Recognition of micro-objects with adaptive models of image processing in a parallel computing environment

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Abstract. Scientific and methodological foundations for optimizing the processing of micro-objects, in particular, pollen grains, have been developed on the basis of models and methods of preliminary information processing with mechanisms for filtering, identifying, and using textural, specific characteristics, and geometric features of images. The efficiency of image filtering mechanisms is investigated based on the use of statistical control rules, adaptive two-threshold control, trend functions, and control of the contour description error, traditional detectors of random noise, and interference. The mechanisms of image identification using biquadratic, orthogonal algebraic polynomials, 4th order splines are proposed. A technique for optimizing image identification by finding a function by its integrals in a family of straight lines based on the Mellin and Fourier transforms has been developed. Combined models with mechanisms for smoothing reference points, segmentation of contours, filtering with detection of changes in dynamics, optimization by the conjugate gradient method, time relaxation have been built. A software complex for the recognition and classification of images of pollen grains in C ++ has been developed, which includes testing identification algorithms based on the Daubechies spline function, orthogonal algebraic polynomials of 4, 8 orders in the parallel computing environment "CUDA".

1. Introduction
Currently, research aimed at the development of methods for recognition, classification, and systematization of images of micro-objects, for example, pollen grains, medical unicellular organisms, images of useful minerals in the rock mass, fingerprints, is in great demand. The computer vision systems (CVS) of micro-objects will far exceed the capabilities of a person engaged in counting pollen in palynology, breeding and seed production, identifying reference points on the contour of images of useful minerals [1,2]. In the structure of the CVS, mechanisms of digital filtering, smoothing, recognition, and classification are used, based on the technology of obtaining and preparing microimages, input, encoding, compression, placing information in memory, selecting reference, and reduction of zero (redundant) points of the contour, representation and identification of images of micro-objects [2]. In the structure of the CVS, mechanisms of digital filtering, smoothing, recognition, and classification are used, based on the technology of obtaining and preparing microimages, input, encoding, compression, placing information in memory, selecting reference, and reduction of zero (redundant) points of the contour, representation and identification of images of micro-objects. CVS, along with the performance of all these functions, organizes the exchange of data for microscopic studies, storage, which in traditional conditions are performed manually [3, 4]. This study is devoted to the development of software for the CVS, image database, and database, mechanisms for extracting statistical, dynamic, specific characteristics, extracting and dividing contours into segments, using templates for filtering, smoothing recognition, and classification of micro-objects.
2. Main part

2.1. Main approaches, principles, and methods of preprocessing images of micro-objects

The results of preliminary image processing require the construction and implementation of filtering and anti-aliasing mechanisms based on the elimination of noise, high-frequency interference, and smearing of contour points. Many traditional technologies are based on the use of Laplacian and Gaussian filters, median, and Sobel, Previta, Cannes detectors, etc. [5,6]. Image components are analyzed in HSV space.

Improving the quality of filtering and smoothing of images is achieved on the basis of a statistical, two-threshold control strategy, reduction of zero points, reduction of the image dimension. However, due to the variability of the points of the image of the images, the traditional approach to identifying and processing information is associated with inadequate segmentation and anti-aliasing [6]. A mechanism has been implemented aimed at using the initial value, centroid, segment, and contour boundaries, a vector of reference points by checking the maximum correspondence of the real and reference contours, the last of which will be placed in the image database. The problems of filtering and smoothing images are based on statistical, dynamic, neural network, fuzzy models, and their analytical solutions are investigated under the assumptions of linearity, stationarity, and the normal distribution law of noise and interference affecting the dynamics of changes in the image contour [7,8].

Let a sequence of frames of the $I_n$ image of a micro-object $V$, which moves in front of a fixed camera, be fed. Moreover, the parameter image brightness is considered an unknown quantity, and the background of its quasi-static [9-11]. For identification, the image is presented in the form

$$I_n = \{K_n(x, y) \mid 0 \leq x < \text{width}, \ 0 \leq y < \text{height}\} \text{ at } n = 1, N,$$

where $\text{width}$ – frame width; $\text{height}$ – frame height; $I_n(x, y)$ is a vector of fixed dimension.

