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Pollen Image Recognition Based on DGDB-LBP Descriptor

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Pollen Image Recognition Based on DGDB-LBP Descriptor

L P Han[1, *] and Y H Xie[1]

[1]College of computer and software, Nanjing University of Information Science and Technology, Nanjing 210044, China

*E-mail: hanliping93@163.com

Abstract. In this paper, we propose DGDB-LBP, a local binary pattern descriptor based on the pixel blocks in the dominant gradient direction. Differing from traditional LBP and its variants, DGDB-LBP encodes by comparing the main gradient magnitude of each block rather than the single pixel value or the average of pixel blocks, in doing so, it reduces the influence of noise on pollen images and eliminates redundant and non-informative features. In order to fully describe the texture features of pollen images and analyze it under multi-scales, we propose a new sampling strategy, which uses three types of operators to extract the radial, angular and multiple texture features under different scales. Considering that the pollen images have some degree of rotation under the microscope, we propose the adaptive encoding direction, which is determined by the texture distribution of local region. Experimental results on the Pollenmonitor dataset show that the average correct recognition rate of our method is superior to other pollen recognition methods in recent years.

1. Introduction

The classification and identification of pollen particle has a wide range of applications in allergic pollen index forecast, drug development, paleoclimatic reconstruction and other fields. At present, pollen identification is mainly done by artificial inspection under microscopy, which requires the operator to have a rich knowledge of sporopollen morphology. The identification process is time consuming and laborious, and the identification result is susceptible to subjective opinions, resulting in a relatively low accuracy. Since pollen images under microscope have similar contours, textures and structural features as common images, it is an effective way to extract pollen features and classify them automatically by computer.

Since Flenley suggested the use of algorithms to classify and recognize pollen in palynology in 1968, plenty of feature extraction and recognition algorithms for pollen images have been proposed. Texture, as an effective pollen image feature, has been extensively studied and focused. For example, E Cernadas et al.[1] proposed a texture and shape based descriptor (TSD), which obtained 89% recognition rate, however, the recognition performance partly depended on the type of pollen and the universality is not high. DS Guru et al.[2] proposed a surface texture based pollen image classification model, using Gabor wavelet, local binary patterns (LBP), gray-level co-occurrence matrix (GLCM) and gray-level difference matrix (GLDM) to extract the texture features of polllen. The combination of these features is used for identifying pollen, and the recognition rate is 91.66%, whereas, the computational cost of this method is high and the scale of the extracted feature is single. JV Marcos et al.[3] extracted the texture features of pollen images by combining gray-level co-occurrence matrix (GLCM), Log-Gabor filter (LGF), local binary patterns (LBP) and discrete orthogonal moments (DTM), and obtained 94.83% recognition rate. However, the method is time-consuming and the extracted feature has a large amount of redundant information. A Daood et al.[4] decomposed the pollen image into multiple layers (Multi-Layer Feature Decomposition), extracting the texture features and geometric features of each layer, respectively, which obtained 86.94% recognition rate, but this method is not robust to the rotation of pollen images.

In this paper, we improve the sampling strategy and encoding scheme of tradional LBP, and propose a new local binary pattern descriptor based on the pixel blocks in the dominant gradient direction. Differing from the traditional LBP and its variants, we calculate the gradient amplitude of pollen images in the dominant gradient direction, which avoids the influence of noise on the extracted feature [5] and eliminates some redundant and non-informative features. In order to fully describe the texture features of pollen images and analyze it under the multi-scales, we propose multi-directional sampling strategy, which uses three types of operators to extract the radial, angular and multiple texture features under different scales. Considering that the pollen images have some degree of rotation under the microscope, we propose the adaptive encoding direction, which is determined by the texture distribution of each local region. We calculate the adaptive encoding direction and set it as initial coded point for binary encoding, which enhances the feature descriptor's robustness to the rotation of pollen images.

2. DGDB-LBP descriptor

In view of the shortcomings of traditional LBP and its variants, we improve the sampling strategy and coding scheme, as shown in Figure 1, the specific steps are as follows:

2.1. Multi-directional sampling

2.1.1. Calculate the dominant gradient direction. We first calculate the gradient of all pixels in the image, then the gradient angle of each pixel is rounded down, so that the gradient direction of the whole image is discretized into eight directions. The gradient magnitude of all pixels is weighted to eight discrete directions, taking the longest for the dominant gradient direction of the image.

