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Application of wavelet transform in the classification of pollen grains

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This paper presents a proposal for the automatic classification of pollen grains, to assist in the analysis of the botanical origin of honey samples. For this task, techniques based on computer vision and machine learning were used. At first, the pollen grain image was segmented using a technique based on watershed. Then, a wavelet transform technique was used to extract texture features from the segmented image. Finally, a supervised machine learning technique was used to classify the pollen grain regarding its floral species. Other attributes based on shape, texture and color were taken for comparison with the proposed method. The technique has been assessed using an image dataset from 7 different pollen species and a 79% F-Score has been achieved.

Key words: Wavelet transform, texture descriptors, machine learning, pollen.

INTRODUCTION

Pollen grain is the male gamete of plants and it is present in anthers of flowers of angiosperms plants. The study of pollen is called palynology and has been used for identification of pollen grains in organic remains, fossils, coprolites, to determine the history of developments races on the planet, in addition to forensic palynology that uses pollen grains present at crime scenes and corpses for crime detecting. Melissopalynology deals with the study of pollen grains in bee products, which is of great importance for determining the botanical origin of bee products. The study of pollen has a wide field of applications and there is a growing interest in the development of computer programs to facilitate the identification of pollen types.

There are different methods of pollen identification but all of them need a human expert to analyze images captured using an optical microscope. Due to the subjective nature of this analysis, the result of the classification can be different than expected when different humans in different moods are involved.

The difficulties and delays in pollen identification led to the search for methods that facilitate the identification of

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pollen grains and its use by non-expert persons. Automating the identification of pollen grains makes the analysis process faster and less laborious, turning the identification of a large number of grains and the pollen identification more precise (Langford et al., 1990). There were several attempts to automate the identification of pollen grains in microscopic images by computer algorithms, yet this is not a cheap and fully automated process (Chica and Campoy, 2012).

This work aims at automating the classification of pollens through a computer vision software. This software takes microscopic images of pollen grains present in honey samples and classifies the pollen types according to their floral origin. At first, the pollen grain image is segmented by the software using a technique based on Watershed, then, a Wavelet Transform technique is used to extract texture features from the segmented image. Finally, a supervised machine learning technique is used to classify the pollen grain regarding its floral species.

The main contributions of this work are: (1) the use of the Wavelet Transform technique to extract texture features for the problem of automatic classification of pollen grain; (2) the analysis of the computational costs involved in the use of different feature extraction techniques and (3) the creation of an image dataset of pollen grains that can be used in other experiments.

This paper is organized as follows: First the materials and methods used are presented, as well as the description of the image dataset and evaluation metrics. After that, the results obtained from the execution of the exploratory tests are reported. Finally, we show the conclusions and future work.

MATERIALS AND METHODS

The proposed technique for pollen species classification is composed of three main modules. The first is for the pollen detection in the image and its segmentation, the second for the extraction of image attributes to be processed and, finally, the third is a classification module based on supervised machine learning. The following topics explain the main technique used for the description of pollen grain images, called Wavelets Transform, and each one of the modules of the software developed.

Wavelets Transform

The Wavelets Transforms are mathematical functions that cut a signal in different frequency components, and each component can be analyzed in different scales, which make them widely used in the analysis of textures (Arivazhagan and Ganesan, 2003; Randen and Husoy, 1999). The central idea of Wavelets Transforms is the use of a family of functions localized in time and frequency. The Wavelets Transforms decompose a signal through a series of functions created by translations and dilations (or contractions) of a transformation function, denoted Wavelet Mother in Equation 1, where j and k are real numbers different from 0. The k parameter controls the displacement while j controls the dilatation to the function. When j is greater than 1, the dilation of the function occurs; and when it is less than 1, contraction of the function occurs.

