On the Road of Automated Pollen Recognition

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Abstract. Identifying all the pollen species present on earth, and more particularly in a territory, is a major concern for palynologists. This is an arduous task that can be automated using artificial intelligence. Many studies have tried to solve this problem by using machine learning and deep learning. In this paper, we present three pollen recognition approaches: Classification with no examples, recognition with a sufficient number of examples, recognition with insufficient number of examples. For each of them, we propose respectively to use Visual Bag of Word and expectation-maximization clustering algorithms, Classification using Local Binary patterns and the Gabor Filter Feature, Local Binary Patterns and Prototypical Networks. We find 77.38% recognition for 10 pollen species rate for the first one, 90.80% for training with a sufficient number of examples and 80 species, and 20 different pollen species and finally 84.30% for the third approach with one example for training and 20 species.

1. Introduction

Computer vision allows fast analysis and processing of images at a lower cost. This is especially true for the analysis of microscopic organisms such as pollen. The processing time, when carried out manually, is extremely long and doesn’t allow the processing of pollen in large numbers. Due to that, some applications, such as full environmental studies, chronological dating, climatology, allergy monitoring and customized treatment, honey characterization and others, that requires the analysis of large amount of pollen samples (> 100 slides) is nearly impossible. Also, the results obtained by palynologists after naked-eye slide analysis may, in some cases, lack precision, or even more rarely not be representative of the total pollen population present on the slide. Automatic processing of images extracted from optical microscopes is currently the cheapest, fastest, and most efficient alternative to hand-crafted processing. In the first part, we present different methodologies for pollen recognition.

2. State of the art

Many pollen studies have investigated this possibility. These studies have focused on the use of common image descriptors such as those of shape (area, circularity, Hue moments), contours (elliptical Fourier descriptor, Freeman chain code), or textures (Haralick’s co-occurrence matrix, Gabor filter). This is particularly the case of the ASTHMA project with the studies of Zhang et al. [1], TRELOAR et al. [2], Ticay-Rivas et al. [3] and Chudyk et al. [4], which have obtained success rates ranging between 77% and 100% for data sets containing 4 to 12 different pollen species. Alternatively, Lozano Vega [5], Chen et al. [6], Nguyen et al. [7] and others have tested the addition of features that they had designed to represent specific pollen attributes. These searchers have noticed an increase in
the recognition rate of their methods. Moreover, Kaya et al. [8] used only palynological characteristics such as the lengths of the polar axis, the equatorial axis, the colpus, the exine, and others. Ronneberger et al. [9] presented only 3D image features that they had designed for the classification of pollen extracted using confocal microscopy. They worked with 26 species and obtained a recognition rate of 99.2%. Finally, Daood et al. [10] used convolutional neural networks and Scanning Electron Microscopy (SEM) pollen images to classify pollen and obtained a 95% recognition rate for 30 different pollen species. In this paper, we present three pollen recognition approaches. The first section is dedicated to classification with no examples, the second one deals with recognition with a sufficient number of examples, and finally the third approach is recognition with un-sufficient number of examples.

3. Classification with no examples
As a matter of fact, unsupervised learning in the research computer vision field is infrequently used. This is damageable as unsupervised learning could help to group species which are unknown by pollen recognition systems and help to prelabel pollen images which can permit to save time when constructing a new recognition system with non-labeled images. Moreover, in an ideal world, palynologist wish the machine to separate pollen without prelabable training.

3.1. Dataset
Honey samples have been taken from different hives by palynologists of the CIRAD based at Reunion Island. The dataset used in this study is composed of ten different pollen species: Schinus terebinthifolius, Syzigium jambos, Aphloia theiformis, type Mimusops, Weinmannia tinctoria, Cordemoya integrifolia, Pandanus spp., Doratoxylon apetalum, Cordemoya integrifolia, Trema orientalis.

