A Classification Method of Epithelial Cells and Clue Cells Based on Multi-scale Texture Analysis

Yukun Guo[1,2], Xiangru Yu[1,2], Jinping Li*[1,2]
1. School of Information Science and Engineering University of Jinan, Jinan, China
2. Shandong Provincial Key Laboratory of Network Based Intelligent Computing, Jinan, China
E_mail: ise_lijp@ujn.edu.cn

***Abstract*—A novel method is proposed for the classification of epithelial cells and clue cells in wet mount microscopic images of vaginal secretions. Generally, there are many complicated ingredients in these images, and different from the gram stain method, no color information can be used. Obviously, the texture information of these cells becomes the main feature in the classification of these ingredients. After careful observation of difference of these two kinds of cells, we found the surface of clue cells is rougher. So, we extract texture features of those cells using the multi-scale texture energy descriptor which can reflect the difference of these two kinds of cells in different scales effectively. After that, the traditional SVM classifier is employed for the classification. The experimental results show that our method can effectively complete the classification task.**

***Keywords*—Multi-scale; Texture energy; Clue cell; Vaginal secretions**

I. Introduction

Microscopic examination is a simple and effective method to diagnose bacterial vaginosis [1]. And the number of clue cells is a very important index in the diagnosis of bacterial vaginosis. At present, the frequently-used detection method of clue cells is the Gram-staining microscopy, by which the clue cells can be easily recognized according to different colors due to the fact that the clue cells show positive reaction after gram staining. Although the Gram-stain can help us easily identify clue cells, the cumbersome operating procedures and other factors lead to low detection efficiency. From Fig. 1, we can see the difference of surface textures between epithelial cells and clue cells, the surface of former is smoother while the latter is rougher (A large number of gardnerella vaginalis is attached to the clue cell surface). So texture feature is a very important factor to distinguish these two kinds of cells.

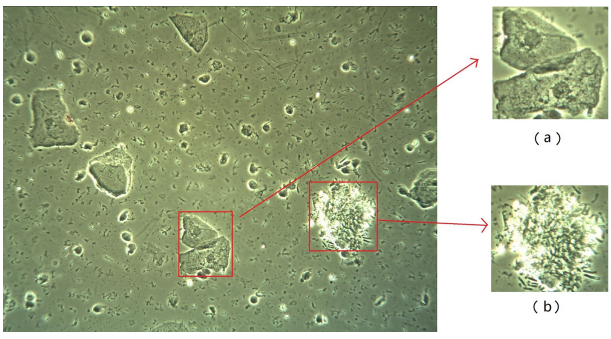

Fig. 1. Epithelial cells and clue cells in wet mount. (a) Epithelial cells. (b) clue cells.

1) Related works.: Texture analysis is a very important task in the field of image processing, and many researchers have proposed many algorithms to analyze different textures. Tuceryan and Jain [2] divided these algorithms into four categories: statistical methods, geometrical methods, model based methods and signal processing methods. The statistical method has been extensively applied due to its strong adaptability and practicability. Autocorrelation function method is a kind of Statistical Methods proposed by Sklansky [3] in 1978. Autocorrelation function can measure the degree of roughness of the spatial structure of texture, but it doesn't work for the irregular natural textures. Researchers usually combine it with other methods to improve its performance [4], [5], [6]. Haralick proposed Gray Level Co-occurrence Matrix (GLCM) [7], which has become one of the most well-known and widely used texture features, and can estimate image properties related to second-order statistics. GLCM is an $N \times N$ matrix, where N is the number of gray levels in an image. The element of GLCM is the number of special gray level distribution patterns in an image and 14 texture features can be calculated from GLCM. Ulaby et al. [8] found that only 4 features (energy, contrast, correlation and entropy) are uncorrelated and higher classification accuracy can be obtained from these 14 features. GLCM can well reflect the spatial distribution characteristics of texture, and based on GLCM many intensive researches have been done by researchers [9], [10], [11]. Local Binary Patterns (LBP) [12] has achieved remarkable results in texture classification and been widely used in the field of medical image processing and face detection. LBP labels pixels of an image by thresholding the 3×3-neighborhood of each pixel with the center value and considering the result as a binary number. Then the texture descriptor can be defined by the histogram of the labels[13]. But the original LBP descriptor's ability is limited by its small spatial support area. And Ojala improved the LBP [14] in 2002. In recent years, researchers have made a series of in-depth researches on LBP and put forward many improved methods, such as DLBP [15], CLBP [16], DDLBP [17], scLBP [18] and SSLBP [19], etc.

