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INFORMATION-EXTREME MACHINE TRAINING OF ON-BOARD RECOGNITION SYSTEM WITH OPTIMIZATION OF RGB-COMPONENT DIGITAL IMAGES

The research increases the recognition reliability of ground natural and infrastructural objects by use of an autonomous onboard unmanned aerial vehicle (UAV). An information-extreme machine learning method of an autonomous onboard recognition system with the optimization of RGB components of a digital image of ground objects is proposed. The method is developed within the framework of the functional approach to modeling cognitive processes of natural intelligence at the formation and acceptance of classification decisions. This approach, in contrast to the known methods of data mining, including neuro-like structures, provides the recognition system with the properties of adaptability to arbitrary initial conditions of image formation and flexibility in retraining the system. The idea of the proposed method is to maximize the information capacity of the recognition system in the machine learning process. As a criterion for optimizing machine learning parameters, a modified Kullback information measure was used, this informational criterion is the functionality of exact characteristics. As optimization parameters, the geometric parameters of hyperspherical containers of recognition classes and control tolerances for recognition signs were considered, which played the role of input data quantization levels when transforming the input Euclidean training matrix into a working binary training matrix using admissible transformations of a working training matrix the offered machine learning method allows to adapt the input mathematical description of recognition system to the maximum full probability of the correct classification decision acceptance. To increase the depth of information-extreme machine learning, optimization was conducted according to the information criterion of the weight coefficients of the RGB components of the brightness spectrum of ground object images. The results of physical modeling on the example the recognition of terrestrial natural and infrastructural objects confirm the increase in functional efficiency of information-extreme machine learning of on-board system at optimum in information understanding weight coefficients of RGB-components of terrestrial objects image brightness.

Keywords*: information-extreme machine learning; information criterion; optimization; on-board recognition system; unmanned aerial vehicle; ground object image*.

Introduction

One of the important tasks of the onboard system of an unmanned aerial vehicle (UAV) for autonomous recognition of ground objects is to determine on the electronic map of the area of interest areas in which there is the highest probability of finding the ground object to be searched. A promising way of information synthesis of such systems is the application of ideas and methods of machine learning and pattern recognition. The segmentation reliability, i.e. the search for areas of interest in the electronic image of the region, depends on the adequacy of the input mathematical description of the onboard frame identification system of the region digital image to real conditions and the functional efficiency of machine learning on-board recognition system (ORS).

At present, there are all technical possibilities for processing and operational analysis of digital images, so the main deterrent to the introduction of autonomous on-board ORS are scientific and methodological complications associated primarily with the construction of an informative learning matrix provided a priori arbitrary division of feature space into recognition classes. Therefore, increasing the functional efficiency of machine learning ORS is an urgent task.

The article includes the method of information-extreme machine learning of weight coefficients ORS with optimization of RGB-components of the region colour digital image, which allows adapting the input mathematical depiction to make highly reliable classification decisions.

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Problem analysis

The analysis of modern approaches and trends in the development of ORS showed that increasing their functional efficiency is associated with the use of intelligent data analysis technologies [1–3]. The use of data mining [4] traditional methods, including artificial neural networks [5–7], for the information synthesis of ORS does not always provide successful identification of the region image frames due to the following scientific and methodological limitations:

– arbitrary initial conditions for the objects images formation in the area that are recognized, due to different angles of aerial photography, the height of the aircraft, the position and location of the object;

– intersection of recognition classes that characterize the image of objects in the recognition features space;

– multidimensionality of the features dictionary and the recognition classes alphabet;

– the influence of uncontrolled factors, such as changes in weather conditions, lighting, camouflage, etc.

One of the promising approaches to the analysis and synthesis of ORS objects in the field is the use of ideas and methods of domestic so-called information-extreme intellectual technology (IEI-technology), which is based on maximizing the information capacity of the system in its machine learning [8, 9]. The main idea of the IEI-technology methods as in artificial neural networks is to adapt in the machine learning process of the input mathematical description to the maximum full probability of making the correct classification decisions. But the main advantage of information-extreme machine learning methods is that they, unlike neuro-like structures, are developed as part of a functional approach to modelling cognitive processes inherent in human formation and classification decisions, i.e. directly model the natural decision-making mechanism. This approach, in contrast to structural methods, allows methods of information-extreme machine learning to provide flexibility in retraining the system by expanding the recognition classes alphabet. In addition, building a geometric approach of decision rules practically solves the problem of multidimensionality of the recognition features dictionary, as modern computer systems can process data sets that consist of a sufficiently large number of 2^{85} recognition features.

