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MODULAR INFORMATION SYSTEM FOR INTELLECTUAL PROCESSING OF GEOSPATIAL DATA

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Abstract. *The purpose of this work is to develop a structure of information technologies for spatial data processing and compression / restoration of digitized images of landscape zone objects analyzed as part of a modular system. It is proposed to add a subsystem «Spatial data processing» and a subsystem «Image compression and restoration» to such a system, the modules of which use intelligent methods of preliminary and main processing of geospatial data (in particular, images of landscape objects). In the future, such a system can be used as a component of the structure of a regional-level geoinformation system for environmental monitoring. regional-level geoinformation system for environmental monitoring.*

Keywords: *geospatial data processing, modular information system, environmental monitoring, data preprocessing, intelligent methods*

Introduction.

Regulation of ecological processes requires the use of modern intelligent technologies in geoinformation systems (GIS) for environmental monitoring (GISEM) to solve various tasks related to environmental protection at levels from local to national. A significant part of spatial information in GISEM is geographical in nature, so it can be analyzed and visually presented in the form of digitized images (maps, diagrams, charts, graphs and drawings). At the same time, the tasks of developing methods for pre-processing such data, their filtering and classification, designed to ensure the possibility of prompt response to changes in environmental and technogenic situations in monitoring areas [1, 2] arise.

Modern technologies for analyzing and visualizing spatial information in GISEM not only allow creating electronic maps based on specialized databases, but also, using intelligent processing of available spatial information, solve problems of environmental protection, management of natural resources and environmental management [3, 4].

GISEM technologies are widely used in landscape architecture and programs for monitoring the condition of landscape objects and industrial zones. GISEMs allow for the prompt interpretation of accumulated spatial information, updating and analyzing it in real time, and using it for making management decisions.

Geoinformation models used in GISEMs are based on the automation of information processes for processing spatial data from GPS measurements, satellite remote sensing of the Earth (RSE), aerial monitoring, data from cartographic databases of monitoring regions, data from topographic and geodetic surveys, and statistical data. GISEM information technologies (IT) allow for the processing of a large volume of monitoring data and cartographic data with their subsequent analysis for specific objects and territories.

The peculiarity of modern GISEMs from the point of view of their functional capabilities is the implementation of spatial data binding to a 2D monitoring object with coordinates x, y (or a 3D object with coordinates x, y, z), as well as automatic increase or decrease in the scale of maps. GISEM technologies significantly facilitate the decision-making process in geoecological management tasks. The trend of development of such technologies is based on the need to ensure modern requirements for GISEMs taking into account the trends in the development of computing and information systems [5].

An important component of the modern approach to the development of information technologies GISEM is conceptual modeling. A conceptual model can be defined as a formal representation of a subject area at the conceptual level [6]. In conceptual modeling, technological details of system implementation are ignored in order to study the objects of the subject area, their properties and interaction at a higher level of abstraction (concepts and the connection between them).

The life cycle of an information system and the effectiveness of its maintenance and development at the operation stage largely depend on the presence of an adequate conceptual model. The conceptual model should provide for the possibility of its transformation into implementation models (i.e. into a logical and physical data model, into a specification of the system's software components, etc.).

The subject area of GISEM reflects the existing level of our knowledge in such branches of science and technology as geodesy, cartography, remote sensing of the Earth, photogrammetry, discrete mathematics, computational geometry, mathematical statistics and other branches of mathematics, systems analysis, database theory, programming, computer graphics, modern information technologies of intelligent data processing, theory of automated information systems, etc. At the beginning of the development of GISEM, cartographic modeling of environmental monitoring objects played a dominant role. In the technologies of spatial data collection and processing, the cartographic approach prevailed (based on the collected primary data, maps of monitoring zones were created, which were subsequently scanned and vectorized in order to form a digital cartographic model for GISEM).

The development of GPS, digital photogrammetry and digital remote sensing methods led to the emergence of intelligent information technologies for collecting and processing geospatial data and caused the transformation of geoinformation methods in mapping it self.

The result of the development of new information technologies in GISEM is the possibility of forming geospatial databases of monitoring zones, where object models are displayed with the accuracy and resolution of geodetic measurements and applied technologies for collecting primary data.

Digital cartographic geoimages are converted into products derived from geospatial databases. In [7], the feasibility of creating a modular information system for intelligent processing of geospatial data (MISIOGD) is substantiated, designed to solve the problems of processing, compressing and restoring spatial data in landscape and industrial zones. In the future, such a system can be used as an integral part of the GISEM structure at the regional level.

The purpose of this work is to develop a structure of information technologies for spatial data processing and compression / restoration of digitized images of landscape zone objects analyzed as part of the modular system MISIOGD.

Main text.

The general scheme of SD (spatial data) processing in MISIOGD is shown in Figure 1.

