Information-Extreme Machine Learning of an On-board Ground Object Recognition System with a Choice of a Base Recognition Class

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Abstract

The aim of the work is to increase the functional efficiency of machine learning of the on-board system for recognizing land-based natural and infrastructural objects by optimizing the incoming mathematical description. Within the framework of information-extreme intelligent data analysis technology, which is based on maximizing the amount of information in the machine learning process, a method of information-extreme synthesis of onboard recognition system has been developed. Within the framework of a functional approach to modeling cognitive processes of natural intelligence, a categorical functional model of information-extreme machine learning of an on-board recognition system with an automatic selection of the base class of recognition is proposed. Based on the proposed category model, an algorithm of information-extreme machine learning has been developed and programmatically implemented. The dependence of the machine learning functional efficiency on the choice of the base recognition class is experimentally investigated, in relation to which a system of control tolerances for recognition features is determined in the machine learning process. As a criterion for optimizing the parameters of machine learning, a modified information measure of Kullback is used, which is considered as a functional from the exact characteristics of classification solutions. Based on the machine learning results, the decision rules ensured high accuracy of digital image segmentation in the region.

Keywords

Information-extreme machine learning, onboard recognition system, digital image of the region, information criterion, optimization

1. Introduction

Use The task of recognizing ground objects by the on-board system of an unmanned aviation complex divided into two stages: searching on an electronic map of the region of interest areas in which there is the greatest probability of finding the object being sought, and direct recognition of the object in the area of interest. Various natural areas of the region and infrastructural constructions, which also include highways and railways, bridges, airports, etc., can be areas of interest when recognizing small-scale terrestrial objects. Modern experience in the use of unmanned aerial vehicles shows that the search and recognition of ground objects is carried out mainly in an interactive mode, in which the onboard recognition system (ORS) performs the functions of the region a digital image translator to the ground control point. At the same time, there is a trend towards the development of autonomous ORS, which allows to expand their functionality to solve a wide range of problems and increases the cyber security of unmanned aerial vehicles. As a promising way of information synthesis of autonomous onboard systems is the application of machine learning ideas, methods and pattern recognition. The reliability

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of the search for areas of interest in the electronic image of the region depends mainly on two main reasons:

- the adequacy of the input mathematical description of the on-board system for identifying digital image frames of the region to real conditions;
- functional efficiency of ORS machine learning.

Since the onboard system of a modern unmanned aerial vehicle is characterized by high computing power, and available on-board video cameras, thermal imagers and other surveillance devices have a high resolution, now there are all the technical conditions for processing and operational analysis of digital images. But the main deterrent to the introduction of autonomous onboard ORS are scientific and methodological complications associated primarily with arbitrary initial conditions for the formation of the ground object image, the intersection in the space of recognition classes features and a large amount of data.

The paper considers the problem of information-extreme synthesis of the learnable on-board recognition system, which identifies frames of the digital image of the region in order to determine the areas of interest in which the vehicle may be located.

2. Related Works

The most common for the formation of the input mathematical description of the BSR are descriptor methods that can distinguish the contours of ground objects [1 - 3]. The main disadvantages of this approach are the lack of information about the recognition features, as they do not take into account the local design features and external characteristics of the vehicle, and low efficiency of recognition. Higher efficiency of object recognition by contour is achieved by applying the method of proportional coefficients [4]. The most promising is detection based on scanning the entire image of a small ground object [5 - 7]. In [8, 9] the possibility of using neuro-like structures to solve the problems of the ORS autonomous functioning is considered. The main disadvantage of this approach is the sensitivity of artificial neural networks to the multidimensionality of the recognition features space and the recognition classes alphabet. n addition, since the recognition classes in practice intersect in the space of features, the works [10] are known, in which fuzzy neural networks are solved using the apparatus of fuzzy logic. The article [11] proposes the method of solving the problem of feature space multidimensionality via dividing the input data on blocks and submit them to multilayer extractors of neural networks. Encoded data from extractor output is submitted to megaclassifier. Such approach leads to data loss and affects accuracy of the classification decisions. It is known that the greatest efficiency of classification decisions is characterized by methods of pattern recognition, which are able to build decision rules within the geometric approach [12]. Within this approach as a promising direction is the use of ideas and methods of so-called information-extreme intellectual technology (IEI-technology), which is based on the implementation of the maximizing information principle in the process of machine learning system [13 - 15]. In [16], the segmentation of the region digital image was considered within the framework of IEI-technology, but the problem of choosing the basic recognition class and its influence on the functional efficiency of ORS machine learning was not investigated.