A set of areas is determined for each video frame in which one or more images move. A set of binary images is formed in which “white” pixels (intensity 255) correspond to pixels belonging to moving objects, and “black” (intensity 0) – to background pixels.

A mechanism has been developed that is aimed at filtering and subtracting the background, segmentation of the image contour, filtering noise to minimize the variance $\sigma$ of the input random process $x(k)$, which are reflected by changes in the contour points in time at the output $x(k + 1) = \Phi(k)x(k) + \nu(k)$, where $\Phi(k)$ – transition matrix; $\nu(k)$ – random vector (noise) having a normal distribution law with the correlation matrix $Q_k$.

Image filtering mechanisms are implemented with the following control strategies:

1) according to the rules of $\pm 3\sigma$, according to which the contour of the object is considered stationary with constant variances, mathematical expectations, and autocorrelation functions;

2) threshold control according to which it is considered that the contour of the object is reflected by a quasi-stationary process with variable variance, mathematical expectation, autocorrelation function;

3) a linear filter based on trend dependencies according to which points of the object contour are described by a non-stationary process with variable variance, mathematical expectation, and autocorrelation function [10].

Linear filtering of the $y(k)$ process with added noise at the output of the mechanism is given in the form

$$y(k) = H(k)x(k) + w(k),$$

where $H(k)$ – observation matrix; $w(k)$ – noise affecting the reference points of the image outline.

The linear filtering mechanism is implemented as a Kalman filter [11]

$$x_0(k | k - 1) = \Phi(k)x_0(k - 1) + B(k)U(k) + D(k)F(k);$$

$$x_0(k) = x_0(k | k - 1) + \sum_{i=1}^{N} K_i(k) [z_i(k) - H(k)x_0(k | k - 1)];$$

$$K_i(k) = S_i(k)P(k | k - 1)H^T \left[ H(k)P(k | k - 1)H^T (k) + V_n[k] \right]^{-1};$$

$$P(k | k - 1) = G(k)V_n(k)G^T (k) + \Phi(k)P(k - 1)\Phi^T (k);$$

$$y(k) = H(k)x(k) + w(k),$$

where $H(k)$ – observation matrix; $w(k)$ – noise affecting the reference points of the image outline.
The lead value of the contour point is specified as
\[ \hat{j}(k) = C(k)\Phi(k)\hat{s}(k-1). \]

The difference between the anticipated and actually observed points is set as
\[ e(k) = y(k) - \hat{y}(k). \]

The Kalman filter gain is defined as
\[ K(k) = P(k-1)C^T(k) \times (C(k)P(k-1)C^T(k) + Q_{\Phi(k)})^{-1}. \]

The proposed image filtering mechanisms for solving smoothing problems are considered in three-dimensional space and implemented on the basis of the cyclic multigrid method in a parallel computing environment. The study was carried out according to the coefficient of gain in filtration, the values of which are determined as the ratio \( \sigma_p/\sigma \), where \( \sigma_p \) – the filtering error on \( \sigma \) – the variance of the input process.

The efficiency of the mechanism is increased by using a differential operator based on adjusting the orders of the approximation model depending on the mesh size. A constructive approach is proposed, aimed at the recognition and classification of micro-objects with implementations of computational schemes of a three-layer neural network (NN), learning algorithms, and retranslation of the process dynamics to an image identification optimization model under conditions of nonstationarity and parametric uncertainty.

Mechanisms for searching for correlations, tendencies, relationships, patterns in the dynamics of images have been used and implemented. Tools for interpreting dependencies, using templates, and regulating variables have been obtained.

