CLASSIFICATION OF WHITE BLOOD CELLS BASED ON SURF FEATURE

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Abstract

Conventional blood analysis using blood smear image were performed manually by experts in hematology is tedious and highly depending on the level of experience. Currently, computer-assist technology is developed to reduce the time-consuming process and improved accuracy. As an example, various image processing techniques used to quantify such as white blood cells (WBCs) morphological conditions or classification in the blood smear image, which assist experts in developing confidence decision making in the analysis of cells conditions linked to the specific diseases. However, the WBCs shape features are arbitrary than the red blood cells (RBCs) because of the maturation state, cell orientations or positions, cell color variations, and the quality of the image captured influences the performance of classification accuracy. Therefore, we proposed a scale and rotation invariance feature for WBCs classification using speed up robust feature (SURF). SURF is suitable to be applied in identifying objects even though the orientation, scale, and position are varying, such as WBCs in microscopic blood smear images. We analyzed the classification performances using a support vector machine (SVM) and an artificial neural network (ANN) of WBCs types in the microscopic image based on the cell nucleus. The results show that the purposed SURF feature method has an excellent performance of accuracy for both methods and suitable to be utilized for the application of cell types classification.

Keywords: **ANN; SURF; SVM; Blood smear; WBCs classification**

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Introduction

Blood cell evaluation plays a vital role as it assists in the overall health screening and diagnosis of blood disorders. Diagnosis of most blood diseases such as leukemia, anemia, etc. could be determined by the evaluation of the three types of human blood cells. The three types of blood cells comprise red blood cells, white blood cells, and platelets, but the primary concern of this project is solely on the white blood cells. Abnormalities condition in white blood cells were analyzed using a process called blood smear analysis (Adewoyin, 2014). Image processing has recently been an essential tool to help experts in various fields and applications. Thus, an expert-machine system developed could provide a pre-result analysis, which is useful for an expert to make a decision or further detail analyzing the conditions.

Numerous studies and various algorithms are developed for this WBCs classification application. WBCs types were identified from their features such as shape, nucleus count, and presence of granules. The five types of WBCs are basophil, eosinophil, monocyte, lymphocyte, and neutrophil. Most of the features used for WBCs classification are texture or statistical (Sabino *et al*., 2004), geometric (Hiremath *et al*., 2010), color (Zhang *et al*., 2014), and combinations from various feature (Benazzouz *et al*., 2013; Al-Dulaimi *et al*., 2018). These WBCs features are classified using machine learning algorithms as an example using the support vector machine (SVM) (Sarrafzadeh *et al*., 2014), fuzzy-based method (Shirazi *et al*., 2016) and Artificial neural network (ANN) (Rezatofighi *et al*., 2011). Although many methods shown a promising results, there still a way to improve and optimize the performance of cells classification, including the time of processing, simplicity of methods developed, and system reliability.

In this paper, we proposed a WBCs classification on microscopic blood smear image using speed up robust feature (SURF) feature. SURF feature is more robust compared to conventional features such as statistical and geometric features that traditional methods used. Furthermore, SURF method is shown to be quite a robustness for illumination variation images, which always occurred in microscopic blood smear images. SURF detects interest points in the image, and it is suitable for scale-invariant feature transform. Therefore, SURF should be ideal for cell classification applications.

On the other hand, SURF can be used to identify same features between two corresponds images although the position (e.g., rotation) and scale are changed. It is also is useful for object recognition, image registration, classification, or 3D reconstruction (Bay *et al*., 2008). In contrast, SIFT (Scale Invariant Feature Transform) algorithm proposed by Lowe in 2004 is the predecessor algorithm for scale-invariant algorithm than SURF (Lowe, 2004). The SIFT descriptor is invariant to translations, rotations, and scaling transformations in the image domain and robust to moderate perspective transformations and illumination variations. However, the advantages of SURF over SIFT fast processing time and has shown better performance including rotation, blur, wrapping image than SIFT (Panchal *et al*., 2013; Mistry and Banerjee 2017).

