Local Decimal Pattern for Pollen Image Recognition

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Abstract. In this paper, we propose local decimal pattern (LDP) for pollen image recognition. Considering that the gradient image of pollen grains has more prominent textural features, we quantify by comparing the gradient magnitude of pixel blocks rather than the single pixel value. Unlike the local binary pattern (LBP) and its variants, we encoding by counting the pixel blocks on different quantization intervals, which makes our descriptor robust to the rotation of pollen images. In order to capture the subtle textural feature of pollen images, we increase the number of quantization intervals. The average correct recognition rate of LDP on Pollenmonitor dataset is 90.95%, which is much higher than that of other compared pollen recognition methods. The experimental results show that our method is more suitable for the practical classification and identification of pollen images than compared methods.

Keywords: Local decimal pattern · Pollen recognition · Textural feature
Gradient magnitude

1 Introduction

The classification of pollen particles has been widely applied for allergic pollen index forecast, drug research, paleoclimatic reconstruction, criminal investigation, oil exploration and some other fields [1]. The traditional identification of pollen grains is mainly done by artificial inspection under microscopy, which requires the operator to have a rich knowledge of pollen morphology and needs a high level of training to get accurate recognition results. The commonly used discriminate criteria is the visual biological pollen grain morphological appearance, such as shape, polarity, aperture, size, exine stratification and thickness, and so on [2]. It takes operator much of time and effort to observe the appearance of pollen grains, and often causes misrecognition.

With the development of image processing and pattern recognition [3–5], using computer to extract and classify pollen features has become an effective way for pollen recognition. The early pollen recognition algorithms focused on extracting shape features, in which the contour shape is a prominent feature for some pollen grains with slender oval shape or rounded triangular shape. However, most pollen grains always have similar contour shapes, so it is difficult to identify different categories of pollen images only by shape features. Considering that pollen images from different categories have large differences in texture, more and more texture based feature extraction

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methods have been proposed for automatic classification of pollen images. For example, Punyasena et al. [6] extracted the texture and shape features of pollen images using dictionary learning and sparse coding (DLSC), which obtained a recognition rate of 86.13%, however, the recognition performance largely depends on the selection and quantity of sample blocks. Daood et al. [7] decomposed the pollen image into multiple feature layers using clustering, then the texture and geometric features (TGF) of each layer were extracted using LBP and fractal dimension respectively. Finally, the SVM classifier was used to classify pollen images and a recognition rate of 86.94% was obtained. Whereas, the method has little robustness to the rotation of pollen grains, and the decomposition of pollen images increases the dimension of features. Boochs et al. [8] proposed a pollen recognition method combining shape, texture and aperture features (STAF), which extracted 18 shape features, 5 texture features (Gabor Filters, Fast Fourier Transform, Local Binary Pattern, Histogram of Oriented Gradients, and Haralick features) and a surface aperture features of pollen images. The method used a random forest classifier to identify pollen images, and obtained nearly 87% recognition rate. Guru et al. [9] proposed a pollen classification model based on surface texture, which combined local binary pattern (LBP), Gabor wavelet, gray-level difference matrix (GLDM), and gray-level co-occurrence matrix (GLCM) for pollen recognition (LGGG), and obtained 91.66% recognition rate. However, the computation cost of these two methods is large due to high dimension of the combined features, which makes them unpractical for real application. Marcos et al. [10] extracted texture features using Log-Gabor filter (LGF), discrete Tchebichef moments (DTM), local binary patterns (LBP) and gray-level co-occurrence matrix (GLCM), which obtained a recognition rate of 94.83%, whereas, the fused texture feature (LDLG) contains large amounts of redundant information and the computational process is complex.