Although many texture descriptors have achieved good experimental results in practical applications, there are still many deficiencies. Researchers have tried to improve the performance of texture descriptors from multi-scale analysis. Pyramid [20] and wavelet transform method [21] are commonly used in multi-scale analysis. Pyramid transform

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lays the theoretical foundation for multi-scale analysis and multiresolution image decomposition. Researchers have done many researches on how to extract texture features in multi-scale space. Lang, et al. [22] developed an algorithm through a unique multi-scale texture identifier integrated in a level-set framework to capture the speculated boundary of the lesion in the ultrasonic image. Abry et al. [23] used an anisotropic multi-scale representation of texture, the hyperbolic wavelet transform (HWT), to classify photographic prints. Although so many texture analysis methods have been proposed, it is very hard to find a paper for the classification of epithelial cells and clue cells. The other problem in cell classification is the choice of classifier. Researchers have proposed a lot of classifier algorithms, such as, decision tree [24], [25], artificial neural network (ANN) [26], support vector machine (SVM) [27], [28], [29], Bayesian classifier [30], [31] and boosting algorithm [32], [33], [34], etc. In recent years, there are many articles about the classification that have been published [35], [36], [37], [38].

2) Our Method: To improve the detection efficiency, we use the different texture features of epithelial cells and clue cells to distinguish these two types of cells. With this method, we don't have to go through the complicated process of Gram stain. After observing a large number of these two kinds of cells, we find distinct differences between them in different scales. The differences are mainly reflected in the smooth degree of surface texture. In small scale, the surface of epithelial cells is flat, while clue cells' is uneven. In large scale, epithelial cells' surface is smoother than clue cells'. First, using the multi-scale energy extraction operators (introduced in section II) to compute the energy distribution maps of an image. Then, calculating the local texture features descriptors from the energy distribution maps. Finally, classifying the texture by using the local texture features descriptors. Because the classification problem in this paper is a binary classification problem, we choose the SVM classifier to do this task considering its strong ability to interpret and access.

II. Multi-scale Texture Analysis

Different textures will show different characteristics in the same scale space. The same texture will have different characteristics in different scale spaces, which are the reasons that we use multi-scale texture analysis in our method.

A. Multi-scale Analysis

The multi-scale analysis method in this paper is different from the original pyramid. We change the size of the operator rather than down-sampling the image to achieve the purpose of multi-scale analysis. Down-sampling may lose a lot of information when we drop the pixels from the original image, while our method expands the operator's size which can preserve more image information. What's more, this type of multi-scale analysis can use the integral image to accelerate the operation (inspired by surf algorithm). These steps of the multi-scale analysis method are described as follows.

First, the image is mapped into multi-scale feature space S (Note: $S = \{s_1, s_2, \cdots, s_N\}$, N is the space's number) using the multi-scale feature extraction operator P, $P = \{p_1, p_2, \cdots, p_N\}$. Then, each pixel's local texture features descriptors $\boldsymbol{v_i}$ $(i = 1, 2, \cdots, N)$ is calculated from each scale space. Finally, all the local texture features descriptors are combined into one feature descriptor $\boldsymbol{V} = [\boldsymbol{v_1}, \boldsymbol{v_2}, \cdots, \boldsymbol{v_N}]$. Thus, $\boldsymbol{V}$ is the texture feature descriptor of each pixel. Fig. 2 shows each step of the multi-scale analysis.

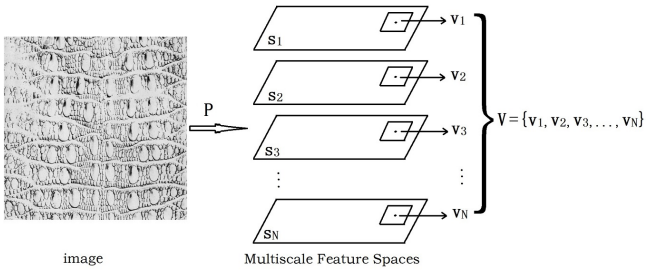


Fig. 2. Multi-scale analysis.

