Information-Extreme Machine Learning On-Board Recognition System of Ground Objects with the Adaptation of the Input Mathematical Description

Anatoliy Dovbysh[1[0000-0003-1829-3318]], Igor Naumenko[2[0000-0003-2845-9246]], Mykyta Myronenko[1[0000-0001-5005-1672]], Taras Savchenko[1[0000-0002-9557-073X]]

[1,3,4]Sumy State University, Rymskogo-Korsakova st. 2, Sumy, 40007, Ukraine,
[2]Scientific-research center of missiletroopsand artillery, Gerasim Kondratyev st, 165, Sumy, 400021, Ukraine,
[1]a.dovbysh@cs.sumdu.edu.ua, [2]790905@ukr.net, [3]nikitam1996@ukr.net,
[4]taras.savchenko01@gmail.com

Abstract. The method of machine learning of the on-board unmanned aerial vehicle system for autonomous recognition of natural and infrastructural terrestrial objects with the optimization of the frame size generated by the optical digital image of the region is considered. The problem of information synthesis of the onboard recognition system is being solved in the framework of information-extreme intellectual data analysis technology. As part of the functional approach to modeling the cognitive processes inherent in man in the formation and making of classification decisions, the method of information-extreme machine learning onboard recognition system, which allows to adapt the input mathematical description to the maximum full probability of correct recognition of terrestrial features. In accordance with the proposed categorical model, an algorithm of information-extreme machine learning was developed and programmatically implemented, during which the parameters of the sys-tem functioning according to the modified Kullback information criterion are optimized. Implementation of the proposed machine learning algorithm was carried out on the example of recognition of natural and infrastructural land objects, among which roads were considered as a zone of interest.

Keywords. extreme machine learning, onboard recognition system, digital image of the region, information criterion, optimization.

1 Introduction

The main way to increase the functional efficiency of onboard systems of unmanned aerial vehicles designed for autonomous recognition of ground objects is the application of ideas and methods of machine learning [1,2]. Thus there is a need to overcome a number of complications of a scientific and methodological nature, due to the following main reasons:

— arbitrary initial conditions for the optical formation of digital images of terrestrial objects;

— significant intersection of the recognition classes that characterize terrestrial objects;

— the multidimensionality of the feature dictionary and alphabet of recognition classes;

— strict requirements for the efficiency of machine learning and the operation of onboard recognition system (ORS) directly in working mode.

Overcoming the above complications depends on both the functionality of the simulator, close to real conditions, and the method of machine learn-ing ORS. In the works [3 – 5], the detection of terrestrial objects is carried out according to its dimensions using descriptive methods or the determination of special (invariant) points by spline methods of different order. The main disadvantage of such methods is poor results with the same or approximate geometric parameters of the objects. It is clear that in order to increase the functional efficiency of machine learning, the ORS needs to increase the in-formativeness of the recognition feature dictionary by scanning the entire digital image of the object. But it is important to choose the method of machine learning ORS, capable of analyzing large amounts of data at high power alphabet a priori fuzzy recognition classes. The main disadvantage of apply-ing neural structures is the dependence of their functional efficiency on the many dimensions of data and the flexibility to retrain [6, 7]. Therefore, a promising area of informational synthesis of ORS is the application of ma

chine learning methods built within the functional approach to modeling the cognitive processes inherent in humans in the formation and decision mak-ing of classification decisions. This area includes methods developed in the framework of the so-called information-extreme intellectual technology (IEI technology) data analysis, which is based on maximizing the information ca-pacity of the recognition system in the process of machine learning [8, 9]. In the methods of information-extreme machine learning, practical invariance of the many dimensions of data is ensured by the construction of decisive rules within the geometric approach. In addition, the decision rules con-structed in the framework of the geometric approach are characterized by high efficiency of making classification decisions, which is especially relevant for the ORS. Extreme machine learning by analogy with human learning is considered as a process of optimization of parameters that affect its func-tional efficiency. In this case, the information criterion of optimization as a measure of diversity is considered as a generalized criterion for the validity of partitioning of the feature space into recognition classes, since it is func-tional both from a remote measure of proximity and from the exact charac-teristics of the classification decisions. But the functional efficiency of infor-mation-extreme machine learning, as well as other methods, is significantly influenced by the method of forming an input mathematical description of the recognition system. The paper [10] considered the problem of informa-tion-extreme machine learning of the onboard system for recognizing terres-trial objects at a given frame size of the digital image of the observed region. The article proposes a method of information-extreme machine learning of the ORS with the adaptation of the frame sizes formed by the optical channel of digital image of the region to the maximum likelihood of making the right classification decisions.