The purpose of the work is to increase the functional efficiency of the ORS of natural and infrastructural ground objects by choosing a base recognition class, in relation to which a system of control tolerances for recognition signs.

3. Methods and Materials

Consider the formalized formulation of the ORS information-extreme synthesis problem of terrestrial objects capable of learning with the automatic selection of the basic recognition class. Let the alphabet of $\{X_m^0 | m = \overline{1, M}\}$ recognition classes be formed, which characterize the frames of the region digital image obtained by aerial photography. For each recognition class, a three-dimensional learning matrix $\left\| y_{m,i}^{(j)} \right\|$ of brightness is formed, in which row $\{y_{m,i}^{(j)} | i = \overline{1, N}\}$, where N is the number of recognition features, is a structured vector of features of the corresponding recogniton class, and the matrix column is a random training sample $\{y_{m,i}^{(j)} | j = \overline{1,n}\}$ of the i-th feature with volume n.

It is known that one of the characteristic features of the methods of IEI-technology is the transformation of the input training matrix Y into a working binary matrix X, which adapts in the process of machine learning to the maximum full probability of correct classification decisions. Therefore, the Hamming binary space is given a vector of functioning parameters that affect the functional efficiency of ORS machine learning to recognize structured feature vectors, for example, recognition class X_m^0:

$$g_m = < x_m, d_m, \delta > , \tag{1}$$

where x_m is the vector of features averaged over the training matrix, the vertex of which determines the center of the hyperspherical container of recognition class X_m^o in the Hemming bemming space; d_m radius of the hyperspherical container of recognition class X_m^o, which is restored in the radial basis of the recognition features space; δ – parameter, the value of which is equal to half the symmetric field of control tolerances for recognition features.

The parameters of the system, which will be called the parameters of machine learning, are subject to appropriate restrictions:

- the recognition container radius values range X_m^o is given by inequality $d_m < d(x_m \oplus x_c)$, where $d(x_m \oplus x_c)$ – is the center-to-center distance between the averaged feature vector x_m and the nearest corresponding feature vector x_c of the neighboring class X_c^o;
- the parameter values range δ is given by inequality $\delta < \delta_H/2$, where δ_H is the normalized field of tolerances for recognition features;

Figure 1 shows a bilateral symmetrical field of control tolerances.

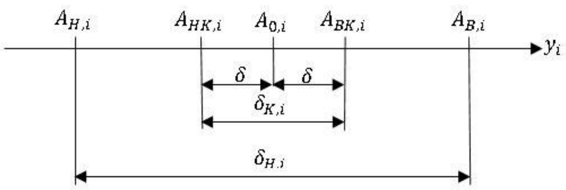


Figure 1: Recognition tolerance fields

In Figure 1 the following designations are accepted: $A_{0,i}$ – nominal (average) value of sign y_i; $A_{H,i}, A_{B,i}$– lower and upper normalized tolerances for feature y_i; $A_{HK,i}, A_{BK,i}$ – lower and upper control tolerances for sign y_i; δ – parameter equal to half of the symmetric field of control tolerances.

It is necessary to find the basic recognition class for a given alphabet, in relation to which the system of control tolerances for recognition features is determined, and in the process of ORS machine learning to optimize machine learning parameters (1), which provide the maximum value of information criterion in the working:

$$\bar{E}^* = \frac{1}{M} \sum_{m=1}^{M} \max_{G_E \cap \{k\}} E_m^{(k)}, \tag{2}$$

where $E_m^{(k)}$ is the value of the information criterion calculated at the k-th step of machine learning; G_E – working area of the information criterion calculation; $\{k\}$ –many machine learning steps.

Thus, the task of information synthesis of the learnable recognition system is to optimize the parameters of its machine learning by approaching the global maximum of the information criterion (2) to its maximum limit value.

The development of information-extreme machine learning methods is carried out within the framework of a functional approach to modeling cognitive processes by natural intelligence. Within the framework of this approach, we represent the categorical functional model of information-extreme machine learning BSR in the form of a directed graph of mapping sets to each other with the help of machine learning operators involved in the process. The input mathematical description of the category model is given in the form of a structure

$$I_B = < G, T, \Omega, K, Y, X; f_1, f_2 >, \tag{3}$$

where G is the set of factors that affect the BSR; T – a set of points in time for reading information; Ω – space of recognition signs; K– the region digital image frames set; Y – input training matrix of image frame pixels brightness; X– working binary training matrix; f_1 – operator formation of the input training matrix Y; f_2– operator for converting the matrix Y into a working binary matrix$X$.

