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Оптимизация распознавания микрообъектов на основе использования морфометрических характеристик изображений

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Аннотация. Разработаны конструктивные подходы, принципы и методы идентификации, распознавания и классификации микрообъектов на основе применения нейронных сетей и механизмов извлечения морфометрических характеристик изображений. Предложена технология обработки информации, основанная на получении изображений микрообъектов из фото, видеокамеры, цифрового микроскопа. Разработана методика интерактивного измерения размеров микрообъектов, подсчета, определения структуры, проведения статистического анализа, выделения и сегментации фрагментов, отбор информативных точек, распознавания и классификации изображений. Разработаны механизмы морфометрического анализа, поиска, извлечения динамических, специфических характеристик изображений. Построена вычислительная схема предварительной обработки изображений, включающая механизмы текстурной, контурной сегментации, детектирования, регулирования переменных. Предложены модели распознавания пыльца на основе правил проверки схожести микрообъектов и механизмов использования специфических особенностей, нужных свойств, характеристик при идентификации изображений. Разработаны вычислительные схемы обучения синтезированных с нейронных сетей моделей изображений с механизмами формирования наборов числовых характеристик, базы данных, базы изображений, базы правил и знаний. Построены алгоритмы обучения нейронных сетей с настройкой переменных в пределах границ допустимых значений, учетом свойств нестационарности точек изображений. Исследована эффективность алгоритмов обучения совмещенной с нейронных сетей динамических моделей с механизмами регулирования линейных, нелинейных, композиционных связей нейронов между слоями сети. Исследование проведено по критерию процентная доля корректного распознавания. Разработан и реализован программный комплекс визуализации, распознавания, классификации изображений пыльцевых зерен, который протестирован при условиях априорной недостаточности, неопределенности и нестационарности.

Ключевые слова: изображение, микрообъект, пыльцевые зерна, идентификация, распознавание, точность.

Optimization of recognition of micro-objects based on the use of morphometric characteristics of images

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Abstract. Constructive approaches, principles and methods of identification, recognition and classification of micro-objects based on the use of neural networks and mechanisms for extracting morphometric characteristics of images have been developed. Information processing technology based on obtaining images of micro-objects from a photo, video camera, digital microscope is proposed. A technique has been developed for interactive measurement of the size of micro-objects, counting, determining the structure, conducting statistical analysis, isolating and segmenting fragments, selecting informative points, recognizing and classifying images. A computational scheme for preliminary processing of images is built, including mechanisms for texture, contour segmentation, detection, and regulation of variables. Algorithms for learning neural networks with setting variables within the limits of permissible values, taking into account the properties of nonstationarity of image points, have been built. The effectiveness of learning algorithms combined with neural network dynamic models with mechanisms for regulating linear, nonlinear, compositional connections of neurons between network layers has been investigated. The study was carried out according to the criterion of the percentage of correct recognition. A software package for visualization, recognition, classification of images of pollen grains has been developed and implemented, which has been tested under conditions of a priori insufficiency, uncertainty and nonstationarity.

Keywords: image, micro-object, pollen grains, identification, recognition, accuracy.

1. Intoduction

In the systems of palynology, medicine, breeding and seed production, environmental protection and ecology, labor-intensive laboratory analyzes are performed [1, 2]. The study is related to the accounting, recognition, classification and systematization of various micro-objects, for example, pollen grains, unicellular organisms, etc [3, 4].

Methods, models, algorithms for the identification of micro-objects are created, which are implemented in the form of software and hardware, information processing complexes that differ from analogues in their functionality, specialization, and level of automation [5, 6].

Traditional image processing technologies are based on tools for obtaining images of micro-objects from a photo, video camera, digital microscope, which also performs interactive measurements of the size of micro-objects, calculations, determination of the structure, statistical analyzes, isolation, and segmentation of the contour, selection of informative points, recognition and classification based on statistical and dynamic models [7-9].

Moreover, existing technologies are characterized by a large value of the error in the identification of images. They do not take into account real conditions reflecting a priori insufficiency, parametric uncertainty, non-stationarity, which negatively affect the recognition of micro-objects [10, 11, 12].

