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Pollen Classification of Four Types of Plants of the Family Palmaceae

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Abstract: The date palm (*Phoenix dactylifera* L.) is a very largely diodic species. The palm trees females are characterized by their fruits whereas the male feet producing pollen pose a problem of characterization. We describe an automatic approach for the distinction between four types of male palm trees. The analysis is based on the morphological characteristics of the ornamentation of the exine to be able to prepare pollen for an artificial insemination. We provide a statistical evaluation of the classification of four types of pollen.

Key words: Image processing, palm-date pollen, watershed segmentation, morpholigical features, neural classification

INTRODUCTION

In the Saharan zone of Algeria, the date palm (*Palmaceae dactylifera* L.) occupies an important place in the economic and cultural field. It very largely belongs to an arborescent monocotyledone heterozygote and diodic species i.e. that the male and female reproductive organs are not carried by the same foot. The palm trees females are characterized easily from their fruits whereas the male feet producing pollen pose a problem of characterization (Boughediri, 1985; Munier, 1973). An automatic selection of the various types of pollen would be very desirable for the biologists in order to be able to control the quality of desired date (Cerceau, 1993). The external wall of pollen called exine is stuctured and delimited by a tectum presenting an ornamentation on the pollen surface.

The observation using the electron microscope with sweeping (Boughediri, 1994; Hideux, 1972; Tesserat and Mason, 1983) shows that palm-date pollen has a reticle tectum (perforated) for the four studied varieties of pollen and that the form and the number of perforations vary from one grain to another the intim has a variable thickness according to types and the aperturale zone is characterized by a complete and thin tectum with a very developed intim (Faegri and Iverson, 1964; Fogle, 1977).

We made a study of bearing laboratory on four varieties of pollen taken from different date palms of the Algerian south to knowing Deglet-Nour (DN), Ghars (GH), Mech-Degla (MD) and Dguel (DG) which are different qualities of dates.

Our aim is to develop an automatic system of pattern recognition for the differentiation between the types of pollen of palm-date trees by using the morphological variations of the tectum like criterion of discrimination (Vezey and Skvarla, 1993; Zavada, 1983). The system will avoid the tedious human work because currently palionology experts cannot achieve this differentiation sufficiently fast in routine analysis of pollen preparations.

IMAGE PROCESSING

Image acquisition process: Usually, experts study the microscopic preparations under electron microscope with sweeping. This instrument enlarges the images enough to study and to analyse the morphology of the exine surface named the ultra-structure (in our case the suface tectum was increased 20000 times).

After a preparation by the technique of the acetolyse and to obtain the same vision as the expert, we connected the microscope with a resolution of 200 dpi to a camera. As a result, we obtained images of differents sizes normalised at 1400×1800 pixels and 256 graylevels. Every image represents tectum ornamentation of one type of pollen. Fig. 1 shows images prototypes of tectum of the four classes. The total number of images per type is 12.

Image segmentation: The goal of the segmentation is to separate the objects in our case the holes of the exine from the image background.

First we apply an 3×3 median filter to reduce speckle noise and then we improve the contrast of the image in order to highlight the holes on the exine and to prepare the segmentation so to speed up the watershed segmentation (Fig. 2).

The segmentation method can be described by the following steps:

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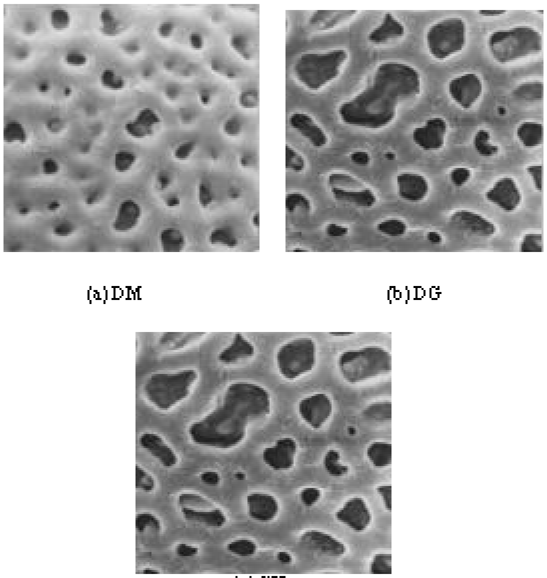

Fig. 1: Image prototypes of tectum of the four classes

First, extended h-maxima transformation of the intensity image was used to find object seeds (Soille, 1999). We know that despite variations object (holes) and background, each object has a certain contrast compared to their local neignborhood, in the h-maxima transform the morphological filters out the relevant maxima using a contrast criterion, all maxima are compared to their local neignbohood and only those maxima treater than a given threshold h are kept. Seeded watershed segmentation (Vincent, 1993; Beucher, 1992; Meyer and Beucher, 1990) is very useful if we perform our segmentation in the gradient magnitude image. We can find seeds in object and background regions based on intensity information in the original image and let the water rise from these seeds placed in the gradient magnitude image.

Seeded watershed segmentation was, so applied to the gradient magnitude image and region borders were created at the crest lines in the gradient image. More than one seed in an object resulted in over-segmentation. After watershed segmentation, over-segmentation was reduced by only keeping those borders that correspond to strong edges. If the seeds are in the same object , the magnitude of the gradient at the region border will be small. The strength of the complete border between two regions can be measured in many ways. A simple measure is to define the strength of a border as the weakest point along the border . this is used for reducing over-segmentation resulting from watershed segmentation.

