POLLEN GRAINS RECOGNITION USING STRUCTURAL APPROACH AND NEURAL NETWORKS

Natalia Khanzhina, Elena Zamyatina

Abstract: This paper describes the problem of automated pollen grains image recognition using images from microscope. This problem is relevant because it allows to automate a complex process of pollen grains classification and to determine the beginning of pollen dispersion which cause an the allergic responses. The main recognition methods are Hamming network [Korotkiy, 1992] and structural approach [Fu, 1977]. The paper includes Hamming network advantages over Hopfield network [Ossowski, 2000]. The steps of preprocessing (noise filtering, image binarization, segmentation) use OpenCV [Bradsky et al, 2008] functions and the feature point method [Bay et al, 2008]. The paper describes both preprocessing algorithms and main recognition methods. The experiments results showed a relative efficiency of these methods. The conclusions about methods productivity based on errors of type I and II. The paper includes alternative recognition methods which are planning to use in the follow up research.

Keywords: image recognition, OpenCV, Hamming network, feature points method, pollen-grains, structural pattern recognition.

ACM Classification Keywords: I.5.1 Pattern Recognition Model - Neural nets, Structural, I.5.4 Pattern Recognition Applications - Computer vision

Introduction

The automated pollen grains recognition problem is a part of rapid-growing and popular intellectual fields - pattern recognition and computer vision. The problem of pollen grains recognition is relevant, as far as the right classification of pollen grains can allow to draw the appropriate conclusions and to solve problems facing biologists (the honey quality control, determination of the pollen dispersion beginning), geologists (determination of the fossil minerals bedding) and experts of other areas. The pollen grains automated recognition problem involves two steps - the image preprocessing and recognition actually.

Today there are some open source software libraries which are used for a particular step of recognition or for some recognition method. One of these libraries is OpenCV. This is the open source computer vision and machine learning software library. The library has more than 2,500 optimized algorithms,

both classic and modern. They can be used for the face recognition and detection, objects identification, movement tracking, and more and, in particular, for the objects classification on an image.

The main steps of pollen grains analysis are collecting (by special-purpose pots), chemical treatment, obtaining images by a microscope, and finally getting statistics [Sladkov, 1967]. At the last stage an expert determines species of plants. Determination of a plant genus is a quite simple task, while the determination of a specie within this genus is often difficult to do. To determine specie of pollen palynologists use a plant atlas, which takes a lot of time. At this stage, the automated recognition of pollen grains would be suitable.

Thus, the recognizing program must be able to determine the amount of pollen grains by input image (a picture obtained by the microscope), localize them on the original image and determine their genuses and species.

The preprocessing step is performed by OpenCV and includes:
1. Image noise reduction, including the feature points method.
2. Image binarization.
3. Pollen grains localization and segmentation.

It was decided to make an attempt of using the structural approach and the neural networks in order to continue the investigations in pollen recognition. The authors [Cherhyh et al, 2013] have tried to use some classical methods of recognition to solve the automated pollen grains recognition problem, but their approach have not produced the desired results, the quantity of correctly recognized images was 54%.

Initial data

A microscope is connected to a computer, so that an expert can get digital photographic images of pollen grains immediately and see them on the computer screen in high quality. As a result of the processing photographic images of pollen grains can be obtained from different sides.

Figure 1 shows images of the same pollen grain from inside and outside. The left image shows inside of the grain. The right image is more blurred, this is the exine, or the outside. The form is less clear, but surface is more clear.
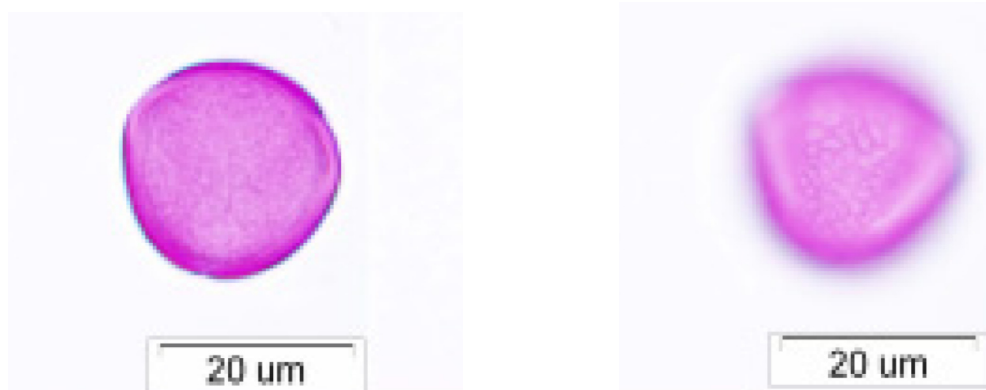
Figure 1. Images of clover pollen grain