3.2. Visual Bag-of-Words
Visual Bag-of-Words using Texture Features Bag-of-words (BoW) was originally a method destined to text classification which had been extended to computer vision. Finally, Lozano-Vega et al. [5] have used the BoW strategy with LBP in order to detect the apertures of pollen. In this paper, we use it as a feature vector for the expectation-maximization clustering algorithm. The process is as follow: Firstly, the image is subdivided into patches of 4-pixel height and 4-pixel width. Then for each patch, the mean and the standard deviation of the hue, and saturation channels is computed. K-means with 15 clusters is applied to extract 15 visual words from the patches. Finally, the histogram of the occurrence of all the visual words for x image is computed and will serve as a feature vector.

3.3. Experimentation
Due to the huge computation time required to compute the codebook of visual words and to cluster the pollen, the dataset has been reduced to only forty pollen per species. Expectation-maximization has been selected because it has obtained the best accuracy score experimentally. The number of clusters has been determined using a crossvalidation method which works as follows: The number of clusters is set to 1 The dataset is split randomly into 10 folds EM is performed 10 times using the 10 folds. the loglikelihood is averaged over all 10 results. if loglikelihood has increased, the number of clusters is increased by 1, and the program continues at step 2.

3.4. Results

| ATTRIBUTES          | ACCURACY |
|---------------------|----------|
| Visual Bag of Word  | 77.38%   |

The proposed method achieved 77.38% of correctly clustered instances.
4. Recognition with sufficient number of examples

4.1. Dataset
Flower samples have been taken by palynologists of the CIRAD based at Reunion Island. Several physicochemical treatments known as acetolysis were carried out in order to separate the pollen from the various components of the flowers. Then pictures of the pollen were taken using an optical microscope camera with an x400 magnification. The dataset obtained contains 3160 pollen grains images with approximately 20 to 40 examples of 80 different species have been used.

4.2. Local binary patterns
The LBP[11] are constructed as follows:

For each pixel of an image, neighboring pixels P within a circle of radius R are selected. The values of the neighboring pixels P are subtracted from the value of the current pixel. The Heaviside function allows us to keep only the positive values for the calculation of the LBP.

\[ LB_P, R(x_c, y_c) = \sum_{p=0}^{P-1} 2^p \delta(g_p - g_c) \]  

(1)

where \( P \) and \( R \) represent the number of neighboring pixels used in the calculation and the radius of the neighborhood circle, respectively. The “\( g_c \)” is the central pixel, “\( g_p \)” is the neighboring pixel, and \( \delta \) is the Heaviside function. From the resulting image, a histogram is formed and used as a feature vector.

4.3. Gabor filter
Gabor filter [12] is created using the formulas below and then applied to the pollen images.

\[ g_c[i,j] = \exp\left( -\frac{i'^2 + j^2}{2\sigma^2} \right) \cos\left( 2\pi \left( \frac{i'}{\lambda} + \psi \right) \right) \]  

(2)

\[ g_s[i,j] = \exp\left( -\frac{i'^2 + j^2}{2\sigma^2} \right) \sin\left( 2\pi \left( \frac{i'}{\lambda} + \psi \right) \right) \]  

(3)

where \( \lambda \) represents the wavelength of the sinusoidal factor, \( \theta \) represents the orientation of the normal to the parallel stripes of a Gabor function, \( \psi \) is the phase offset, \( \sigma \) is the standard deviation of the Gaussian envelope and \( \gamma \) is the spatial aspect ratio which specifies the ellipticity of the support of the Gabor function. The mean and the variance of the images obtained after the application of the filter are used as features vector. Gabor filters for 0°, 60°, 90° and 180° were computed with 0.2, 0.3, 0.4 as \( \gamma \), 2, 5, 10 as \( \sigma \), 1, 2, 3, 4 as \( \lambda \), and 0.5,1 as \( \psi \).

4.4. Experiments
For each pollen image, each of the features presented in the sections above were extracted and a Random Forest [13] cross-validation classification with a usual \( k=10 \) (1/10 example for test and 9/10 for learning) was performed on the data obtained. We have chosen Random Forest algorithm because of its ability to process large feature vectors and to exclude the least relevant features during its training. By using other classifiers such as the neural network, the classification rate varies greatly depending on the chosen features and the species present in the data set.