2.1.2. Calculate the gradient magnitude of the pixel block. We accumulate the gradient magnitude of all the pixels in the dominant gradient direction as the gradient magnitude of the pixel block, which is denoted as $G\left(B_{r,P,m,i}\right)$. $B_{r,P,m,i}$ is the pixel block on the circle with radius r and sampling points P, i is the serial number of pixel blocks with size $m \times m$, and $G\left(B\right)$ is the accumulation of the dominant gradient magnitude on pixel block B.

2.1.3. Extract radial, angular and multiple texture features. In order to obtain more texture information, we also extract the radial texture feature, angular texture feature and multiple texture feature of pollen image. The three operators for extracting different texture features are named DGDBLBP_RD, DGDBLBP_AD and DGDBLBP_MD, respectively.

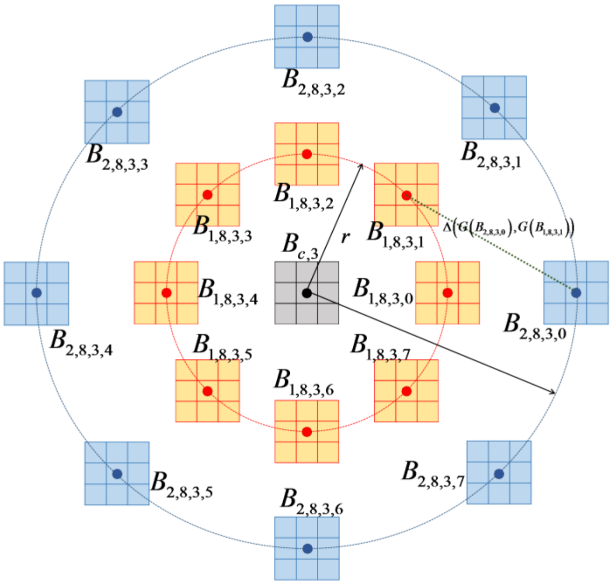

Figure 1. The sampling figure of DGDB-LBP.

2.2. *Adaptive encoding*

2.2.1. DGDBLBP_RD. The adaptive coding direction of DGDBLBP_RD is defined as the symbol of circular adjacent pixel block with the largest gradient difference from the center pixel block, which is denoted as D_R. The specific formula of radial texture feature is as follows:

$$DGDBLBP\_RD(x_c)=\sum_{i=0}^{P-1}S\left(G\left(B_{r,P,m,i}\right)-G\left(B_{c,m}\right)\right)2^{\mathrm{mod}(i-D_R+P,P)} \tag{1}$$

$$D_R=\underset{i\in(0,1,\cdots,P-1)}{\arg\max}\left|G\left(B_{r,P,m,i}\right)-G\left(B_{c,m}\right)\right| \tag{2}$$

Where $S(x)$ is a symbolic function, which is defined as follows:

$$S(x)=\begin{cases}0 & x<0\\ 1 & x\geq 0\end{cases} \tag{3}$$

2.2.2. DGDBLBP_AD. The adaptive coding direction of DGDBLBP_AD is defined as the symbol of pixel block with the largest gradient difference from the adjacent pixel blocks on the circular neighborhood, which is denoted as D_A. The specific formula of angular texture feature is as follows:

$$DGDBLBP\_AD_{r,P}(x_c)=\sum_{i=0}^{P-1}S\left(2G\left(B_{r,P,m,i}\right)-\left(G\left(B_{r,P,m,\mathrm{mod}(i+P-1,P)}\right)+G\left(B_{r,P,m,\mathrm{mod}(i+P+1,P)}\right)\right)\right)2^{\mathrm{mod}(i-D_A+P,P)} \tag{4}$$

$$D_A=\underset{i\in(0,1,\cdots,P-1)}{\arg\max}\left|2G\left(B_{r,P,m,i}\right)-\left(G\left(B_{r,P,m,\mathrm{mod}(i+P-1,P)}\right)+G\left(B_{r,P,m,\mathrm{mod}(i+P+1,P)}\right)\right)\right| \tag{5}$$