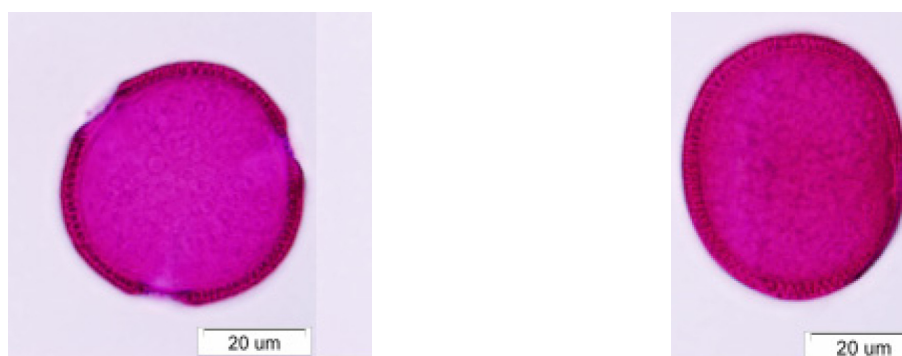Fig. 2 shows the image of the same pollen grain from different angles:

Figure 2. Image of buckwheat pollen grain from different angles
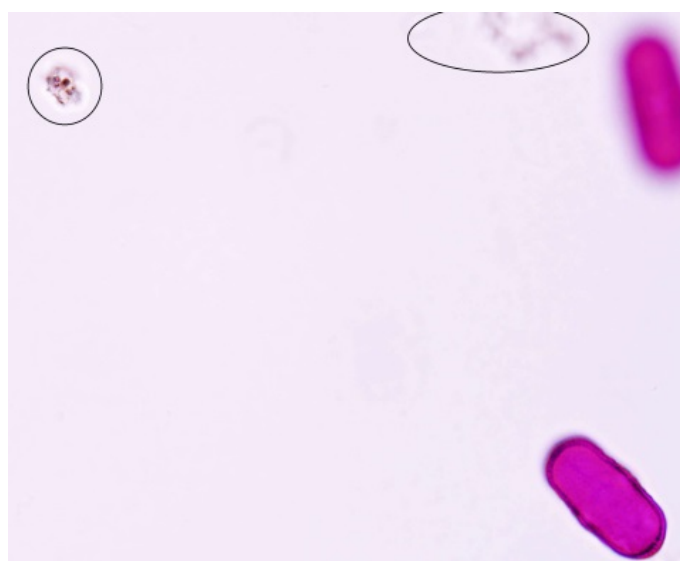
The images may have stains, see Fig. 3:

Figure 3. Image with stains

All these things are causes of complexity of the automated recognition. Therefore it is necessary to perform the preprocessing step in a quality manner. Let's consider the steps of preprocessing: the noise reduction, binarization etc.

Preprocessing

1.1   Noise Reduction

The first operation of noise reduction is smoothing. Smoothing, or blurring, is the simple and frequently used image processing operation. There are many cases where smoothing is needed, but usually it is used to reduce the noise.

The method used for noise reduction is Gaussian blur. Gaussian blur, also known as Gaussian smoothing, is done by convolving each point in the input array with a Gaussian kernel and then summing to produce the output array. The Gaussian filter changes every point by setting its value to the average of all points in some radius (corresponding to the kernel of smoothing).

The following steps of noise removing are using such morphological operations as the dilation and erosion functions.

The erode operation is often used to eliminate "speckle" noise in an image. The idea here is that the speckles are eroded to nothing while larger regions that contain visually significant content are not affected. The dilate operation is often used when attempting to find connected components. The utility of dilation arises because in many cases a large region might otherwise be broken apart into multiple components as a result of noise, shadows, or some other similar effect. A small dilation will cause such components to "melt" together into one [Bradsky et al, 2008].

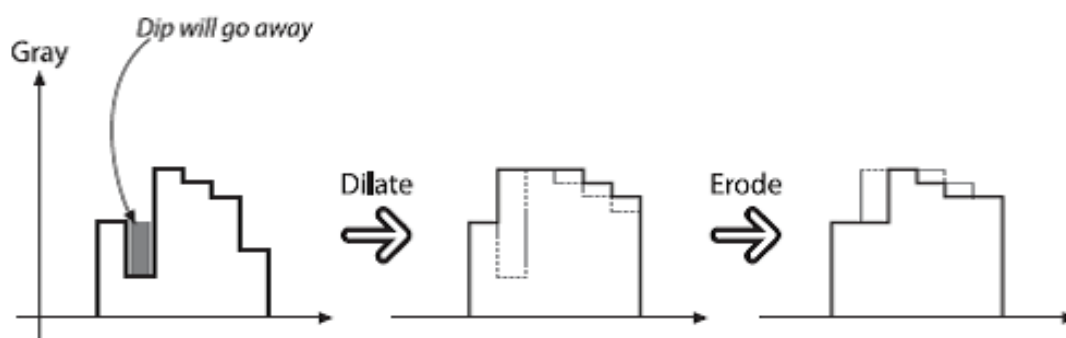A good example of using of these operations is shown in Figure 4:

Figure 4. Using of dilation and erosion

Repeated using of these functions on the same image can give a significant noise reduction as a result.