2.2. Mechanisms for adaptive identification of micro-objects of various dimensions
The solution to the problem of identifying micro-objects is based on scaling tools, selection of reference points of the contour, threshold control, reduction of zero points, calculation of the root-mean-square error from the corresponding functions of the input and reference images. Many micro-objects have different dimensions, which negatively affect the quality of image identification and the loss of useful information occurs, therefore, it is necessary to study the effect of the operation of reducing the size of digital images to a certain threshold. A technique has been developed, mechanisms obtained by which do not depend on the size of the image. And it is aimed only at finding the required function by its integrals in the family of lines on the basis of the Mellin transformation.
Let the carrier of the function of two variables $f(x, y)$ be concentrated in the strip $-1 \leq x \leq 1$. For this, it is sufficient to calculate the integrals only along those lines that intersect the segment $[-1, 1]$ on the axis $x$. The function $\psi(\eta_1, \eta_2)$ is defined as

$$u(x_1, p_1) = \int_0^\infty \psi(x_1 + p_2 s, s) ds,$$

from it along all straight lines intersecting the segment $[-1, 1]$ on the axis $\eta_2 = 0$.

It is believed that the carrier of the $\psi(\eta_1, \eta_2)$ function is contained in the $-1 \leq \eta_1 \leq 1$, $-\infty < \eta_2 < \infty$ band.

Computing the $\psi(\eta_1, \eta_2)$ function from the $u(x_1, p_1)$ integral is a difficult task. In this regard, the assumption is made that the support of the function $\psi(\eta_1, \eta_2)$ is contained in a rectangle $-r \leq \eta_1 \leq r$, $h_1 \leq \eta_2 \leq h_2$, $0 < r < 1$, $0 < h_1$.

The movement of the object only along this segment is considered and it is forbidden to go around it from all sides. The Mellin transform engine is implemented in a parallel computing environment.

Modified to calculate integrals along straight lines intersecting only one of the sides in a two-dimensional representation of the image. The results of the image conversion problem based on the Mellin integral of the $50 \times 50 \times 50$ mesh are obtained. The mechanism first registers the passage of the image along the one-dimensional line of the detector. The object rotates around a certain axis, remaining in a plane orthogonal to it. The two-dimensional cut plane is assumed to be thin.

Further, after each step of restoring the two-dimensional slice plane, the image moves along the rotation axis and the processes are repeated. The result is a set of a thin slice of a two-dimensional plane, the thickness of which can be practically neglected.

Figure 2. illustrates the implementation of the Mellin transform with indexing $i$ and $j$ on a grid of flows with two cycles. And for a three-dimensional problem with an additional index $k$, calculations of the $i$, $j$ indexes are used with limited problem size.

The study was carried out using the GPU core tools and approximation by the Gauss-Seidel method. Calculations were performed with data in video memory. The number of data reloads from RAM to video memory is set to a minimum.

The achievement of the required accuracy of identification of images of micro-objects in a parallel computing environment is established.

2.3. A generalized algorithm for identifying images of micro-objects in the parallel computing environment "CUDA"

A sequence of images with a large number is considered. Information processing is performed on the basis of a cyclic multigrid method with a graphics processor based on the NVIDIA CUDA platform. The application of the method of parallel computing based on graphic adapters (GPU) is proposed. The shared memory sharing tool is used to speed up calculations.

The effectiveness of the method is estimated by the index of computational complexity equal to $O(N \ln(\varepsilon^{-1}))$, where $N$ is the total number of images; $\varepsilon$ is the error in identifying contour reference points presented in the vector-spatial form.
Realizations are considered on the grid space as a convex cube \( \Omega = [1, \ldots, M; 1, \ldots, N; 1, \ldots, K] \), represented in the form
\[
L_h U_h = F_h \quad \text{to} \quad \Omega_h , \quad \Omega_h \subseteq \mathbb{R}^3 , \quad \partial \Omega_{h0}(U) = U_0 , \quad \partial \Omega_{h1}(U) = \frac{\partial U}{\partial n} .
\] (1)
where \( L \) is an elliptic operator of the form
\[
L = \sum_{i,j} \frac{\partial}{\partial x_i} \left( a_{ij} \frac{\partial U}{\partial x_j} \right) ; \quad a_{ij} - \text{ellipticity condition} \quad a_{ij} = a_{ji} ;
\]
\( \alpha > 0 \) such a constant that the condition
\[
\sum a_{ij} \xi_i \xi_j \geq \alpha \sum \xi_i^2 \quad \xi \in \mathbb{R}^3 \quad \text{and} \quad i,j \in [1,2,3] ;
\]
\( F \) – known function; \( U \) – unknown function that belongs to \( C^2 \); \( h \) – index, which means that the point belongs to the grid space; \( M, N, K \) – dimension of the task in \( \mathbb{R}^3 \). \( \Delta h_j = \frac{1}{X_j} \); \( X_j = \{ M, N, K \} ; \quad j \in [1,2,3] \) - side of the cube.