2 Formulation of the problem

Let's consider the scheme of algorithm of information-extreme machine learning with optimization of the size of frames of digital image of the region according to the procedure (3): Consider the formalized formulation of the problem of information synthesis capable to learn ORS with optimization of the size of frames of digital image of the region. Let the alphabet of the $\{X_m^o \mid m = \overline{1,M}\}$ classes of recognition characterize the frames of the image of natural and infrastructural objects. For each recognition class, a three-dimensional training matrix $\| y_{m,i}^{(j)} \|$ of the pixel brightness of the receptor frame of frames is formed, in which a row $\{y_{m,i}^{(j)} \mid i = \overline{1,N}\}$, where N is the number of recognition features, is a structured vector of the recognition class features X_m^o, and the column of matrix $\{y_{m,i}^{(j)} \mid j = \overline{1,n}\}$ s a random learning sample of the i -th values n. In accordance with the concept of IEI technology, the input training matrix Y is transformed into a working binary matrix X, which is changed by optimal coding of recognition features by the level of control tolerances in the process of machine learning. Therefore, in the binary Hamming space is given a vector of parameters of operation that affect the functional efficiency of machine learning ORS to recognize the vectors of features of recognition class X_m^o:

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

where x_m is a vector averaged over the ensemble of realizations, the apex of which defines the center of the hyperspherical container of recognition class X_m^o and the size of which is determined by the number of recognition features; d_m is the radius of the hyperspherical container of recognition class X_m^o, $d_m < d\{x_m \oplus x_c)$, where $d(x_m \oplus x_c)$ is the inter-center distance between vector x_m and vector x_c of the nearest neighboring class X_c^o; δ is a parameter whose value is equal to half the symmetric field of control tolerances for recognition features, $\delta < \delta_H / 2$, where δ_H is the normalized tolerance field for recognition features; r is the side of a square frame of a digital image of a region.

It is necessary to optimize the parameters of the vector (1) in the process of machine learning of the ORS, which provide the maximum value of the information optimization criterion in the working (allowable) region of determining its function:

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

where $E_m^{(k)}$ is the value of the information criterion for optimization of vector parameters calculated at the k-th кроці step of machine learning (1); G_E – work area of calculation of information criterion; $\{k\}$ – set of learning steps.

When operating the ORS in exam mode, it is necessary to check the functional effectiveness of machine learning.

Thus, the problem of information synthesis capable of learning ORS is to optimize the parameters of its machine learning by approaching the global maximum of information criterion (2) to its maximum limit value.

3 Mathematical model of machine learning

Within the functional approach to the modeling of cognitive processes, a categorical model of information-extreme machine learning is constructed in the form of an oriented graph. The input mathematical description of the categorical model is presented as a structure

$$I_B = < G, T, \Omega, Z, K, Y, X; f_1, f_2 >,$$

where G is the set of factors that influence the ORS; T is the set of moments in which information is received; Ω – recognition features space; Z – the space of states of the system, (alphabet of recognition classes); K – multiple frames of digital image of the region; Y – the input training matrix of the pixel brightness of the image frame; X – working binary learning matrix; f_1 is the operator of forming the input training matrix Y; f_2 is the operator of converting the matrix Y into a working binary matrix X.

A categorical model of information-extreme machine learning of the ORS with the optimization of the coordinates of the structured vector (1) is shown in Fig. 1.

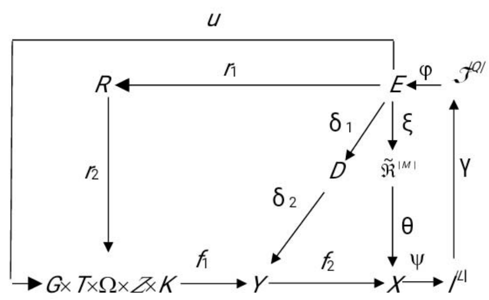

Fig. 1. Categorical model of machine learning of the ORS

In Fig. 1 Cartesian product $G \times T \times \Omega \times Z \times K$ sets the test universe, which is the source of information. The thermal set E of the information criterion values is common to all contours of machine learning parameter optimization. Operator