1.2   Binarization

The next step of the preprocessing is the image thresholding.

To perform this step, the following algorithm is applied:

1. The image is converted from the RGB color model (Red, Green, Blue) to the HSB color model (Hue, Saturation, Brightness).

2. All pixels of the necessary hue (from claret to violet, the dye used in a treatment of pollen always has a color of that hue) are converted to the black. This kind of binarization is double-threshold according to the following formula (1):

$$f'(m,n) = \begin{cases} 0, f(m,n) \geq t_1; \\ 1, t_1 < f(m,n) \leq t_2; \\ 0, f(m,n) > t_2, \end{cases} \qquad (1)$$

where t_1, t_2 - threshold values, f - the input image, f' - the output image, m,n - pixel coordinates, $t_1 < t_2$.

3. Saturation of all the pixels whose saturation value is more than 30 (where maximum is 255) is maximized, saturation of the rest is minimized. Thus, this is the low-threshold binarization.

This operation is a quiet simple and uses the only one threshold value according to the formula (2):

$$f'(m,n) = \begin{cases} 255, f(m,n) \geq t \ ; \\ 0, f(m,n) < t \ , \end{cases} \qquad (2)$$

where t - threshold value,f - the input image, f '- the output image, m, n - pixel coordinates.

4. Calculating the conjunction of the hue and saturation layers.

Let's consider the next step - segmentation.

1.3   Segmentation

The goal of segmentation in this case is to separate pollen grains contained on the image.

One of the stages of segmentation is contour finding. OpenCV has several methods for this, one of them is the Canny edge detector.

The most significant dimension to the Canny algorithm is that it tries to assemble the individual edge candidate pixels into contours. These contours are formed by applying an hysteresis threshold to the pixels. This means that there are two thresholds, an upper and a lower. If a pixel has a gradient larger than the upper threshold, then it is accepted as an edge pixel; if a pixel is below the lower threshold, it is rejected. If the pixel's gradient is between the thresholds, then it will be accepted only if it is connected to a pixel that is above the high threshold [Bradsky et al, 2008].

The found edges can help to find the contours of pollen grains. Then recursive algorithm builds from the contours tree a list of those that can be pollen grain contour:

1. The first stage is to remove too small areas of contours.
2. The areas containing contour is compared with pollen grains patterns using Hu-moments.
3. The rest of contours are filled with black color. These are the separate pollen grains already.

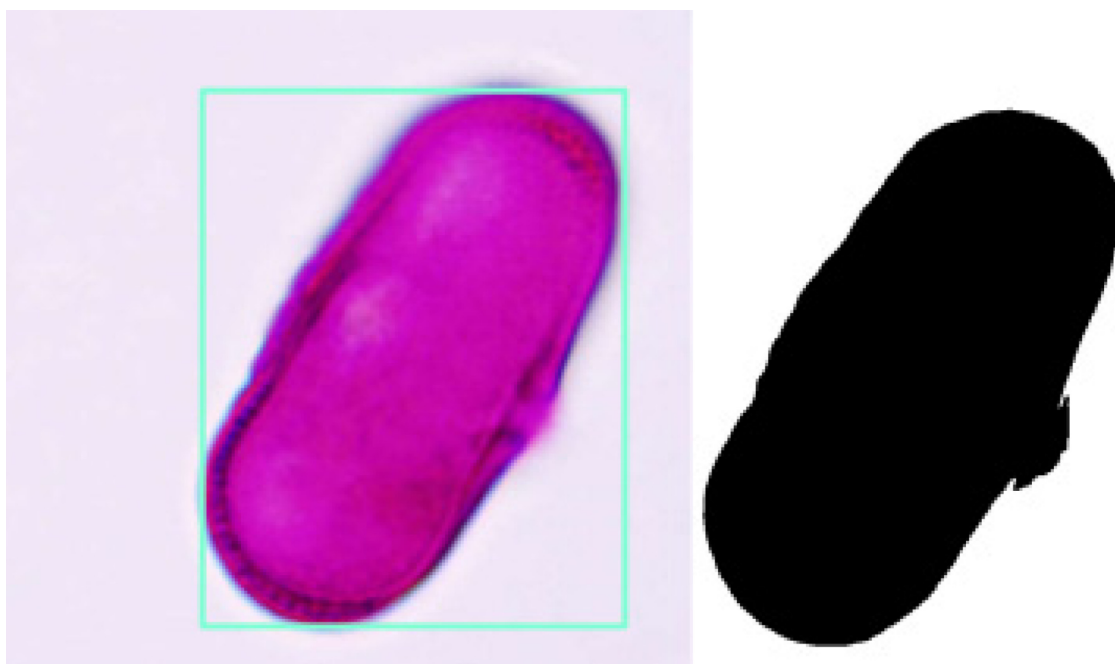There are the results of the preprocessing (Fig. 5-7):
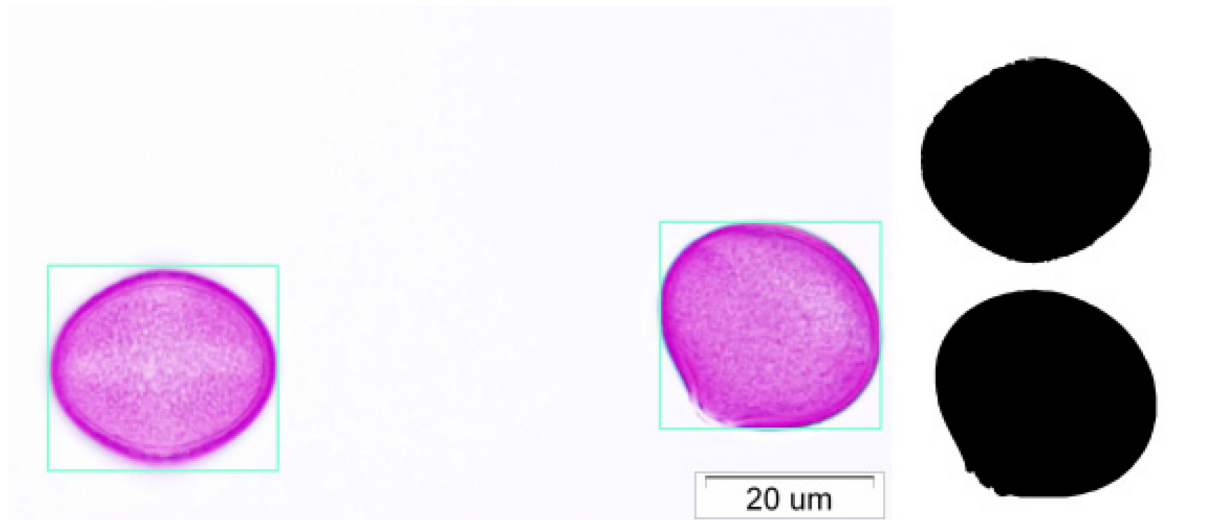