The use of three-point and five-point finite-difference templates in the form of differential and elliptic operators is proposed:
\[
L^{\text{a}}_h (\lambda) = \frac{1}{2} \left( \lambda \Delta x_i + \lambda \Delta x_j \right) \left( \Delta x_i \Delta x_j \right) + o(\Delta h^2),
\] (2)
\[
L^{\text{a}}_h (\lambda) = \frac{1}{12 \Delta h_i^2} \left( 6 \Delta x_i \Delta x_j + 2 \Delta x_i \Delta x_k + 2 \Delta x_j \Delta x_k \right) \left( \Delta x_i \Delta x_j \Delta x_k \right) + o(\Delta h^4).
\] (3)
\( \Delta h \)
\( 2\Delta h \)
\( 4\Delta h \)
\( 8\Delta h \)

Figure 3.

The side of the cube on each of the grids has the following sequence:
\( \Delta h_i \leftarrow 4 \Delta h_i \leftarrow \ldots \leftarrow q \Delta h_i \),
where \( q \) – grid level defined as \( q = 1,2,4,\ldots,2n, \quad n \in \mathbb{N} \).

In Figure. 3. a diagram is shown that illustrates the sequential movement from a grid of order \( q \) to a grid of order 1, i.e. to the most accurate grid.

When solving problems based on Gauss-Seidel for conjugate gradient optimization, the implemented identification model is capable of eliminating high-frequency components of the \( U \) function. The contributions of Gauss-Seidel mechanisms (GS), conjugate gradients (CG), and upper relaxation (UR) to the efficiency of the generalized identification algorithm based on the grid function from the \( q \) level are investigated to the \( q-1 \) level and bilinear interpolation.

2.4. Bilinear interpolation mechanism based on a grid function.

We introduce the interpolation operator \( I \), which maps the grid functions from the \( q \) level to the \( q-1 \) level. In this regard, the \( I \) bilinear interpolation operator \( U^{q-1}_h \rightarrow U^{q-1}_{q+1} \), \( U^q_h \in S_q \), \( U^{q-1}_h \in S_{q-1} \) is written as:
\[
U^{q-1}_{q+1} = U^q_h \rightarrow U^{q-1}_{q+1} = \frac{1}{8} (U^q_h + U^{q-1}_{q+1,1} + U^{q-1}_{q+1,2} + U^{q-1}_{q+1,3} + U^{q-1}_{q+1,4} + U^{q-1}_{q+1,5} + U^{q-1}_{q+1,6} + U^{q-1}_{q+1,7} + U^{q-1}_{q+1,8}).
\] (4)

A bilinear single point interpolation is written as
\[
U^{q-1}_{q+1} = \frac{1}{12} (12 U^q_h + U^{q-1}_{q+1,1} + U^{q-1}_{q+1,2} + U^{q-1}_{q+1,3} + U^{q-1}_{q+1,4} + U^{q-1}_{q+1,5} + U^{q-1}_{q+1,6} + U^{q-1}_{q+1,7} + U^{q-1}_{q+1,8}).
\]

The task algorithm is presented in the following steps.
Step 1. The grid system (4) is defined.
Step 2. A system of variables of the smoothing problem is formed on the entire family of grids (4).
Step 3. Using the direct method, a solution to problem (1) is found on the coarsest level grid.
Step 4. Using the interpolation operator (4) the value of the grid function is transferred to the grid level $q-1$.
Step 5. Using one of the iterative methods (GS, CG, UR), a solution to problem (1) is found, thereby eliminating the highest frequency discrepancies obtained on the level grid $q$. Iterations continue until the error of the problem becomes equal to the energy norm.
Step 6. If the calculation is not achieved to the required accuracy, go to step 4.