The SURF algorithm is simple. At first, the interest points are selected at the distinctive locations in the object, such as blobs, corners, and T-junctions. Then, the neighborhood of every interest points is represented by a feature vector. Here, the descriptor must be distinctive. Also, it must be robust to noise, detection errors, and deformations (e.g., geometric and photometric). Finally, the descript vectors are matched between different images.

SURF is useful for many applications of image matching. However, detected SURF points of interest and feature descriptor of local shape extracted from the WBCs image might also be useful for classifying WBCs types of the blood smear image. Besides, WBCs positions on the blood smear image such as cell rotation and orientation could provide misclassification using other local shape feature descriptors such as histogram of gradient (HOG) (Cheon *et al*., 2011) and convolution neural network (CNN) features (Choi *et al*., 2017).

For example, the classification of white blood cells for the application of acute Lympotic Leukemia (ALL) cells counting and size determination developed by Nazlibilek *et al*. (2015) used SURF for the detection of ALL cells. The performance of cells classification could be achieved by up to 96%, where the average effectiveness performance is about 77%.

Chris *et al*. (2016) used SIFT for the leukocytes type detection on blood smear images. In their work, they reported that although the image lighting and window size is varied, the detection of leukocytes still shows high accuracy. They concluded that the method proposed is dependent on the threshold value of keypoint localization. Thus, to improve efficiency, they suggested that color information is useful for enhancing the system accuracy where minimizing the lighting and thresholding effect in general.

On the other hand, Lopez-Puigdollers *et al*. (2019) show that cells such as white blood cells can be recognized utilizing local descriptors, including on the cell contour (oFAST), SIFT, and the CENter SURround Extrema (CenSurE) and conventional bag-of-words pipeline just using the gray-level image. The process is far simple and less complicated and more robust.

Another cells classification application example using a combination of SURF and SIFT features (De Faria *et al*., 2018). They introduced a simple and efficient combination of SIFT and SURF by stacking the key points descriptors in a single matrix. They found that the combination of the methods tends to perform better than other methods. The work has demonstrated a simple and efficient with high accuracy. The SIFT and SURF features are based on Bag-of-Visual-Words (BoVW) model. In addition, they show that Multi-Layer Perceptron (MLP) performed better than the Support Vector Machines (SVM).

One of the distinctive characteristics of SURF is that it is rotation, scale, and contrast agnostic, making it an optimal algorithm for cell identification in microbiology applications. Where it is not possible to fixate the cells, and it is difficult to maintain the contrast, light intensity, and light color temperature levels constant. Therefore, SURF is much more robust to the scale and rotation conditions. For WBCs classification, the SVM and ANN were implemented, and both classification performance analysis was determined. Figure 1 shows the microscopic blood smear a image.

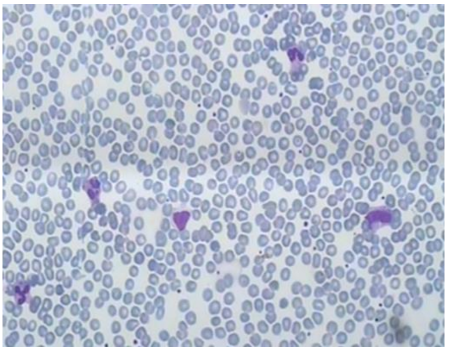

Figure 1. The microscopic blood smear image (Adewoyin *et al*., 2014)

Method

Image datasets

Blood image datasets from Leukocyte Images for Segmentation and Classification (LISC) were used for this purposed (Rezatofighi *et al*. 2011). The samples were smeared and stained by Gismo-Right technique, and images were acquired by a light microscope (Microscope-Axioskope 40, Carl Zeiss AG, Germany) with a 100X magnification lens. These images were recorded by a digital camera (Sony Model No. SSCDC50AP, Japan) contain 720×576 pixels area. The hematological images were taken from 8 healthy subjects. 239 ground truth images were classified by a hematologist into normal WBCs: basophil, eosinophil, lymphocyte, monocyte, and neutrophil.