Figure 5.The result of angelica image preprocessing
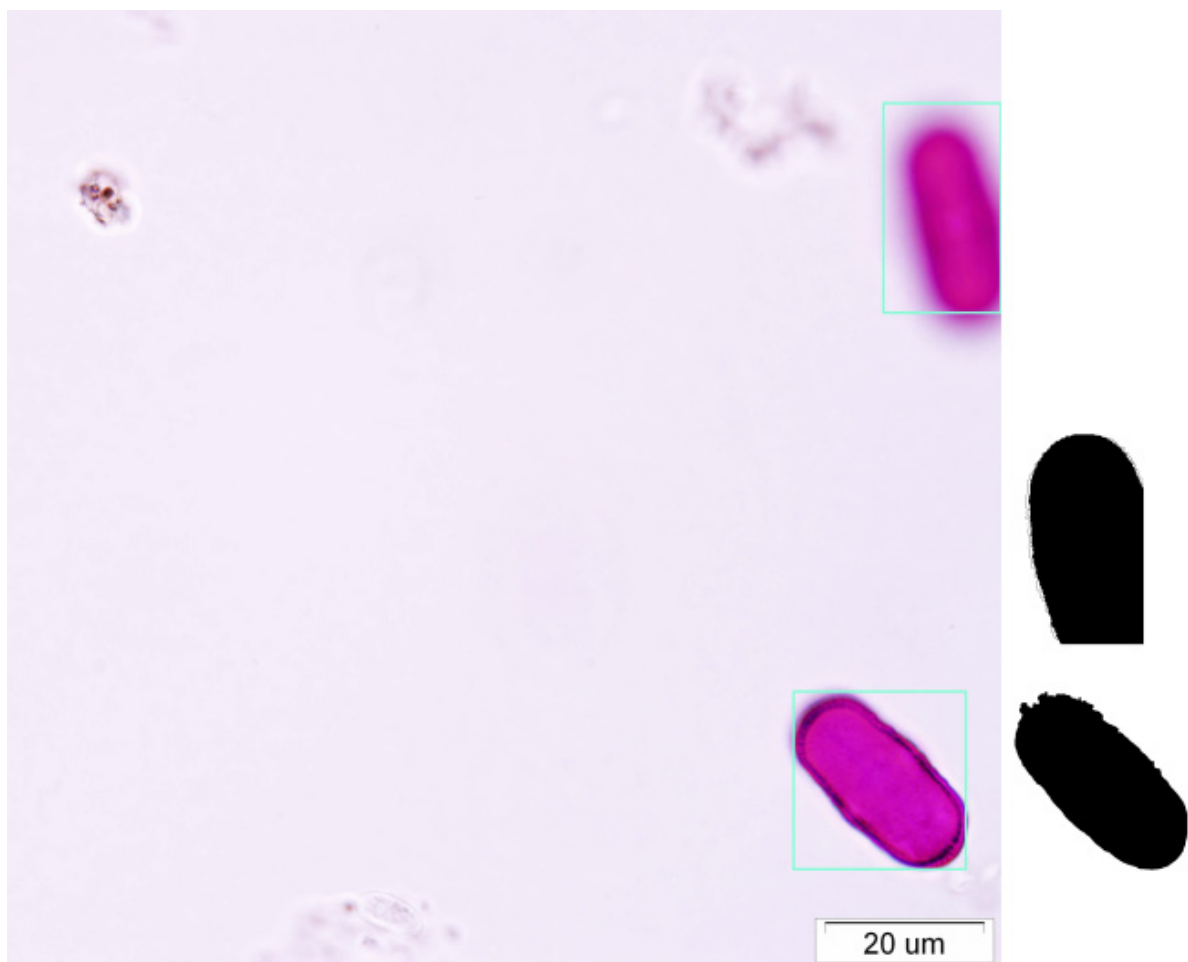
Figure 6. The result of clover image preprocessing