$$\psi j,k(x) = \frac{1}{\sqrt{j}}\psi\left(\frac{x-k}{j}\right) \quad (1)$$

There are several examples of specific Ψ functions that can be used in practical problems and three of the most cited in current literature are the Mexican Hat (or Laplacian of a Gaussian), Morlet (or Gabor) and the Haar functions presented in Equations 2, 3 and 4, where σ is the standard deviation of the Mexican Hat Gaussian, and k is the Morlet wave number.

$$\psi_{mexican\ hat}(x) = \frac{2}{\sqrt{3\sigma}}\pi^{-\frac{1}{4}}\left(\frac{x^2}{\sigma^2} - 1\right)\ e^{-\frac{x^2}{\sigma^2}} \quad (2)$$

$$\psi_{morlet}(x) = \pi^{-\frac{1}{4}}\cos(kx)e^{-\frac{x^2}{2}} \quad (3)$$

$$\psi_{haar}(x) = \begin{cases} 1, & for\ x \in [0,\frac{1}{2}) \\ -1, & for\ x \in [\frac{1}{2},1) \\ 0, & otherwise \end{cases} \quad (4)$$

The functions presented are used for the analysis of continuous signals, however, in practice the signal analysis should be performed in discrete time or space intervals. Thus, it is more convenient to use the Discrete Wavelet Transform (DWT), in which both the signal and the parameters j and k are discretized. An efficient implementation of this type of processing for multiresolution analysis (Mallat, 1989) is the Fast Wavelet Transform (FWT).

The Wavelet Transform was originally formulated for one-dimensional signals analysis, for image analysis it must be expanded to the two-dimensional space. In most cases, this expansion can be obtained from one-dimensional transformations applied separately in the vertical and horizontal directions.

Detection

The aim of the detection and segmentation of pollens module is to reduce the unnecessary information of the image for later stages. For this purpose, preprocessing techniques, extraction of texture attributes and segmentation based on Watershed were used. The execution of this module consists of a blurring of the original image using Gaussian smoothing, the extraction of texture attributes and the application of a watershed based segmentation algorithm using texture information. An example of the results of this module can be seen in Figure 1.

Extraction of attributes

Three families of attributes have been extracted from each pollen image to be used in the classification step: shape, color and texture attributes. For the extraction of shape attributes the k-curvature (Rosenfeld and Johnson, 1973) and shape descriptors (Jain et al., 1995) algorithms have been used. For color attributes, the RGB and HSB models were used. Each color component was used separately.

For texture extraction the Fractional Splines Wavelets were used (Unser and Blu, 2000). With the application of a Wavelet Transform, the image is decomposed into four sub-bands, designated as LL, HH, LH, and HL. The sub-band LL has low frequency and it is an image approximation, the other sub-bands highlight frequency information in the vertical (HL), horizontal (LH) and diagonal (HH) directions (Figure 2).

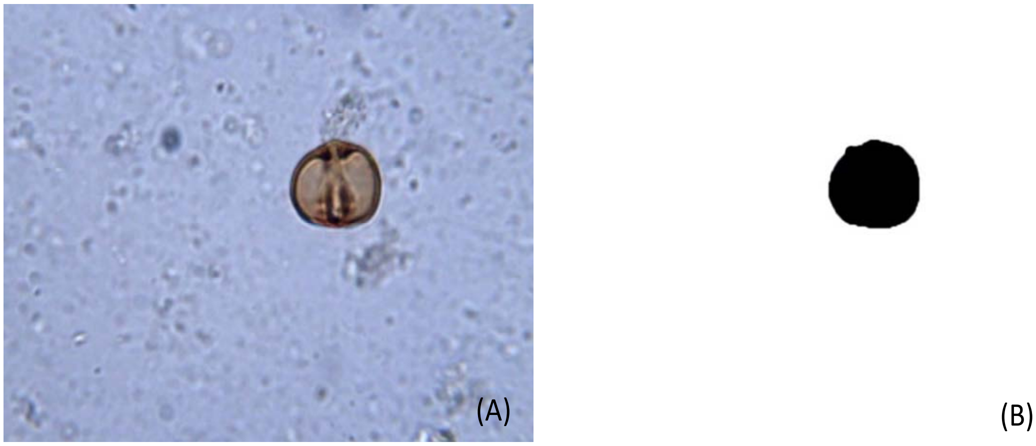

Figure 1. This image exemplifies the detection and the segmentation of a pollen grain. The Figure (A) shows the original image and (B) shows the same image after its segmentation.