This study is devoted to the development of mechanisms for optimizing the identification of micro-objects using morphometric, dynamic, specific characteristics of images [13, 14, 15]. Preliminary processing of images with mechanisms of texture, contour segmentation, detection, regulation of variables, identification of micro-objects based on the use of neural networks (NN) is assumed, as a popular technology for visualization, recognition, classification of micro-objects of various types [16-19].

2. Main part

2.1. Optimization of recognition of micro-objects based on the use of morphometric characteristics of images

A mechanism for the recognition of micro-objects is proposed, which is based on the use of morphometric characteristics of images with the solution of problems of tracking, detection, search for informative fragments, and features of images from frames of a video stream.

The mechanism performs transformations, detection (filtering) of non-stationary parts, noise, blurring of image points. It is required to ensure high accuracy of recognition of micro-objects with minimal computing resources [23].

The key task of selecting informative fragments, features, and reference points of the contour of images of micro-objects is associated with the calculation of the entropy to K. Shannon [20, 21, 22].

The calculation of the entropy of the image fragment $\{x, R\}$ is given in the form

$$H_D(x,s,R) = -\sum_{d_i \in (1 \ldots r)} P_D(d_i,x,s,R)\log P_D(d_i,x,s,R),$$

where s - selected scale size;

x - average point of the contour of the fragment (segment) of the image;

d_i - the value of the pixel intensity descriptor of the color image points.

The maximum entropy of the parameter is determined at $s = s_p$. The probability distribution function is optimized in the form

$$W_D(x,s_p) = \sum_{i \in (1 \ldots r)} \left| \frac{\partial}{\partial s} P_D(d_i,x,s_p) \right| s_p .$$

The scale is selected in the form

$$Y_D(x,s_p) = H_D(x,s_p)W_D(x,s_p).$$

The extrema of the parameters included in the image model are found and its scalable representation is carried out. The values of x are ranked for different sections (fragments) of the image in descending order.

The point of the image with the highest value is selected. The size of the scale of the image is limited both at the top and at the bottom to $s_{\min} < s < s_{\max}$.

The range of values of the variables of function $Y_D(x, s_p)$ is set in the search space for the "visibility" of the image fragments. The mechanism for searching for the visibility of an image fragment is implemented according to an algorithm that has the following steps.

Step 1. Selecting the pixels of the image points, checking the pixel intensity based on image I_t, the threshold function.

Step 2. Calculation of the maximum entropy for the selected point in the search space for the visibility of the image fragment Y.

Step 3. Formation of points in the visibility space of the image fragment by the method k - nearest neighbors, k - const.

Step 4. Determine the coefficients of variation V_k for k points and the distance D_k to the center point.

Step 5. Check conditions $D_k > \hat{s}$ and $V_k < V_t$. If they are executed, then parameters $\hat{s}$ are added to the array - the average value, the scaling factor, V_k - the threshold value.

Step 6. For the next point, the process is repeated starting from step 2.

Unique image fragments filtered from noise are formed and the extrema of the parameters are found in them. The difference between the Gaussians and the Hess determinant is estimated. When the image I is represented as a function of two variables $f(x, y)$, then its scalable representation $L(x, y, t)$ is given by the convolution $f(x, y)$ of the Gaussian function in the form [24, 25, 26]

$$L(x, y, t) = g(x, y, t) * f(x, y), \text{ where } g(x, y, t) = \frac{1}{2\pi t^2} e^{\frac{x^2+y^2}{2t^2}}.$$

According to Laplace $L(x, y, t)$, the normalized scaling operator is specified

$$\nabla^2_{norm} L(x, y, t) = t(L_{xx} + L_{yy}).$$

The Laplace operator improves the filtering of image points in bright areas of background heterogeneity with a radius of $2t$. The normalized Laplacian represents the differences between Gaussians $f(x, y)$ with parameters $t - \Delta t$ and $t + \Delta t$ in the form

$$\nabla^2_{norm} L(x, y, t) \approx \frac{t}{\Delta t} L(x, y, t + \Delta t) - L(x, y, t - \Delta t).$$

Differences of Gaussians are used in the mechanism of morphometric analysis of the characteristics of images of micro-objects.