Figure 7. The result of preprocessing of angelica image with stains

1.4   Scaling

For those recognition methods which are not invariant to image scale it needs to apply another stage of the image preprocessing called scaling.

All the images are scaled to the size of 200x200. That allows, for example, to compare the input images with patterns using Hamming metric (an amount of distinct bits in a two-dimensional vector representing an image).

Image recognition methods

1.5   Structural approach

This method is also called structural, because an object is described as a grammar, not as a features vector. The recognition presents parsing.

The adaption of this approach to two-dimensional objects like images is difficult. Firstly, there is no obvious way of choice of finite elements. Secondly, there is no obvious way of choice of reduction rules [Fu, 1977].

The alternative for the structural approach is the Freeman chain code. Finite elements are the numbers from 0 to 7. The encoder moves along the boundary of the object and, at each step, transmits a symbol representing the direction of this movement (Fig. 8).
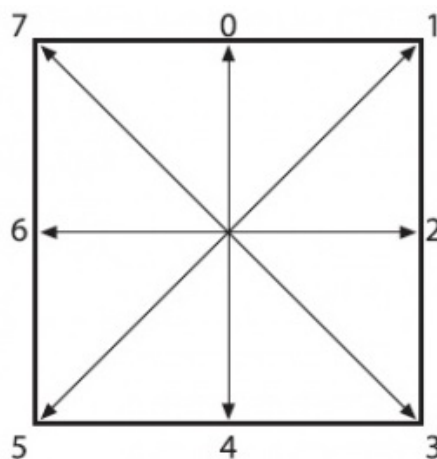
Figure 8. Directions of movement

Thus, the Freeman code is a sequence of numbers describing the boundary of the image. An example of such code is shown in Figure 9, the entry arrow is red.

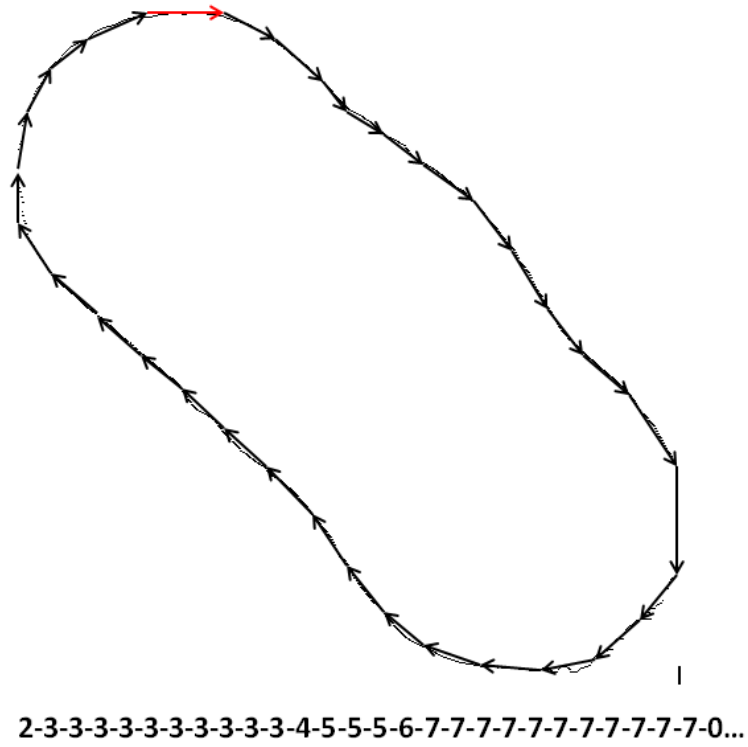2-3-3-3-3-3-3-3-3-3-3-4-5-5-5-6-7-7-7-7-7-7-7-7-7-7-7-0...