Recognition of terrestrial moving and immovable objects in the works [10, 11] is solved in two stages. Initially, the ORS uses an optoelectronic surveillance system to determine the frame of the area of interest in which the object in question is most likely to be located. For example, such an area of interest for the detection of a land vehicle is usually a highway or other road. In the second stage, each object that is in the frame of the interest area is compared with the objects formed at the stage of machine learning ORS. In this case, the functional efficiency of ORS machine learning, the main components of which are the reliability and efficiency of the decisive rules, significantly depends on the ORS machine learning method. The accumulated experience of information-extreme machine learning application methods of different functions and their recognition systems has shown that at the formation of a training matrix it is necessary to consider the specificity of input data. In [12, 13] it was shown that setting limits on the brightness of RGB components of a colour image increases the image recognition reliability. In [14], an algorithm for processing colour images obtained by an RGB-D camera is proposed, which allows increasing the informativeness of the input data in recognition problems in robotic systems. In [15, 16] the optimization of weight coefficients of RGB components of images based on genetic algorithms is considered. The disadvantage of this approach is the low efficiency of genetic algorithms, which limits their use for the development of information support for autonomous ORS.

The article goal is to increase the recognition reliability of the autonomous on-board UAV system of terrestrial natural and infrastructural objects by optimizing in the process of machine learning the weights of RGB-component frames of the region digital image.

Formalized problem statement

Consider in the framework of IEI-technology formalized formulation of the problem of information synthesis able to learn ORS to identify frames of the region digital image.

Let the alphabet of recognition classes $\{X_m^o \mid m = \overline{1, M}\}$ be formed, which characterize the frames of the image of the area. For each recognition class, a three-dimensional training matrix $\| y_{m,i}^{(j)} \|$ of brightness is formed, in which row $\{y_{m,i}^{(j)} \mid i = \overline{1, N}\}$, where N is the number of recognition features, is a structured vector of the corresponding recognition class features, and column matrix $\{y_{m,i}^{(j)} \mid j = \overline{1, n}\}$ is a random training sample of i-th feature with volume n.

It is known that one of the IEI-technology methods features is the transformation of the input training matrix Y into a working binary matrix X, which changes in the process of machine learning. Therefore, for the Hamming binary space the vector of functioning parameters is set, which influence the functional efficiency of the ORS machine learning to recognize the implementations of the recognition class X_m^o:

$$g_m = \langle x_m, d_m, \delta, w_{RGB}. \rangle, \quad (1)$$

where x_m is the averaged structured vector of pixel brightness values of the image receptor field; d_m – radius of the hyperspherical container of the recognition class X_m^o, which in the machine learning process is restored in the radial basis of the recognition features space; δ – parameter, the value of which is equal to half of the symmetric field of control tolerances on the signs of recognition; $w_{RGB} = \{w_R, w_G, w_B\}$ – the set of weights of the corresponding RGB-components of the region digital image frame.

Hereinafter, the structured feature vectors will be called implementations of the corresponding recognition classes.

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

– the range of pixel brightness values is in the range [0; 255] brightness gradations;

– the range of container radius values of the recognition class 1 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 vector of features x_m and a similar vector x_c of the nearest class X_c^o;

– the range of values of the parameter δ is given by the inequality

$$\delta < \delta_H / 2,$$

where δ_H is the normalized field of tolerances for recognition features, which determines the control tolerances values range;

– the value of parameter w_{RGB} is limited by the brightness scale [0, 255].

It is necessary in the process of machine learning ORS:

1) optimize the parameters of machine learning (1), which provide the maximum value of the information criterion of optimization in the working (permissible) area of its function definition:

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

where $E_m^{(k)}$ is the value of the information criterion calculated at a given radius of the recognition class hyperspherical container X_m^o, which is restored in the Hamming space radial basis; G_E – working area for determining the information criterion; G_d – valid range of recognition class container radii values;

2) at the stage of examination in order to verify the functional effectiveness of machine learning to decide whether the implementation of the recognized image to one of the classes of a given alphabet $\{X_m^o\}$.

Thus, the task of information synthesis of the learnable on-board UAV system for autonomous recognition of ground objects is to optimize the parameters of its machine learning (1) by approaching the global maximum of the information criterion (2) to its maximum limit value.

Categorycal model

We will present the functional categorical model of information-extreme machine learning of ORS in the form of the directed graph of sets which are applied in the course of training. The mathematical description of the learnable ORS is presented by a structure

$$I_{BX} = \langle G, T, \Omega, Z, K, Y, X; f_1, f_2 \rangle,$$

where G is the space of factors that affect the reliability of classification decisions;

T − the set of information reading time moments;

Ω − recognition signs space;

Z – the space of the ORS possible states;

K − the set of frames of the region digital image;

Y – input training matrix;

X – working binary training matrix, which in the process of information-extreme machine learning adapts to the maximum full probability of making the correct classification decisions;

f_1 – the operator of the formation of the input training Y matrix from the source of information, which is given by the Cartesian product $G \times T \times \Omega \times Z \times K$;

f_2 – the transformation operator of the training matrix Y into a working binary training matrix X.