Local binary pattern is an effective method for representing texture feature, which has been widely used in face recognition and texture classification [11]. The traditional local binary pattern and its variants usually use wide quantization intervals to quantize the neighboring pixels, which enhances the descriptor's robustness to the illumination changes of images, but also loses some detailed textural information at the same time. Unlike the general texture images, the textural variation range of pollen images is relatively small, so it's difficult to capture the subtle textural differences of pollen images from different categories in wide quantization intervals. In order to solve the problem, the local decimal pattern (LDP) was proposed. The advantages of our method are as follows: Quantizing using the gradient magnitude of pixel blocks instead of single pixel value to eliminate the effects of image noise. Encoding by referring to the number of pixel blocks in each quantization interval making the descriptor invariant to the rotation of pollen grains. The combination of LDP features in multiple directions increases the descriptor's discrimination. Experimental results on Pollenmonitor dataset show that the recognition rate and computation speed of our method is higher than that of most pollen recognition methods.

2 Local Decimal Pattern (LDP)

Most of the current methods for extracting pollen features are those combining different single features: LBP and fractal dimension as in [7], and LBP, GLCM, LGF and DTM as in [10], and LBP, Gabor, etc. as in [8, 9]. All of these take advantages of different features to construct the optimal representation of pollen images, but the use of multiple features leads to a higher computational costs.

In order to build pollen feature descriptor with high computational efficiency, and high robustness to rotation and noise, we proposed Local Decimal Pattern (LDP). Figure 1 shows the implementation of LDP feature for representing pollen images, and Fig. 2 presents the step of the algorithm based on LDP for pollen recognition. The specific calculation process of LDP is as follows:

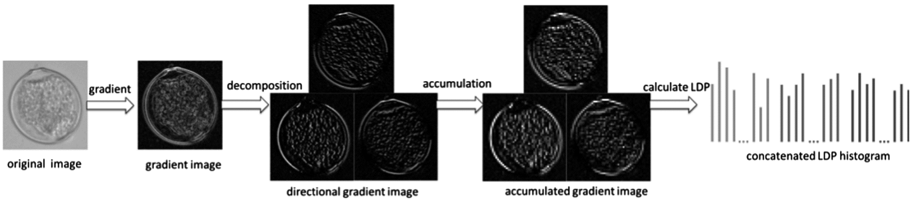

Fig. 1. Implementation of LDP feature for representing pollen.

TRAINING STAGE:
Input: T – Training set(t_i represents the pollen image in training set);
r – Sampling radius;
m – Block size;
L – Quantization interval number;
Output: Trained classifier;
1. for t_i in T do
2. Calculate the image gradient;
3. Weighting the gradient into 8 directions and find out the maximum, minimum and median radient directions, which is denoted as D_1, D_2 and D_3 respectively;
4. for D_1 to D_3 do
5. Calculate the gradient magnitude of pixel blocks under D_*;
6. Calculate the LDP under D_* and compute the statistical histogram of LDP;
7. end for
8. Concatenating the LDP histogram in 3 directions;
9. end for
10. Training using SVM classifier;
TEST STAGE:
Input: M– Test set(m_j represents the pollen image in test set);
Output: The predicted category of test image;
11. for m_j in M do 2 - 8
12. Predicting the category of test image using trained SVM classifier;
13. end for

Fig. 2. The step of the algorithm based on LDP for pollen recognition.

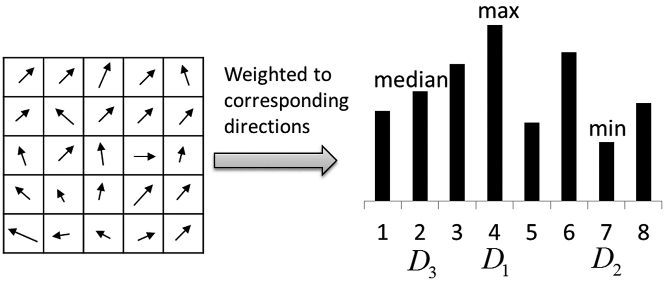

Fig. 3. Calculation of gradient histogram of an image block. The lengths and directions of arrows represent the gradient magnitude and gradient direction of pixels respectively.