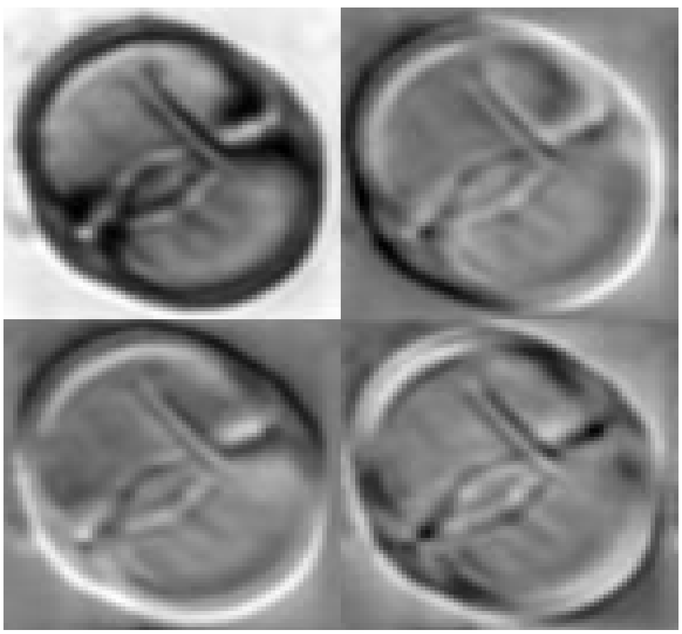

Figure 2. This image illustrates the decomposition generated by the Wavelet Transform.

A co-occurrence matrix (Haralick et al., 1973) was used in the directions of 0, 90, 180 and 270° for describing the textures for each sub-band generated by the Wavelet Transform. The attributes extracted from each co-occurrence matrix were Second Angular Momentum, Contrast, Correlation and Entropy.

Classification

After attributes extraction, a supervised learning machine module was used for training some classifiers. The implementation available through the software Weka 3.6 of the following algorithms have been tested: Decision Trees C4.5 (Utgoff, 1989), Support Vector Machines (Suykens and Vandewalle, 1999) and K-Nearest Neighbors (Guo et al., 2003).

Experiments

The main goal of the experiments conducted in this work was to determine the best arrangement of attributes and classifiers to be used in the pollen grain classification problem. All tests were performed in a set of images selected by a specialist in the field.

Dataset

To construct the image dataset used in these experiments seven classes of floral species were selected. These species were chosen due to their high prevalence in honeys collected in the Brazilian central region, where this research has been conducted. Some examples of pollens from each of the seven species used in the experiment can be seen in Figure 3; for each species 30 images were collected.

Sampling method

The cross-validation sampling method, with 10 folds, was used to select the training and testing set used for supervised machine learning. The cross-validation divides the samples into X sets, with the same size each, where X is the number of folds. After splitting the sets, X-1 sets are used to train the classifier, while the remaining set is used for the test, this process is repeated X times, considering a different set for the test in each iteration.