The algorithm for calculating the function $\psi(\eta_1, \eta_2)$ function from the $u(x_1, p_1)$ function based on the Mellin transform is carried out in the following steps.

Step 1. By function $u(x_1, p_1)$, the function is calculated,

$$g_\rho^x(G, t) = G^{p+1}[f(G, t) \pm f(-G, t)], \text{ at } G > 0, t > 0,$$

where $\rho$ – fixed number satisfying $0 < \rho < 1$ conditions.

The function $f(G, t)$ is defined by

$$f(G, t) = \frac{2}{|G|^2 + 1} u\left(\frac{t^2 - 1}{(t^2 + 1)^2} \right) \frac{2G}{(t^2 + 1)^2}.$$

Step 2. The Mellin transform of the $g_\rho^x(G, t)$ function is calculated as,

$$\tilde{g}_\rho^x(\mu, v) = \int_0^\infty G^{p+1}t^{-1}G^\mu t^\mu dGdt, \quad \mu \in \mathbb{R}^1, \ v \in \mathbb{R}^1.$$

Step 3. The function $\tilde{g}_\rho^x(\mu, v)$ is the function $\hat{v}_\rho^x(\mu, v)$. What equality used for

$$\hat{v}_\rho^x(\mu, v) = \frac{\tilde{g}_\rho^x(\mu, v)}{\lambda_\rho(\mu, v)},$$

where $\lambda_\rho^x(\mu, v) = 2^{-p+\mu}(B(\rho - i\mu, 1 - \rho + i\mu, 1 - \rho - i\mu + iv))$.

$B$ is the Euler integral of the first kind; $\lambda_\rho^x(\mu, v)$ is a function that is calculated in advance.

For small values of the $\lambda_\rho^x(\mu, v)$ module, the use of the regularization operator is required, the algorithm of which is implemented in the following steps.

Stage 1. By the inverse Mellin transform $\lambda_\rho^x(\gamma, \tau)$ is a function

$$v_\rho^x(\gamma, \tau) = \int_0^\infty \tilde{v}_\rho^x(\gamma, \tau) e^{\mu v} d\mu d\tau.$$

Step 2. The function $v_\rho^x(\gamma, \tau)$ is the function $\psi(\eta_1, \eta_2)$. Why are equalities used

$$\psi\left(\frac{\tau^2 - 1}{\gamma^2 + 1}, \frac{2\tau}{\gamma^2 + 1} \right) = \frac{\gamma^{(1-p)(\tau^2 + 1)}}{8r^2} [v_\tau^x(\gamma, \tau) + v_\rho(\gamma, \tau)];$$

$$\psi\left(\frac{\tau^2 - 1}{\gamma^2 + 1}, \frac{-2\tau}{\gamma^2 + 1} \right) = -\frac{\gamma^{(1-p)(\tau^2 + 1)}}{8r^2} [v_\tau^x(\gamma, \tau) - v_\rho(\gamma, \tau)],$$

which allows you to calculate the values of the $\psi(\eta_1, \eta_2)$ function for any $\eta_1 \in [-1, 1], \ \eta_2 \in \mathbb{R}^1$.

To find $\tau$, we used the following equality $\eta_1 = \frac{\tau^2 - 1}{\tau^2 + 1}$, and to find the variable $\gamma$ equality

$$\eta_2 = \frac{2\tau}{\gamma(\tau^2 + 1)} \text{ or } \eta_2 = -\frac{2\tau}{\gamma(\tau^2 + 1)}.$$

Algorithm testing was carried out in the following steps.
Step 1. On a uniform lattice, images are generated on a circle with a radius of 0.4 and centered at 
(0, 0, 5), \( \rho = 0.5 \). The object moves in a straight line, the parameters \( G, \tau, \) change in the interval 
[0.01 + 9.2]. The samples on the \((G, \tau)\) lattice are represented by matrices: \((256*256), (512*512), \)
\((1024*1024), (2048*2048), (4096*4096)\).