First, we calculate the image gradient, the gradient information of each pixel includes gradient magnitude and gradient angle. The gradient angle range from $-\pi$ to π, and we divide $[-\pi, \pi)$ into 8 equal-sized direction intervals. Then, a histogram of gradient is calculated by weighting all pixels' gradient magnitude into corresponding gradient directions, and the directions with maximum, minimum and median gradient are marked as D_1, D_2 and D_3 respectively (as shown in Fig. 3). The gradient magnitude of pixel blocks under different gradient directions is calculated as follows:

$$B_m^D = \sum_{k=1}^{m^2} \left(m_{P_K} \times E^D\left(\theta_{P_k}\right) \right) \tag{1}$$

$$E^D\left(\theta_{P_k}\right) = \begin{cases} 1 & \theta_{P_k} \in D \\ 0 & \theta_{P_k} \notin D \end{cases} \tag{2}$$

Where: D is the gradient direction; m is the pixel block size; m_{P_K} and θ_{P_K} are the gradient magnitude and gradient angle of the pixel P_K.

Second, the number of pixel blocks in ith quantization interval under gradient direction D is counted as follows:

$$N_i^D = \sum_{j=1}^{n} S_i\left(B_{r,n,m,j}^D - B_{m,c}^D \right) \tag{3}$$

$$S_i(x) = \begin{cases} 1 & |x| \in Q_i \\ 0 & |x| \notin Q_i \end{cases} \tag{4}$$

$$Q_i = \left[l_i, l_{i+1} \right) \tag{5}$$

Where: n is the number of neighboring pixel blocks; $B_{r,n,m,j}^D$ is the gradient magnitude of the $m \times m$ pixel block in the square neighborhood with sampling radius r; j is the serial number of pixel blocks; $B_{m,c}^D$ is the gradient magnitude of the central pixel block under gradient direction D; Q_i is the ith quantization interval; l_i is the threshold of Q_i.

After counting the number of neighboring pixel blocks located at different quantization intervals, we can define the Local Decimal Pattern (LDP) as follows:

$$LDP^D = \sum_{i=1}^{L} N_i^D \times 10^{i-1} \quad (6)$$

Where L is the total number of quantization intervals.

At last, we calculate the LDP feature histograms under three gradient directions, and the final representation of pollen images is the concatenation of these LDP histograms:

$$LDPH = \left\{ LDPH^{D_1}, LDPH^{D_2}, LDPH^{D_3} \right\} \quad (7)$$

Figure 4 shows the calculation process of LDP of an image block under direction D_1, the color of the square in figure represents the gradient magnitude difference between the neighboring pixel blocks and the central pixel block under the gradient direction D_1, and the same color indicates that the difference of gradient magnitude belongs to the same quantization interval. In Fig. 4, the gradient magnitude of pixel blocks under gradient direction D_1 are quantized into 4 intervals, and the number of pixel blocks under 4 quantization intervals is counted as 4, 2, 1 and 1, respectively. So we can get a local decimal pattern 1124.

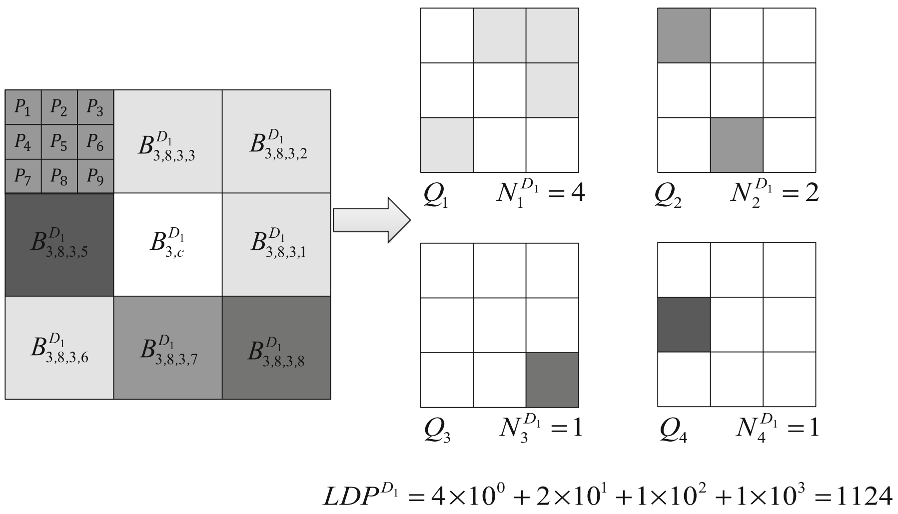

Fig. 4. Calculation of LDP of an image block under direction D_1.