The categorical model of ORS information-extreme machine learning with optimization of RGB-components weight coefficients of a frame of the region digital image is shown in Fig. 1.

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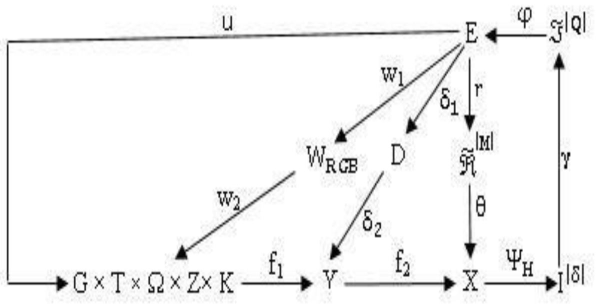

Fig. 1. Categorical model of information-extreme machine learning

Term set E (Fig.1), which consists of the values of the information criterion calculated at each step of machine learning, is common to all circuits for optimizing the parameters of the vector (1). The operator $r: E \to \tilde{\Re}^{|M|}$ in the process of machine learning restores in the radial basis of the binary feature space containers of recognition classes, which form in the general case a fuzzy partition $\tilde{\Re}^{|M|}$. The operator θ displays the partition $\tilde{\Re}^{|M|}$ on the distribution of a priori classified binary vectors of the recognition classes features. Next, the operator $\psi: X \to I^{|S|}$, where $I^{|S|}$ is a set of hypotheses, tests the basic statistical hypothesis $\gamma_1 : x_m^{(j)} \in X_m^o$. Operator γ determines the set of accuracy characteristics $\Im^{|Q|}$, where $Q = S^2$, and operator φ calculates the set of values E of the information criterion for optimizing the parameters of machine learning, which is a functional of the accuracy characteristics. The categorical model contains a contour of operators of optimization of control tolerances on signs of recognition which is closed through term set D of admissible values of control tolerance system. In this case, the operator δ_1 at each step of machine learning changes the control field, and the operator δ_2 determines whether the recognition features of a given control field of tolerances. The contour of the weights optimization of the RGB-component frames of the region image is closed through the term set W_{RGB} of the allowable values of the corresponding weights. Operators w_1 changes the values of weights, and operator w_2 implements an algorithm for their many parametric optimization by the method of gradient descent [11]. Operator u regulates the process of machine learning.

Thus, the functional set-theoretic model (Fig. 1) can be considered as a generalized structural scheme of the algorithm of information-extreme machine learning ORS.

Machine learning with optimization of RGB weight components of the image

According to the categorical model (Fig. 1), the algorithm of information-extreme machine learning ORS with optimization of RGB-components of the digital image of the region will be presented in the form of an iterative procedure for finding the global maximum.

$$\{w^*_{RGB}\} = \arg\max_{G_{RGB}}\{\max_{G_\delta}\{\max_{G_E \cap \{k\}} \overline{E}^{(k)}\}, \qquad (3)$$

where w^*_{RGB} is a set of optimal weights of the ORS components of the digital image frame; $\overline{E}^{(k)}$ – calculated on the k-th step of machine learning averaged on the alphabet of recognition classes information criterion for optimizing the machine learning parameters; G_{RGB} – allowable range of weights values w_{RGB}; G_δ – the range of permissible values of control tolerances for signs of recognition.

The internal cycle of procedure (3) implements the so-called basic algorithm, which at each step of information-extreme machine learning calculates the information criterion, finds its maximum value in the work area G_E and determines the extreme value d_m^* of the radius of the recognition class container X_m^o by procedure

$$d_m^* = \arg\max_{G_E \cap \{k\}} E_m^{(k)}.$$

As a criterion for optimizing the parameters of machine learning, a modified Kullback information measure is used. For two-alternative equally probable solutions it is described as follows

$$E_{K,m} = [D_{1,m}(d) - \beta_m(d))] * \log_2\left(\frac{1 + D_{1,m}(d) - \beta_m(d)}{1 - D_{1,m}(d) + \beta_m(d)}\right), \qquad (4)$$

where $D_{1,m}(d)$ is the first reliability of decision-making at the k-th step of machine learning; $\beta_m(d)$ – an error of another kind; d – distance measure that determines the radii of hyperspherical containers of recognition classes constructed in the radial basis of the binary Hamming space.

The normalized form of criterion (4) has the form

$$E_m = \frac{E_{Km}}{E_{K\max}}, \qquad (5)$$

where $E_{K\max}$ is the maximum value of the information criterion (4) at $D_{1,m}(d) = 1$ and $\beta_m(d) = 0$.