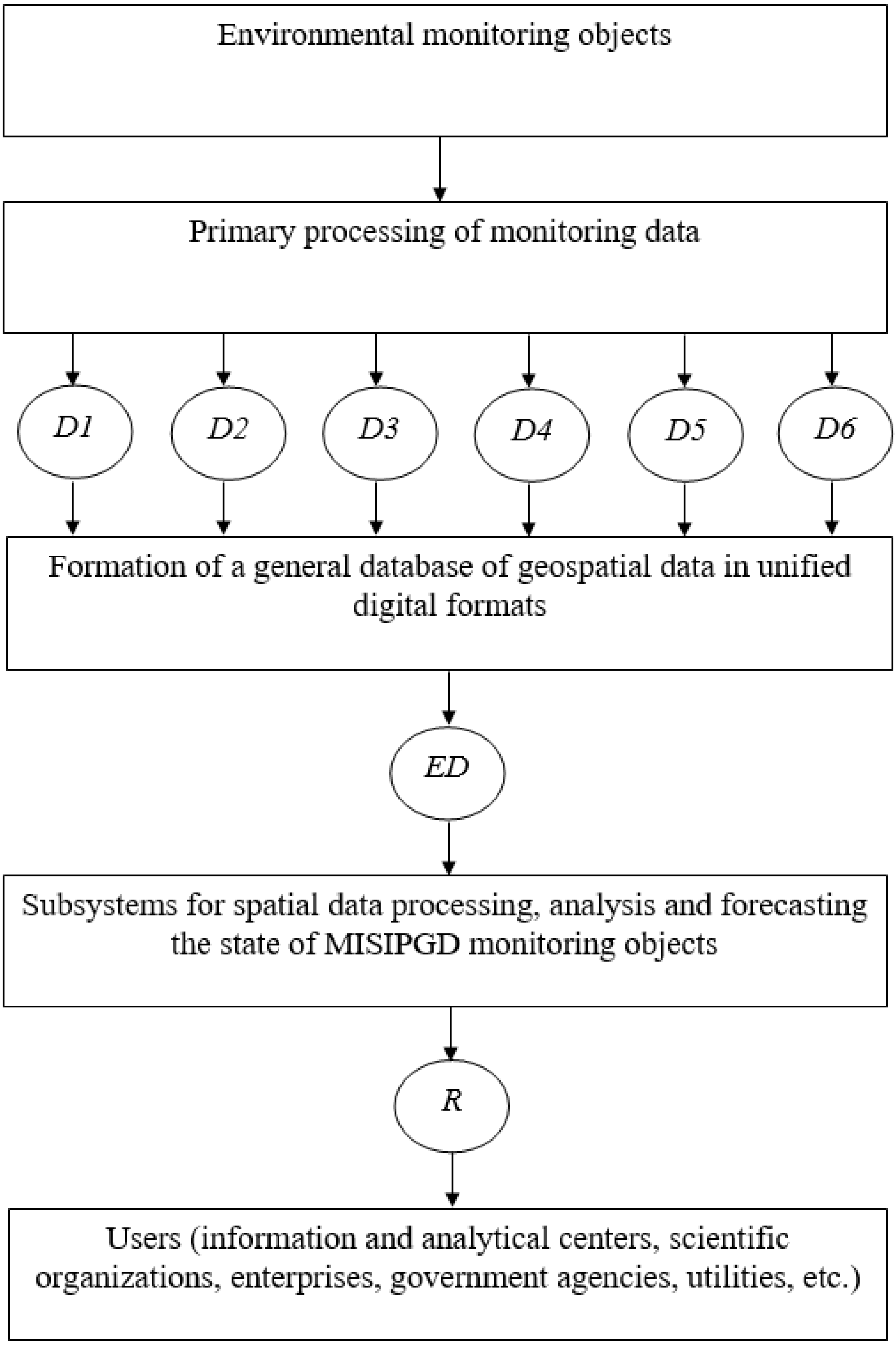

Figure 1 - General scheme for processing geospatial data in MISIPGD

In Fig. 1 the following notations are used: *D1* – GPS measurement data; *D2* – remote sensing data; *D3* – aerial monitoring data; *D4* – data from the cartographic database of the monitoring region; *D5* – statistical data; *D6* – topographic and geodetic survey data; *ED* – set of data in unified digital formats; *R* – MISIOGD output data (SD analysis results, recommendations).

The conceptual model of SD processing in MISIOGD, which corresponds to the scheme in Fig. 1, should reflect the processes of converting the totality of the input set of primary data into a set of complex geoimages, which replenish the MISIOGD geospatial database and are provided to system users as a result of modeling for analyzing the state of the ecosystem and making management decisions.

At the input of the MISIOGD of environmental monitoring of the state of landscape objects (LO) and industrial zones spatial data $D = \{D1, D2, D3, D4, D5, D6\}$ is received in the formats of primary geoimages.

According to the scheme in Fig. 1 such primary geoimages must be pre-processed for the purpose of their submission in unified digital *ED* formats (with an attributive binding of each image to the time scale) to the general database of digitized geospatial data characterizing the studied environmental monitoring area. Such pre-processing of primary images is carried out using a set of methods M_0, that implement the type of transformation $M_0 : D \rightarrow ED$. Let a set of processing methods M_1 be used to perform *ED* data processing tasks in a specific MISIOGD. These methods usually include methods for highlighting the contours of landscape monitoring objects and subsequent clustering or classification of such objects. The result of applying the methods M_1 is a set of processed images $ED1$, i.e. $M_1 : ED \rightarrow ED1$. Images $ED1$ can either be directly used to implement MISIOGD tasks to form the results of analyzing the state of the monitoring area and obtaining relevant recommendations R, or previously submitted to the MISIOGD database (with the obligatory attributive binding of each image to the time scale). In the latter case, it is necessary to compress images (and their subsequent restoration for use in MISIOGD if necessary) using a set of compression / restoration methods M_2. The result of applying the methods M_2 is a set of images $ED2$, i.e.