The categorical functional model of the SBR information-extreme machine learning with automatic determination of the basic recognition class is shown in Figure 5.

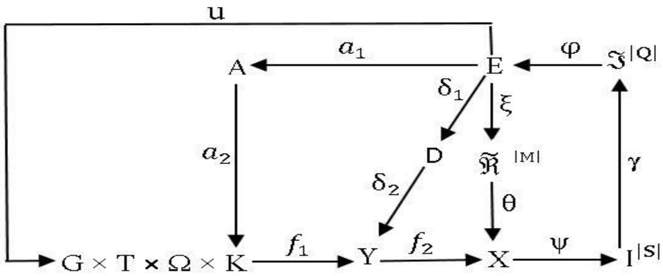


Figure 2: Categorical functional model of ORS machine learning

In Figure 2 Cartesian product $G \times T \times \Omega \times K$ specifies the source of information. The term set E of the information criterion values is common to all circuits for optimizing the parameters of machine learning. The operator $\xi: E \rightarrow \tilde{\Re}^{|M|}$ builds at each step of the machine learning partition $\tilde{\Re}^{|M|}$, which is displayed by the operator θ on the distribution of binary feature vectors. Next, the operator $\psi: X \rightarrow I^{|S|}$, where $I^{|S|}$ is the set S of statistical hypotheses, tests the basic statistical hypothesis $\gamma_1: x_{m,i}^{(j)} \in X_m^o$. The operator γ determines the set of the classification solution exact characteristics, where $Q = S^2$, and the operator ϕ calculates the set of values E of the information optimization criterion, which is a functional of the exact characteristics. The contour of control tolerances optimization for recognition features is closed through the term set D the elements of which are the values of the system of control tolerances for recognition features. The contour, which includes the set A – the ordered alphabet of recognition classes, automatically determines the basic recognition class by searching, which provides the maximum value of the information criterion for optimizing the parameters of machine learning (2). Operator u regulates the process of machine learning.

Within the framework of the functional approach to modeling of cognitive processes of classification decisions making the categorical functional model (Figure 2) is considered as the generalized structural scheme of information-extreme machine learning algorithm.

4. Experiment

According to the categorical model (Figure 2), the machine learning algorithm with optimization of the control tolerances system for recognition features was implemented in the form of a two-cycle procedure for finding the global maximum of information criterion (2) in the working area of its function.

$$\delta^* = arg \max_{G_\delta} \left[\frac{1}{M} \sum_{m=1}^{M} \max_{G_{Em} \cap \{k\}} E_m^{(k)} \right], \tag{4}$$

where G_δ is the allowable range of the control tolerances field parameter δ values for recognition features.

Optimization of control tolerances for recognition features was carried out according to a parallel-sequential scheme. The extreme values of machine learning parameters obtained in the process of parallel optimization are quasi-optimal, because they changed at each step of learning by the same amount for all features simultaneously. To increase the functional efficiency of ORS, it is advisable to implement a machine learning algorithm with consistent optimization of control tolerances. Thus the control tolerances received at a stage of parallel optimization were accepted as starting at consecutive optimization which can be carried out, for example, by iterative procedure of search of a global maximum of an information criterion in the form [10]

$$\delta_{K,i}^* = arg \bigotimes_{L}^{l=1} \left\{ \max_{G_{\delta i}} \left[\frac{1}{M} \sum_{m=1}^{M} \max_{G_{Em} \cap \{k\}} E_m^{(l)}(d_m) \right] \right\}, i = \overline{1, N}, \tag{5}$$

where L is the number of the optimization sequential procedure runs of control tolerances due to suboptimal starting values of control tolerances for all features; $\otimes$ – symbol of the repeat operation.

Machine learning ORS with parallel-sequential optimization of control tolerances allows to increase the reliability of classification solutions and at the same time significantly increases the efficiency of machine learning, because the search for a global maximum criterion is carried out only in the work area to determine its function.