Due to the limited number of training samples when calculating the optimization criterion (4) it is necessary to use estimates of accuracy characteristics:

$$D_{1,m}(d) = \frac{K_{1,m}(d)}{n_{\min}}; \ \beta_m^{(k)}(d) = \frac{K_{2,m}(d)}{n_{\min}}, \qquad (6)$$

where $K_{1,m}(d)$ is the number of events that indicate that the recognition class belongs to X_m^o "their" implementations; $K_{2,m}(d)$ – the number of events that indicate that the recognition class belongs to X_m^o "foreign" implementations; $n_{\min}$ – the minimum size of a representative training sample.

After the appropriate substitution of estimates of accuracy characteristics (6) in expression (4) we obtain a working formula for calculating the information criterion for optimizing the machine learning parameters

$$E_m^{(k)} = \frac{\left[(K_{1,m}^{(k)}(d) - K_{2,m}^{(k)}(d))\right]}{n_{\min}} *$$
$$* \log_2 \left\{ \frac{n_{\min} + K_{1,m}^{(k)}(d) - K_{2,m}^{(k)}(d) + 10^{-p}}{n_{\min} - K_{1,m}^{(k)}(d) + K_{2,m}^{(k)}(d) + 10^{-p}} \right\}, \qquad (7)$$

where 10^{-p} is a small enough number that is entered to avoid division by zero; p − a number that in practice is selected from the interval $1 < p \leq 3$.

Optimization of parameter 1 of the control tolerances field is carried out in the middle cycle of procedure (3):

$$\delta^* = \arg \max_{G_\delta} \{ \max_{G_E \cap \{k\}} \overline{E}^{(k)} \}. \qquad (8)$$

Thus at first parallel optimization at which control tolerances change for all signs of recognition at the same time is carried out. The control tolerances obtained during parallel optimization are used as starting points, which allows to increase the efficiency of the sequential optimization algorithm, which is carried out according to the procedure.

$$\{\delta_i^*\} = \arg \left[\bigotimes_{l=1}^{L} \{ \bigotimes_{i-1}^{N} \max_{G_\delta} \{ \max_{G_E \cap G_d} \overline{E}_l^{(i)}(d) \} \} \right], \qquad (9)$$

where $\otimes$ is the symbol of the iteration operation; $\overline{E}_l^{(i)}(d) \cdot$ – the average value of the information criterion for optimizing the machine learning parameters, calculated during the optimization of the control tolerances of the i-th recognition feature on the l-th run of the iterative procedure for optimizing the system of control tolerances for the recognition features; L – the number of runs of the iterative procedure for optimizing control tolerances for recognition features; N – the number of signs of recognition; G_d – the number of signs of recognition d, which determines the radius of the hyperspherical container of the recognition class;

According to the optimal parameters $\{\delta_i^*\}$ the lower $\{A_{HK,i}^* \mid i = \overline{1,N}\}$ and upper $\{A_{BK,i}^* \mid i = \overline{1,N}\}$ optimal control tolerances for the recognition features are calculated:

$$A_{HK,i}^* = y_m - \delta_i^*; \ A_{BK,i}^* = y_m + \delta^*. \qquad (10)$$

With optimal control tolerances for recognition features, an external cycle of procedure (3) is implemented using the gradient descent method to find the global maximum of the averaged criterion (4), which is represented as a multi-parameter function $\overline{E} = f(w_R, w_G, w_B)$.

Consider the main steps of the information-extreme machine learning algorithm with the optimization of RGB-component frames of the digital image of the region.

1) the value Δ of the function change $\overline{E}$ and the gradient step h;

2) set the initial values for each of the weights of RGB-components: $w_R = w_G = w_B = 1$;

3) the machine learning algorithm with parallel-sequential optimization of control tolerances is implemented and the control tolerances are optimal in the information sense according to formula (10);

4) partial derivatives are calculated:

$$\frac{df}{dw_R} = \frac{f(w_R + \Delta, \ w_G, w_B) - \overline{E}^*}{\Delta};$$

$$\frac{df}{dw_G} = \frac{f(w_R, w_G + \Delta, w_B) - \overline{E}^*}{\Delta};$$

$$\frac{df}{dw_B} = \frac{f(w_R, w_G, w_B + \Delta) - \overline{E}^*}{\Delta};$$

5) the value of the gradient is calculated

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$$\text{grad(RGB)} = \sqrt{(\frac{df}{dR})^2 + (\frac{df}{dG})^2 + (\frac{df}{dB})^2};$$

6) the weights of the RGB components change in the direction of increasing the gradient:

$$w_R(k) = w_R(k-1) - h\frac{df}{dw_R};$$

$$w_G(k) = w_G(k-1) - h\frac{df}{dw_G};$$

$$w_B(k) = w_B(k-1) - h\frac{df}{dw_B};$$

7) the input training matrix is formed, in which the recognition features for each RGB-component change in proportion to the corresponding new weights;

8) if $|\text{grad}| < c$, where c is the specified error, then point 9, is fulfilled, otherwise 3;

9) STOP.