$M_2 : ED1 \rightarrow ED2$ (note that it is advisable to add methods to the set M_2 that allow restoring distorted image fragments if necessary). Images $ED1$ and $ED2$ are processed using a set of methods M_3 in the subsystem of analysis and forecasting the state of monitoring objects MISIOGD with the formation of the corresponding results R, i.e. $M_3 : ED1, ED2 \rightarrow R$.

Thus, in general terms, the conceptual model of representation and transformation of PD (geoimages) in MISIOGD can be represented by the following tuple:

$$S_{im} = \{ D, M_0, ED, M_1, ED1, M_2, ED2, M_3, R \} . \quad (1)$$

Let's consider further the existing modern IT collection and processing of PD in MISIOGD.

In [3], the analysis of models of integration of GIS, DDD and GPS technologies in the tasks of monitoring the state of the surrounding environment was carried out.

The development of GPS technology and the proliferation of GPS receivers have led to the integration of GPS and mobile GIS. At the same time, GPS data (data $D1$, fig. 1) can be used as a source of coordinate-related information for MISIOGD.

In turn, MISIOGD can be useful for planning and organizing aerial photographs, for maintaining catalogs of aerial photographs. At the same time, the RSE data processing system (data $D2$, fig. 1) is an important data provider for GIS. The integration of RSE with MISIOGD is based on the detection of changes in the earth's surface using an overlay analysis for a certain period. This allows for segmentation of images of landscape objects (LO) and their subsequent classification for loading into the MISIOGD database.

The growth of modern computer capabilities has led to the development of software for processing and analyzing remote sensing materials in MISIOGD (primarily, these are programs for pre-processing and thematic decoding of images; programs for digital photogrammetric image processing; programs for generating MISIOGD cartographic databases). It should be noted that most image processing software (in particular ErMapper, ENVI, ERDAS Imagine, PCI, etc.) designed for use in remote sensing systems can also be used in MISIOGD.

Data from electronic geodetic instruments (data $D6$, fig. 1) and aerial monitoring data (data $D3$, fig. 1) are formed as a set of files with coordinates and identifiers of survey points. These data files can be created in special formats or in the ASCII text format. There are special software packages for processing geodetic measurement data that read such data using special converters and automatically enter them into the attribute database.

Statistical data received by MISIOGD (data $D5$, fig. 1), as well as data from the cartographic database of the monitoring region (data $D4$, fig. 1) are used mainly for comparing geoimages (taking into account their attributes) at the stage of analyzing the state of ecosystems.

A promising direction for processing and storing geoimages in MISIOGD is the creation of GIS-oriented CASE tools that allow visually constructing UML diagrams of geospatial classes of monitoring objects at the level of conceptual models, generating the structure of the MISIOGD database and forms of the MISIOGD user interface.

The problem of ensuring the independence of MISIOGD applications from specific GIS platforms and geodata formats remains relevant. One of the directions for overcoming it is the introduction of a unified GIS server into the MISIOGD structure, which should be an intermediary between client applications and instrumental GIS of specific manufacturers.

The main approaches to unifying the functions of such a GIS server are global unification of a wide range of functions as a prerequisite for standardizing the functional interface of most GIS applications and local unification within a specific area of use of GIS technologies [8].

We should also note the extreme importance of the problem of forming a database of geospatial digitized images in MISIOGD. Such a database can be local, client-server (including one built according to a three-level architecture) or integrated (based on the use of relational geodata models).

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Let us consider a variant of the general structure of the MISIOGD, designed to solve the problems of processing, compressing and restoring spatial data in landscape and industrial zones. It is proposed to add the subsystem «MISIOGD spatial data processing» and the subsystem «Image compression and restoration», the modules of which use intelligent methods of preliminary and main processing of geospatial data (in particular, LO images).

The subsystem «MISIOGD spatial data processing» (according to its functional purpose) should include the following modules: SD preprocessing module with the formation of initial digitized images; image segmentation and contour selection module; categorical classification module of digitized images of landscape objects.

Let us consider the functions of each of these modules and methods of their implementation.

The SD pre-processing module with the formation of initial digitized images provides for the need to improve their quality before further operations of the «MISIOGD spatial data processing» subsystem.

In addition to standard noise reduction filters (in particular, smoothing, median and ranking filters implemented using the method m_{01}), the module offers the use (if necessary) of the following operations: additional binarization and scaling of processed images with an uneven background; improving the quality of the initial images using a modified gamma correction method; improving the quality of the initial images using a locally adaptive neural network approach.