Figure 9. Chain of the pollen grain image

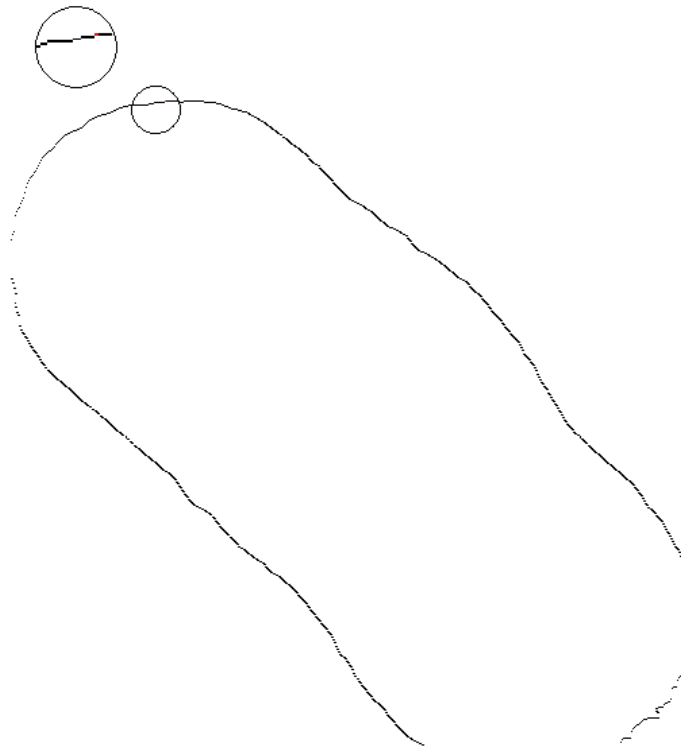Fig. 10 shows how boundary looks in a program:

Figure10. The boundary of pollen grain image in program

Next, the chain code of the image is compared with the chains of patterns, the closest one is the answer (in sense of Euclidean distance). Consider the next method of recognition.

1.6   Hamming neural network

The usage of a neural network is one of non-classical methods of pattern recognition. The training set here is the set of patterns including each plant's specie, from different angles of pollen grains.

The chosen architecture is Hamming network. This network requires a few memory and small amount of computation, against, for example, Hopfield network. Figure 11 shows Hamming neural network layout.

The advantage of that network is a small amount of weighted connections between neurons. Hopfield network with input size of 100 can memorize 10 patterns, while its layout will have 10,000 synapses. The Hamming network layout with the same capacity will have only 1000 synapses [Ossowski, 2000].

The Hamming network consists of two layers. The first and second layers each have m neurons, where m is the training set capacity. The first layer neurons have n synapses connected to the input (which is called zero layer). The second layer neurons are linked by negative synaptic feedback. For each neuron the only one synapse with positive feedback is connected to his own axon.
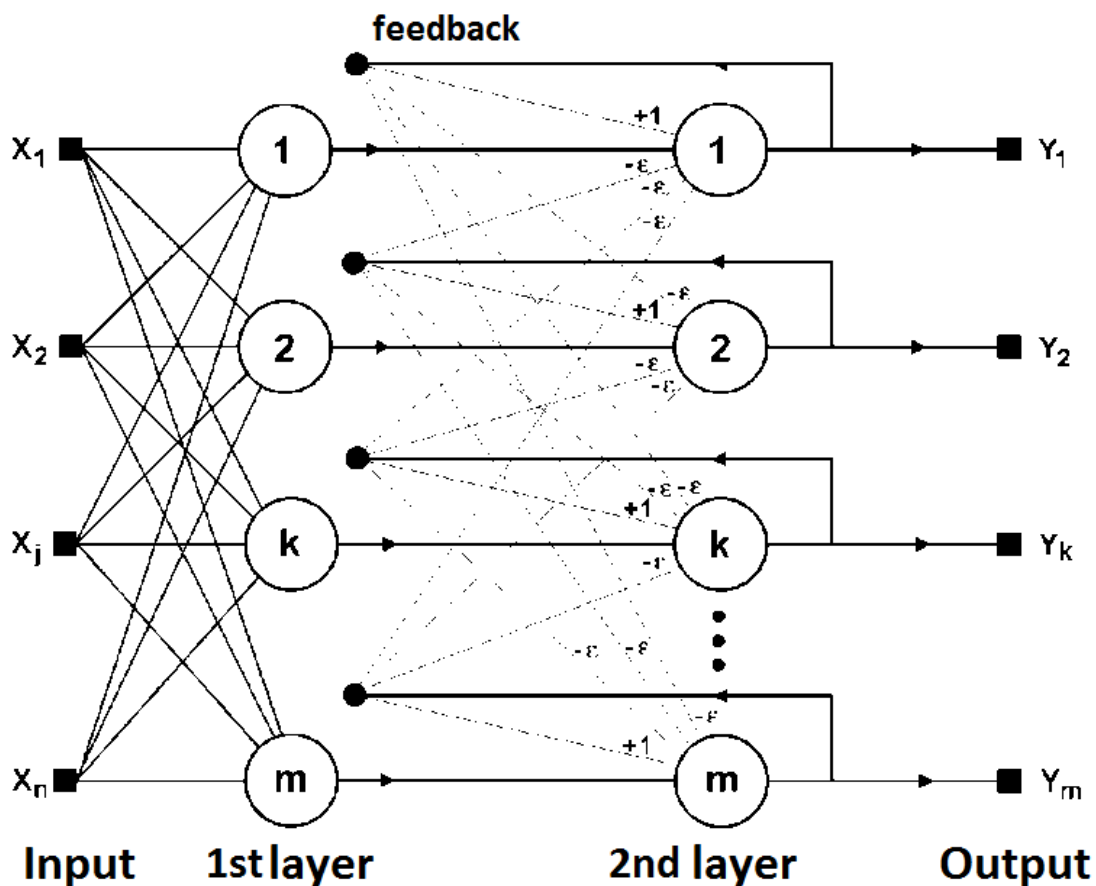

