

Feature Extraction of Gram-Negative Bacteria Texture Using Grey Level Co-Occurrence Matrix and Scale-Invariant Feature Transform

1st Budi Dwi Satoto

S3 student Applied Mathematics, Sains
and Technology Faculty
Airlangga University
Surabaya, Indonesia

2nd Imam Utoyo

Applied Mathematics, Sains and
Technology Faculty
Airlangga University
Surabaya, Indonesia
m.i.utoyo@fst.unair.ac.id

3rd Riries Rulaningtyas

Physics Department, Sains and
Technology Faculty
Airlangga University
Surabaya, Indonesia

Abstract—Gram-negative bacteria are one of the pathogenic bacteria in the respiratory tract. The presence of these bacteria should be identified correctly so that a doctor can do the proper handling of antibiotic therapy. Observations are still made under a microscope by a microbiology clinic or hospital team. This research uses image processing to replace visual inspection. One of the stages in image processing is feature extraction. This research uses a texture approach that is the Grey Level co-matrix matrix and Scale-Invariant Feature Transform. The first method uses the grey level approach, while the second method uses the texture object direction approach. Data used in this research get from a sample of 50 patients. It exposed to Gram-negative pathogenic bacteria. The selected bacteria are *Klebsiella pneumonia* and *Pseudomonas aeruginosa*. Of the two methods used, the results were compared to obtain information on which method was more suitable for the observation of Gram-negative bacterial objects. The results of the view by examining the effect of object features with ground truth found that the level of accuracy using the grayscale with the similarity of objects approaching and using the object texture direction approach obtained an accuracy of 89%.

Keywords: *Gram-negative bacteria, segmentation, Grey Level co-occurrence matrix, scale-invariant feature transform*

I. INTRODUCTION

Prasso et al. (2017), in his research, said that in the process of identifying bacteria through sputum testing and the staining process on glass objects, the bacteria that cause pneumonia are classified into two categories, namely Gram-Positive bacteria where bacteria are blue, and Gram-negative bacteria are red.[1]. Gram-negative bacteria are bacteria that do not retain violet crystalline dyes during the Gram staining process, so they will turn red when observed under a microscope [2]. Research into the identification of Gram-positive and negative bacteria using image processing carried out by Hiremath (2009) said that image analysis has automatically been developed to monitor bacterial staining characteristics. Experimental results are compared with manual results obtained by microbiologists [3]. Research conducted by Muhammad Tahir (2018) is to conduct several experiments using the GLCM algorithm with multilevel quantization to obtain different offset values. Haralick descriptors are used to extract GLCM, which is then trained with a support vector machine [4]. The result is the highest

accuracy value using a gray level value of 4 is 82%, 12 is 88.4%, and 16 is 89.2% with a distance of $d = 3$ [5]. Ryfial Azhar (2015) researched a combination of types of bag features (BOF) extracted using the Scale-Invariant Feature Transform (SIFT) feature extraction and the classification process using Support Vector Machine (SVM) applied to the classification of batik images in Indonesia. The experimental results in this research show the average accuracy using SIFT and SVM is 97.67%, 95.47%, and 79%, which are applied to images with the normal position, images that rotate with certain angles, and images using scale rules [6]. This research is needed to replace visual observations made in clinical microbiology laboratories. At the stage of obtaining the desired features to distinguish images, texture features are used, which are features that consider statistical variables such as contrast or light-dark differences, correlations or relationships between variables, levels of energy, and homogeneity similarity levels. Also, in the texture feature is used key point and rotation angle of the object. Gaps with previous research are studies conducted previously still using consideration of the morphological form of the object. The novelty in this research is the addition of consideration of the texture feature elements in the image in the hope of being more observant in distinguishing bacterial objects after morphological identification.

II. LITERATURE REVIEW

The discussion in the literature review is the definition of Gram-negative bacteria, the definition of image processing, texture analysis on image processing, Grey Level Co-occurrence Matrix and Scale-invariant feature transform.