During experimental studies of the proposed methods of the subsystem «MISIOGD spatial data processing», binarization and scaling of processed images were carried out (for image segmentation tasks with an uneven background). To enable segmentation of images of objects with a small and large number of pixels, the method of binarization of the image of the selected area and its scaling with a given coefficient (method m_{02}) is used. The binarization operation allows you to avoid difficulties associated with image distortion during the scaling process. Scaling changes the size of the image of the segmented object. Image segmentation involves the selection of image areas with important objects, with checking each pixel of the selected area for belonging to the image of the object. The segmentation result can be represented as a binary image: a pixel belonging to the image of the object is represented by a unit or the object number, otherwise it is zero. To reduce the amount of processed information and computational costs of the proposed method of segmenting images of objects, it is advisable to apply image binarization. The main parameter of converting the original image of the segmentation area into a binary image is the limiting pixel selection factor . The units in the binary image are filled with pixels whose brightness satisfies the rule for converting the original image into a binary format (binarization rule):

$$A_{ik} > k_c \cdot \sigma_{noi} + \hat{\bar{\Delta}}_{noi}, \tag{2}$$

where A_{ik} – the brightness of the ik-th pixel of the digital frame; σ_{noi} – the estimate of the root mean square deviation (RMSD) of the brightness of the background substrate; $\hat{\Delta}_{noi}$ – the estimate of the average brightness value of the pixels of the background substrate.

An example of binarization of the input image (Fig. 2) is shown in Fig. 3.

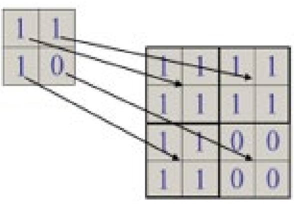
3390	3396	3401	3408	3404	3394	3405	3417	3407	3397	3397	3398	3400	3404	3397
3391	3394	3392	3396	3393	3394	3409	3418	3410	3396	3394	3398	3408	3415	3403
3377	3381	3388	3391	3392	3408	3431	3440	3428	3406	3397	3396	3406	3411	3397
3362	3369	3381	3393	3418	3467	3534	3564	3520	3455	3416	3398	3401	3405	3388
3362	3364	3374	3409	3481	3634	3882	4021	3889	3651	3491	3420	3406	3402	3384
3367	3377	3393	3450	3605	4047	4825	5331	4984	4207	3679	3478	3422	3400	3387
3370	3392	3417	3490	3767	4669	6396	7713	7082	5266	3996	3554	3442	3397	3383
3378	3396	3423	3515	3867	5054	7537	9761	9153	6412	4341	3620	3451	3396	3373
3385	3392	3415	3504	3808	4815	7067	9392	9175	6584	4419	3632	3442	3389	3367
3382	3383	3405	3462	3641	4206	5481	6933	6989	5491	4112	3572	3428	3382	3365
3383	3375	3393	3422	3499	3725	4178	4701	4762	4248	3726	3488	3413	3388	3374
3396	3382	3384	3401	3435	3506	3617	3733	3749	3639	3514	3436	3399	3390	3388
3397	3397	3391	3400	3416	3433	3460	3476	3468	3448	3436	3423	3400	3386	3389
3385	3396	3399	3402	3406	3405	3405	3401	3390	3392	3414	3420	3398	3380	3382
3380	3385	3393	3394	3388	3377	3373	3382	3383	3382	3403	3409	3384	3368	3374

Figure 2 - Example of digitized input image (pixel brightness values)

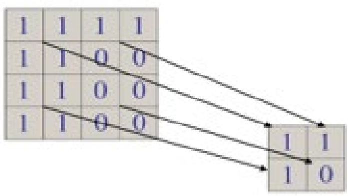
0	0	0	0	0	0	0	1	0	0	0	1	0	1	0
0	0	0	0	0	0	1	1	1	0	0	0	1	1	1
0	0	0	0	0	0	1	1	1	0	0	0	0	1	0
0	0	0	0	1	1	1	1	1	1	1	0	0	0	0
0	0	0	1	1	1	1	1	1	1	1	1	0	0	0
0	0	0	1	1	1	1	1	1	1	1	1	1	0	0
0	0	1	1	1	1	1	1	1	1	1	1	1	0	0
0	0	1	1	1	1	1	1	1	1	1	1	1	0	0
0	0	1	1	1	1	1	1	1	1	1	1	1	0	0
0	0	0	1	1	1	1	1	1	1	1	1	1	0	0
0	0	0	1	1	1	1	1	1	1	1	1	1	0	0
0	0	0	0	1	1	1	1	1	1	1	1	0	0	0
0	0	0	0	1	1	1	1	1	1	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
0	0	0	0	0	0	0	0	0	0	0	1	0	0	0

Figure 3 - Result of binarization of the input image

The efficiency of binarization of an image with an uneven background is determined, among other things, by the accuracy of estimating the background parameters in the vicinity of the segmented image of the object [9]. On the one hand, for a more accurate estimation of the background substrate parameters of an image fragment, it is advisable to reduce the size of the fragments in order to exclude the influence of highlights from the images of bright image fragments. On the other hand, when reducing the size of the fragments, there is a danger that the images of segmented objects, the sizes of which are a priori unknown, will exceed the sizes of the fragments to which they belong. In the automatic shooting mode, digital frames can be obtained from different sections of the dandshaft. The distribution of object images and the area they occupy on the digital frame may differ from frame to frame. Under these conditions, it is advisable to perform luminance equalization of the background of the digital image. When using luminance equalization, the background substrate parameters with an accuracy acceptable for practice can be considered the same on the entire digital frame. In other words, in expression (2) it is possible to use the estimation of the global background substrate parameters. This will avoid overestimation of the background substrate parameters in individual fragments of the frame. To be able to segment images of objects with a small and large number of pixels by one method, it is advisable to modify the image of the selected area by scaling it with a given coefficient. The binarization operation allows to avoid difficulties associated with image distortion during the scaling process. Of the existing scaling methods for a binary image, it is advisable to use the nearest neighbor method. Scaling changes the size of the image of the segmented object. During the operation of increasing the image size, the resulting image is formed by repeatedly copying each pixel of the input image (Fig. 4a). Within the framework of the operation of reducing the image size, each pixel of the source image forms a single pixel in the resulting image (Fig. 4b). In this case, if the value of at least one of the pixels of the source image was equal to one, the value of the resulting pixel will also be equal to one.