According to the optimal geometrical parameters of the containers of recognition classes, decisive rules are built, which we present in the form of production in the form:

$$(\forall X_m^o \in \tilde{\Re}^{|M|})\Big(\text{if } [(\mu_m > 0)\,\&\,(\mu_m = \max_{\{m\}}\{\mu_m\}]$$
$$\text{then } x^{(j)} \in X_m^o \quad \text{else } x^{(j)} \notin X_m^o\Big), \qquad (11)$$

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

In expression (11), the membership function for a hyperspherical container of recognition class X_m^o is determined by the formula

$$\mu_m = 1 - \frac{d(x_m^* \oplus x^{(j)})}{d_m^*}, \qquad (12)$$

where $d(x_m^* \oplus x^{(j)})$ is the code distance between the vector x_m^* and the recognized vector.

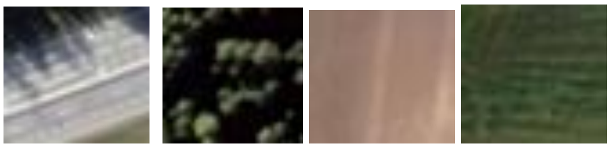
Thus, the decisive rules (11) constructed in the machine learning process within the framework of the geometric approach due to insignificant computational complexity are characterized by high efficiency and are practically invariant to the multidimensionality of the recognition features dictionary.

An example of a machine learning algorithm implementation

The implementation of the information-extreme algorithm of machine learning ORS was carried out on the example of identification of frames of the digital image of the region shown in Fig. 2.

Fig. 2. The region image

As recognition classes, frames with a size of 39x39 pixels shown in Fig. 2 images: class X_1^o – highway; class X_2^o – liquid forest; class X_3^o – plowing field; class X_4^o – sown field. Selected frames are shown in Fig. 3.



a b c d

Fig. 3. The region images: a − highway (class X_1^o); b – liquid forest (class X_2^o); c – plowing field (class X_3^o); d – sown field (class X_4^o)

The highway frame image is non-stationary in brightness, and the images of the frames shown in Fig. 3, b – Fig. 3, d, belong to the type "texture". In addition, the road can occupy an arbitrary position in different frames. Therefore, in order to ensure the invariance of the decisive 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 centre of the frame was calculated by the formula [9]

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

where Θ_j is the average brightness of the pixels of the reading circle 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 in the j-th reading circle.

According to the calculated by formula (12) the average brightness of the reading circles of the formed and structured implementations of the input training matrix for those shown in Fig. 3 frames of the region image. Machine learning was carried out according to procedure (3), which optimized the parameters of machine learning (1) by finding the global maximum of the information criterion (7) in the working area of determining its function, in which the first reliability is $D_{1,m}(d) > 0,5$, and the error of the second kind $\beta_m(d) < 0,5$.

Fig. 4 shows a graph of the dependence of the average normalized information criterion (7) from the parameter δ of the control tolerances field on the signs of recognition, obtained by the iterative procedure (8) at the initial weights $w_R = w_G = w_B = 1$. The calculation of the criterion for optimizing the machine learning parameters was carried out at parameters $n_{min} = 40$ and $p = 2$.

In Fig. 4 and further, the working areas for determining the function of criterion (7) are marked in dark colour.

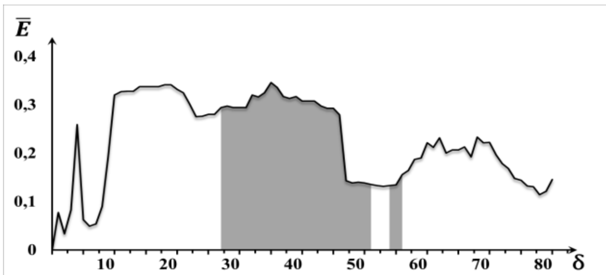


Fig. 4. The dependence graph of the information criterion on the parameter of the control tolerances field at the initial values of the RGB components weights

Analysis of Fig. 4 shows that the quasi-optimal value of the parameter of the control tolerances field is equal to $\delta^* = 35$ gradations of brightness at the maximum value of the optimization criterion $\overline{E}^* = 0,33$.

In order to increase the functional efficiency of machine learning, a consistent optimization of control tolerances for recognition features according to the procedure was implemented (9). The quasi-optimal value of the control tolerances field determined during parallel optimization was taken as the starting point for sequential optimization. Fig. 5 shows a graph of changes in the average normalized information criterion (7) in the process of sequential optimization of control tolerances for recognition features.