A. Gram negative bacteria

Characteristics of this bacteria, according to Silhavy et al. (2010) is having a thin cell wall structure, about 10–15 mm, triple, or multilayer. The cell wall contains fatter (11-22%), peptidoglycan is contained in a rigid layer, the inside with a little amount of $\pm 10\%$ of dry weight, does not contain Teapot Acid and is less susceptible to penicillin compounds [7].

B. Image Processing and Texture Analysis

To be able to process images produced by a microscope, as said by Shamir et al. (2010), the required software is

needed to be able to recognize images read by a microscope known as image processing software [8]. The stages of image processing that are used include the initial processing stages, division of the object area, determination of features to be used, and identification of objects [9].

C. Gray Level Co-occurrence Matrix (GLCM)

There are 4 features of GLCM, namely the level of contrast of the dark light of the screen, the relationship between input and output in the form of a correlation level, the Energy Level of a collection of pixel points of the image, and the Similarity level of Homogeneity by paying attention to the search angle 0° , 45° , 90° and 135° with distances $d = 1$ [10].

1) *Homogeneity. Angular Second Moment (ASM) is used to measure the concentration of intensity pairs on the co-occurrence matrix [11].*

$$ASM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{P(i, j)\}^2 \quad (1)$$

2) *Contrast. Contrast is used to measure variations or differences in the intensity of gray levels in the image*
 $Contrast = \sum_{n=0}^{G-1} n^2 \{ \sum_{i=1}^G \sum_{j=1}^G P(i, j) \}, |i - j| = n \quad (2)$

3) *Correlation. Correlation is used to measure the correlation and dependence between pixel with gray level i and pixel with gray level j in the image [13].*

$$Correlation = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{\{i \cdot j \cdot \sum_{i,j} P(i, j)\} - \{\mu_x \mu_y\}}{\sigma_x \sigma_y} \quad (3)$$

D. Scale-invariant feature transform

This method is used to identify and explain the local features of an image. As said by Giovany et al. (2017), by using SIFT, an image is converted into a local feature vector which is then used as an approach in detecting and recognizing the object in question through points or Key points [14].

1) Scale Space Extreme Detection

SIFT uses scale space to go to the next level. From an original image produces images that are increasingly blurred, by resizing to half the original size and continuously repeated up to 4 octaves or four stages[15]. The function used is a Gaussian Blur

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad (4)$$

with $G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$. The value of L is a Scale-space function by calculating the difference between 2 successive scale-spaces. σ is the width of a gaussian function and I is the input image [16].

2) Key point localization

According to research do by Zhu (2014), there are total checks on 26 neighbouring pixels consisting of 8 own neighbouring pixels, nine upper neighbours, and nine lower neighbours. X is the "Key point" if it is the largest or at least greater than 26 neighbours around that point. For white or blank marker, there is no checking, just compare, or just skip it [17]. Taylor's expansion of a space-scale function $D(x, y, \sigma)$ is shifted such that the sample point is an origin

$$D(x) = D + \frac{\partial D}{\partial x} x + \frac{1}{2} x^T \frac{\partial^2 D}{\partial x^2} x \quad (5)$$

3) Orientation Assignment

To get the orientation used functions:

$$m(x, y) = \sqrt{(L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2} \quad (6)$$

$$\theta(x, y) = \tan^{-1} \left(\frac{L(x, y+1) - L(x, y-1)}{L(x+1, y) - L(x-1, y)} \right) \quad (7)$$

where $m(x, y)$ is the gradient value, $\theta(x, y)$ is the orientation direction, and L is the image at the space scale [18].

4) Key point Descriptor

To simplify the calculation, a very unique Key point must be generated. To do this, take the 16 or 4 x 4 area window around the Key point [19]. This area 16 is divided into sixteen 4 x 4 windows each as shown in Figure 1.