a)



b)

Figure 4 - Operations of increasing (a) and decreasing (b) the size of a binary image when scaling

The module provides the ability to improve the quality of input images for further use in MISIOGD. At the same time, the task of processing color cartographic images is solved based on a modified gamma correction method, which would increase the detail and quality of the output image (method m_{03}). Gamma correction of the image is performed in order to increase or decrease its detail.

Incorrect use of gamma correction can lead to a decrease in the number of halftones and the predominance of areas of one tone. During photometric processing of images, there is a need for various kinds of their transformations. The main task of processing a color cartographic image is to correct its brightness while maintaining the color tone. According to the method proposed in [10], the initial RGB image is converted to the HSI color model, and after improving the image quality by changing the brightness components, the image is converted back to the RGB system. This approach allows you to increase the detail of the output image and determine the value of the gamma correction coefficient based on the analysis of the intensity histogram. The method can be effectively used for pre-processing of images in MISIOGD, which is the preliminary stage of further neural network processing of spatial data for the purpose of classifying monitoring objects.

The procedure for improving the quality of the initial digitized images in the SD pre-processing module is implemented using the locally adaptive neural network approach proposed in [2] and consists of procedures 1 and 2.

In this case, the following are performed: pre-processing of the brightness of the input image; image processing at the local level using ANN; image processing at the global level using the algorithm for self-tuning brightness levels. In procedure 1, which is implemented in the SD pre-processing module, a locally adaptive approach to image processing (method m_{04}) is used. The peculiarity of this approach is the independent processing of each pixel of the image, based on the existing set of its local and global characteristics. Unlike known approaches, where a full-pixel image is fed to the ANN input for processing (for example, Hopfield networks and Kohonen maps), in this method of image processing, the ANN is trained in pixel-by-pixel processing.

The image segmentation and contour extraction module of the «MISIOGD spatial data processing» subsystem implements a number of methods and computational procedures considered in [2]. In particular, this module includes procedure 2 of neural network contour selection in an image previously improved using procedure 1 of the preprocessing module (method m_{11}). The result of processing the improved image is a matrix describing the contours of the processed image. To form the value of each element of the contour matrix, NxN elements of the original image matrix (after procedure 1) are used, which define a square mask of the contour filter. Contour selection is performed using a neural network detector containing a linear and nonlinear part.

The module for categorical classification of digitized images of landscape objects of the subsystem «MISIOGD spatial data processing» implements a categorization operation based on the need to organize objects that make up the GIS database in order to reduce computational complexity (computing time, required memory space, etc.). The proposed method for categorical classification of landscape objects MISIOGD (method m_{13}) involves the implementation of the following stages: performing multi-criteria segmentation to obtain complete indices (texture, shape, and color characteristics); category selection; performing segmentation by a combination of criteria and reducing the number of categories; categorization; recognition using categories. The peculiarity of this method lies in the possibility of implementing the recognition process from a low level of image processing to the highest level. In this case, the tasks of highlighting objects in images with their subsequent segmentation and recognition of selected objects are solved.

The image contour detection module using the Markov model of the subsystem «MISIOGD spatial data processing» implements the method m_{12}, which consists in presenting the image using windows that define the area of interest. The window operator processes the pixels of the window to determine whether the feature of the selected attribute is present in it. This operator calculates the difference between the average values on each side of the window from the central pixel, performing exponential weighting. In this case, smoothing is implemented, controlled by the contours of the segmentation map, and a weight table is formed at each iteration to determine the dominant classes for each segment. To select the threshold for segmenting the contour image, the use of accuracy and completeness parameters is proposed. The final contour map corresponds to the most acceptable segmentation option. This approach to computer processing of raster images allows taking into account the nature of the surroundings of the analyzed pixel and specifying the dependence between the classes of neighboring pixels.

The subsystem «Image compression and restoration» (according to its functional purpose) includes the following modules: image compression module in MISIOGD using a fractal model and genetic algorithm (GA); image compression and restoration module using noise-suppressing autoencoders.

Let us consider the functions of each of these modules and their implementation methods.

The image compression module in MISIOGD using a fractal model and GA implements a hybrid method for compressing raster data (method m_{21}), based on the combined use of genetic optimization and fractal algorithms for compressing photorealistic images represented by a quadtree. The fractal compression algorithm uses an additional procedure, which for the class of photorealistic images MISIOGD can significantly reduce the amount of calculations. The parameters of such a procedure are the level of loss during encoding and the size of image regions. This procedure ensures uniform quality of encoding of the entire image.

The image compression and restoration module using noise-suppressing autoencoders implements the method proposed in [11] for neural network processing of noisy digital images MISIOGD, which may contain distorted fragments (method m_{22}). The method is based on the use of evolutionary noise-suppressing autoencoders (ESNAE).