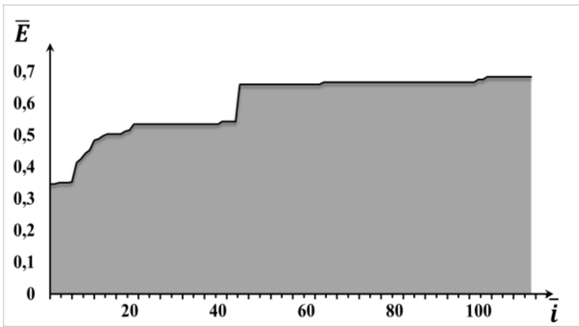


Fig. 5. The graph of the information criterion change in the process of sequential optimization of control tolerances at the initial values of the weight coefficients of the images RGB components

Analysis of Fig. 5 shows that the information criterion for optimization on the third run, which is determined by the ratio of the number of iterations to the number of features N in the implementation, has doubled and reached a value of $\overline{E}^* = 0,68$.

Checking the functional efficiency of machine learning was carried out in the examination mode according to the decisive rules (10). Fig. 7 shows the result of the region image frames identification (Fig. 2). In the figure the numbers correspond to the ordinal numbers of the recognition classes, and the number 0 indicates the frame that the system did not recognize.

Fig. 6. The Identification result of the image frames of the region at the initial values of the RGB-component images weights

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Visual analysis of Fig. 6 shows that the highway and the sparse forest were recognized almost infallibly, and other frames were recognized with low reliability.

According to the results of the algorithm implementation (3) of information-extreme machine learning, the optimal weight coefficients of the RGB-components of brightness shown in Fig. 3 frames of the region image, which were equal to, respectively $w_R^* = 0,45;$ $w_G^* = 0,99$ and $w_B^* = 0,3$.

Fig. 7 shows a dependence graph of the average normalized information criterion (7) on the parameter of the control tolerances field on the recognition features, obtained by the iterative procedure (8) at the optimal weights of RGB-component images.

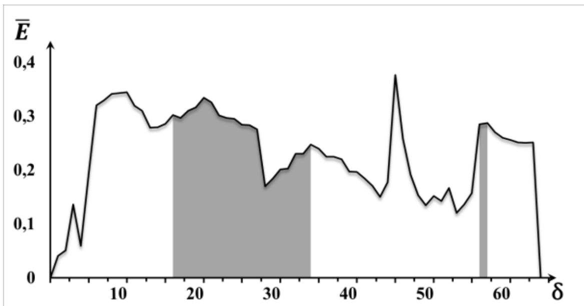

Fig 7. The dependence graph of the information criterion on the parameter of the field of control tolerances at optimal weights RGB components

Analysis of Fig. 7 shows that the maximum value of the parameter of control tolerances the field is equal to $\delta^* = 20$ gradations of brightness at the maximum value of optimization criterion $\overline{E}^* = 0,34$. In order to increase the criterion, the procedure (9) of sequential optimization of control tolerances was implemented. $\delta^* = 20$. Fig. 8 shows a graph of changes in the average normalized information criterion (7) in the process of sequential optimization of control tolerances for recognition features at optimal weights of RGB components.

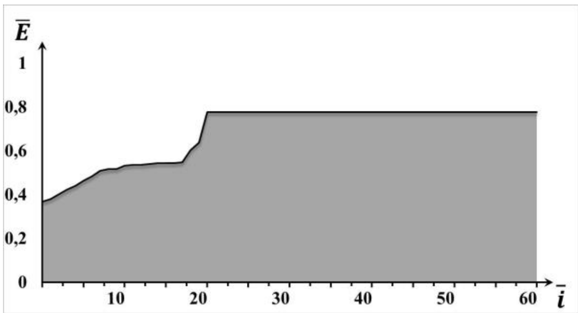

Fig. 8. Graph of information criterion change in the process of sequential optimization of control tolerances with optimal weight coefficients of RGB components of images

Analysis of the machine learning results with parallel-sequential optimization of control tolerances for recognition features shows that after sequential optimization the maximum value of the average normalized information criterion (7) increased from 0,68 (Fig. 5) to 0,80.

Fig. 9 shows the dependence graph of the information criterion (7) on the radii of the recognition classes containers, obtained at the optimal weights of the RGB-component images.