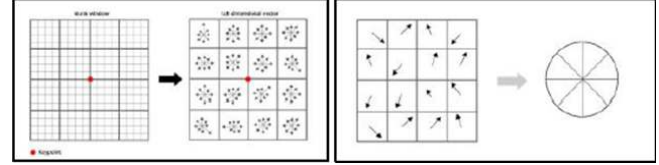


Fig.1. Determination of the Key point Descriptor

Every change in a gradient within the radius of 0-44 degrees adds to the first bin. The next number of 45-89 becomes the next bin. The amount added to the bin is considered based on the size of the gradient used [20]. Angles that are far from the Key point will add a smaller value to the histogram. Its functions are:

$$f(\theta, x, y) = |J(x, y)| \delta(\theta - J(x, y)) \quad (8)$$

E. Accuracy

Calculation of accuracy in this research was done by calculating the value of Accuracy, Sensitivity, Specificity and Precision Rate

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$Specificity = \frac{TN}{TN+FP} \quad (11)$$

$$Sensitivity/ Recall = \frac{TP}{TP+FN} \quad (10)$$

$$Precision Rate = \frac{TP}{TP+FP} \quad (12)$$

With Real positive (TP) is the number of pneumonia bacteria classified as pneumonia bacteria, negative True (TN) is the number of non-pneumonia bacteria, False negative (FN) is the number of pneumonia bacteria classified as non-pneumonia, and False positive (FP) is the number of non-pneumonia bacteria classified as pneumonia bacteria.

III. RESEARCH METHOD

The Research methods used in this research is shown in Figure 2 and 3.

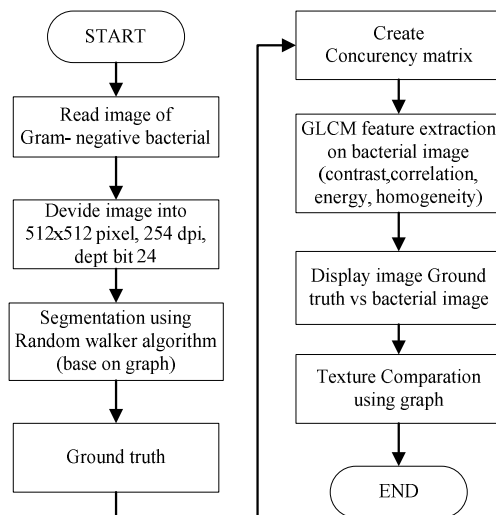


Fig.2. GLCM Method

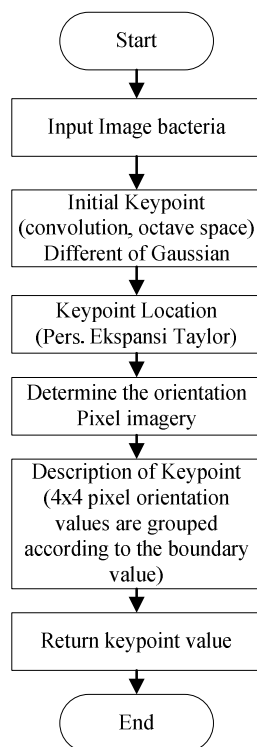


Fig.3. SIFT Method

Figure 2and 3 shows the research methodology used in which bacteria were observed based on texture features. The first method is the grey level matrix (GLCM), and the second is the Scale-invariant feature transform (SIFT). These two methods are run to get feature comparisons and will be used for the next process.

IV. RESULTS AND DISCUSSION

The hardware used in this research is an Intel Core i-7 processor with 8GB of RAM with an Nvidia GTX 1050 4GB VGA. The software used is the MATLAB 2019a. This section discusses the running of the program and the stages of testing. It is starting with reference to the ground truth that was made manually and validated by medical analysts to

determine the bacteria sought. This reference is then used to look for bacterial objects in the object-glass image. The GLCM process is shown in figure 4,5.