3 Pollen Recognition Experiments

To evaluate our method, we performed experiments on pollenmonitor dataset with a computer of Intel(R) Core(TM) i5-3210 M @ 2.50 GHz processor and 6 GB memory, and the software we used is MATLAB R2014a. We randomly selected 60% of the pollen images of each category on pollenmonitor dataset as training images and the rest were used as test images. A SVM classifier [12, 13] was used for the classification and recognition of pollen images, and the correct recognition rate (CRR), recall rate (RR), F1-measure and recognition time (RT) were used to measure the experimental performance, where, F1-measure is the harmonic average of CRR and RR.

3.1 Parameter Selection

(1) Neighbor number, sampling radius and block size:

We use a sampling strategy with fixed number of neighboring pixel blocks ($n = 8$), and different block size and sampling radius ($m = \{2, 3, 4, 5, 6, 7, 8, 9, 10\}$, $r = \{2, 3, 4, 5, 6, 7, 8, 9, 10\}$).

(2) Quantization interval number:

We performed experiments with different number of quantization intervals and find that 2 quantization intervals is not enough to represent pollen texture feature, but too many (more than 4) leads to a higher dimension of LDP histogram. When the number of quantization intervals is 3, 4, the corresponding dimensions of LDP histogram are 8×10^2 and 8×10^3, respectively. In fact, many decimal patterns do not exist, resulting in large columns of LDP histogram are empty. That's because the total number of quantized pixel blocks in the neighborhood is fixed ($n = 8$). Take 3 quantization intervals for instance, if the number of pixel blocks located at first quantization interval is 7, the decimal pattern only can be 107 or 017, and other patterns such as 117, 127, etc. can never appear. So, we delete the nonexistent decimal patterns from the LDP histogram, and the dimension of LDP histogram is 45, 165 when the quantization interval is 3, 4, respectively.

(3) Quantization thresholds:

The quantization thresholds with $L = 3, 4$, are presented in Table 1, which depends on pixel block size (m).

Table 1. The quantization thresholds of different quantization levels

	l_1	l_2	l_3	l_4
$L = 3$	0	2 m	m^3	–
$L = 4$	0	$\mathrm{m} + 1$	$(\mathrm{m} + 1)^2$	$2(\mathrm{m} + 1)^2$

3.2 Experimental Results on Pollenmonitor Dataset

The Pollenmonitor dataset comprises air pollen samples from 33 different taxa collected in Freiburg and Zurich in 2006. The number of pollen images in this dataset is about 22700. Affected by the micro-sensors and irregular collection methods, some pollen images have some degrees of deformation and contamination, and the image quality is generally not high.

By varying the pixel block size and sampling radius from 2 to 10, we get the correct recognition rates as presented in Fig. 5. Obviously, 4 quantization intervals ($L = 4$) performs better, and the best recognition rate was obtained with the block size 5.

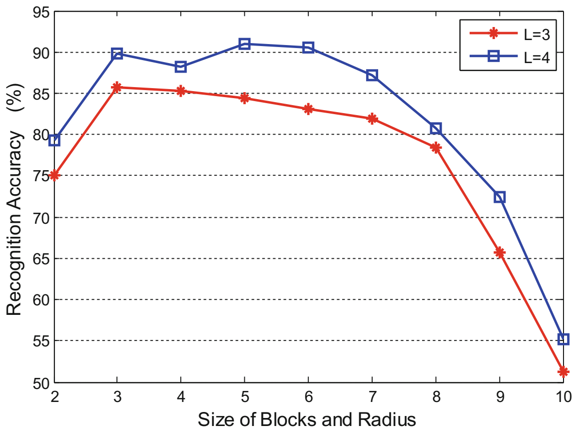

Fig. 5. Recognition results (%) on Pollenmonitor dataset with different block size and quantization intervals.

