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Research Article

Features extraction for pollen recognition in honey using Gabor filters

Dimitar Nikolov[1], Diana Tsankova[1]✉

[1] *Department of Automation, Information and Control Systems, Technical Faculty, University of Food Technologies, Plovdiv, Bulgaria*

Abstract

The aim of the research is to investigate the features extraction from microscope images of pollens for classifying honey on the base of its botanical origin. A filter-bank of Gabor filters (as a biologically inspired recognition system) is used to obtain features, which are then post-processed using normalization, down-sampling (by bicubic interpolation), and principal components analysis. The latter is used for reducing the features size and a proper visualization of the features extraction results. Based on these features linear discriminant analysis is used for a pollen classification. Microscope images from a few Internet available pollen databases, including pollen images of linden, acacia, lavender, rape and thistle are used to illustrate capabilities of the proposed features extraction approach. The performance of the proposed algorithm was evaluated by simulations in MATLAB environment.

Keywords: features extraction, Gabor filter, pollen recognition, principal components analysis, linear discriminant analysis

Abbreviations:

ANN - artificial neural network
LDA - linear discriminant analysis
PCA - principal components analysis
PCs - principal components
PalDat - Palynological Database
SAPS - Science & Plants for Schools

✉*Corresponding author: Prof. Diana Dimitrova Tsankova, PhD, Department of Automation, Information and Control Systems Technical Faculty, University of Food Technologies, Plovdiv 4002, 26 Maritsa Blvd., Bulgaria, tel.: +359 (32) 603 692; mobile: +359 895 587 431, E-mail: dtsankova@yahoo.com*

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Introduction

Production of natural honey is a laborious process. The botanical and geographical declaration of the origin seems to be one of the fundamental aspects of the honey quality that affects its commercial value (Robbins 2003; Sergiel et al. 2014). At the current stage of knowledge, a reliable authentication of floral origin of honey can be achieved by a complex interpretation of sensory, pollen and physicochemical analyses carried out by an expert (Persano Oddo et al. 2004; Ruoff 2006; Ruoff et al. 2005). Unfortunately, the most of these methods are generally too time-consuming, complex, and labour intensive for quality control application or require very specialized personnel to interpret the results.

The pollen analysis is one of the most accurate methods for determining the floral origin of honey, which is also the most labour-intensive and prolonged test in the normative physicochemical analysis of honey. It is therefore appropriate to look for ways to improve it in the following directions: (1) relieving the expert's work and increasing the accuracy of the analysis by developing a computer intelligent pollen recognition system; (2) looking for a correlation between pollen study and other alternative and sufficiently accessible methods for exploring and recognizing honey.

There have been a large number of research proposals for automatic pollen species classification: most of them have treated the shape and ornamentation of the grains (Treloar et al. 2004), measurement of textures using optical images of pollen grains (Li et al. 2004), combination of both techniques and an artificial neural network (ANN) (Zhang et al. 2004; Rodriguez-Damian et al. 2006; Kaya et al. 2013), GLCM (grey level co-occurrence matrix) texture features and ANN (Kaya et al. 2013). But, accurate differentiation between pollen grains records is hampered by the combination of poor taxonomic resolution in pollen identification and the high species diversity of many families (Kaya et al. 2013). For this purpose the biological inspirations for pattern recognition are very useful. Hubel and Wiesel (1968) empirically have shown the existence of receptive fields as a fundamental aspect of early visual processing in mammalian vision systems. Jones and Palmer (1987) have applied linear Gabor filters on visual input data to model these receptive fields. Biologically plausible recognition systems should be robust to variance in pose and lighting (Serre et al. 2004).

The approach of filter-banks is a successful biologically inspired object recognition one, in which a battery of linear filters (often Gabor filters are used as linear filters) is applied to an image and used the filtered images as primary features (Jarrett et al. 2009; Jones et al. 1987; Serre et al. 2004; Hamilton 2013).