As an information criterion for optimizing the parameters of machine learning, a modified Kullback measure was considered, which for two-alternative solutions with a priori equally probable hypotheses has the form

$$E_m^{(k)} = [D_{1,m}^{(k)}(d) - \beta_m^{(k)}(d))] \times log_2 \left[\frac{1+[D_{1,m}^{(k)}(d)-\beta_m^{(k)}(d)]+10^{-r}}{1-[D_{1,m}^{(k)}(d)-\beta_m^{(k)}(d)]+10^{-r}}\right], \tag{6}$$

where $D_{1,m}^{(k)}(d)$ is the first reliability, which characterizes the probability of the recognition features vector correct classification X_m^o; $\beta_m^{(k)}(d)$ is an error of the second kind, which characterizes the erroneous assignment to class X_m^o of the vector of features of the nearest neighboring class; d – remote measure, which determines the radii of hyperspherical containers of recognition classes, built in the radial basis of Hamming binary space; 10^{-r}– a sufficiently small number, which is entered to avoid division by zero (the value of r in practice is selected from the interval $1 < r \leq 3$).

Since the information criterion is a functional of the exact characteristics, it is necessary to use their estimates for a representative volume of the training sample:

$$D_{1,m}^{(k)}(d) = \frac{K_{1,m}^{(k)}(d)}{n_{min}}; D_{2,m}^{(k)}(d) = \frac{K_{4,m}^{(k)}(d)}{n_{min}} \tag{7}$$

where $K_{1,m}^{(k)}(d)$ is the number of events that indicate the belonging of “their” implementations of recognition class X_m^o; $K_{4,m}^{(k)}(d)$ – the number of events that mean the non-belonging of “foreign” implementations of recognition class X_m^o; n_{min} – the minimum size of a representative training sample, which is determined by the method proposed in the work [10].

After substituting the corresponding notation (6) in expression (5) we obtain a working formula for calculating within the IEI-technology criterion for optimizing for optimizing the parameters of machine learning to recognize the vectors of the signs of classX_m^o:

$$E_m^{(k)} = \frac{1}{n_{min}}\left[K_{1,m}^{(k)} - K_{2,m}^{(k)}\right] \times log_2 \left[\frac{1+[K_{1,m}^{(k)}-K_{2,m}^{(k)}]+10^{-r}}{1-[K_{1,m}^{(k)}-K_{2,m}^{(k)}]+10^{-r}}\right] \tag{8}$$

The normalized form of criterion (7) has the form

$$E_{K,m}^{(k)} = \frac{E_{Km}^{(k)}}{E_{Kmax}^{(k)}} \tag{9}$$

where $E_{Kmax}^{(k)}$ is the value of criterion (7) for $K_{1,m}^{(k)}(d) = K_{2,m}^{(k)}(d) = n_{min}$.

The calculation of coefficients $K_{1,m}^{(k)}$ and $K_{2,m}^{(k)}$ was carried out according to the procedures

$$if x_m^{(j)} \in X_m^o \; then \; K_1(j) := K_1(j-1) + 1; \; if x_c^{(j)} \in X_c^o \; then \; K_2(j) := K_2(j-1) + 1.$$

In this case, the assignment, for example, implementation $x^{(j)}$ to the recognition class X_m^o is carried out according to the rule:

1. the code distance $d[x_m \oplus x^{(j)}]$ is calculated;
2. comparison: if $d[x_m \oplus x^{(j)}] \leq d_m$, then $x^{(j)} \in X_m^o$, else – $x^{(j)} \notin X_m^o$;

According to the optimal geometric parameters of the recognition classes containers obtained in the machine learning process, decision rules are built for the identification of frames of the digital image of the region during the operation of the ORS in the examination mode.

For hyperspherical containers of recognition classes, the decision rules have the form [11]

$$(\forall X_m^o \in \Re^{|M|})(\forall x^{(j)} \in \Re^{|M|})[if(\mu_m > 0) \& \left(\mu_m = \max_{\{m\}}\{\mu_m\}\right)$$
$$then \; x^{(j)} \in X_m^o \; else \; x^{(j)} \notin X_m^o], \tag{10}$$

where $x^{(j)}$ is a recognizable vector; μ_m – membership function of vector $x^{(j)}$ of the container of the recognition class X_m^o.