Figure 6 presents the partial recognition instances of 6 representative pollen categories on Pollenmonitor dataset. It can be seen that most pollen images with clear texture and have not been contaminated and deformed can be correctly identified. The specific recognition results are shown in Table 2, we can find that the correct recognition rates of most pollen categories are more than 90%, and the recall rates of all categories are

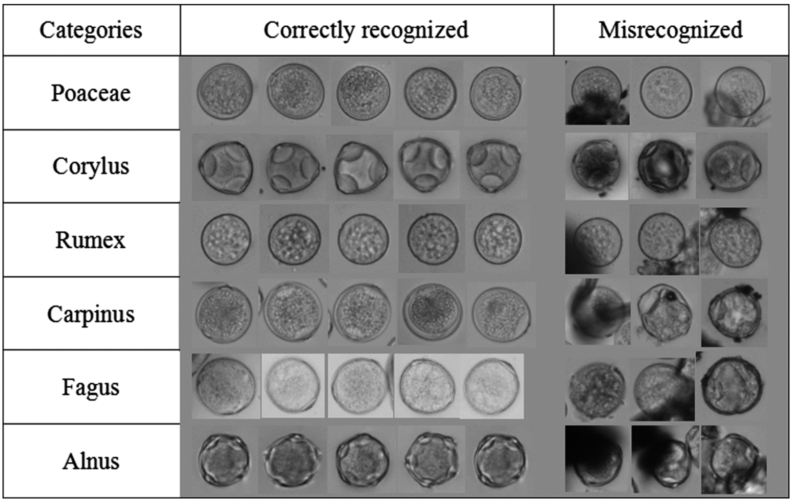

Fig. 6. Recognition instances of 6 classic pollen taxa from the Pollenmonitor dataset.

more than 73%. For Corylus category with varying degrees of rotation, our method achieved 94.02% correct recognition rate. For Fagus category with severe noise, our method can also obtained 83.18% correct recognition rate.

Table 2. Recognition results of 6 classic pollen taxa in Pollenmonitor dataset

Pollen category	CRR/%	RR/%	F1-measure	RT/s
Poaceae	90.33	79.10	84.34	6.5
Corylus	94.02	85.27	89.43	6.4
Rumex	92.15	73.64	81.86	6.4
Carpinus	88.62	78.13	83.05	6.5
Fagus	83.18	76.65	79.78	6.3
Alnus	92.50	88.74	90.58	6.9

3.3 Experimental Comparison and Analysis

We compared the best recognition rates achieved by our method using different block size with state-of-the-art pollen recognition methods, the experimental results on Pollenmonitor datasets are listed in Table 3. The average correct recognition rate of our method on Pollenmonitor datasets is 90.95%, which is on average 6.81 percentage points higher than that of compared pollen recognition methods. The experimental results show that our proposed method has a better recognition performance and the computational efficiency is higher than most of the compared methods.

Table 3. Comparison of the average recognition results of our method and 5 pollen recognition methods on Pollenmonitor dataset

Method	CRR/%	RR/%	F1-measure	ART/s
DLSC	74.83	82.97	78.69	4.1
TGF	85.50	69.62	76.75	7.2
STAF	83.29	80.53	81.89	23.9
LGGG	87.21	70.15	77.76	19.2
LDLG	89.87	75.46	82.04	20.9
LDP	90.95	78.25	84.12	6.8

4 Conclusions

In this paper, we presented a LDP descriptor for pollen image recognition. Unlike most pollen recognition methods fusing different kinds of features in recent years, our method extracts single texture feature in three directions, which decreases the dimensionality of pollen features and increases the discrimination at the same time. Experimental results show that our method outperforms 5 compared pollen recognition methods in extracting pollen texture feature, and has robustness to the noise and rotation of pollen images.

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