4.5. Results
We chose to test and combine different features frequently used in the automated pollen recognition literature. They are image processing commonly known shape and textural attributes. Kaya et al. [8] have studied the use of palynological features such as the polar axis, colpus length and others. The
latter are regularly used by palynologist to do their pollen identification. But, admittedly, the regular features of image analysis are more fitted to automated pollen recognition than human ones. As for now, popular shape image characteristics in pollen recognition are area, perimeter, moments and circularity[6]. GABOR filters, GLCM and LBP have also been proven to extract significant insight about the texture of the pollen[1,5]. Finally, we also test Convolutionnal neural network [10] as it is a promising approach. The results are shown in table 1.

### Table 1. The results.

| ATTRIBUTES              | ACCURACY |
|------------------------|----------|
| SHAPE                  | 0.796    |
| GLCM                   | 0.796    |
| LBP                    | 0.835    |
| GABOR                  | 0.809    |
| SHAPE + GLCM           | 0.833    |
| SHAPE + LBP            | 0.828    |
| SHAPE+GABOR            | 0.868    |
| GLCM + LBP             | 0.820    |
| GABOR+LBP              | 0.908    |
| GLCM+GABOR             | 0.857    |
| CNN (DAOOD ET AL., 2016)| 0.609    |
| ALL                    | 0.868    |

In Table 4, we note that the best classification score, 90.8% , is obtained using LBP and Gabor Filter.

### 5. Recognition with un-sufficient number of examples

Until now, only machine learning and deep learning have been applied to pollen recognition. A major inconvenience is that they require a large number of examples in order to obtain good results. However, palynologist datasets generally consist of a single example of different views of the same variety. This type of database doesn't fit well with machine learning or deep learning methods. This is why, we have tested few-shot learning and Local Binary Patterns and few-shot learning for the purpose of pollen identification.

#### 5.1. Dataset (See 2)

#### 5.2. Method prototypical networks

As in the work of Snell et al. [14] the data were encoded by a 4-block CNN. For each block, we used a 32- filter $3 \times 3$ convolution, a batch normalization layer [15], a ReLU nonlinearity and a $2 \times 2$ max-pooling layer. We didn’t notice better classification rates with other parameters. The same encoder has been used for the support examples and query examples. The training was done via SGD using Adam [16]. The Euclidean distance and a learning rate of 0.01 were used. The dataset was divided into 44 training, 16 validation, and 20 test classes. We computed classification accuracy for our model averaged over 1,00 randomly generated episodes from the test set. The results are shown in Table 1.
6. Results

Table 2. The results.

| ATTRIBUTES          | 1-Shot 5-ways | 1-shot 20-ways | 5-Shot 5-ways | 5-Shot 20-ways |
|---------------------|---------------|----------------|---------------|---------------|
| Prototypical Network| 73.80%        | 45.83%         | 87.05%        | 54.28%        |
| LBP + Prototypical Network | 95.81% | 84.30% | 98.00% | 93.08% |

Table 1 shows that the results obtained using LBP associated with the prototypical network are higher. This is probably due to the fact that pollen are strongly textural elements and LBP has a strong texture generalization capacity.

7. Conclusion and perspectives

In this paper, we showed how to solve pollen recognition problem. Classification with no examples, recognition with a sufficient number of examples, recognition with an un-sufficient number of examples. We propose respectively 3 solutions to solve this problem, Visual Bag of Word and the expectation-maximization clustering algorithm, Local Binary pattern and Gabor Filter Feature with Random Forest classifier, Local Binary Patterns with Prototypical Network.

A recognition rate of 77.38% with only 10 species, but no parallel training for the first one, 91% with 80 pollen species has been obtained for the second one and finally the third one obtained 84.30 % with 20 species and one example per species for training. From this study, it emerged that Local binary patterns are particularly efficient to characterize pollen texture, and even natural images in a supervised learning approach and a Visual Bag of Word is more fitted for unsupervised learning.

Our future work will focus on the application of the proposed methodologies for the automation of biological arduous visual tasks such as recognition of viruses and spores.

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