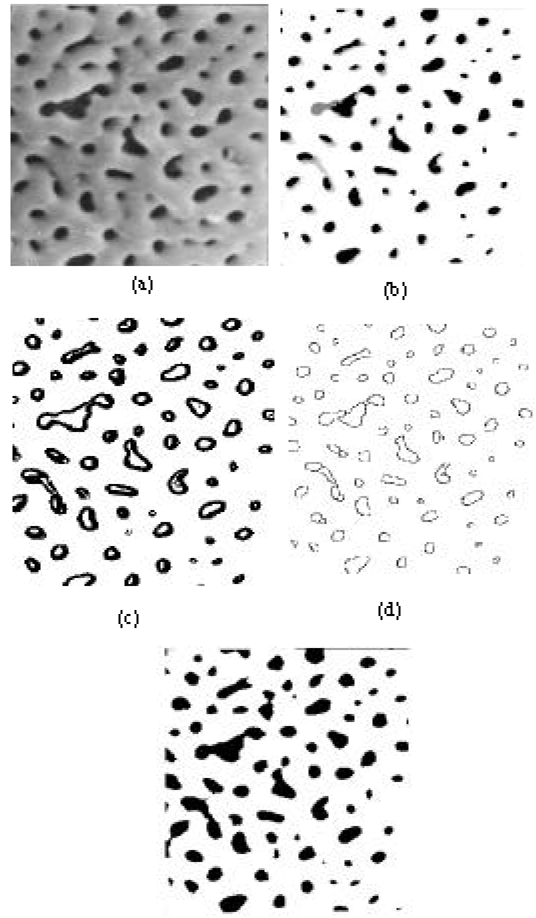

Fig. 2: Segmentation combining intensity and edge information, original DN pollen image, seeds found by the h-transformation of the original image, the gradient magnitude image, result of seeded segmentation: Some objects are over segmentated and final result segmentation after merging

RESULTS AND DISCUSSION

Feature generation: The segmentation being realized, we will extract from each type of pollen the characteristic features which allow its classification. Morphological information is used by human experts to distinguish the different types of pollen. In the literature, many approaches have been proposed to object classification by shape analysis (Luciano and Roberto, 2001). Once the shape of interest has been detected , we measure the features as described in Table 1 (where a summery description is provided for each feature). The initial

Table 1: Feature set used to characterise the pollen grains

Feature	Description
Tectum percentage (Tp) The holes on total surface	Report/ratio of the surface occupied by
Number of holes (N)	Number of objects in the image
Density of perforation (Dp) Perforations on total surface	Report/ratio of the total number of
Average Diameter of Wadell (ADW)	The average of the diameters of the circles having same surface as the holes
Mean Maximum Distance to centoide (MDmax)	Average Largest distance between center of gravity and boundary of the holes
Mean minimum Distance to centroide (MDmin)	Average smallest distance between center of gravity and boundary of the holes
Average ratio of distance (avDmax /Dmin)	Average of the ratios Dmax/Dmin of all the holes

selection of the shape features was done taking into account the morphological characteristics employed by the palionology experts in their diary job.

Classification: Once the values if all features have been calculated the data are passed to a classifier. The approach taken in this research to pollen recognition is one based on a neural network. A neural network is a system that can be trained to classify input data (in our case images pollen grains) into one of a number of classes. They are particularly well suited to this type of application because they do not require the individual setting up the system to define key characteristics of the objects. Instead the system creates its own internal representation of the objects based on a training data set. We choose for our system the Multi-Layer Perceptron (MLP) (17) and a Probalistic Neural Network (PNN) (Bishop, 1995).

Our MLP is composed of 7 neurons of entry, a hidden layer of 6 neurons and 4 neurons of exit representing the number of classes (DN, DG, GH and MD).

The PNN is composed of tho layers , a radial basis and a competitive layer. When an input is presented , the first layer computes distances from the input vector to the training input and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally a compete transfer function on the output of the second layer picks the maximum of these probabilities and produces a one for that class and a 0 for the others.

Considering the low size of our data base which comprises 12 samples for each type of pollen. We will use the ‘leaven-one-image-out ‘approach, the training set is constructed using N-1 (N is the number of images) and the test is carried out using the excluded image. If this image is correctly classified a hit is counted. The process is repeated N times, each time excluding a different image (Duda *et al.*, 2001; Maria and Panagiota, 2000).

As test cases, we use the set of 48 images containing 12 images of each type of pollen, the samples of each class are taken from differents palms. The normalisation of the feature values is necessary as well under the perspective that the input images come from different sources possibly taken under different amplifications or a size modification . For this reason we normalised the features dividing by the square root of the area.

We obtained a percentage of correct classification of 83% for the MLP classifier and a percentage of correct classification of 95% for the PNN classifier with a faster execution. The result is excellent but we believe that it may not be extrapolated when applied to a large data set being more representative as reported by the palionologists.

CONCLUSION

We presented a working prototype of a system to classify four types of date pollen the results are encouraging but more experiments have to be performed and other spices of date have to be integrated. The shape description can renforced by other texture features to describe the ornamentation intim .

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