Figure11. Hamming neural network layout

The idea of the network is to compute the minimum of Hamming distances between an input image and all patterns. The network should activate the only one output corresponding to the pattern with the minimum distance.

At the stage of initialization weights of the first layer and the activation function threshold have the following values:

$$w_{ik} = \frac{x_i^k}{2}, \ i=0...n\text{-}1, \ k=0...m\text{-}1 \tag{3}$$

$$T_k = n \, / \, 2, \ k = 0...m\text{-}1 \tag{4}$$

where x_i^k - i-th element of the k-th pattern.

The weights of inhibiting synapses in the second layer have a value between 0 and 1/m. A synapse neuron which is connected with his own axon has a weight of 1.

The Hamming network has the following algorithm [Korotkiy, 1992]:

1. The input is an unknown vector $X = \{x_i : i=0 \, ... \, n\text{-}1\}$, the first layer neurons state is calculated from the input (the superscript means the layer number):

$$y_j^{(1)} = s_j^{(1)} = \sum_{i=0}^{n-1} w_{ij} x_i + T_j \ , \ j=0...m\text{-}1 \tag{5}$$

The resulting values are the inputs to the axons of the second layer:

$$y_j^{(2)} = y_j^{(1)}, \ j = 0...m\text{-}1 \tag{6}$$

2. The second layer neurons new state calculation:

$$s_j^{(2)}(p+1) = y_j(p) - e\sum_{k=0}^{m-1} y_k^{(2)}(p), k^l j, \ j = 0..m-1 \tag{7}$$

and their axons values calculation:

$$y_j^{(2)}(p+1) = f\left[s_j^{(2)}(p+1)\right], \ j = 0..m-1 \tag{8}$$

The activation function f is a threshold, the F value must be large enough to avoid the oversaturation.

3. Check if the second layer outputs changed since the last iteration. If yes then go to the step 2. Else this is the end.

The only problem with Hamming neural network is when images with noise are at the same Hamming distance from two or more patterns. In this case, the choice between these patterns is random [Ossowski, 2000].

1.7   The feature points method

The following image recognition method is the feature points method.

The image is represented as a set of special key points. A scene feature point or a point feature is a point of the image, whose neighborhood is stand out from other points neighborhood [Bay et al, 2008].

A feature point can be determined as a point of a sudden gradient drop in the image by two directions (corner points).

The feature points are compared with each other by their descriptors. There is the class in OpenCV for describing the feature points named SURF (Speeded up Robust Features). This is one of descriptors, which searches feature points and describes them in invariant to the scaling and rotation way. Besides, the feature points are invariant in the sense that the object on the image from different points of view has the same set of feature points [Bovyrin et al, 2013].

The feature points method does not give good results: only 35% of the right classification. On Fig. 12 feature points comparison gave the right answer, in Fig. 13 - the wrong answer.