Gabor filters have been successfully used as a features extraction method for pollen classification in studies of Chudyk et al. (2015) and Daood et al. (2016). The former has explored the usefulness of the shape features, texture features and aperture features, and the latter has used the image decomposition into layers on the basis of certain levels of grey intensity. In the first case a random forest classifier is used and in the second - support vector machines. In both papers the authors have made a comparative analysis of the proposed methods with such popular methods as: fast Fourier transform, local binary patterns (LBP), histogram of oriented gradients, Haralick features and others. In both cases, the highest reported classification accuracy is about 87%.

Marcos et al. (2015) have achieved a better classification result - 95%. In their study the authors have combined features derived from the following four features extraction methods: Haralick's grey-level co-occurrence matrices, log-Gabor filters, LBP and discrete Tchebichef moments. Then they have applied Fisher's discriminant analysis and k-nearest neighbour to perform multivariate classification.

In their experiments the authors, mentioned above, have processed all microscope slides under the identical conditions (preliminary preparation, light-field microscope and digital camera, experience of the specialist) and therefore the pollen images have the same noise level. The interesting question is how would such a classifier react if the slides were prepared under different conditions, i.e. at a much higher noise level. For example, the same software program for pollen analysis is used by different beekeepers to control the quality of their honey with hand-made samples. Which of these methods would be appropriate and what classification results would be obtained.

Hu et al. (2002) have claimed that frequency feature extraction methods are proved to be very effective for the recognition of low-resolution grey characters (such as characters in vehicle license plate). For this purpose they have proposed a novel Gabor filter-based feature extraction method, that "achieves high recognition accuracy and is not sensitive to noise and other distortions" (Hu et al. 2002). Therefore, such an approach would also be suitable for recognizing the noisy images of pollen.

The goal of this study was to develop an approach for features extraction of honey pollens and their classification on the base of their noisy microscope images. The following methods were employed in this approach: (i) Gabor filter; (ii) principal component analysis; (iii) linear discriminant analysis; (iv) leave-one-out-cross-validation test.

Materials and Methods

Pollen image database acquisition. According to the Bulgarian State Standard (BDS 2673-89; Ordinance No.9-MAF, 2005) the pollen characteristics of the monofloral nectar honey must contain pollen from the respective plant, not less than: 30% for acacia, 15% for lavender and 40% for other plant species. In Bulgaria, the following types of monofloral honey are available: acacia, linden, lavender, sunflower, rape, thistle, coriander, and others. Recognizing the botanical origin of honey requires the determination of pollen content qualitatively and quantitatively (in percents).

The study focuses on extracting characteristic features for recognizing (and therefore for classifying) five types of pollens: acacia, linden, lavender, rape, and thistle. For this purpose 93 photos of optical microscope slides were used. They were extracted from the following freely available databases:

1.PollenWiki
http://pollen.tstebler.ch/MediaWiki/index.php?title=Artenliste);
2.Science & Plants for Schools (SAPS) (http://www-saps.plantsci.cam.ac.uk/pollen/);
3.PalynologicalDatabase(PalDat) (https://www.paldat.org/search/A);
4.MicrolabNW Photomicrograph Gallery (http://www.microlabgallery.com/);
5.Pollenatlas (https://www.pollenwarndienst.at/aerobiologie/pollenatlas.html).

The following number of pollen image samples were selected: acacia - 17 samples of *Robinia Pseudoacaci*a, linden – 22 samples of *Tilia Platyphyllos*, lavender - 18 samples *Lavandula Angustifolia*, rape - 16 samples *Brassica Napus*, and thistle – 20 samples *Cirsium Arvense*. Fig. 1 shows the five types of pollen images taken from the Pollen-Wiki. It should be noted that the pollen images were selected so that all pollens were viewed in their polar view i.e. the equatorial view of pollens was not taken into consideration. Pollen images extracted from different databases were images of different quality including different resolution, focus (upper, optical section and lower focus) etc. The data used here with such differences in quality will be considered as an imitation of noise pollen images.