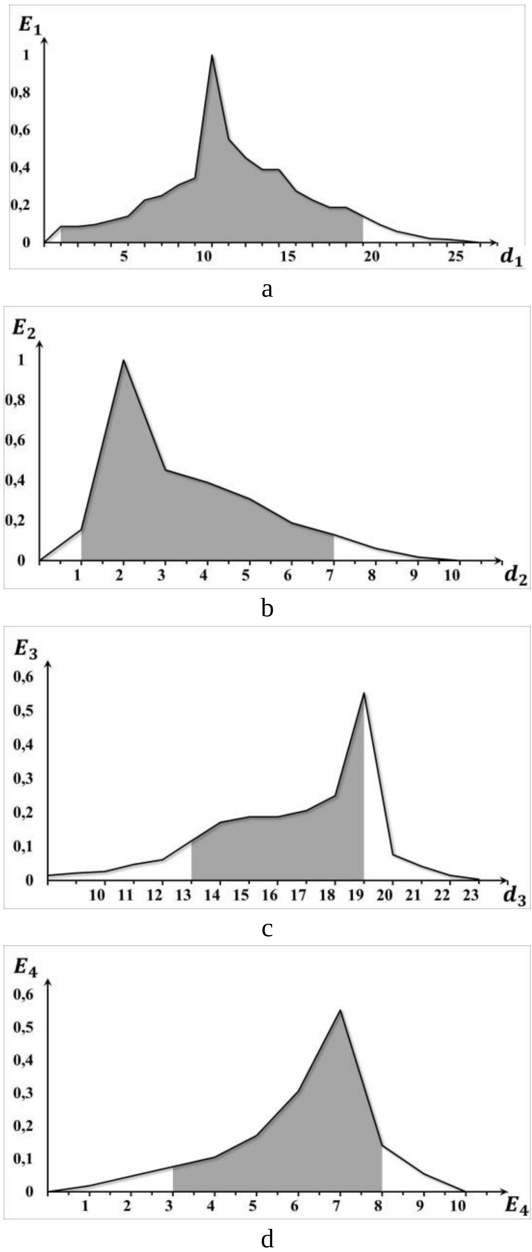

Fig. 9. The dependence graph of the information criterion on the radii of the recognition classes containers at the optimal weights of the RGB components: a – class X_1^o; b – class X_2^o; c – class X_3^o; d – class X_4^o

Analysis of Fig. 9 shows that the information criterion takes the maximum limit value for the first and second recognition classes, so these classes do not intersect in the feature space with other classes. For the third and fourth recognition classes, the maximum values of information criterion $E_3^* = 0,56$ and $E_3^* = 0,58$, are obtained, which exceed the corresponding values shown in Fig. 6. Thus, at a given depth of machine learning failed to build a clear breakdown, but built for him the decisive rules in the exam mode will allow smaller errors of the first and second kind. The optimal values of the radii of the recognition classes containers are equal to: for class X_1^o – $d_1^* = 10$; for class X_2^o – $d_2^* = 2$; for class X_3^o – $d_3^* = 7$ and for class X_4^o – $d_4^* = 19$.

According to the geometrical parameters of the recognition classes containers, obtained at the optimal weights of the RGB components, the decisive rules (10) were constructed, according to which the frames of the region image were identified. Fig. 10 shows the result of frame identification at optimal weights of RGB-component images

Fig. 10. The result of the identification of the region image frames at the optimal weights of RGB-component images

Visual comparative analysis of the results presented in Fig. 6 and Fig. 10, shows that the region image frames belonging to the first and second recognition classes are identified almost unmistakably. Thus reliability of shots of identification of the third and fourth classes of recognition increased almost three times.

Thus, the basic paradigm of information-extreme machine learning is confirmed, which consists in the adaptation of the input mathematical description of the recognition system to the maximum full probability of making the correct classification decisions. At the same time, the expediency of optimal in the information sense selection of weight coefficients of RGB-component images in order to increase the functional efficiency of information-extreme machine learning of the image recognition system is experimentally proved.

Conclusions

The analysis of the obtained results of the ORS machine learning of an unmanned aerial vehicle confirms the expediency of taking into account the influence of the formation parameters of the input mathematical description on the reliability of the recognition of terrestrial natural and infrastructural objects.

One such important parameter is the weighting coefficients of the RGB components of the brightness of the images, which directly affect the recognition features. The article proposes a new method of information-extreme machine learning of the on-board system of an unmanned aerial vehicle, which allows increasing the reliability of the region image frames identification by optimizing the information criterion of weight. In this case, the decisive rules are built in the process of machine learning on a multi-cycle iterative procedure of finding the global maximum of the information criterion and optimizing the weights of RGB components of image brightness is carried out by gradient descent.

Further increase in the functional efficiency of information-extreme machine learning ORS is associated with the need to increase the depth of machine learning by optimizing other parameters of the system, including the parameters of the input training matrix. With the increasing power of the recognition classes alphabet, there is a need to move from the above linear data structures to hierarchical.