$\xi : E \to \tilde{\Re}^{|M|}$ builds at each step of learning partition $\tilde{\Re}^{|M|}$, which is displayed by operator θ on the distribution of binary feature vectors. Next, operator $\psi : X \to I^{|S|}$, where $I^{|S|}$ is the set of S hypotheses, tests the main statistical hypothesis $\gamma_1 : x_{m,i}^{(j)} \in X_m^o$. The operator γ determines the set $\Im^{|Q|}$ of the precision characteristics of the classification solutions, 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 precision characteristics. The loop of optimization of control tolerances for recognition features is closed through a term set of D elements which is the value of the system of control tolerances for recognition features. An optimization loop that includes a term set of R values of the sides of a square image frame optimizes the area of the frame. The operator r_1 resizes the frame, and the operator r_2 resizes the space of the recognition features. The operator u governs the process of machine learning.

4 Information-extreme machine learning algorithm

According to the categorical model (Fig. 1), the information-extreme algorithm of machine learning of the ORS with optimization of the frame size of the digital image of the region will be presented in the form of an iterative procedure for finding the global maximum of alphabet-averaged classes of recognition of the information criterion in the working (allowable) area of determining its

$$r^* = \arg\max_{G_r}\{\max_{G_\delta}\{\max_{|G_E \cap \{r\}} \overline{E}^{(r)} \tag{3}$$

where r^* is the optimal side size of the square frame of the digital image; $\overline{E}^{(r)}$ – the information criterion for optimization of vector parameters calculated on the r-th step of machine learning averaged by the alphabet of recognition classes (1); G_δ is a valid value range for parameter δ of the tolerance field.

The input to the machine learning algorithm is a training matrix in the form of a three-dimensional array of feature vectors $\{y_{m,i}^{(j)}\}$ and a system of fields of normalized tolerances $\{\delta_{H,i}\}$ for recognition traits that specifies the range of values of the corresponding control tolerances.

The main stages of information-extreme machine learning of the ORS are:

1. definition for a given alphabet of recognition classes $\{X_m^o\}$ of base class X_1^o, relative to which a system of control tolerances for recognition features is specified;
2. optimization by the information criterion (2) of the parameters of machine learning of the ORS, which are included in the structure (1);
3. construction of decisive rules for optimal geometric parameters of containers of recognition classes, which were restored in the process of machine learning in the radial basis of the binary space of recognition features;
4. check the functional efficiency of machine learning ORS in exam mode.

The definition of base class X_1^o is made according to the scheme:

1. the counter of base recognition classes is reset: $b := 0$;
2. the counter of base recognition classes is initialized: $b := b+1$;
3. the counter of the recognition classes is reset: $m := 0$;
4. $m := m = 1$;
5. the counter of steps of changing the radii of containers of recognition classes is reset: $k := 0$;
6. the averaged y_m vector is defined for array $\{y_{m,i}^{(j)}\}$;
7. if $b = b+1$ and $m = m+1$, then $y_m := y_b$, that is, vector y_m is taken as the base and the point 8 is fulfilled, otherwise – the point 9;
8. are calculated for each i -th sign of vector y_b lower $A_{HK,i}[b]$ and upper $A_{BK,i}[b]$ control tolerances by the formulas

$$A_{\hat{A}K,i}[b] = y_{b,i} + \delta ,$$

9. where $y_{b,i}$ is the value of the i-th sign of the average vector of class y_b recognition X_m^o;
10. formed a three-dimensional array of binary learning matrix $\{x_{m,i}^{(j)}\}$, elements of which are calculated by the rule

$$x_{m,i}^{(j)} = \begin{cases} 1, \, if \;\; A_{HK,i}[b] < y_{m,i}^{j} < A_{BK,i}[b]; \\ 0, \, if \; else. \end{cases} \tag{4}$$

11. for array $\{x_{m,i}^{(j)}\}$ is determined by the average binary vector x_m;
12. if $m \le M$, then item 4, is fulfilled, otherwise – item 12;
13. for the set of vectors $\{x_m\}$, a code distance matrix is constructed and pairs of nearest neighbors for which hyperspherical containers of recognition classes are restored in the process of machine learning;
14. $m := m+1$;
15. the counter of steps of change of radius of containers of recognition classes is initialized: $k := k+1$;
16. the information criterion $E_m^{(k)}$ of optimization of machine learning parameters is calculated according to the learning matrices of class X_m^o and its closest neighbor, for example, in the form of a modified Kullback information measure:

$$E_m^{(k)} = \frac{1}{n}\{n - [K_{1,m}^{(k)} + K_{2,m,}^{(k)}]\}\log_2\left\{\frac{2n - \left[K_{1,m}^{(k)} + K_{2.m}^{(k)}\right] + 10^{-p}}{\left[K_{1,m}^{(k)} + K_{2,m}^{(k)}\right] + 10^{-p}}\right\}, \quad (5)$$

where $K_{1,m}^{(k)}$ is the number of events in which “their” recognition attribute vectors did not belong to class X_m^o; $K_{2,m}^{(k)}$ is the number of events in which “alien” feature vectors belonged to class X_m^o; n is the number of feature vectors in the learning matrix of each recognition class; 10^{-p} is a sufficiently small number that is entered to avoid division by zero (in practice, p is selected from the interval $1 < p \leq 3$.

17. if $k < d(x_m \oplus x_c)$, then item 14 is fulfilled, otherwise – item 17;

18. in the work area G_E is determined by the maximum value $E_m^{*(k)}$ information criterion (5);

19. if $b \leq M$, then item 2 is fulfilled, otherwise – item 19;

20. according to formula (2) the average maximum value $\overline{E}^*$ of criterion is calculated (5);

21. the recognition class for which the value of criterion $\overline{E}^*$ (5) is maximum is taken as the base;

22. STOP.

After determining the base class, the ORS machine learning procedure (3) is started with the optimization of the control tolerance system for the features of recognition and frame size. The main functions of the inner cycle of procedure (3) are:

- mation criterion (5) at each step of machine learning with values of control tolerance field δ and frame size of region image set in corresponding external cycles;
- search for the global maximum of the information criterion for optimization of machine learning parameters in the working (valid) area of determining its function;
- determination of the geometric parameters of recognition classes optimal in the information understanding.

The input for the implementation of procedure (3) is the alphabet of recognition classes $\{X_m^o\}$, in which class X_1^o is the base, the corresponding three-dimensional array of the training matrix $\{y_{m,i}^{(j)}\}$, parameter δ_H, which determines the system of normalized tolerances for recognition features and the maximum permissible size $r_{\max}$ side square frames of digital image of the region .

Consider the scheme of the algorithm of information-extreme machine learning with optimization of the frame size of the digital image of the region by the procedure (3):

1. resetting the step counter of resizing frames in the region image: $r := 0$;
2. $r : r + 1$;
3. reset the counter of recognition classes: $m := 0$;
4. $m : m + 1$;

5. resetting the training frame resizing step counter: $r := 0$;

6. $r : r + 1$;

7. resetting the step counter to change the tolerance field parameter: $\delta := 0$;

8. $\delta := \delta + 1;$;

9. calculation of the lower and upper $\{A_{B,i}\}$ control tolerances for recognition signs according to the rules

$$A_{H,i} = y_{1,i} - \delta; \quad A_{B,i} = y_{1,i} + \delta, \qquad (6)$$

10. where $y_{1,i}$ is the i -th sign of the averaged vector y_1 of the base recognition class X_1^o;

11. resetting the counter of the steps of changing the radius of the hyperspherical container: $k := 0$;

12. $k := k + 1$;

13. formed a three-dimensional array of binary learning matrix, the elements of which are calculated by the rule (4);

14. the formation of an array of averaged vectors of signs $\{x_m\}$ whose elements are determined by the rule

$$x_{m,i} = \begin{cases} 1, & if \ \dfrac{1}{n}\sum_{j=1}^{n} x_{m,i}^{(j)} > \rho_m; \\ 0, & if \quad else, \end{cases}$$

15. where ρ_m is the quantization level of the coordinates of binary vector x_m, which by default is 0,5.

16. splitting the set of vectors $\{x_m\}$ into pairs of nearest “neighbors” $\Re_m^{|2|} = < x_m, x_c >$, where x_c is the averaged vector of the nearest neighbor class X_c^o;

17. the information criterion (2) is calculated;

18. if $k \le N$, then item 11 is executed, otherwise – item 17;

19. if $\delta < \delta_H$, then item 8 is executed, otherwise – item 18;

20. the maximum value of the criterion in the workspace of determining its function is determined, where the first and second reliability are greater than 0.5;

21. if $m < M - 1$, then item 4, otherwise – item 20;

22. if $r \le r_{\max}$, then item 6 is executed, otherwise – item 21;

23. determines the global maximum of average information criterion $\overline{E}^*$ in the work area of determining its function;