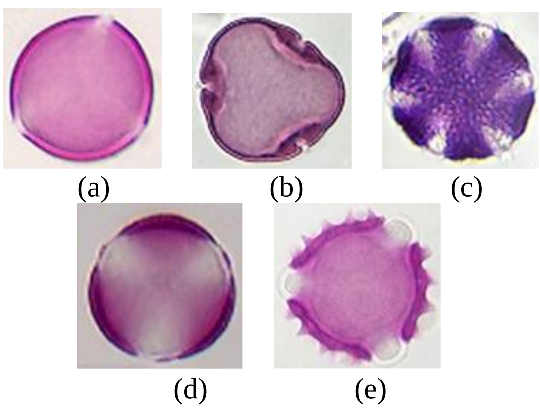

Figure 1. Pollen images from the Pollen-Wiki (http://pollen.tstebler.ch/MediaWiki/index.php?title=Artenliste): (a) Acacia; (b) Linden; (c) Lavender; (d) Rape; (e) Thistle.

Gabor filters. In this section, Gabor filters are presented in such a way as they have been reported by Hamilton (2013). In two-dimensions Gabor filter is an elliptic Gaussian kernel modulated by a sinusoidal wave (Jones et al. 1987; Movellan 2002).

An elliptic Gaussian kernel centered at the origin can be represented as

$$g(x,y) = K \times \exp\left(-\frac{1}{2}\left(\frac{x^2}{a^2} + \frac{y^2}{b^2}\right)\right), \qquad (1)$$

where the parameters *a* and *b* determine the spatial extent in the *x* and *y* axis directions, respectively, and K is a constant determining the scale. The Gaussian envelope can be modified by a rotation, and therefore (1) can be transformed to:

$$g(x,y) = \exp\left(-\frac{X^2 + Y^2\gamma}{2\sigma^2}\right), \qquad (2)$$

where $X = x\cos\theta + y\sin\theta$ and $Y = -x\sin\theta + y\cos\theta$ (θ is a clockwise angle); $\sigma = a$ and $\gamma = \sigma^2 / b^2$; K is chosen to be 1.

For the sinusoidal part $s(x,y)$ of the Gabor filter only the real portion is used:

$$\mathrm{Re}(s(x,y)) = \cos(2\pi(u_0 x + \upsilon_0 y) + \Phi), \qquad (3)$$

where (u_0, υ_0) specifies the spatial frequency of the wave (in the x and y directions, respectively), and Φ is a phase shift (here, $\Phi = 0$). By combining (u_0, υ_0) into a single variable λ and using the same rotation as in (2), (3) can be presented as (Serre et al. 2004):

$$\mathrm{Re}(s(x,y)) = \cos\left(\frac{2\pi}{\lambda}X\right). \qquad (4)$$

Combining (2) and (4) through multiplication gives the final form of the 2D Gabor filter used here:

$$G(x,y) = \exp\left(-\frac{X^2 + \gamma Y^2}{2\sigma^2}\right) \times \cos\left(\frac{2\pi X}{\lambda}\right). \qquad (5)$$

Four parameters of the Gabor filter determine its orientation, extent, shape, and spatial frequency. Specifically, θ determines the orientation of the filter, σ the extent (i.e. the width of the Guassian), λ the wave-length of the sinusoidal component (i.e. the spatial frequency), and γ the spatial aspect ratio (i.e.

the extent in the *X*-direction relative to the extent in the *Y* -direction) (Hamilton 2013).

Principal components analysis (PCA) . The aim of the method is to reduce the dimensionality of multivariate data whilst preserving as much of the relevant information as possible. PCA is a linear transformation that transforms the data (observations of possibly correlated variables) to a new coordinate system such that the new set of variables, the principal components, are linear functions of the original variables. Principal components are uncorrelated, and the greatest variance by any projection of the data comes to lie on the first coordinate, the second greatest variance on the second coordinate, and so on. This is achieved by computing the covariance matrix for the full data set. Then, the eigenvectors and eigenvalues of the covariance matrix are computed, and sorted according to decreasing eigenvalue (Jolliffe 2002). All the principal components are orthogonal to each other. The full set of principal components is as large as the original set of variables. Usually the sum of the variances of the first few principal components exceeds 80% of the total variance of the original data (Statistics Toolbox 2014).