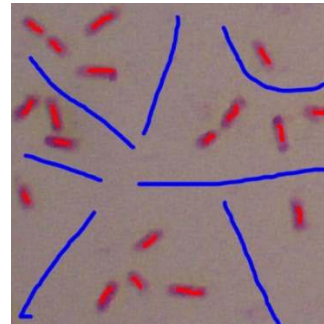


Fig.4. Ground truth

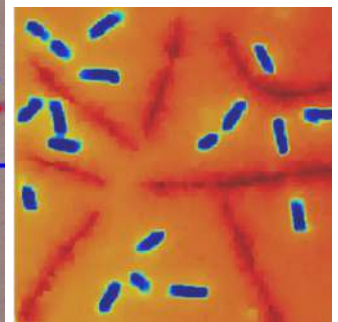


Fig.5. Random walker segmentation

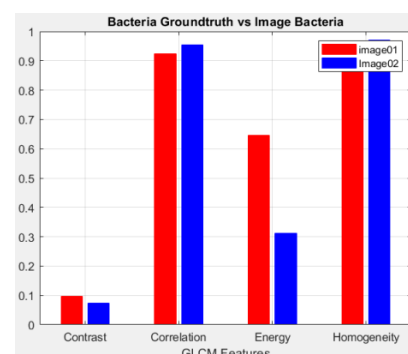


Fig.6. GLCM Feature Extraction

From Figure 6 shows that the results of the process of identifying bacteria using the GLCM feature shows the level of similarity based on the parameters of the contrast or sharpness of the image, Correlation which is the relationship between output and input, Energy which shows the level of power and Homogeneity which shows the degree of similarity. The higher the percentage of Correlation, the more similarity of bacteria with the predetermined truth image of the soil. The results of the GLCM are shown in table 1.

TABLE 1. COMPARATION OF IMAGE COMPARE TO GROUND TRUTH

Object bacteria	Contrast	Correlation	Energy	Homogeneity
Image Ground truth	0.09	0.92	0.64	0.96
average Image with the same class	0.08	0.87	0.53	0.96
average Image with the different class	0.14	0.73	0.41	0.85

After getting a comparison of the texture values of an object using GLCM, the next step is to process the feature values using SIFT, and the results are shown in Figure 7,8,9 below.

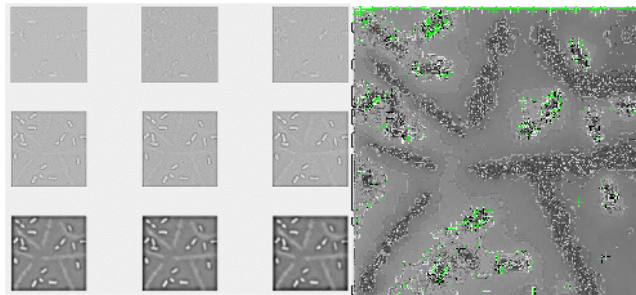


Fig.7. Different of Gaussian

Fig.8. Key point localisation

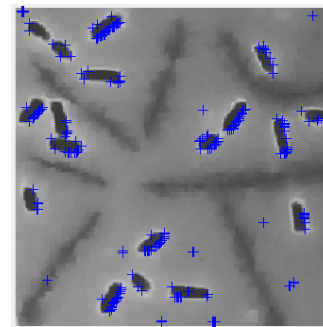


Fig.9. key point descriptor

SIFT algorithm for bacterial images using MATLAB 2019a requires Elapsed time is 0.210774 seconds. The result on orientation assignment is 230 key points, while the keypoint descriptor is 337 key points. Furthermore, the key point results are used to calculate accuracy using recall and precision. In this research, four images of Gram-negative bacteria divided into 512x512 pixels, 96 dpi with a bit depth of 24. The search for key points for the SIFT algorithm is shown in Table 2.