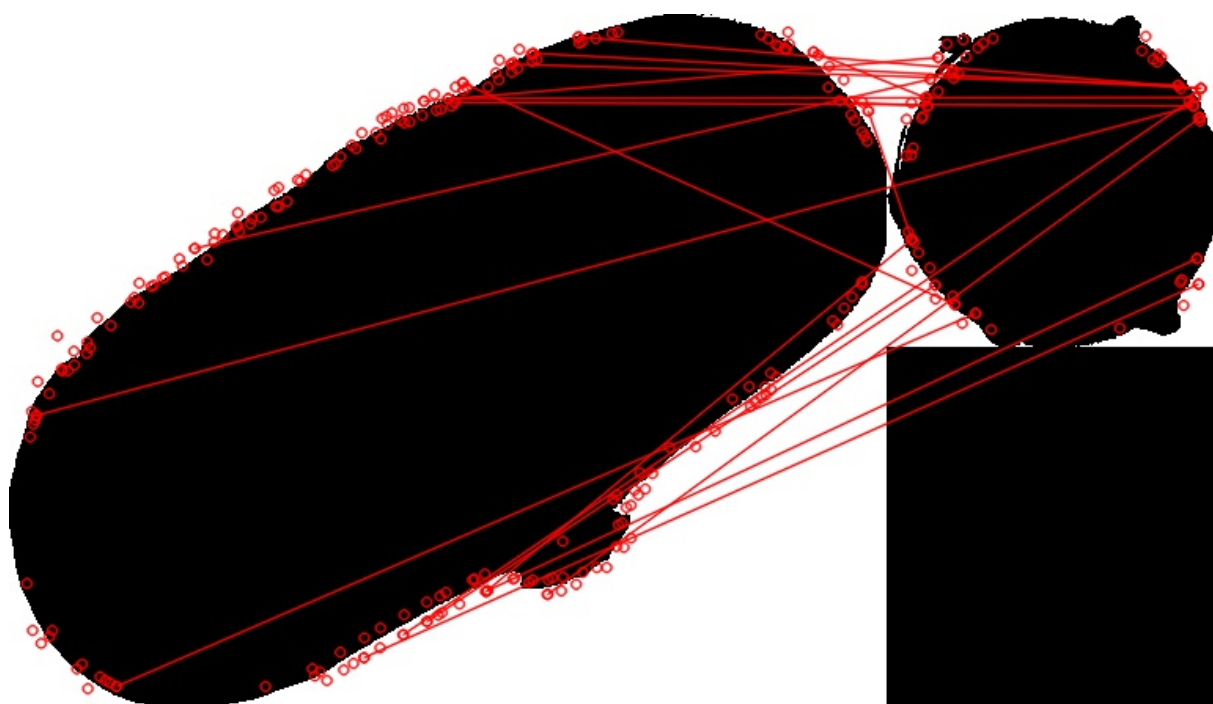Figure 121. Example of correct recognition by the feature points method

Figure13. Example of incorrect recognition by feature points method

The feature points method was less effective in the pollen grains images classifying, but good enough to throw out stains, which are not pollen grains, but have the same color. Perhaps the cause of low efficiency is the rounded shape of pollen grains of different species. Thus, this method completes the preprocessing.

Results

The estimation of efficiency of all methods is based on measure of errors of the first and second kinds.

The error of the first kind is the incorrect miss (false negative), when an event of interest is not detected.

The error of the second kind is incorrect detection (false positive), when an event of interest is absent, but is detected [Vezhnevec, 2007].

Let us consider the neural network estimation results (Table. 1):

Table 1. Results of testing the neural network

	Angelica	Clover	Buckwheat	Pigweed	Carnation	Averages
Pollen grains amount	122	135	53	74	73	452
Normalized rate of errors of the first kind	20%	36%	26%	23%	32%	28%
Normalized rate of errors of the second kind	28%	5%	0%	0%	0%	7%
Percent of correct misses	72%	95%	100%	100%	100%	93%
Percent of correct detections	80%	64%	74%	77%	68%	72%

The structural method gave the highest result of angelica recognizing: 44% of errors of the first kind, 0% of errors of the second kind, 100% of correct misses and 56% of correct detections. The average of correct detections across five species is 42%.

The combination of all three methods gave a good result in the sense of errors of the second type, the average is 7% for the neural network, and 0% for the structural method.

The average of correct detections is 72% for the neural network and 42% for the structural method.

The cause of the most of the errors of the first kind is the pollen grains taken from the exine.

Conclusion

The feature points method is well suited for exclusion from the list for recognition those objects which are not pollen grains, like stains. Hamming neural network and structural approach do not distinguish stains from grains, this is their main disadvantage. The combination of preprocessing basic methods with the feature points method maximizes stains elimination for further recognition by the neural network.

This approach has the following results: for the neural network an average error rate of the first kind is 27%, of the second kind - 7%. Accordingly, neural network recognized correctly about 72% of the pollen grains. Structural method detected correctly about 42% of the pollen grains.

The cause of the most of the first kind errors is the pollen grains taken from the exine, that is, their boundaries are blurry. The next problem is the pollen grains stuck together, but this happens rare, about two pairs per 250 grains.

The next step in research is to use the OpenCV's boosting. It is also planned to apply a texture recognition, a support vector machine. Research of neural networks is not finished: the next network would be convolutional neural network.

One of the major drawbacks of the used methods is that the speed of processing and recognition is quite low. It takes about 40 seconds per an image with one pollen grain. Obviously, the program needs an optimization. Therefore, one of the following stages of development is the usage of concurrency.

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Authors' Information

Natalia Khanzhina – *Dept. Informational technologies and programming, Saint Petersburg National Research university of information technologies, mechanics and optics, Russia, 197101, St. Petersburg, 49 Kronverksky Pr.; e-mail: nehanzhina@gmail.com*

Major Fields of Scientific Research: Image recognition, Neural networks

Elena Zamyatina – *Researcher; Perm State National Research University, Russia, 614990, Perm, Bukireva st., 15; e-mail: e_zamyatina@mail.ru*

Major Fields of Scientific Research: Pattern recognition, Simulation