Image Processing

The segmentation process is the first step for acquiring the image of the cells. Firstly, the microscopic image containing RBCs and WBCs are converted to a gray level image. Next, the histogram equalization was performed to enhance the gray image. Then OTSU thresholding was performed. Morphological operations will further eliminate noises such as particles from RBCs image objects. The morphological operations, including opening, erode, and dilation was performed to segmenting the WBCs nucleus image. Next, we performed a binary mask to the original RGB image and cropped the image to the size of 150x150 pixels. This size of the image was carefully determined to satisfy all WBCs types were some of the cells such as monocyte is biggest than another type of cells which satisfy the selected image size. Figure 2 shows the proposed WBCs segmentation process.

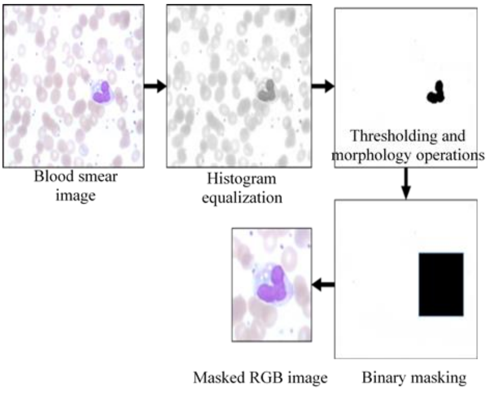

Figure 2. The WBC segmentation process. Segmented image size is 150×150 pixels

Feature Extraction

The feature detection of SURF process is based on two steps; first, find the interest points in the image by comparing the Difference of Gaussian (DoG) in each location in the image (segmented WBCs) under different scales. The value of each pixel in the DoG-filtered images is compared to its eight neighbors on the same scale, plus the nine corresponding neighbors at neighboring scales. If the pixel corresponds to a local maximum or minimum, it is selected as a candidate key point. Then, the scale-invariant descriptor was determined on each point of location detected in the previous step. The SURF was extracted from the converted gray-scale image of the masked segmented RGB image where the length of the SURF vector was set to be 64, and the feature threshold used is 1,000. The SURF extraction is based on 5 and 10 points of interest from the image. An example of the SURF detection points on WBCs image shows in Figure 3.

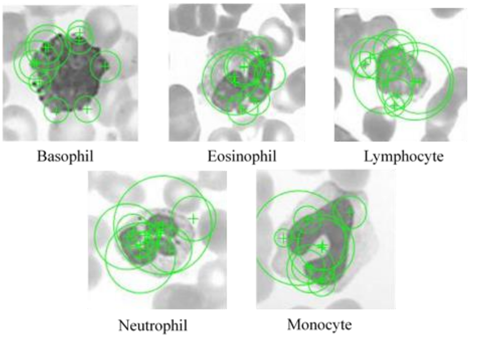

Figure 3. Example of 10 SURF points detected on the segmented WBCs image

Classification Performance Analysis

Classification of the WBCs using five-folds cross-validation to ensure no overfitting in the SVM model. SVM is based on one-vs-one class method with the quadratic kernel. For ANN, 20% of testing and validation and 60% training were used on the WBCs dataset. The ANN has a three layers' model; input, hidden and output. 10 hidden nodes are used in the model. The performance of both classifiers will be determined by its classification accuracy (acc), sensitivity (sen) and specificity (spe). The accuracy is its ability to differentiate the WBCs types across groups correctly where the proportion of true positive (TP) and true negative (TN) for all classes being calculated. Mathematically this can be determined in Equation (1) as:

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \quad (1)$$

where false positive (FP) and false negative (FN) is the numbers of WBCs types incorrectly identified. The sensitivity of classification is its ability to determine the WBCs types correctly. It can be determined by the proportion of true positive. Mathematically this can be determined in Equation (2) as:

$$\text{Sensitivity} = TP/(TP+FN) \quad (2)$$

For the specificity also called a true negative rate, is its ability to determine the portion of actual negatives that correctly identified. The proportion of true negative of WBCs types can be mathematically stated as Equation (3):

$$\text{Specificity} = TN/(TN+FP) \quad (3)$$

Results and Discussion

Classification Performance

The evaluation of 5 SURF points and 10 SURF points classification performance are shown in Tables 1 and 2 for both classifiers SVM and ANN, respectively. The classification performance for both SVM and ANN using 5 SURF points, as shown in Tables 1 and 2 respectively. For both methods, the high number of SURF point feature vector extracted increased the accuracy of classification. This is because of where more edges, corners, junctions, blobs being detected in the WBCs segmented image. Therefore, a higher number of points is preferable for increasing the accuracy of the cells classification. Although, increasing points will increase the feature vector, as an example, 10 points of SURF having a 640 features vector, and it is affecting the computational cost. Both classifiers performance based on 10 SURF points shows a slight difference which less than 3% average difference for both SVM and ANN classifiers performance analysis.

Conclusions

In this work, we presented the WBCs classification from microscopic image based on SURF. The classifications of WBCs show 10 SURF points performance having more accuracy, specificity, and sensitivity than 5 SURF points using SVM and ANN methods. In SURF extraction, the value threshold is 1,000 where maximum suitable points in the images using this value was in between 10 to 15 points. Therefore, a 15 points SURF was not suitable to be used based on this threshold value. This will have caused some errors (unable to extract 15 interest points on the

Table 1. SVM classification performance based on 5 and 10 SURF points

WBC	5 SURF points			10 SURF points		
	Acc.	Spe.	Sen.	Acc.	Spe.	Sen.
Basophil	87.50%	97.37%	77.78%	100.00%	100.00%	100.00%
Eosinophil	72.73%	91.89%	88.89%	80.00%	94.59%	88.89%
Lymphocyte	100.00%	100.00%	66.67%	100.00%	100.00%	77.78%
Monocyte	72.73%	91.89%	88.89%	81.82%	94.44%	100.00%
Neutrophil	100.00%	100.00%	100.00%	100.00%	100.00%	88.89%
Average	86.59%	96.23%	84.44%	92.36%	97.81%	91.11%

Table 2. ANN classification performance based on 5 and 10 SURF points

WBC	5 SURF points			10 SURF points		
	Acc.	Spe.	Sen.	Acc.	Spe.	Sen.
Basophil	92.31%	98.11%	92.31%	92.86%	98.08%	100.00%
Eosinophil	87.50%	96.88%	89.74%	95.00%	98.73%	100.00%
Lymphocyte	97.22%	99.37%	89.74%	92.11%	98.13%	92.11%
Monocyte	86.49%	96.93%	82.05%	100.00%	100.00%	84.62%
Neutrophil	90.70%	97.44%	100.00%	90.48%	97.45%	97.44%
Average	90.84%	97.75%	90.77%	94.09%	98.48%	94.83%

image) to some segmented WBCs image due to the threshold. The threshold determines how large the output from the Hessian filter must be in order for a point to be used as an interest point. A larger threshold value will result in fewer SURF points, however, theoretically, more significant interest points, whereas a smaller value will result in more numerous but less salient points. The classification of WBCs types in microscopic blood smear image shows that the purposed SURF is suitable to be used in this application. SURF algorithm which invariant to object rotation and scale provide an advantage to others method. The algorithms use a Hessian matrix to determine the key-points or blob and Haar wavelet for the feature. Both of the classifiers algorithms mostly depend on predefined parameters set, which was not being tuned to the optimum performance. Therefore, further optimization on the classifiers for more efficient and sensitive, SURF properties such as points, thresholding, and increase the number of datasets will greatly affect the performance analysis are highly recommended. Therefore, SURF it is suitable to be used to others cell classification application.

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