Linear discriminant analysis (LDA). Linear discriminant analysis is an algorithm for classification, with, as its name suggests, a linear decision surface. The basic idea of LDA is to find a linear transformation, such that the ratio of the between-class scatter and the within-class scatter is maximized. Samples are projected to a new space with smallest within-class distance and largest inter-class distance (Kim et al. 2007). Although LDA usually gives a good discrimination performance, it suffers from some deficiencies if variables are highly correlated or class boundaries are complex or nonlinear (Li et al. 2012). To avoid such deficiencies, in the former case, variables are often transformed by correlation-reducing methods such as PCA, and in the latter case, LDA could be replaced by some sort of non-linear classifier.

Results and Discussion

Developed algorithm for features extraction, classifying and testing

The algorithm developed comprises several procedures for features extracting, pollens classifying and testing. The algorithm, presented in Fig. 2, includes three general stages as follows:

Stage 1: Preprocessing

1.1 Single pollen images are extracted manually from the pollen databases, so each of pollens is entered in a rectangular frame. The resulting images are of different sizes and quality.

1.2 The pollens images are transformed from a colour palette to a grey one. Grey levels are represented by numbers ranging from 0 to 1, with "0" corresponding to black, and "1" for white.

1.3 The input images are normalized in two steps. In the first step they are down-sampled using a bicubic interpolation so that their largest dimension is 100 pixels. The aspect ratio of the images is kept constant at this stage. Then, in the second step, the images are normalized so that the intensity values range between -1 and 1 and the mean value is 0.

Stage 2: Features Extraction

2.1 The normalized images are filtered using a battery of Gabor filters. Four orientation and two wavelength parameter settings are used, and thus, there are unique filtered images from a single original image.

2.2 The filtered images are down-sampled (again using bicubic interpolation) to pixels. Then a features vector of length pixels is formed for each original image.

2.3 The size of each of the pollens (in a polar view) is introduced as an additional feature with a weight factor. The weight factor is the number of pollen size repeats. It is set as a specified percent of the features dimension.

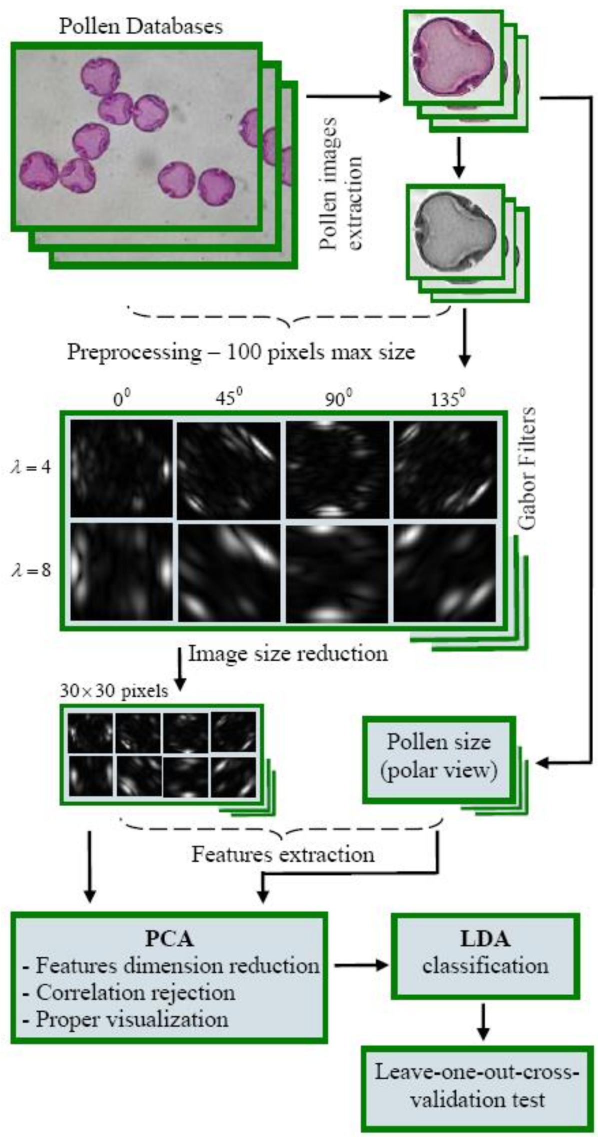

Figure 2. Pollen image acquisition, features extraction and classification process

