Global and Adaptive Thresholding Technique for White Blood Cell Image Segmentation

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Abstract. Global and local thresholding are two thresholding approaches for white blood cell (WBC) image segmentation. Global thresholding determines the threshold value based on the histogram of the overall pixel intensity distribution of the image. In contrast, adaptive thresholding computes the threshold value for each fractional region of the image, so that each fractional region has a different threshold value. In this work, we are assessing both of these approaches for two threshold values. We extended the Otsu’s equation to calculate more than one threshold as it originally designed to find only a single threshold value. Adaptive thresholding first divides an image into fractional-image by considering an imaginary bounding box that surrounds the location of WBC, which involves the Gram-Schmidt orthogonalization method. For segmentation performance evaluation, we compare 35 blood smear test images which segmented by our proposed method, with their corresponding ground truth image to representing them in Zijdenbos Similarity Index (ZSI), precision, and recall measurement. Experimental results show that adaptive thresholding achieves average ZSI, precision and recall, 92.5%, 91.79%, 94.03%, while global thresholding achieves 30.72%, 23.38%, and 99.39% respectively.

1. Introduction

White blood cell (WBC) image segmentation is the earliest and most crucial step in computer-aided hematology diagnosis systems [1][2] that based on microscopic blood smear digital images, such as automated detection systems of leukemia as well as automated blood cell counting system. Three major components are composing microscopic blood smear images, as shown by Figure 1. They are red blood cells, WBCs, and image backgrounds [3][4]. WBC segmentation aims to extract the WBCs region from other component regions [4]. An accurate method of WBC segmentation is needed to improve the accuracy of the next step in the automated detection system [5].

Several studies have been developed to improve the segmentation of WBC. Some of them are a boundary or edge detection technique [6], while the others are unsupervised learning [7-13], region-based segmentation using active contour [14][15] and morphological operation [16][17][18]. The problem with boundary-based techniques arises when the points in the edge line of the region of interest are not fully connected, so the region's boundaries are unclearly defined. Unsupervised learning technique employs the clustering method to classify the region of an image into three clusters, which are background, red blood cells, and WBCs pixels. The clustering technique will successfully extract WBCs when the distribution of WBC and red blood cell pixels are in a balanced manner. In other ways, active contour suffers from topology changing in object contours, e.g., when two contours are incorporated into a contour [19].
In this work, WBC image segmentation based on thresholding technique is proposed. The thresholding operation employs one or more threshold values to classify gray-level intensity of each image pixel into two classes, black and white. Two approaches used in the thresholding operation are global thresholding and adaptive thresholding. Both in global and adaptive thresholding, we calculate two threshold values using the Otsu’s equation [20]. In global thresholding, the threshold value is determined based on the histogram of the overall pixel intensity distribution of the image. In contrast, adaptive thresholding calculates the threshold value for each fractional region of the image, so that each fractional region has a different threshold value.

2. Literature Review

2.1. Otsu’s Equation

The Otsu equation [20] is originally designed to calculate two threshold values, in the case of our work, it is extended to determine two threshold values that divide gray-level pixels into more than two classes. See equation (1).

\[ th_1, th_2 = \text{Arg}(\max_{\text{min}(H) \leq th \leq \max(H)} \left( \sigma^2(th) \right) ) \]  

(1)

where \( \sigma^2 \) is inter-class variance, \( th_1 \) and \( th_2 \) is threshold value from histogram \( H \), while \( \text{min}(H) \) and \( \text{max}(H) \) are minimum and maximum gray-level intensity in histogram \( H \).