Metrics

The metric used to evaluate the performance of the different configurations of the proposed techniques was the F-Score, which is the harmonic mean of Precision and Recall values (Goutte and Gaussier, 2005). Its formula can be found in Equation 2. It is worth mentioning that, as there are more than two classes, the F-Score calculation is performed for each class separately, and the final result is the weighted average of the results obtained.

$$F = \frac{2 * precision * recall}{precision + recall} \qquad (2)$$

After the evaluation of the F-Score for each configuration the Friedman test (García and Herrera, 2008; Demšar, 2006), with a

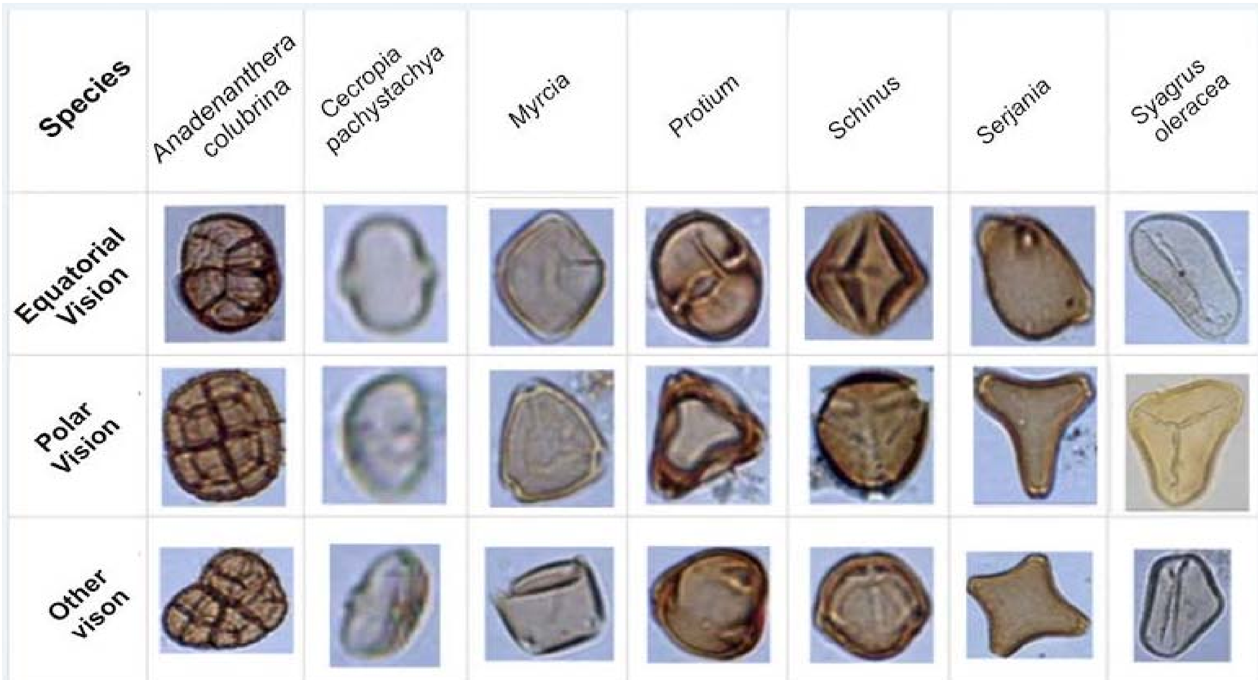

Figure 3. Pollen types used in the experiments separated in three classes.

Table 1. The final F-Score results obtained in the experiment.

Attribute	KNN	SVM	C4.5
S	0.57 (±0.10)	0.54 (±0.10)	0.57 (±0.10)
C	0.69 (±0.09)	0.74 (±0.10)	0.67 (±0.09)
W	0.50 (±0.10)	0.36 (±0.09)	0.61 (±0.10)
S+C	0.72 (±0.09)	0.79 (±0.08)	0.70 (±0.10)
S+W	0.59 (±0.11)	0.66 (±0.09)	0.66 (±0.10)
W+C	0.69 (±0.09)	0.74 (±0.10)	0.67 (±0.08)
S+W+C	0.72 (±0.09)	0.79 (±0.08)	0.70 (±0.10)

Each column represents one of the three classifiers tested. The value in parentheses is the standard deviation for each classifier (derived from the 10-Fold cross validation). Each line represents a different combination of the attributes extracted: S represents the use of only shape and colors, C represents the use of co-occurrence matrices and W are the attributes obtained by using the Wavelet Transform. S+C the combination of shape, color and co-occurrence attributes, S+W a combination of shape, color and Wavelets, and so on.

