognition system. First, we evaluated the performance of the SIFT method for detecting the white blood cells. Table I shows the detection results using SIFT method. It is shown in Table I that the proposed system was able to detect white blood cells with more than 86.67% accuracy.

TABLE I: The Detection Results Using SIFT Method

Blood Cell Type	Σdata	Σtraining	Σ testing	Accuracy (%)
Neutrophil	112	67	45	86.67
Eosinophil	10	6	4	100
Basophil	3	2	1	100
Lymphocyte	37	22	15	86.67
Monocyte	21	12	9	100

TABLE II: The Detection Results Using SIFT Method for Darken Lighting Effects

Blood Cell Type	Σdata	Accuracy (%)		
		Natural Lighting	Darken 5%	Darken 10%
Neutrophil	112	86.67	82.22	80
Eosinophil	10	100	100	75
Basophil	3	100	100	100
Lymphocyte	37	86.67	86.67	80
Monocyte	21	100	100	88.89

In the next experiments, we tested the system with various lighting conditions. Table II and Table III show the detection

results using SIFT method for images with various darken and brighten lighting conditions, respectively. The natural lighting means the condition where images were taken with microscope standard lighting, while darken and brighten effects were done by adjusting the contrast of the natural lighting images using a picture editing software. As shown in Table II, the detection accuracies for images with darken lighting effects were lower than that of with natural lighting. However, the detection accuracies were still higher than 75%. Meanwhile, the detection accuracies for images with brighten lighting effects were lower than that of the natural lighting and the darken effects. However, the detection accuracies were still higher than 75% as shown in Table III.

TABLE III: THE DETECTION RESULTS USING SIFT METHOD FOR BRIGHTEN LIGHTING EFFECTS

Blood Cell Type	Σdata	Accuracy (%)		
		Natural Lighting	Brighten 5%	Brighten 10%
Neutrophil	112	86.67	84.44	75.56
Eosinophil	10	100	100	75
Basophil	3	100	100	100
Lymphocyte	37	86.67	86.67	86.67
Monocyte	21	100	100	88.89

We also tested various threshold values for keypoint localizations in SIFT method. Table IV shows the detection results using SIFT method with three different threshold values: 0.02, 0.03, and 0.05. It is clearly seen that the detection accuracies using θ=0.03 gave the highest results compared to the other threshold values.

Finally, we conducted experiments to recognize leukocyte types from images which have fixed window sizes, both for training and testing images, i.e. 47×47 pixels and 57×57 pixels. These dimensions were the average size of leukocyte cells that were captured from the microscopic images. The recognition accuracies for images with various cropping sizes are shown in Table V. We applied two recognition methods for the leukocyte recognition system: 1) the Euclidean Distance method and 2) the Co-occurrence Matrix method. Based on Table V, the overall recognition accuracies for images with 47×47 pixels and 57×57pixels sizes with the Euclidean Distance method were 82.79% and 84.93%, respectively. Meanwhile, the overall recognition accuracy for leukocyte recognition system using the Co-occurrence Matrix method was 75.93% for images with 47×47 pixels and 61.78% for images with 57×57pixels sizes. In general, for both recognition methods, it is clearly seen that Basophilwas the most difficult leukocyte type to find and to recognize.