24. determine the optimal values of parameter δ^*, lower $A_{H,i}^*$ and upper $A_{B,i}^*$ control tolerances for all recognition features and size r^* side square frames of the digital image of the region;

25. STOP.

According to the optimal geometric parameters of the containers of recognition classes obtained in the process of machine learning, productive decision rules were constructed in the form

$$(\forall X_m^o \in \Re^{|M|})(\forall x^{(j)} \in \Re^{|M|})[if\ (\mu_m > 0)\ \&\ (\mu_m = \max_{\{m\}}\{\mu_m)$$
$$then\ x^{(j)} \in X_m^o \quad else\ x^{(j)} \notin X_m^o], \tag{7}$$

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

In expression (7), the membership function for a hyperspherical container of recognition class X_m^o is determined by the formula [3]

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

where x_m^*, d_m^* – the optimal parameters of machine learning: averaged feature vector and radius of hyperspherical container recognition class X_m^o respectively.

Thus, in the exam, it is determined by decisive rules (7) that the recognizable feature vector belongs to one of the classes in the given alphabet. At the same time, the decisive rules, built within the geometric approach, are characterized by low computational complexity, which provides high efficiency of making classification decisions in the operation of ORS in the operating mode.

5 Simulation results

An algorithm of information-extreme machine learning of ORS is implemented with the purpose of optimizing the image of the region in understanding the information, the receptor field of which is shown in Fig. 2 [11].

Fig. 2. Image of the region obtained by aerial photography

The input training matrix was formed by processing the image frames shown in Figure 3 in the polar coordinate system according to [12]. As recognition classes, the frames of the sections shown in Fig. 2 images of the region: class X_1^o – highway; class X_2^o – liquid forest; class X_3^o – plowing field; class X_4^o – sown field.

The selected frames are shown in Fig. 3.

a *b* *c* *d*

Fig. 3. Picture frames: *a* – class X_1^o; *b* – class X_2^o; *c* – class X_3^o; *d* – class X_4^o

In the previous stage of machine learning, the results of the implementation of the above algorithm were identified as the base class of recognition X_1^o– highway. Therefore, the system of control tolerances was determined relative to the averaged vector of features of recognition class X_1^o.

In the process of machine learning ORS according to procedure (3), the value of parameter r increased from one to 71 pixels of the receptor field of the video card.

Table 1 shows results of machine learning using side of the square frame optimization.

Table 1.– Results of machine learning

r	35	37	39	41	43	45	47	49	51	53	55
$\overline{E}$	0,59	0,62	0,63	0,64	0,61	0,67	0,70	0,67	0,66	0,64	0,63

The analysis of Table 1 shows that, in the process of machine learning, the optimal frame size of the image value is equal to $r^* = 47$ pixels with a maximum value of $\overline{E}^* = 0{,}70$ information criterion.

Fig. 4 shows a graph of the averaged normalized information criterion (5) from parameter of control tolerances system δ using optimal side of the square frame

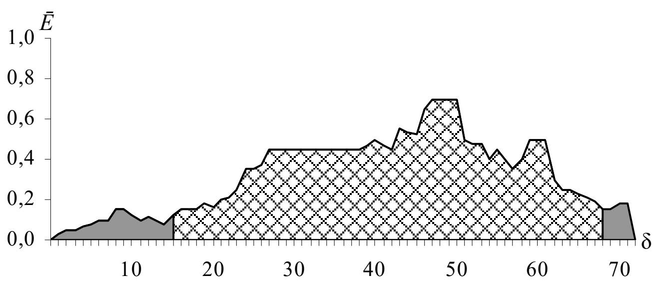

Fig. 4. Graph of information criterion dependence on parameter of control tolerances system

Fig. 4 shows a dark area on the graph of the working (admissible) area of determining the function of the information criterion of optimization, in which the first and second reliability exceed respectively the errors of the first and second kind.

The analysis of Fig. 4 shows that, in the process of machine learning, the optimal value of parameter of control tolerances system is equal to $\delta^* = 50$ (scale of pixel's brightness) with a maximum value of $\overline{E}^* = 0{,}70$ information criterion. Fig. 5 shows graphs of information criterion (5) dependence on the radii of containers of recognition classes the optimal values of which allow us to construct the decisive rules (7).