The operator of the Hess determinant is used in the mechanism for detecting the inhomogeneous intensity of image points with coordinates (x, y) to select a scale of t, as well as when searching for a maximum point $\det HL(x, y, t) = t^2 \left(L_{xx} L_{yy} - L_{xy}^2\right)$, where HL - Hess matrix.

To filter the scaled fragment, the differential operator is specified $\left(\hat{x}, \hat{y}, \hat{t}\right) = \arg\max_{x,y,t}(\det HL(x, y, t))$.

The mechanism for determining, the coordinates of the points of the areas of inhomogeneity of the background $(\hat{x}, \hat{y})$, radius $\hat{t}$ according to the Hess determinant will be combined with the operators of translation, rotation, scaling of images.

The mechanism allows you to detect both bright and dark areas of the background inhomogeneity of the image.

2.2. A mechanism for detecting an image fragment based on the point offset operator

A mechanism has been developed that has the ability to detect image fragments based on the operators of displacement (transformation) of points in the video stream of frames.

The frames of images I_t, $I_{t+\Delta t}$ and points of the first frame $I(x, y, t)$, t are considered - the moment in time. Let the points in the first and second frames be shifted by Δx, Δy

$$I(x, y, t) = I(x + \Delta x, y + \Delta y, t + \Delta t).$$

To approximate images taking into account the frame mixing operator at $\Delta t \to 0$, the Taylor series is set [27, 28]

$$I(x + \Delta x, y + \Delta y, t + \Delta t) = I(x, y, t) + \frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y \frac{\partial I}{\partial t}\Delta t .$$

Derivatives $\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}, \frac{\partial I}{\partial t}$ are determined, at the mixing points

$$\frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y \frac{\partial I}{\partial t}\Delta t = 0, \quad \frac{\partial I}{\partial x}\frac{\Delta x}{\Delta t} + \frac{\partial I}{\partial y}\frac{\Delta y}{\Delta t}\frac{\partial I}{\partial t}\frac{\Delta I}{\Delta t} = 0, \quad \frac{\partial I}{\partial x}V_x + \frac{\partial I}{\partial y}V_y \frac{\partial I}{\partial t} = 0,$$

where V_x, V_y - components of motion of points of the fragment of the image along the axes x and y;

$V_x \Delta t$, $V_y \Delta t$ - horizontal and vertical displacement;

f - distance to point.

The offset operator is used when forming a "weighted window" of pixels of points and is given by a system of equations [29, 30]:

$$
\begin{aligned}
&I_x(q_1)V_x + I_y(q_1)V_y = -I_t(q_1);\\
&I_x(q_2)V_x + I_y(q_2)V_y = -I_t(q_2);\\
&\vdots \qquad\qquad\quad \vdots \qquad\qquad\quad \vdots\\
&I_x(q_n)V_x + I_y(q_n)V_y = -I_t(q_n),
\end{aligned}
$$

where $q_1, q_2, ..., q_n$ - pixels within the window;

$I_x(q_i), I_y(q_i), I_z(q_i)$ - partial derivatives taken at points q_i of image I with respect to variables x, y and t.

When $Av = b$ is given by the system of equations

$$
A = \begin{pmatrix} I_x(q_1) & I_y(q_1) \\ I_x(q_2) & I_y(q_2) \\ \vdots & \vdots \\ I_x(q_n) & I_y(q_n) \end{pmatrix}; \quad v = \begin{pmatrix} V_x \\ V_y \end{pmatrix}; \quad b = \begin{pmatrix} -I_t(q_1) \\ -I_t(q_2) \\ \vdots \\ -I_t(q_n) \end{pmatrix}.
$$

The system of equations is solved by the least squares method.

Consider the derivatives of the system of two equations in the form

$$
A^T A v = A^T b, \quad v = \left(A^T A\right)^{-1} A^T b\,.
$$

To determine the parameter of the image fragment $b = (x, y, t, t)$, an algorithm has been developed, which is performed in the following steps.

Step 1. A search is made for points lying within a rectangle with sides $a = t$, $b = t$, and center (x, y).

For the found points of P_b images I_j, I_{j+1}, the vertical and horizontal displacement V_x^b, V_y^b are determined.