(The pollen photos were extracted from http://pollen.tstebler.ch/MediaWiki/index.php?title=Artenliste, http://wwwsaps.plantsci.cam.ac.uk/pollen/')

Stage 3: Pollen Classifying and Testing

3.1 PCA is applied to reduce the large dimension of features vectors and reject data correlations. Features vectors of such a large size (as shown above) can cause computational difficulties of pollen classifiers.

3.2 The first few principal components are selected and used for inputs of a LDA-based classifier. The degree of successful identification of the five classes of pollen is used to assess the usefulness of the extracted features.

3.3 A leave-one-out-cross-validation test is used to verify the success of classifying. For this purpose, each sample is subtracted from the plurality of classifier's training samples, and then used for a test. The test continues until all the samples are alternated.

The algorithm for features extraction, classifying and testing, described above, was carried out in MATLAB environment. The following parameters for the Gabor filters bank were chosen: the wave-length of the sinusoidal component $\lambda = 4; 8$, the orientation of the filter $\theta = 0; 45^0; 90^0; 135^0$, the spatial aspect ratio $\gamma = 0.5$, and the extent $\sigma = 1$. The magnitude characteristics of the 8 Gabor filters for the grey-transformed linden pollen image (Fig.1(b)) after the first size reduction (up to a maximum of 100 pixels) are shown in the block diagram in Fig.2. The magnitude characteristics after the second reduction to 30 by 30 pixels are shown in the same diagram. The features vector contained the pixel information ($30 \times 30 \times 8 = 7200$ pixels) plus the pollen size, repeated 360 times (5 percent of 7200), i.e. it is a 7560 dimensional vector.

The input data dimensionality was reduced to a small number of principal components using PCA. Table 1 shows the sum of the variances of the first 50 principal components (all inputs/principal components are 7560) calculated over all the 93 samples.

Table 1. The first 50 principal components (PCs) and their significance

Number of PCs	Sum of variances, %	Number of PCs	Sum of variances, %	Number of PCs	Sum of variances, %	Number of PCs	Sum of variances, %	Number of PCs	Sum of variances, %
1	21.52	11	72.34	21	82.98	31	88.91	41	92.91
2	40.56	12	73.85	22	83.73	32	89.37	42	93.23
3	47.28	13	75.14	23	84.41	33	89.81	43	93.54
4	53.04	14	76.30	24	85.04	34	90.24	44	93.83
5	57.66	15	77.44	25	85.65	35	90.66	45	94.10
6	61.69	16	78.54	26	86.25	36	91.06	46	94.37
7	65.03	17	79.60	27	86.83	37	91.46	47	94.62
8	67.09	18	80.56	28	87.38	38	91.84	48	94.87
9	69.03	19	81.40	29	87.92	39	92.21	49	95.10
10	70.76	20	82.19	30	88.43	40	92.57	50	95.33

The scores scatter plot of the first two principal components is shown in Fig.3. The figure shows relatively well-distinguishing clusters of the 5 types of pollen.