Noise-suppressing autoencoder (SNAE) is a variant of AE in which the inputs are combined with some noise (such as additive noise or masking) and the system is trained to recover the data without noise [11]. Thus, SNAE can be viewed as a stochastic extension of the classical autoencoder, which forces the model to learn to recover the input signal when fed a noisy version of it.

The stochastic process of data corruption randomly sets some of the input data to zero, forcing the SNAE to predict missing (corrupted) values for randomly selected subsets of the missing patterns. The SNAE training scheme can be used in noise reduction applications and is an effective way to train the autoencoder with a more meaningful hidden representation of the data. Fig. 5 illustrates the principle of recovering partially corrupted or noisy landscape images using SNAE.

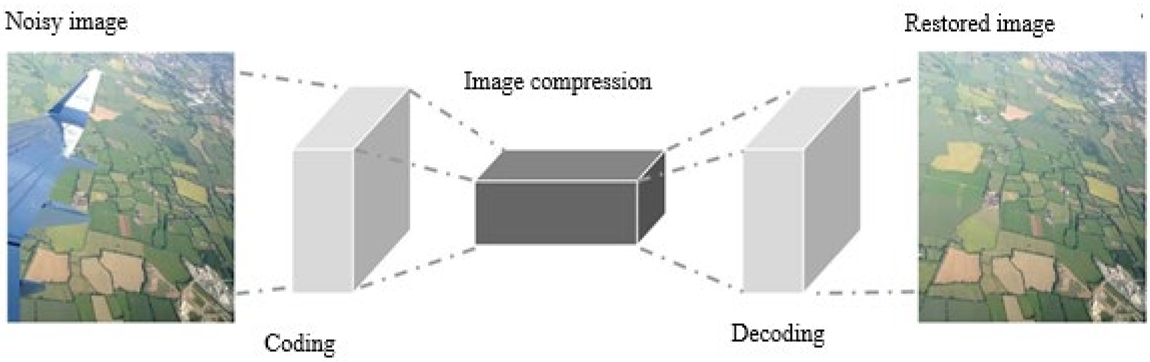


Figure 5 - The principle of processing noisy images using SNAE

This principle consists in the fact that the network is presented with a number of noiseless (clean) images for training, on which the network is trained. During training, all the presented images are compressed and stored in the autoencoder's memory (in the form of its parameters). After the network has been trained, it can be used in real conditions. It should be noted that when processing spatial data in GIS, real images are sometimes noisy or partially damaged, as can be seen, for example, in Fig. 5. After presenting such an image to the trained SNAE, a search is carried out in its memory for the image closest to the presented one, which allows eliminating partial information losses. It is obvious that the SNAE can only use images from the set of samples stored in memory, which is why the problem of forming a training sample arises. The widespread use of SNAE in practical applications related to image processing is often hindered by the lack of a training sequence of truly clean (noiseless) data necessary for tuning encoders. In addition, gradient algorithms are usually used to adjust the parameters of the SNAE, for the implementation of which it is necessary to perform cumbersome matrix inversion operations.

The subsystem proposes the use of a modification of the SNAE (ESNAE - evolutionary SNAE), where a neuroevolutionary approach is applied, which allows not only to adjust the network parameters, but also to determine its structure. The evolution of the structure of the ESNAE is carried out here using a genetic algorithm (GA) [126]. The main stages of the GA operation are: population initialization, population evaluation (calculation of the fitness function), selection, crossover, mutation. The GA stopping criterion is usually either the execution of the maximum permissible number of iterations, or the achievement of a solution variant by the fitness function that corresponds to some predetermined threshold value.

The restoration properties of the autoencoder on partially damaged images of the terrain were studied. For this purpose, a population of autoencoders consisting of 300 people was used. For training, a training sample of 1000 different photographs of the terrain was used, which were previously reduced in size. The size of the images offered to the autoencoder was 80×80 pixels. Training was carried out for 30000 epochs. As a result of the evolutionary algorithm, an optimal seven-layer network was obtained, which made it possible to compress the original images. After training, various extraneous objects were superimposed on some images, which partially hid the original information.

The results of restoring damaged images indicate that the evolving autoencoder is a fairly effective neural network model that can solve the problem of restoring partially damaged terrain images.

The main difference between the neuroevolutionary algorithm ESNAE and gradient algorithms implemented using ANNs is that all operations here are performed not with one network, but with some set of them (population). This eliminates the need to perform such complex operations as matrix inversion when training the network. At the same time, the need to determine the network structure (number of hidden layers), the number of neurons in the hidden layer and the type of basis functions disappears. In addition, the task of determining the coefficients included in the training algorithm and affecting the duration of the ESNAE training process itself is automatically solved.

In accordance with the purpose of the study, schemes of information technology for processing SD and compression and restoration of images as part of MISIOGD were developed.

The general scheme of information technology (IT) for processing SD (in particular geoimages) in the subsystem «MISIOGD spatial data processing» is presented in Fig. 6.