Step 2. The Mellin \( \tilde{v}_\rho^\pm(\mu, \nu) \) transformation is calculated as

\[
\tilde{v}_\rho^\pm(\mu, \nu) = \int_0^\infty \int_0^\infty \frac{1}{t^\mu} G^{-1} t^\nu dG dt, \quad \mu \in \mathbb{R}^1, \nu \in \mathbb{R}^1,
\]
for function \( v_\rho^\pm(\mu, \nu) \).

Step 3. The inverse Mellin transform is calculated as

\[
\text{obr} v_\rho^\pm(G, \tau) = \int_0^\infty \int_0^\infty \frac{1}{t^\mu} G^{-1} t^\nu d\mu dt.
\]

Step 4. Compare the \( v_\rho^\pm(G, \tau) \) value with the \( \text{obr} v_\rho^\pm(G, \tau) \) value

\[
s = \int_{0.01 \times 0.1}^{0.92 \times 0.9} \left| \frac{v_\rho^\pm(G, \tau) - \text{obr} v_\rho^\pm(G, \tau)}{G \tau} \right| dG d\tau.
\]

\((\mu, \nu)\) values vary at intervals: \([-9.2+9.2], [-18.4+18.4], [-30+30], [-36.8+36.8], \)
\([-45+45][-73.6+73.6]\).

The reliability of the research results is substantiated by the implementation of algorithms and software for preliminary information processing, image identification based on various standard tools and technologies of parallel computing [9, 10].

Figure 4. graphs of the gain coefficient in the accuracy of information processing are shown depending on the volumes of the processed data under given conditions and identification models of reference points of the image contour. The mechanisms included in the identification model are indicated by the following lines: 1 – Gauss – Seidel (2/2); 2 - upper relaxation (2/2); 3- conjugate gradients with approximation (2/2); 4– Gauss – Seidel (4/4); 5- upper relaxation (4/4); 6- conjugate gradients with approximation (4/4); 7– Gauss – Seidel (4:2/4:2); 8- upper relaxation (4:2/4:2); 9 - conjugate gradients with approximation (4:2/4:2). It was found that the generalized image identification algorithm has the property of smoothing the high-frequency components of the AA function under the mechanisms of relaxation and conjugate gradients; identification using biquadratic interpolation and interpolation spline function of the 4th order [10]. A generalized algorithm based on the indicated models is implemented in C++. The graphs of the coefficient of the laboriousness of information processing are obtained, which depend on the amount of information. As can be seen from the graphs, the algorithm that is built on the basis of models 2, 5, 8 is the most advantageous in the labor intensity coefficient.

To start the computing system, a shared memory mechanism was used, which helps to increase the speed of access to memory by almost two orders of magnitude higher than the speed of access to the global system, and also significantly reduces the size of the task.

A mechanism for block loading data into shared memory with two-dimensional indexing \( i \) and \( j \) by parallel streams has been implemented. It has been proven that the index retrieval time is almost 2 times faster than a block loading mechanism with 3D indexing.
When testing the software modules of the complex, the NVIDIA GeForce GTX 1050Ti graphics adapter with 4Gb of RAM was used. It is determined that the error of the results of parallel calculations from analytical calculations differs by the value $6 \times 10^{-5}$. The speed of information processing in parallel computing using eight nuclear processors is increased by an order of magnitude, equal to $10^{-8}$ than four nuclear processor. Under the same conditions, the speed of access to memory with cells increases 200 times.

3. Conclusion
The methodology of preliminary information processing is investigated and mechanisms for filtering high-frequency, non-stationary components of images, blurred points, smoothing, interpolation of selection, segmentation, determining the parameters of segments, reference points of contours, smoothing based on dynamic models, and a three-layer NN are proposed.

A generalized image identification algorithm is proposed, which combines the capabilities of the Mellin transformation mechanisms, and is implemented in the "CUDA" parallel computing environment with a non-uniform function representation grid. It is proved that due to its application, the complexity of information processing is reduced by almost 8 times, and the gain in the relative identification error increases to two orders of magnitude.

The results of the study are recommended as a toolkit for synthesizing algorithms for dynamic filtering, smoothing, selection of informative features and training models for identifying images of micro-objects.

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