2.2.3. DGDBLBP_MD. The adaptive coding direction of DGDBLBP_MD, we record as D_M, is defined as the symbol of pixel block on the outer ring that maximizes the gradient difference between the pixel block pairs on the outer ring and inner ring. The specific formula of multiple texture feature is as follows:

$$DGDBLBP\_MD_{r,r+1,P}\left(x_c\right)=\sum_{i=0}^{P-1}S\left(\Delta\left(G\left(B_{r+1,P,m,i}\right),G\left(B_{r,P,m,\mathrm{mod}(i+1,P)}\right)\right)-\Delta\left(G\left(B_{r+1,P,m,\mathrm{mod}(i+3,P)}\right),G\left(B_{r,P,m,\mathrm{mod}(i+4,P)}\right)\right)\right)2^{\mathrm{mod}\left(i-D_M+P,P\right)} \tag{6}$$

$$D_M=\underset{i\in(0,1,\cdots,P-1)}{\arg\max}\left|\Delta\left(G\left(B_{r+1,P,m,i}\right),G\left(B_{r,P,m,\mathrm{mod}(i+1,P)}\right)\right)\right| \tag{7}$$

3. Experimental results and analysis

We performed the experiments on the Pollenmonitor dataset with 22750 pollen grains from 33 taxa, in which the images were automatically collected, prepared and recorded by the first prototype of the pollenmonitor in Europe in 2006. The Correct Recognition Rate (CRR), False Recognition Rate (FRR) and Recognition Time (RT) were used to measure the recognition performance of the algorithm. Figure 2 shows the results of our method for classifying six representative pollen images on the Pollenmonitor dataset. It can be seen from the experimental results that most of the unpolluted and undeformed pollen images with rich texture information can be correctly classified and identified. In order to verify the effectiveness of the proposed method, we compare the DGDB-LBP with four recent pollen recognition methods. Table 1 shows the experimental results of our method and the other four methods on the Pollenmonitor dataset. It can be seen that the correct recognition rate of our method is higher than that of other four methods on the Pollenmonitor dataset, and the computational efficiency is higher than that of most methods.

Table 1. The results of our method and other methods.

Dataset	Method	CRR/%	RT/s
Pollenmonitor	TSD	84.00	17.3
	Combined Gabor-LBP-GLCM-GLDM	84.27	16.2
	Combined GLCM-LGF-LBP-DTM	89.75	18.1
	Multi-Layer Feature Decomposition	86.20	8.5
	DGDB-LBP	91.82	12.8

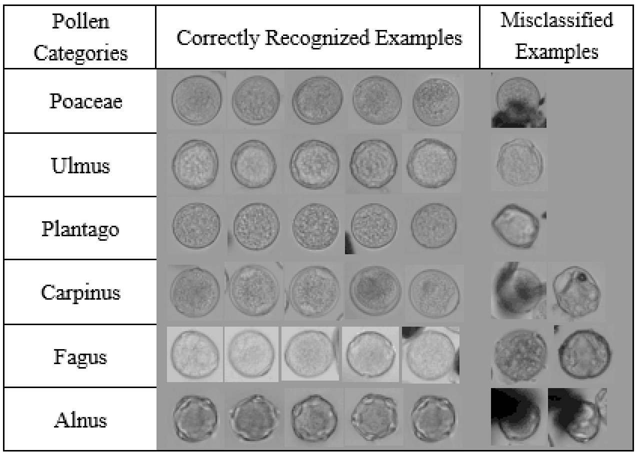

Figure 2. Experimental results of the Pollenmonitor dataset.

4. Conclusions

In this paper, we propose a local binary pattern descriptor based on the pixel blocks in the dominant gradient direction, which has a number of advantages. Firstly, the center pixel is quantified by comparing the gradient magnitude of each pixel block in the dominant gradient direction, which avoids saltations in the binary pattern caused by noise. Secondly, the analysis of pollen images under the multi-scales improves the discrimination of the descriptor. Thirdly, the adaptive encoding with

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reference to the texture features of adjacent regions enhances the descriptor's robustness to the rotation of pollen images.

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