Inter-class variance \( \sigma^2 \) could be computed by equation (2) through equation (6).

\[
\sigma^2(th) = \sum_{i=1}^{r} \sigma_i = \sum_{i=1}^{r} \omega_i (\mu_i - \mu_T)^2
\]

(2)

\[
\mu_T = \sum_{i=1}^{3} \bar{\omega}_i \mu_i
\]

(3)

\[
\bar{\omega}_1(th) = \sum_{s=\text{min}(H)}^{\text{th}_1} P(s), \quad \bar{\omega}_2(th) = \sum_{s=\text{th}_1+1}^{\text{th}_2} P(s), \quad \bar{\omega}_3(th) = \sum_{s=\text{th}_2+1}^{\text{max}(H)} P(s)
\]

(4)

\[
P(s) = \frac{h(s)}{N_p} \sum_{i=1}^{3} P(s) = 1
\]

(5)

\[
\mu_i = \sum_{s=\text{min}(H_i)}^{\text{th}_i} s P(s), \quad \mu_2 = \sum_{s=\text{th}_1+1}^{\text{th}_2} s P(s), \quad \mu_3 = \sum_{s=\text{th}_2+1}^{\text{max}(H)} s P(s)
\]

(6)

where \( \omega_i \) is cumulative number of gray-level occurrence probability and \( \mu_i \) is cumulative average for \( i \)-th class, \( h(s) \) is the number of pixel with gray-level \( s \), \( N_p \) is total number of pixels, and \( P(s) \) is probability of the pixel with gray-level \( s \).

2.2. Image Cropping using Gram-Schmidt Orthonalization

The process of cropping the input image into fractional-image requires information about the location of WBC’s nucleus. We are multiplying each pixel from a gray-level image with a weighted

![Figure 1. Components structuring microscopic blood smear digital images.](image_url)
vector $u_3$, to obtain that location [15]. See equation (9). A weighted vector $u_3$ can be calculated by applying Gram-Schmidt orthogonalization [15] shown by equation (7).

$$u_1 = v_1, e = \frac{u_1}{\|u_1\|}$$

$$u_2 = v_2 - p \quad u_2 v_2, e_2 = \frac{u_2}{\|u_2\|}$$

$$u_3 = v_3 - p \quad u_3 v_3, e_3 = \frac{u_3}{\|u_3\|}$$

$$\vdots$$

$$u_k = v_k - \sum_{i=1}^{k-1} proj_{u_i} v_k, e_k = \frac{v_k}{\|u_k\|}$$

where

$$p \quad u v = \frac{(u v)}{(u v)}$$

$$(u, v)$$ is inner product of vector $u$ with vector $v$.

$$I_l(x, y) = I(x, y) \times u_3$$  \hspace{1cm} (9)

### 3. Research Methodology

#### 3.1. Global Thresholding

In global image thresholding, each pixel in the image is mapped into two classes shown in equation (10).

$$\begin{align*}
C_1 & \leftarrow p, \text{ if } 0 \leq p < th_1 \\
C_2 & \leftarrow p, \text{ if } th_1 \leq p < L - l
\end{align*}$$  \hspace{1cm} (10)

where $p$ is one pixel of gray-level image in $L$ gray-level, $L = \{0, 1, 2, \ldots, 255\}$, $th$ is specified threshold value, while $C_1$ and $C_2$ are pixel class.

In our proposed method, two threshold values are specified so that equation (10) is expanded to equation (11).

$$\begin{align*}
C_1 & \leftarrow p, \text{ if } 0 \leq p < th_1 \\
C_2 & \leftarrow p, \text{ if } th_1 \leq p < th_2 \\
C_3 & \leftarrow p, \text{ if } th_2 \leq p < L - l
\end{align*}$$  \hspace{1cm} (11)

where $\{th_1, th_2\}$ are different threshold value.

The proposed global thresholding algorithm is described as follows:

**Step 1:** Convert $RGB$ color-space image, $I(x, y)$, to $LAB$ color-space image $I_{l_{}} (x, y)$.

**Step 2:** Create an image histogram $H$ from gray-level image $I_{l_{}} (x, y)$ from $B$ channel of $LAB$ image.

**Step 3:** Using Otsu’s equation, compute two threshold values ($th_1$ and $th_2$) from histogram $H$ so that satisfy equation (1).