The multi-scale feature extraction operator P is a set of operators of the same type, but each operator has different scale (defined by S). Each value in the scale space s_i contains the information about the corresponding local area in the original image. For example, $s_i(x, y)$ contains the mean of those pixel values in the local area of the image I with (x, y) as the center after the operation of Eq. 1. The amount of information contained in the same location in different scale spaces is also different. Furthermore, P can be defined as any local feature operator, such as edge detection operator, LBP operator, GLCM operator and energy operator, etc. And the output of P is not necessary to be a constant, it can also be a matrix.

$$s_i(x, y) = p_i(I(x, y)), p_i(\cdot) = mean(\cdot), i = 1, 2, \cdots, N \quad (1)$$

The local texture features descriptor V is a very important factor in our method because it is directly related to the accuracy of classification. The selection of V is very flexible. Such as mean, autocorrelation, energy, entropy and variance, etc. One or more values can be selected as features into V according to the texture's attribute.

B. Multi-scale Texture Energy

The main difference between epithelial cells and clue cells is the degree of surface roughness. So, we use the local energy operator (see Eq. 2) as the multi-scale feature extractor P. Laws [39] use the "absolute value windowing" filter to measure the local texture energy on the filtered image (filtered by a set of "texture energy" transforms, which can be made invariant to changes in luminance and contrast). To simplify operation, we use Eq. 2 as the local texture energy operator, which is invariant to changes in luminance and contrast, to

measure the local energy on the original image.

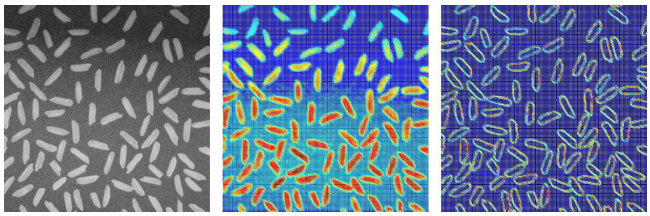
$$E(x,y) = \frac{1}{n^2} \sum_{i=-k}^{k} \sum_{j=-k}^{k} [I(i,j|x,y) - \mu(x,y)]^2 \quad (2)$$

$$\mu(x,y) = \frac{1}{n^2} \sum_{i=-k}^{k} \sum_{j=-k}^{k} I(i,j|x,y) \quad (3)$$

Where $\mu(x,y)$ in Eq. 3 is the mean of pixel values in window W. n^2 is the size of window W, and $n = 2k+1$, $k \in S$, S is the set of space scale. $I(x,y)$ is the pixel value at (x,y) of the image.

The result of Eq. 2 is different from Eq. 4 (the commonly used energy formula). Through two equations, we can see that Eq. 2 is more appropriate to measure the roughness of the texture in the local window. As shown in the subfigure (b) of Fig. 3, the result of Eq. 4, the energy of the inner part of a grain of rice is very high, although its interior is very flat. This energy cannot properly measure the roughness of the texture. In the subfigure (c) of Fig. 3, the energy is concentrated around the edges of rices, and the energy of the interior area is very low.

$$E(x,y) = \frac{1}{n^2} \sum_{i=-k}^{k} \sum_{j=-k}^{k} [I(i,j|x,y)]^2 \quad (4)$$



(a) (b) (c)

Fig. 3. The energy distribution maps by different equations. (a) Original image. (b) Energy distribution maps by Eq. 4. (c) Energy distribution maps by Eq. 2.

The space scale set S is also very important for the classification accuracy. Fig. 4 shows the energy distribution maps of the epithelial cells and clue cells in different scale spaces. The energy of epithelial cells is mainly distributed around edges and nucleus. While clue cells' is more uniform and higher due to its rough surface.

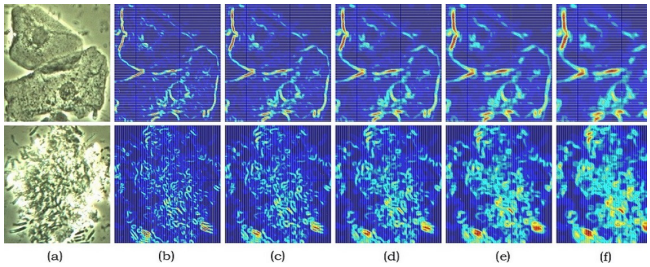


Fig. 4. Energy distribution of epithelial cells and clue cells in different scale spaces. (a) Epithelial cells and clue cells. (b) to (f) The energy distribution maps in $S = \{3,4,5,6,7\}$.