Step 2. The center of the visibility fragment of image I_{j+1} is transferred with a minimum value of $P_b{}'$.

Step 3. Checking the correspondence of the obtained points of the tracked image fragment (x', y') to the center b'.

Step 4. Comparisons of the coordinates of points P_b and P_b', adaptation of the sides of the rectangle, scaling by coefficients are made:

$$a' = a\frac{\max(P'_{b_x}) - \min(P'_{b_x})}{\max(P_{b_x}) - \min(P_{b_x})}; \qquad b' = b\frac{\max(P'_{b_y}) - \min(P'_{b_y})}{\max(P_{b_y}) - \min(P_{b_y})}.$$

Step 5. The results $b' = (x', y' a', b')$ are checked in image I_{j+1}. Each C_i is believed to contain elements of the $b_1^i, b_2^i, \ldots b_j^i$ signature fragment. If these points coincide, then the process of training the model is performed in the following steps.

Step 5.1. Form and initialize the buffer of informative points of visibility of the image fragment $C_1, C_2, \ldots, C_b$.

Step 5.2. For each, the last element b_j^i is retrieved. There is b_{j+1}^i, which is added to the sequence.

Step 5.3. If the detected fragment is not included in the existing sequence, then the search for new fragments of visibility is performed. New sequences $b_1, b_2, \ldots b_j$ are formed in the common buffer.

A heuristic mechanism for searching for a fragment of image visibility is proposed, which is based on the use of a three-dimensional feature map. For each three-dimensional point of the object (X_i, Y_i, Z_i), the projection of the point on the image is determined as $x_i = \frac{X_i f}{z}$; $y_i = \frac{Y_i f}{z}$, f - the focal length of the camera. The algorithm for adjusting the camera matrix C and focal length f is performed in the following steps.

Step 1. A stereo pair is made up of two consecutive images I_j, I_{j+1}. The distance between them is measured by the step of the video camera T_j.

Step 2. The transformation function $r(I)$ is applied to each image so that the projections of the same points in the stereo pair frames are located on the same horizontal line in the form I_j^r, I_{j+1}^r.

Step 3. Obtaining a distance difference map D_j. The offset distance of points in the image frame is inversely proportional to the distance to the 3D point.

Step 4. The coordinates of the (X,Y) three-dimensional point are calculated

$$X = z\left(x - \frac{w}{2}\right)/f; \quad Y = z\left(x - \frac{h}{2}\right)/f,$$

where w and h - image dimensions;

$I_j \ (x,y)$ - coordinates of a point in the image frame;

$z = \frac{Tf}{\Delta x}$, $\Delta x = D(x,y)$ - distance to point.

Step 5. Converting point coordinates to absolute scale

$$(X_{abs}, Y_{abs}, Z_{abs}) = (X,Y,Z) + (X_0, Y_0, Z_0).$$

The camera movement is the offsets of the $(\Delta X, \Delta Y, \Delta Z)$ points. The offset value ΔX is used as an estimate of the distance to the point. А значения And the values $\Delta Y, \Delta Z$ correspond to the offsets and distances for points $p_1 = I(x_i, y_j)$ and $p_2 = I(x_k, y_l)$.

These distances are Z_1 and Z_2, respectively, in the 3D feature map engine, which are used as $\frac{Z_1}{Z_2} = \frac{Z'_1}{Z'_2}$.

For neighboring frames, fragments of the image I_j, I_{j+1} are determined with probabilities $P(R_j, R_{j+1})$. If all the constituent elements of the fragment are present in the image frame I_{j+1}, then the image point I_j is considered recognized with a high probability.

The implementation of the heuristic search mechanism is based on modeling along a truncated Markov chain.

The results of the execution of the mechanism are formed in the form of a training sample, which contains all the properties of the transformation of points, the specific characteristics of image fragments.

2.3. Optimization of recognition of micro-objects with learning mechanisms of NN

The NN training algorithm consists of the following steps.

Step 1. The learning error $E=\frac{1}{2}(h-t)^2$ is determined, which is set in vector form with parameters $h=(h_1,h_2,...,h_m)$, $t=(t_1,t_2,...,t_m)$, m - the number of observations in the training sample.