In expression (10), the membership function for a hyperspherical container of recognition class X_m^o is determined by the formula

$$\mu_m = 1 - \frac{d(x_m^* \oplus x^{(j)})}{d_m^*}, \quad (11)$$

where x_m^* is the optimal averaged binary vector of features; d_m^* – optimal radius of the hyperspherical container

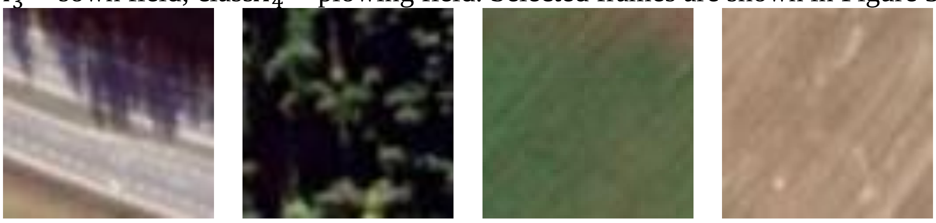
Thus, during the functioning of the ORS in the exam mode, the belonging of the feature vector is recognized, to one of the classes from the given alphabet is determined by the decision rules (10). the same time, the decision rules due to low computational complexity are highly efficient.

5. Results

The input training matrix in the implementation of the information-extreme machine learning algorithm ORS with optimization of control tolerances for recognition features by procedure (3) was formed by processing the image size 1920x1060 pixels, obtained by aerial photography of the region from a height of 300 m (Figure 3) [17].

Figure 3: Region plan

The alphabet consisted of four recognition classes, which characterized the frames with a size of 60×60 pixels of different areas shown in Figure 2 images: class X_1^o – highway; class X_2^o – liquid forest; class X_3^o – sown field; classX_4^o – plowing field. Selected frames are shown in Figure 3.



a b c d

Figure 4: Image frames: a – class X_1^o; b – class X_2^o; c – class X_3^o; d – class X_4^o

In order to ensure the invariance of the decision rules for the shift and rotation of objects within the frames, the formation of the input training matrix was carried out by processing images in the polar coordinate system. The average brightness of the pixels of each reading circle, built around the geometric center of the frame, was calculated by the formula

$$\Theta_j = \frac{1}{N_j} \sum_{i=1}^{N_j} \theta_i, \quad (12)$$

where Θ_j is the average value of the pixels brightness included in the reading range of the j-th radius, $j = \overline{0, R}$; θ_i – brightness value of the RGB component in the i-th pixel of the receptor field of the frame image; N_j – the total number of pixels j-th reading circle; R – radius of the reading circle.

The geometric center of the frame was determined by the formula

$$i_c = round\left(\frac{1+N^2}{2}\right), \quad (13)$$

where N is the number of pixels on the side of the square frame.

According to the averaged luminance of the reading circles calculated by formula (3), structured vectors of recognition features of the input training matrix were formed for those shown in Figs. 3 the region frames image.

According to the concept of IEI technology, a mandatory machine learning procedure is to optimize the system of control tolerances for recognition features, which play the role of quantization levels in the transformation of the input Euclidean learning matrix into a working binary learning matrix at each step of machine learning. This raises the problem of choosing the basic class of recognition, in relation to which is determined in the process of machine learning system of control tolerances. A working hypothesis put forward that it is expedient to choose a recognition class as the basic one, the educational matrix of which has the maximum variance of the brightness of the recognition features. The rationale for this hypothesis is that the recognition class that has the largest scatter of feature brightness is the closest to all classes in a given alphabet. Dispersion σ_m^2 was defined as a measure of the brightness deviation of the l -th feature from the average value of the input training matrix brightness $\overline{\Theta}_m$:

$$\sigma_m^2 = \frac{1}{(N\times n)-1}\sum_{l=1}^{N\times n}(\Theta_l - \bar{\Theta}_m)^2. \quad (14)$$

where θ_l is the brightness value of the RGB component in the l-th pixel of the image frame receptor field of the recognition class X_m^o.

According to the results of statistical analysis of the input training matrix for a given alphabet of recognition classes, it was found that the maximum sample variance of feature brightness was obtained for the training matrix of recognition class X_1^o, relative to which the system of control tolerances was determined. This hypothesis was experimentally confirmed by the results of information-extreme machine learning, in which each class from a given alphabet was consistently chosen as the basic one. Figure 5 shows a graph of the dependence of the averaged normalized criterion (8) on the parameter δ, obtained in the process of implementing information-extreme machine learning ORS with parallel optimization of control tolerances according to procedure (4) for the basic recognition class X_1^o. On the graphs below, the working area for determining the function of criterion (7) is marked in dark color, in which the first and second reliability exceed the errors of the first and second kind, respectively.