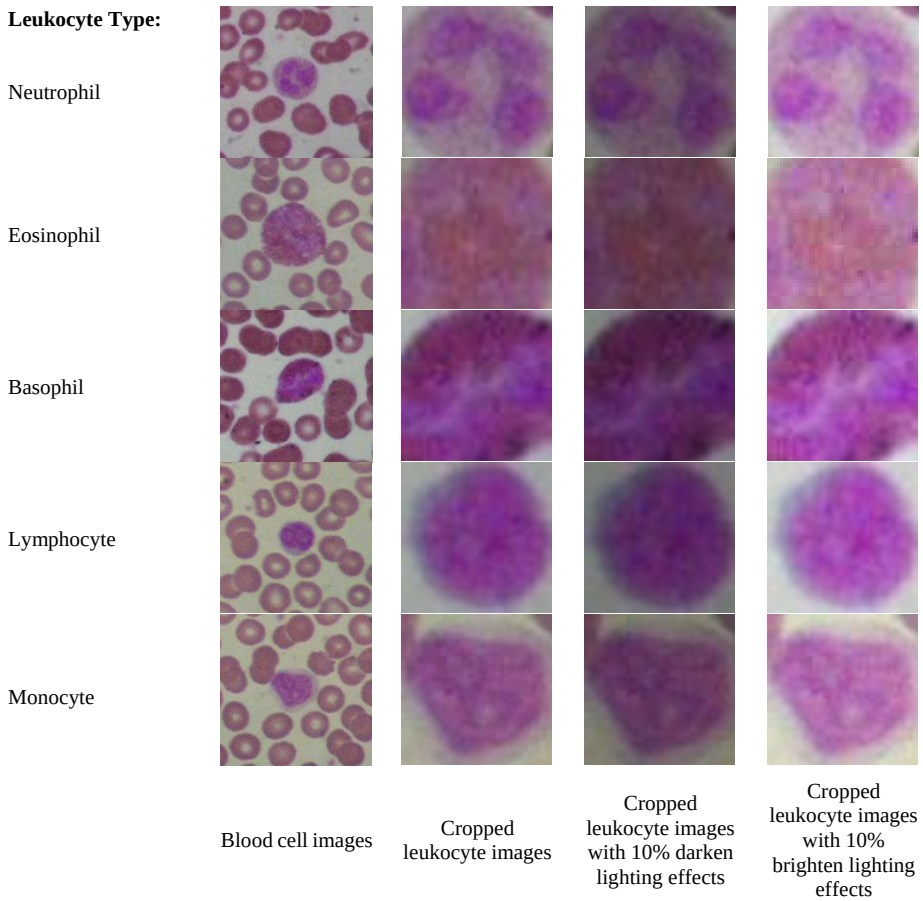

Fig. 3. The image samples of white blood cells used in the experiments.

TABLE IV: THE DETECTION RESULTS USING SIFT METHOD WITH VARIOUS THRESHOLD VALUES FOR KEYPOINT LOCALIZATION

Type	Σdata	Σtraining	Σtesting	Accuracy (%)		
				θ=0.02	θ=0.03	θ=0.05
Neutrophil	112	67	45	77.78	86.67	93.33
Eosinophil	10	6	4	50	100	75
Basophil	3	2	1	0	100	100
Lymphocyte	37	22	15	66.67	93.33	93.33
Monocyte	21	12	9	88.89	100	100

TABLE V: THE RECOGNITION RESULTS FOR LEUKOCYTE IMAGES WITH VARIOUS CROPPING SIZES

Type	Σtraining	Σtesting	Accuracy (%)			
			Image size 47×47 pixels		Image size 57×57 pixels	
			Euclidean Distance	Co-occurrence Matrix	Euclidean Distance	Co-occurrence Matrix
Neutrophil	213	53	90.62	73.58	96.88	90.56
Eosinophil	100	22	83.33	63.63	77.78	59.09
Basophil	74	20	40	55	50	30
Lymphocyte	10	3	100	66.67	100	100
Monocyte	3	2	100	50	100	100

V. CONCLUSION

We have presented the Scale Invariant Feature Transform method to automatically detect leukocyte areas and recognize the leukocyte types from microscopic images. The detection results of the leukocyte images using SIFT method are highly dependent on the threshold value of keypoint localization. Other parameters such as lighting condition and window size also give significant effects on the accuracy of the system. For the recognition system, the Euclidean Distance method gives a slightly better result than that of the color based recognition, i.e. the Co-occurrence Matrix method**.**

In the future, we consider to develop a dynamic window model for detecting the leukocyte area, the use of other color domains, i.e. Hue, Saturation, and Value (HSV) for improving the system's accuracy.

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