The function of activating the neurons of the network is selected

$$z_j=a_j=\sigma(z_i)\left(\sum_{i=1}^{n}\omega_{ij}x_i\right),$$

where ω - neuron weight function;

ω_{ij} - weights of interneuronal connections;

x_i - input neurons.

To optimize the training of the network, partial derivatives with respect to the weights of neural connections ω_{jl} are determined, which are given in the form, $\Delta\omega_{jl}=-\alpha\delta_j$, where δ_j - network learning rate.

Partial derivatives are determined $\frac{\partial E}{\partial\omega_{ij}}=\frac{\partial E}{\partial a_j}\frac{\partial a_j}{\partial z_j}\frac{\partial z_j}{\partial\omega_{ij}}$. Taking into account derivative $\frac{\partial z_j}{\partial\omega_{ij}}$, the network learning error function is given in the form,

$$\delta_j=\frac{\partial E}{\partial a_j}\frac{\partial a_j}{\partial z_j}f(x)=\begin{cases}(a_j-t_j)\sigma(z_j)(1-\sigma(z_j) & ,\ l=4;\\ \sum_{l\in L}\delta_j\omega_{jl} & ,\ l=3;\\ (\sum_{l\in L}\delta_j\omega_{jl})\sigma(z_j)(1-\sigma(z_j)), & l\in(0,1).\end{cases}$$

The network is trained using a back propagation algorithm that adjusts the value of variable δ_j.

A criterion for sparseness is introduced in the form

$$\delta_j=\delta_j+\beta\left(-\frac{s}{\hat{s}_j}+\frac{1-s}{1-\hat{s}_j}\right)\sigma(z_j)(1-\sigma(z_j)),$$

where β and s - sparsity parameters.

The efficiency of the network learning algorithm is analyzed under the following conditions, when:

- $\Delta E = E - E' < \varepsilon_l$, i.e. network convergence achieved;
- $h - t < \varepsilon_r$ the required training accuracy has been achieved;
- the maximum number of algorithm iterations has been reached.

To optimize the learning of the network, a parameter control mechanism is introduced. For this, the training sample is formed on the basis of the selection of two pairs of fragments s_1 and s_2 with the coordinates of points (x_1, t_1) and (x_2, t_2); cumulative transformations are performed; expanding the sample, which contributes to the implementation of the recognition of micro-objects with a stable algorithm with a minimum value of the network learning error; an array of $m > 100$ images is set; the network training sample is divided into unequal parts in a ratio of 7:2:1; allowable intervals for parameter values are set; the network is trained for each parameter β, s, α; the root-mean-square error of training the network $E_{\beta,s,\alpha}$ is calculated; testing the network learning algorithm with a sparsity coefficient. The implemented learning mechanism of the network shows the possibility of reducing its sensitivity to the negative effects of dissimilar image fragments.

A mechanism is proposed aimed at sequential activation of image detectors according to an algorithm that is performed in the following steps.

Step 1. An image model is considered in the form of HM - a set of levels, training sample sizes. The maximum number of levels is determined.

For each image detector corresponding to level $b_j^{(l)}(x, y, h, w)$, the function of identifying all local fragments of the image $I(x...x + w, y...y + h)$ is set.

Step 2. Check. If for level L_l the values of the activation function of all detectors are negative and equal to "0", then it is considered that the image does not belong to class c_i. To activate the detectors, the operations of the algorithm are repeated.

Step 2.1. If the values of the activation function of the detectors of the last level are positive and equal to "1", then it is considered that the image fragment belongs to class c_i.

For many models of fragments M_0, $M_1, ..., M_n$, their belonging to a class is determined by the maximum number of active levels.

The effectiveness of the generalized algorithm for recognizing micro-objects by the criterion of the percentage of correctly recognized images is investigated [31-35]. Results are

F-measure, TP - the number of pixels of the correctly identified area; TN - number of pixels, correctly detected area as background; FP is the number of pixels of the falsely identified area, FN is the number of pixels of the falsely detected area as background.

Table 1 shows the results of testing a generalized image recognition algorithm based on 5 training samples.

Table 1. The results of the generalized algorithm with a cell size of 4×4.