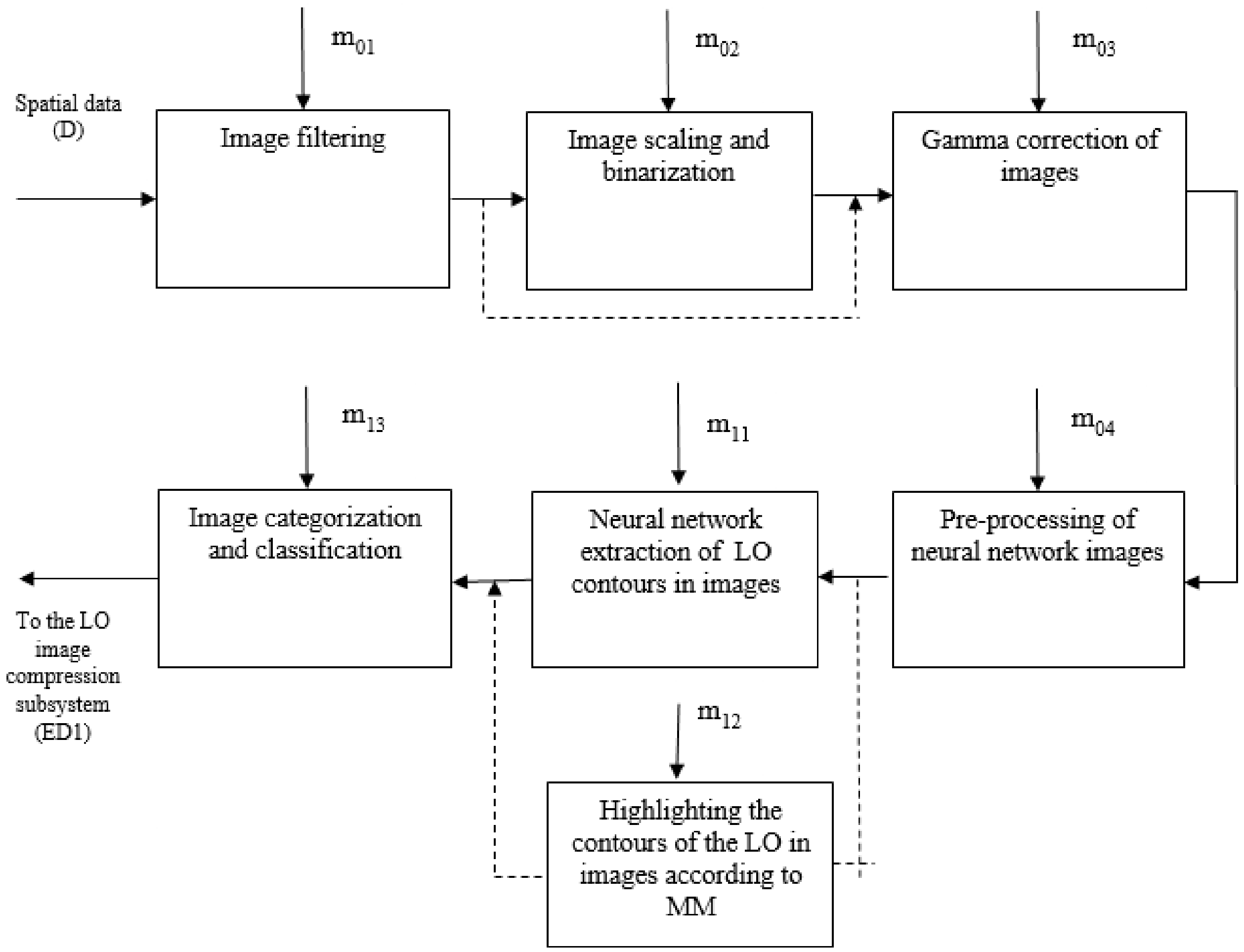


Figure 6 - General scheme of IT image processing in the subsystem «MISIOGD spatial data processing»

The scheme in Fig. 6. includes the following main processes: smoothing filtering of input images by the method m_{01}; binarization of input images and their scaling by the method m_{02}; gamma correction of input images by the modified method m_{03}; preliminary neural network processing of input images by the method m_{04} (procedure 1); neural network selection of LO contours on pre-processed images by the method m_{11} (procedure 2); selection of LO contours on images according to the Markov model

(MM) by the method m_{12}; categorization and classification of LO images by the method m_{13}.

Such information technology corresponds to the conceptual model (1) and the general scheme of SD processing in MISIOGD (Fig. 1) for the sets of methods $M_0 = \{m_{01}, m_{02}, m_{03}, m_{04}\}$; $M_0 : D \rightarrow ED$ and $M_1 = \{m_{11}, m_{12}, m_{13}\}$; $M_1 : ED \rightarrow ED1$.

The general scheme of the information technology for compression and restoration of LO images in the subsystem «Image compression and restoration» is presented in Fig. 7.