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ІНФОРМАЦІЙНО-ЕКСТРЕМАЛЬНЕ МАШИННЕ НАВЧАННЯ БОРТОВОЇ СИСТЕМИ РОЗПІЗНАВАННЯ З ОПТИМІЗАЦІЄЮ RGB-СКЛАДОВИХ ЦИФРОВИХ ЗОБРАЖЕНЬ НАЗЕМНИХ ОБ’ЄКТІВ

І. В. Науменко, М. І. Мироненко, Т. Р. Савченко

Метою дослідження є підвищення достовірності розпізнавання автономною бортовою системою безпілотного літального апарату наземних природних та інфраструктурних об’єктів. Запропоновано метод інформаційно-екстремального машинного навчання автономної бортової системи розпізнавання з оптимізацією RGB-складових цифрового зображення наземних об’єктів. Метод розроблено в рамках функціонального підходу до моделювання когнітивних процесів природнього інтелекту при формуванні та прийнятті класифікаційних рішень. Такий підхід на відміну від відомих методів інтелектуального аналізу даних, включаючи нейроподібні структури, дозволяє надати системі розпізнавання властивості адаптивності до довільних початкових умов формування образу та гнучкості при перенавчанні системи. Ідея запропонованого методу полягає в максимізації інформаційної спроможності системи розпізнавання в процесі машинного навчання. Як критерій оптимізації параметрів машинного навчання використовується модифікація інформаційної міри Кульбака, яка є функціоналом точнісних характеристик класифікаційних рішень. Як параметри оптимізації розглядалися геометричні параметри гіперсферичних контейнерів класів розпізнавання, і контрольні допуски на ознаки розпізнавання. які відігравали роль рівнів квантування вхідних даних при перетворенні вхідної евклідової навчальної матриці в робочу бінарну навчальну матрицю. Шляхом допустимих перетворень робочої навчальної матриці запропонований метод машинного навчання дозволяє адаптувати вхідний математичний опис системи розпізнавання до максимальної повної ймовірності прийняття правильних класифікаційних рішень. З метою підвищення глибини інформаційно-екстремального машинного навчання здійснювалася оптимізація за інформаційним критерієм вагових коефіцієнтів RGB-складових спектру яскравості зображень наземних об’єктів. Результати фізичного моделювання на прикладі розпізнавання наземних природних та інфраструктурних об’єктів підтверджують підвищення функціональної ефективності інформаційно-екстремального машинного навчання бортової системи при оптимальних в інформаційному розумінні вагових коефіцієнтах RGB-складових яскравості зображень наземних об’єктів.

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Ключові слова: інформаційно-екстремальне машинне навчання; інформаційний критерій; оптимізація; бортова система розпізнавання; безпілотний авіаційний комплекс; зображення наземного об'єкту.

ИНФОРМАЦИОННО-ЭКСТРЕМАЛЬНОЕ МАШИННОЕ ОБУЧЕНИЕ БОРТОВОЙ СИСТЕМЫ РАСПОЗНАВАНИЯ С ОПТИМИЗАЦИЕЙ RGB-СОСТАВЛЯЮЩИХ ЦИФРОВЫХ ИЗОБРАЖЕНИЙ НАЗЕМНЫХ ОБЪЕКТОВ

И. В. Науменко, Н. И. Мироненко, Т. Р. Савченко

Целью исследования является повышение достоверности распознавания автономной бортовой системой беспилотного летательного аппарата наземных природных и инфраструктурных объектов. Предложен метод информационно-экстремального машинного обучения автономной бортовой системы распознавания с оптимизацией RGB-компонент цифрового изображения наземных объектов. Метод разработан в рамках функционального подхода к моделированию когнитивных процессов природного интеллекта при формировании и принятии классификационных решений. Такой подход в отличии от известных методов интеллектуального анализа данных, включая нейроподобные структуры, позволяет придать системе распознавания свойства адаптивности к произвольным начальным условиям формирования образа и гибкости при переобучении системы. Идея предложенного метода состоит в максимизации информационной способности системы распознавания в процессе машинного обучения. В качестве критерия оптимизации параметров машинного обучения используется модифицированная информационная мера Кульбака, являющаяся функционалом точностных характеристик классификационных решений. В качестве параметров оптимизации рассматривались геометрические параметры гиперсферических контейнеров классов распознавания и контрольные допуски на признаки распознавания, являющиеся уровнями квантования входных данных при преобразовании входной эвклидовой обучающей матрицы в рабочую бинарную обучающую матрицу. Путём допустимых преобразований рабочей обучающей матрицы предложенный метод машинного обучения позволяет адаптировать входное математическое описание системы распознавания к максимальной полной вероятности принятия правильных классификационных решений. С целью увеличения глубины информационно-экстремального машинного обучения осуществлялась оптимизация по информационному критерию весовых коэффициентов RGB-компонент спектра яркости изображений наземных объектов. Результаты физического моделирования на примере распознавания наземных природных и инфраструктурных объектов подтверждают повышение функциональной эффективности информационно-экстремального машинного обучения бортовой системы при оптимальных в информационном смысле весовых коэффициентах RGB-компонент яркости изображений наземных объектов.

Ключевые слова: информационно-экстремальное машинное обучение; информационный критерий; оптимизация; бортовая система распознавания; беспилотный летательный аппарат; изображение наземного объекта.

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