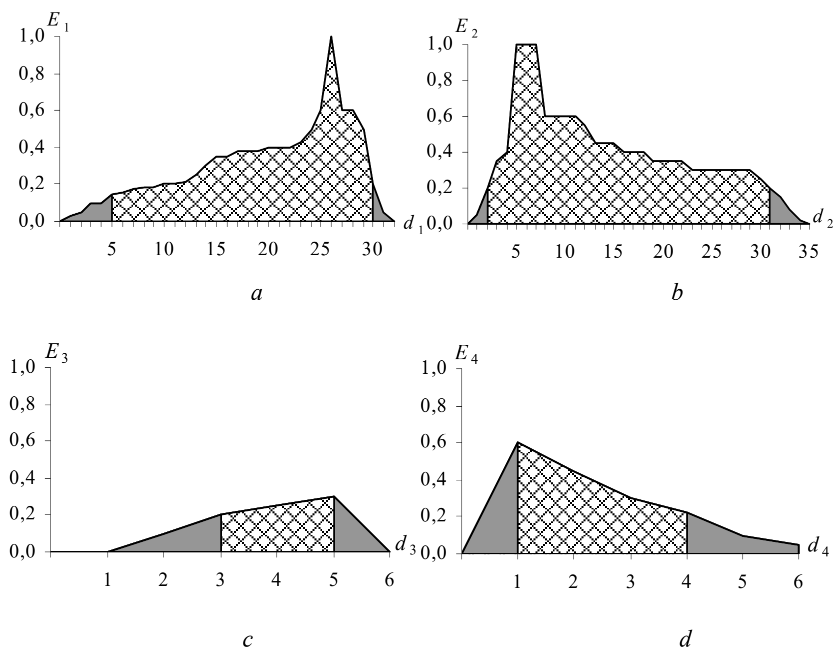

Fig. 5. Graphs of the criterion (5) on the radii of containers of recognition classes: *a* – class X_1^o; *b* – class X_2^o; *c* – class X_3^o; *d* – class X_4^o

The analysis of Fig. 5 shows that the optimum values of the radii of the containers of the recognition classes are: for the class X_1^o – $d_1^* = 26$ (hereinafter in code units); for class X_2^o – $d_2^* = 6$; for class X_3^o – $d_3^* = 5$ and class X_4^o – $d_4^* = 1$.

Fig. 6 shows a digitized image (Fig. 3), obtained by the results of the identification of frames by the decisive rules (7) with the optimal frame size of the pixel image. The numbers in the frames correspond to the numbers of the recognition classes.

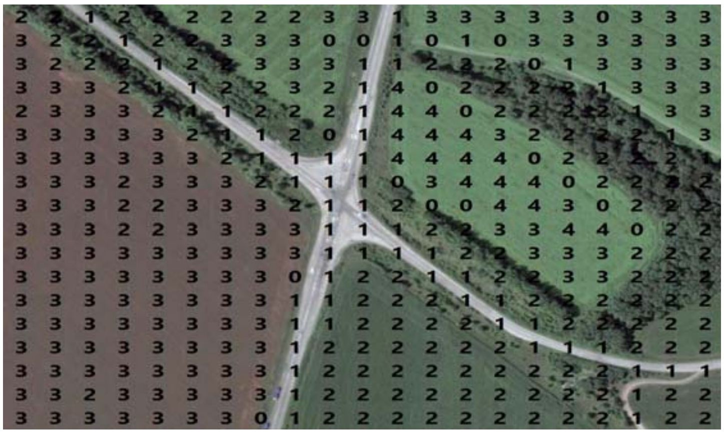

Fig. 6. Results of the identification of frames

Visual analysis of Fig. 6 shows that highways that are of interest for vehicle recognition are identified with a sufficiently high accuracy when the frame size is optimal.

6 Conclusion

1. Within the framework of functional approach to modeling of cognitive processes of formation and decision-making of classification decisions, a catheter model is proposed, which is considered as a generalized structural diagram of the algorithm of information-extreme machine learning of the image recognition system
2. On the basis of the proposed categorical model, an algorithm of information-extreme machine learning of the onboard recognition system was developed with optimization according to the information criterion of the frame size of the digital image of the region. The algorithm allows for a given flight altitude of an unmanned aerial vehicle complex to determine quickly and with high accuracy the area of interest in which the wanted land object may be located.
3. Since the decisive rules are not infallible by the learning matrix, to increase the functional efficiency of ORS, it is necessary to increase the depth of machine learning by optimizing other parameters of operation, including the parameters of the formation of the input mathematical description.

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