Kit number	*TP*	*FN*	*FP*	*TN*	Accuracy	Completeness	*F*-measure
1	40	23	3	176	0,93	0,63	0,75
2	51	30	5	156	0,91	0,62	0,74
3	39	31	5	167	0,88	0,55	0,68
4	40	29	5	168	0,89	0,57	0,70
5	45	30	5	162	0,90	0,60	0,72
The average	43	28,6	4,6	165,8	0,90	0,60	0,72

Table 2. The results of the generalized algorithm with a cell size of 8×8.

Kit number	*TP*	*FN*	*FP*	*TN*	Accuracy	Completeness	*F*-measure
1	40	23	12	167	0,77	063	0,69
2	50	31	15	146	0,77	0,62	0,68
3	38	32	16	156	0,70	0,54	0,61
4	43	26	13	160	0,76	0,62	0,69
5	44	31	9	158	0,83	0,58	0,69
The average	43	28,6	13	157,4	0,77	0,60	0,67

Generalized algorithm with a 4x4 cell size using gradient optimization mechanisms, linear kernels of support vectors gives the best results. To assess the effectiveness of the mechanisms for recognizing micro-objects, the indicator of the correctness of image recognition was used in the form of a function:

$$c(x_i) = \begin{cases} 1, & h(x_i) = y_i; \\ 0, & \text{otherwise}. \end{cases}$$

The proportion of correctly recognized micro-objects is estimated as $Q = \frac{\sum_{i=1}^{n} c(x_i)}{n}$, where n - the number of images in the test sample.

In figure 1 shows the graphical dependence of function Q - the proportion of correct recognition of micro-objects on the number of images in the test training sample. The graphs are built for the following identification models:

1. parabolic polynomial (solid line);
2. orthogonal algebraic polynomial of the 7th order (dashed line);
3. interpolation spline - Daubechies function of the 5-th order (dash-dotted line);
4. spline combined with a three-layer NN - Daubechies function of the 5th order (a line with two dashed lines).
5.

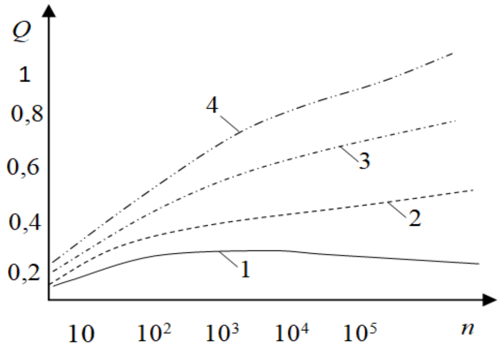

Figure 1. Dependences of the function Q on the length of the test sample.

3. Conclusions

Scientific and methodological foundations of optimization of recognition and classification of micro-objects based on the use of morphometric characteristics with mechanisms for calculating the parameters of localized fragments of images in three-dimensional space have been developed. A hierarchical approach has been implemented, aimed at implementing mechanisms for activating local image fragments and detecting.

It is proved that the sample of training neural network with the number of points $\approx 10^2$ at the first level of image detection with the mechanism of shifting the point of fragments demonstrates a positive effect. When identifying low-level fragments, their edges, borders, corners and increasing tendencies are used. It has been determined that generalized identification algorithms are executed with rarefaction mechanisms in a short time and do not require significant computing resources. There is a 5% decrease in the reliability of image recognition due to the occlusion of fragments. To eliminate the occlusion of image fragments, mechanisms for the reduction of uninformative points are recommended. It has been determined that detectors of local fragments of images increase the stability of generalized classification algorithms by the discriminant function. Each local fragment detector provides robustness to noise errors.

Generalized algorithms for recognizing micro-objects with mechanisms, tracking, detecting, highlighting local features in the space of visibility of image fragments of the entire video stream are implemented. To use the mechanism of the feature map of a three-dimensional image, the OpenCV package was used, which was used to calculate the offsets of the coordinates of points in three-dimensional space. Software has been developed in the form of a specialized framework for image analysis and processing in Python with libraries numpy, scipy, OpenCV, scikit-learn. The software tools have been tested in a parallel computing environment on GPUs of Nvidia CUDA technology for high-speed micro-object recognition.

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