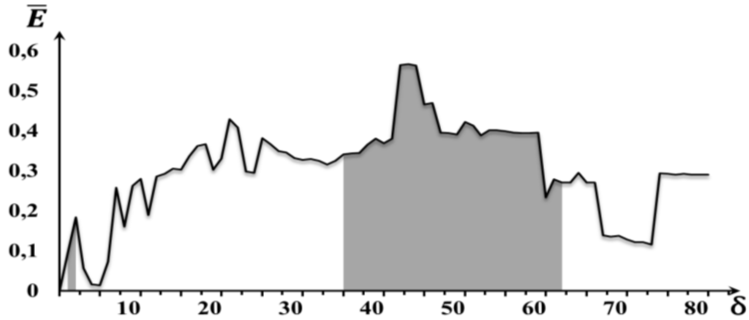


Figure 5: Graph of information criterion dependence on parameter of control tolerances system

The analysis of Figure 5 shows that, in the process of machine learning, the optimal value of parameter of control tolerances system is equal to $\delta^* = 43$ (scale of pixel's brightness) with a maximum value of $\overline{E}^* = 0{,}56$ information criterion.

To increase the functional efficiency of machine learning, a consistent optimization of control tolerances according to procedure (5) was implemented. In Figure 6 shows a graph of changes in the normalized criterion in the process of sequential optimization of control tolerances for recognition features.

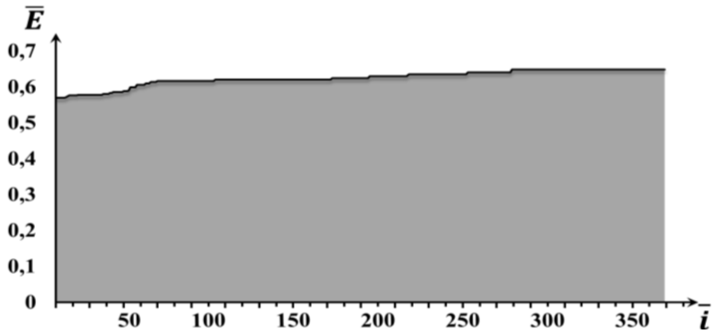


Figure 6: The graph of the information criterion changes with sequential optimization of control tolerances

Analysis of Figure 6 shows that the information optimization criterion reached a maximum value of 0.64 on the fourth run, the number of which is determined by the iterations number ratio to the features number in the structured vectors of recognition features.

Below are graphs of the dependence of the information criterion on the radii of recognition classes containers (9)

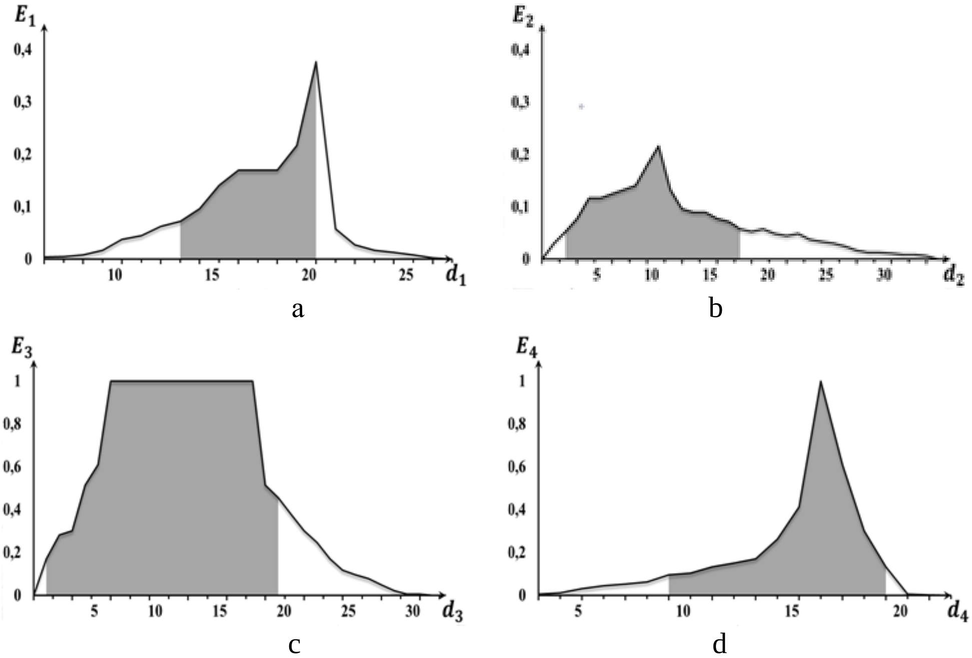


Figure 7: Graphs of the information criterion dependence on the radii of the recognition classes containers: a – class X_1^o; b – class X_2^o; c – class X_3^o; d – class X_4^o

Analysis of Figure 7 shows that the optimal values of the recognition classes containers radii are equal to: $d_1^* = 20$ (hereinafter in code units) for class X_1^o; $d_2^* = 10$ for class X_2^o; $d_3^* = 9$ for class X_3^o and $d_4^* = 16$ for class X_4^o.