III. Experiments and Discussion

In order to verify the effectiveness of our method for the classification of epithelial cells and clue cells, we compare our method with uniform LBP (ULBP), CLBP and GLCM. We use all the microscopic images of vaginal secretions containing epithelial cells and clue cells to verify the accuracy of four methods. In this comparative experiment, we focus on the effectiveness of the features that extracted by four methods. So, we employ the same classifier SVM in four methods to do this classification task. Parameters of these four methods are given in Table I. From Table I, we can easily get the dimension of the feature extracted by each method. In ULBP, the bin's number determines that the dimension of the feature vector is 59. CLBP contains two parts information the sign components and magnitude components. Each component contains 59 bins, so, the feature vector dimension is 118. GLCM contains 4 co-occurrence matrices in 4 directions and extracts 4 features from each co-occurrence matrix. So, the dimension of feature vector is 16. Our method has 5 scale spaces and each scale space contains 4 features. Therefore, the feature vector consists of 20 elements.

TABLE I
Parameters setting of each method.

Method ID	Settings
ULBP	Neighborhood = 8, radius = 1, bin's number = 59.
CLBP	Neighborhood = 8, radius = 1, Features=$[CLBP\_S, CLBP\_M]$.
GLCM	Distance = 1, Angle = $\{0, 45, 90, 135\}$, LevelNum = 8, Features=$[energy, contrast, entropy, correlation]$.
Our Method	P=Energy operator, $S = \{3,4,5,6,7\}$, $\boldsymbol{v} = [mean, energy, contrast, entropy]$.

The accuracy of the four methods is shown in Table II. Accuracy of CLBP is 9% higher than that of ULBP, because the CLBP retains more information in the original image than ULBP. Accuracy of GLCM is higher than CLBP although the dimension of the feature vector of GLCM is lower than that of CLBP. The reasonable explanation is that the feature vector of CLBP contains too much redundant information and the information contained in GLCM's feature vector is more effective. Due to the fact that the main difference between epithelial cells and clue cells is the roughness of the surface, and we use the multi-scale texture energy descriptor to describe the difference. So, our method has the best performance among the four methods.

TABLE II
The classification accuracy of each Method on epithelial cells and clue cells.

Method ID	ULBP	CLBP	GLCM	Our Method
Accuracy	83.44%	92.48%	92.86%	94.35%

To test our method in practical application, we compare the proposed method with the other three algorithms in clinical

microscopic images. The other components (lactobacilli, white blood cells and impurities, etc.) in the image may bring negative influence on the accuracy of the classification. So, we use the former method proposed in ref [40], to remove the other components from the image. As shown in Fig. 5, our method is better than the other methods for the classification of clues cells, but there are still some problems. For example, the overlap of the epithelial cells and the clue cells may have a negative effect on the classification as shown in subfigure 3f). This is because the texture features of pixels belonging to epithelial cells are influenced by the neighboring pixels belonging to clue cells.

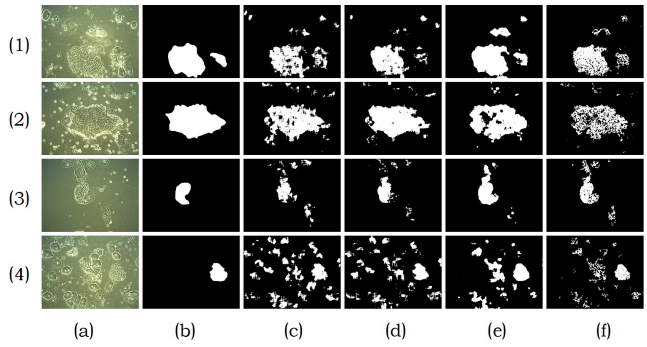


Fig. 5. Classify result of four methods. (a) Original images. (b) Ground truth. (c) ULBP. (d) CLBP. (e) GLCM. (f) Our Method.

IV. Conclusions

In this paper, we present a novel method to classify epithelial cells and clue cells in wet mount microscopic images of vaginal secretions based on multi-scale texture analysis. The experimental results show that our method can effectively classify epithelial cells and clue cells. Due to the fact that our method can skip the complicated process of Gram stain, it can save a mass of time and realize automatic processing easily. But there are still some problems in our method. For example, the adhesion between the components will affect the classification accuracy. And at the early stage of evolutional process from epithelial cells to clue cells, the classification result is not very well. We will address these issues in future research.

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