95% confidence interval (p-value < 0.05), was used to check whether there were statistical differences between the results obtained by the classifiers. The FWER (Family-wise Error Rate) based post hoc test implemented in R was used when the null hypothesis was rejected.

RESULTS AND DISCUSSION

As a large set of exploratory tests were carried out in order to determine the several parameters associated to each algorithm used in the proposed approach only the best results for each classifier are shown in Table 1. A p-value of 0.007017 resulted from the application of the Friedman test which, at a 5% level of significance (95% confidence interval), can be used to discard the null hypothesis.

The post hoc test indicated a statistical significant difference (p-value = 0.04489) between the texture attributes alone and the combination of texture and shape attributes. There is also a significant difference (p-value = 0.04502) between the texture attributes alone and the combinational of all attributes used (texture + shape + color).

Figure 4 presents the box-plots generated by the

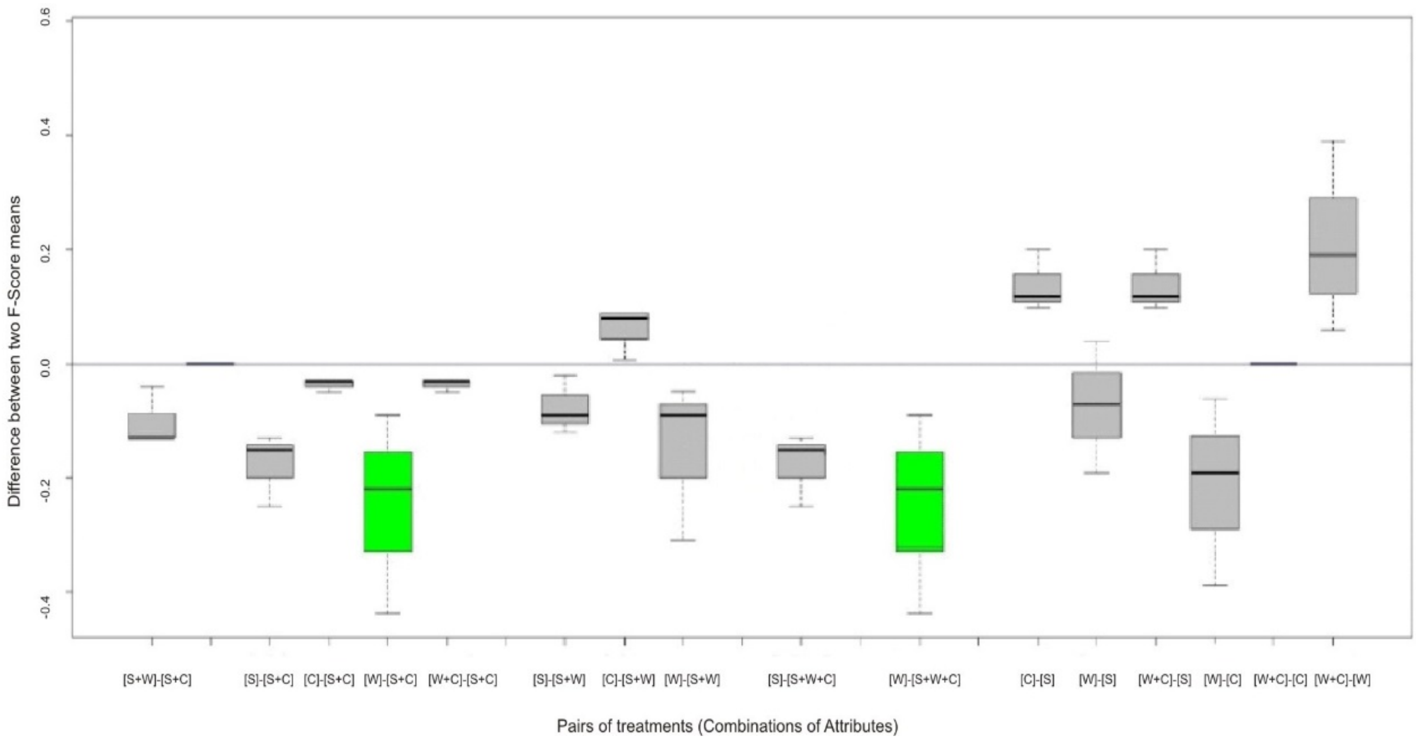

Figure 4. A box plot diagram for analysis extractor attributes.