TABLE 2. NUMBER OF KEY POINTS AND ACCURACY FOR EACH BACTERIUM

NO		Orientation Assignment	Key point descriptor	T P	T N	F P	F N	Accu- racy	Sensit- ivity	Speci- fity	Precision Rate
1	Klebsiella pneumonia	282	177	14	4	1	1	0.90	0.93	0.80	0.93
2	Acinetobacter Baumanii	8974	4376	21	5	2	1	0.90	0.95	0.71	0.91
3	Pseudomonas aerugenusa	3645	3159	37	1	1	1	0.95	0.97	0.50	0.97
4	Eschericia Coli	1719	2191	10	3	2	1	0.81	0.91	0.60	0.83
Average								0.89	0.94	0.65	0.91

V. CONCLUSION

The results of this research are the extraction of texture characteristics from Gram-negative bacteria. The use of GLCM texture is done to recognize bacterial objects based on the value of Contrast, Correlation, Energy, and Homogeneity of an image. The proximity value is calculating as a percentage. SIFT algorithm provides a sign to use key points to recognize objects. At the testing stage, the test scenario was performed with cross-validation for 50 images to identify four classes of bacteria. The results on observations by comparing the effects of object features with ground truth found that the level of accuracy using a grey level to the similarity of objects approaching and using the object texture direction approach obtained 89% accuracy.

ACKNOWLEDGMENT

Thank you to the Dr. Soetomo Hospital microbiology lab team in Surabaya for supporting primary data and promoters and co-promoters who have allowed this publication.

REFERENCES

- [1] Farzaneh Dehghan, N.Z. and A.S. Vahid Boostani, Tasnim Eghbal. Resistance of gram negative bacteria in hospital acquired pneumonia: a prospective study. *The Brazilian Journal of Infectious Diseases*. 2016; 20: 113-114.
- [2] Prasso, J.E. and J.C. Deng. Postviral Complications: Bacterial Pneumonia. *Clinics in Chest Medicine*. 2017; 38: 127-138.
- [3] Hiremath, P.S. An Improved Automated Method for Identification of Bacterial Cell Morphological Characteristics. *International Journal of Advanced Trends in Computer Science and Engineering*. 2013; Vol.2: No.1, 11-16 (2013).
- [4] Shabat, A.M. and J.-R. Tapamo. A comparative study of the use of local directional pattern for texture-based informal settlement classification. *Journal of Applied Research and Technology*. 2017; 15: 250-258.
- [5] Tahir, M. Pattern analysis of protein images from fluorescence microscopy using Gray Level Co-occurrence Matrix. *Journal of King Saud University - Science*. 2018; 30: 29-40.
- [6] Azhar, R., D. Tuwohingide, et al. Batik Image Classification Using SIFT Feature Extraction, Bag of Features and Support Vector Machine. *Procedia Computer Science*. 2015; 72: 24-30.
- [7] Silhavy, T.J., D. Kahne, and S. Walker. The bacterial cell envelope. *Cold Spring Harbor perspectives in biology*. 2010; 2: a000414-a000414.
- [8] Jackman, P. and D.-W. Sun. Recent advances in image processing using image texture features for food quality assessment. *Trends in Food Science & Technology*. 2013; 29: 35-43.
- [9] Shamir, Lior Delaney, et al. Pattern recognition software and techniques for biological image analysis. *PLoS computational biology*. 2010; 6: e1000974-e1000974.
- [10] Öztürk, Ş. and B. Akdemir. Application of Feature Extraction and Classification Methods for Histopathological Image using GLCM, LBP, LBGLCM, GLRLM and SFTA. *Procedia Computer Science*. 2018; 132: 40-46.

- [11] Berbar, M.A. Hybrid methods for feature extraction for breast masses classification. *Egyptian Informatics Journal*. 2018; 19: 63-73.
- [12] Sun, J.-Y., S.-W. Kim, et al. A novel contrast enhancement forensics based on convolutional neural networks. *Signal Processing: Image Communication*. 2018; 63: 149-160.
- [13] Abd Latif, M.H., H. Md. Yusof, et al. Implementation of GLCM Features in Thermal Imaging for Human Affective State Detection. *Procedia Computer Science*. 2015; 76: 308-315.
- [14] Giovany, S., A. Putra, et al. Machine Learning and SIFT Approach for Indonesian Food Image Recognition. *Procedia Computer Science*. 2017; 116: 612-620.