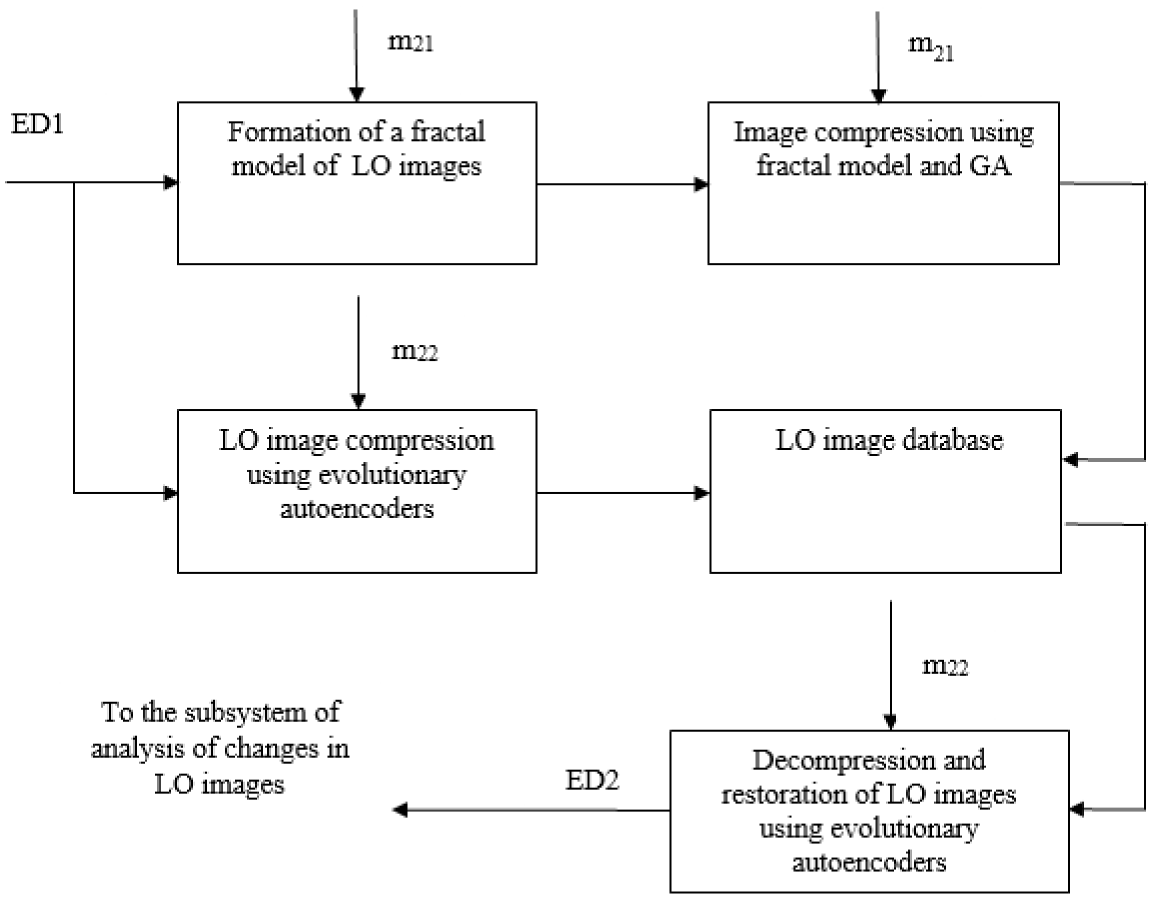


Figure 7 - General scheme of IT for compression and restoration of LO images in the subsystem «Image compression and restoration»

The scheme in Fig. 7. includes the following main processes: formation of a fractal model of images using the method m_{21}; compression of images using the fractal model and GA using the method m_{21}; compression of LO images using ESNAE using the method m_{22}; decompression and restoration of distorted LO images using ESNAE using the method m_{22}.

Such information technology corresponds to the conceptual model (1) and the general scheme of SD processing in MISIOGD (Fig. 1) for the sets of methods $M_2 = \{ m_{21}, m_{22} \}$; $M_2 : ED1 \rightarrow ED2$.

Note that according to the purpose of this work, only methods for implementing the functions of the subsystems «MISIOGD spatial data processing» and the subsystem «Image compression and restoration» were considered. The tasks of other subsystems (namely, the subsystems «Prediction of the state of monitoring objects» and «Analysis of landscape change dynamics»), which in the future may be included in the MISIOGD structure, and the methods for their implementation were not studied. However, there is an undeniable possibility of using the results of the dissertation for analyzing the ecological state of landscape objects and for forming relevant recommendations for improving the ecology of ecosystems (for example, for analyzing the state of deforestation zones, amber mining, monitoring the spread of fires and analyzing their consequences, etc.) [12].

Experimental studies have revealed the advantages of using some methods of neural network processing of spatial data in MISIOGD [3].

The results obtained during the experiments indicate a reduction in the calculation time for some of the proposed data processing procedures and an improvement in the quality of spatial image processing in MISIOGD for environmental monitoring (in particular: a reduction in the computational complexity of image processing using ESNAE by 10% due to the use of an intermediate data compression procedure and the elimination of matrix inversion operations; an increase in the accuracy of estimating background parameters in the vicinity of a segmented image of an object by 7% due to binarization of an image with an uneven background).

Summary and conclusions.

The article presents the results of research into information technologies for processing geospatial data, as well as compression and restoration of digitized images of landscape objects, which are analyzed as part of a modular information system.

The structure and functions of the subsystem «Spatial data processing» and the subsystem «Image compression and restoration» are considered, in the modules of which intelligent methods of preliminary and main processing of geospatial data are used. The possibilities and advantages of the proposed solutions are analyzed.

The considered modular information system can be used as a component of the structure of a regional-level geoinformation system for environmental monitoring.

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