execution of the post hoc test. It is clear by the box-plots that when the Wavelet Transform method (texture attribute) is applied without any other extractor it does not show a good performance in the classification. However, when combined with other attributes extractors, a good classification of the pollen grains can be achieved. The poor performance of the Wavelet Transform when applied alone could be explained by the fact that in the formulation used in this paper, no color or explicit shape information is used during wavelet calculations (only the gray level is used), and so, when color and shape attributes are added, the classification performance is enhanced.

In general, the combination S, C and W isolated, do not show good results, but when combined together, two by two, or all three, the results were improved. For example, the result of S, on the SVM technique, was 54% with 10% of standard deviation. Furthermore, using the combination S+C, the percentage of correct classification goes to 79 and 8% of standard deviation. With this combination, it had the best classification performance, with a lower standard deviation. Hence, the results tend to have a lower range of values and stay closer to the classification value presented, which increases the credibility of the classifier. When all three attributes are combined with the same supervised learning technique, S+W+C, the percentage and standard deviation are the same. In this case, the difference between them is only the processing time. This behavior is repeated for KNN and C4.5 techniques for the same combinations of attributes, that is, they have the highest percentage of correct classification and lower standard deviation using the combination S+C and S+W+C for each respective technique. Thus, as the approaches have the same percentage of correct answers for two different combinations, the most appropriate choice may be based on the processing time of the classification.

The processing times to train the classifiers with each different extraction methods were also analyzed in this paper. Table 2 presents the data obtained by the processing time of each method of attributes extraction. However, in the analysis of training time, the chi-square value in the Friedman test was 10.6154, with p-value of 0.101. So, the null hypothesis was accepted, once the level of significance of 5% was also adopted, demonstrating the similarity between the different types of extractions. Thus, considering the computational cost, they are statistically equals.

From the computational cost of extraction using Wavelet Transform and a combination of Wavelet Transform with some attributes, it is possible to observe that they were higher compared to other extractors. Thus, when all attributes were extracted, even with a larger number of attributes to be analyzed, the processing time was lower for those three classifiers. Therefore, it becomes feasible to use all attributes in the classification process, once the processing time is acceptable and the quantity of features to be analyzed allows a better

Table 2. Training time of each method of attributes extraction.

Attribute	KNN	SVM	C4.5
S	0.00 (±0.00)	0.08 (±0.02)	0.29 (±0.09)
C	0.00 (±0.00)	0.07 (±0.01)	0.20 (±0.06)
W	0.00 (±0.00)	0.12 (±0.02)	0.50 (±0.14)
S+C	0.00 (±0.00)	0.07 (±0.01)	0.21 (±0.06)
S+W	0.00 (±0.00)	0.12 (±0.02)	0.45 (±0.12)
W+C	0.00 (±0.00)	0.08 (±0.01)	0.20 (±0.05)
S+W+C	0.00 (±0.00)	0.08 (±0.01)	0.21 (±0.06)

classification of the pollen grains.

Conclusion

According to the results obtained, the use of Wavelet Transform for extracting texture attributes with shape attributes, do not show satisfactory results, in addition to requiring a lot of processing time. However, the application of all extractors together, showed better results in the test performed and had a relatively low processing time compared to other combinations of techniques, being feasible for application in the extraction of attributes for the pollen grain classification.

Conflict of Interests

The author(s) have not declared any conflict of interests.

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