**Step 4:** Apply thresholding by substituting $th_1$ and $th_2$ into equation (11).

#### 3.2. Adaptive Thresholding

Before applying thresholding to a gray-level image, adaptive thresholding first divides an input image into a fractional-fractional region of the image or we can call it as fractional-images of the input image. Then, it calculates two threshold values for each fractional-image, so that we have adaptive threshold values in which they are different between each fractional-image.

The proposed adaptive thresholding algorithm is described as follows:
Step 1: Calculate a weighted vector $u_3$ from RGB image, $I(x, y)$, using equation (7);
Step 2: Apply equation (9) then apply threshold value $= 0.5$, so that we have a binary image $I_{bin}$.
Step 3: Consider imaginary bounding box of $I_{bin}$, then crop $I(x, y)$ correspond to its imaginary bounding box into several fractional-images.
For each fractional-images:
Step 4: Convert RGB image to LAB image.
Step 5: Create an image histogram $H$ from gray-level image from $B$ channel of LAB image.
Step 6: Using Otsu’s equation, compute two threshold values ($th_1$ and $th_2$) from histogram $H$ so that satisfy equation (1).
Step 7: Apply thresholding by substituting $th_1$ and $th_2$ into equation (11).

4. Result and Discussion
Peripheral blood smear test image used in this study was taken from the database of acute lymphoblastic leukemia images: ALL-IDB1 [10]. A digital camera acquires the blood smears under a microscope, so that produce a $1712 \times 1368$ blood smear images. In order to evaluate the algorithm performance, we employed 35 blood smear images consisting of 269 white blood cells. We calculate false negative (FN), false positive (FP), and true positive (TP) by comparing the proposed method with its corresponds ground truth image. Then, we represent it in the Zijdenbos Similarity Index (ZSI), precision, and recall measurement for the algorithm performance evaluation. ZSI is computed using equation (12), while precision and recall are computed using equation (13) and equation (14) respectively.

$$ZSI = \frac{2 \times |A \cap G|}{|A| + |G|}$$ (12)

where $A$ represents the total pixels resulting from the proposed segmentation method, and $G$ represents the total pixels of the ground truth image.

$$Precision = \frac{TP}{TP + FP}$$ (13)

$$Recall = \frac{TP}{TP + FN}$$ (14)

Figure 2 presents our experimental result of the global thresholding technique.

![Figure 2](image-url)

**Figure 2.** Global thresholding segmentation result. (a) original image (b) segmented image

The experimental results of each step of the adaptive thresholding technique are presented in Figure 3.
Figure 3. Adaptive thresholding segmentation result. (a) original image (b) after multiplication by weighted vector $u_3$ (c) imaginary bounding box (d) fractional-images (e) final segmentation results.

Performance of global and adaptive thresholding shown by Table 1.

|             | Average ± Std | Thresholding |
|-------------|--------------|--------------|
|             |              | Global (%)   | Adaptive (%) |
| ZSI         | 30.72 ± 30.2 | 92.5 ± 7.16  |
| Precision   | 23.38 ± 29.33| 91.79 ± 7.48 |
| Recall      | 99.39 ± 1.34 | 94.03 ± 9.66 |
Table 1 said that global thresholding has lower ZSI and precision than adaptive thresholding. This phenomenon comes due to, in most cases in the test images, the number of WBC pixels are only a small part compared to the number of other objects pixels in an image so that Otsu’s equation is difficult to find optimum threshold between the peak and the valley of a histogram. These will be arising in segmentation errors, which global thresholding will be misclassifying several background pixels and red blood cell as WBC region. However, the global thresholding technique produces the best segmentation results when the number of WBC pixels have a balanced number compared to other objects in an image.

5. Conclusion

Segmentation of WBC with global thresholding does not always appropriate for all varieties of microscopic blood smear images. Some important information in the image may be lost due to this global threshold. It is because the number of pixels of the WBC among one image to another is not the same. If the number of pixels composing WBC is smaller than others, then the solution is segmentation using adaptive thresholding. However, if, the image has a situation in which the number of the WBC pixels is balanced with the number of other objects pixels in the image, then the global thresholding technique offers an alternative solution.

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6. References

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