Maximum values of the optimization criterion(8) that are showed on Figure 7c according to machine learning results created on the chart plateau area. Therefore, optimum value for radii of class X_3^o recognition container was considered by the minimum of η_δ coefficient which describes overlap degree for recognition classes of given alphabet of classes:

$$\eta_\delta = \frac{d_m}{d(x_m \oplus x_c)} \to \min_{\{d\}}, \tag{15}$$

where $d(x_m \oplus x_c)$ – the Hamming code distance between the averaged feature vector x_m of the recognition class X_m^o and corresponding feature vector x_c of the nearest neighbor recognition class X_c^o.

Recognition class overlap coefficient may be considered as generalization of two basic principles of image recognition theory: the one based on minimum distance, which demands minimization of radii for recognition class containers and one based on maximum distances, which demands maximization of the distances between centers of classes from given alphabet.

Figure 8 shows a digitized image (Figure 3) obtained at the stage of the exam according to the decision rules (9).

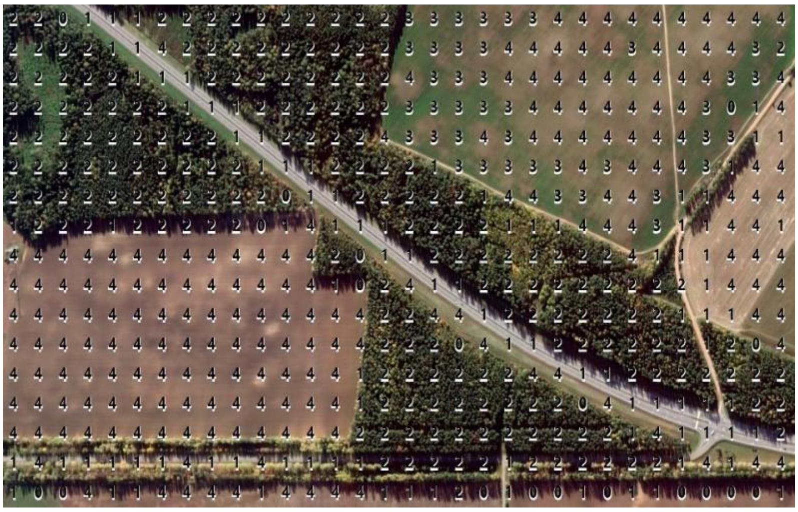


Figure 8: The region image frames identification result

Analysis of Figure 8 shows that the identification of a highway that may be an area of interest, for example, when searching for a vehicle, is carried out with a sufficiently high reliability. But the constructed decision rules are not infallible. One of the ways to increase the functional efficiency of BSR is the transition from a linear data structure to a hierarchical one with the definition for each tier stratum of the hierarchical data structure of the basic recognition class. In addition, according to the principle of deferred decisions of O. G. Ivakhnenko, it is necessary to increase the depth of machine learning

6. Conclusions

Within the framework of the functional approach to modeling of cognitive processes of natural intelligence the categorical functional model of information-extreme machine learning of ORS of natural and infrastructural ground objects in the form of the directed graph of display of sets on each other by machine learning operators is offered.

On the basis of the categorical model the algorithm of information-extreme machine learning with optimization of control tolerances on recognition signs which allows to define a base class of recognition on the greatest dispersion of the training matrix pixels brightness values is developed and programmatically implemented. Experimentally, the results of physical modeling confirmed that the choice of the basic recognition class, in relation to which the system of control tolerances for recognition features is determined, directly affects the functional efficiency of machine learning.

To increase the functional efficiency of ORS it is necessary to increase the depth of machine learning by optimizing additional parameters of the system, including the parameters of the input mathematical description, and to increase the recognition classes alphabet the power to carry out information-extreme machine learning hierarchical data structure.

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