A classifier of the LDA type was developed in 50 variants, including: the first principle component, the first two principal components, the first three principal components, and so on. Leave-one-out-cross-validation test was used to check the performance of the classifiers. The best result was obtained from the classifier using the first 11 principal components (90.32% successful classification). The average value of success rate of the classifiers using the first one to fifty principle components is 85.72 %, and the standard deviation is 4.83%. Fig. 4 shows the performance of the classifier using the first two principal components which success rate was 86.02 %. Table 2 shows the predicted results by the best classifier, one that was based on the first 11 principal components. In this case, 2 samples from observed class 'acacia' were predicted wrong as 'linden' and 'rape', while 1 sample from class 'linden' and 1 sample from class 'rape' were predicted wrong as 'acacia'. From class 'lavender', 2 samples were predicted wrong as 'linden', and 1 sample – as 'thistle', while 2 samples from class 'thistle' were predicted wrong as 'lavender'.

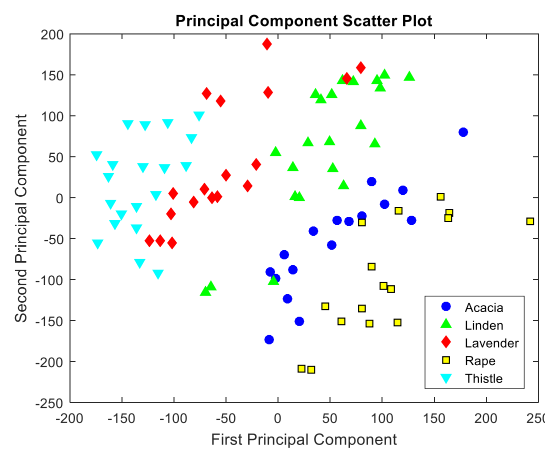

Figure 3. Principal components analysis - the scores scatter plot of the first two principal components.

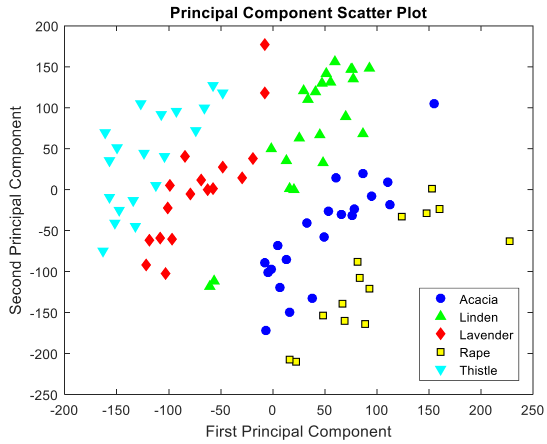

Figure 4. Linear discriminant analysis classifier - the scores scatter plot of the first two principal components.

Table 2. Discrimination accuracy of PCA-LDA classifier

Success: **90.32 %**		**Predicted Class** by PCA-LDA (11 Principal Components)					
		Acacia	Linden	Lavender	Rape	Thistle	
Observed Class	Acacia	**15**	1	0	1	0	**17**
	Linden	1	**21**	0	0	0	**22**
	Lavender	0	2	**15**	0	1	**18**
	Rape	1	0	0	**15**	0	**16**
	Thistle	0	0	2	0	**18**	**20**
		17	24	17	16	19	

This PCA-LDA model predicted 84 out of 93 samples correctly (88.2 % class 'acacia', 95.4 % 'linden', 83.3 % 'lavender', 93.8 % 'rape', and 90.0 % 'thistle'). Therefore, the proposed algorithm for extracting pollen features, dimensionality reduction and classifying give a good result for the samples under consideration.

Conclusions

An approach for pollen features extraction was proposed for classifying honey on the base of its botanical origin. A filter-bank of Gabor filters is used to obtain features. To take into account the different size of pollens it is proposed to introduce that size as a feature with a specific weighting factor. PCA is used to reduce the features size, reject correlated data and visualize the features extraction results. For illustration of the approach proposed, pollen images of linden, acacia, lavender, rape and thistle were used. They were derived from different pollen databases and these images were of different quality, making them difficult to recognize. The success rate of the features to form clusters according to the botanical origin of pollens was confirmed, visually by the scatter plot of the first two principal components, and quantitatively by the LDA classifier.

The approach will be validated as real honey samples will be classified according to their botanical origin. So-defined and identified features for honey pollens will be used as inputs in intelligent classifiers which are under development.

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