Information-Extreme Learning of On-Board System for Recognition of Ground Vehicles

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Abstract. The article deals with the task of information synthesis of on-board recognition system of ground vehicles. Machine training of the system is carried out within the framework of information-extreme intellectual technology of data analysis, which is based on maximizing the information ability of the recognition system. The modified Kulbak information measure is used as a criterion for optimizing the parameters of machine learning. The proposed algorithm of machine learning is realized on the example of recognition of monochrome coloring cars on approximately identical chassis.

Keywords. information-extreme machine learning, on-board recognition system, categorical model, training matrix, optimization, information criterion, vehicles.

1 Introduction

The widespread use of unmanned aerial vehicles to monitor the earth's surface makes it urgent to create autonomous on-board recognition systems (ORSs) for ground objects, including vehicles of various uses [1, 2]. The main way of solving this problem is to apply methods of machine learning and the theory of pattern recognition [3 – 5]. In this case, the functional efficiency of the ORS essentially depends on the method of processing images of the object being recognized and the method of machine learning. In addition, when creating the ORS it is necessary to ensure the invariance of the constructed in the process of machine learning decisive rules to the arbitrary position of the vehicle in the frame of the area of interest. One of the ways to solve this problem is to process images of recognition objects in a polar coordinate system [6, 7]. But within the framework of this approach necessarily there is a need to solve the problem of determining the polar coordinate system on the ground vehicle. The overwhelming majority of the methods of the information synthesis of the ORS, which are taught, is based on the application of neural networks [8, 9]. In this case, there are complications of scientific and methodological nature, associated with arbitrary initial conditions for the formation of the input mathematical description, the intersection in the space of signs of recognition classes, a large measure of the space of signs and the complexity of retraining.

One of the promising ways of information synthesis of highly effective ORS is the application of ideas and methods of the so-called information-extreme intellectual technology (IEI-technology) of data analysis, which is based on maximizing the information ability of the recognition system in the process of its machine learning [10 – 12]. The main idea of the methods in the framework of IEI-technology as in neural networks is to adapt the input mathematical description of the recognition system to the maximum functional efficiency of machine learning. But in contrast to the neural networks built on the results of machine learning in the framework of the geometric approach, the decisive rules are practically invariant to many of the dimensionality of the recognition signspace.

The article discusses, in the framework of the IEI-technology, the formulation of the problem and the algorithms for the operation of the onboard vehicle recognition system in machine learning modes of the exam.

2 Formulation of the problem

Consider the formalized formulation of the task of information-extreme machine learning on-board recognition of a land vehicle. Let the alphabet $\{X_m^o \mid m = \overline{1,M}\}$ of the recognition classes characterizing the terrestrial vehicles and the input brightness $\| y_{m,i}^{(j)} \|$ of the pixels of the receptor field of the image objects of the recognized objects be given. In this case, the line $\{y_{m,i}^{(j)} \mid i = \overline{1,N}\}$ of the matrix, where N is the number of signs of recognition, is a structured vector-realization (hereinafter simply realization) of the image, and the matrix column is a random educational sample of $\{y_{m,i}^{(j)} \mid j = \overline{1,J}\}$ with a volume of J.

In the process of machine learning it is necessary:

in accordance with the concept of IEI-technology, convert the input training matrix into a binary working matrix $\| x_{m,i}^{(j)} \|$, which, through admissible transformations, can be adapted to the maximum full probability of making the correct classification decisions;

optimize according to the information criterion the parameters of the machine learning ORS, which for each class of recognition X_m^o are given by structured vector

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

where x_m is the averaged binary implementation of the recognition class X_m^o; d_m is the radius of the hyperspherical container of the recognition class X_m^o, which is restored in the radial basis of the space of signs; δ – parameter, the value of which is equal to half of the symmetrical field of control tolerances on the signs of recognition; for determining the optimal geometric parameters of the classes of recognition of hyperspherical containers, determined by the machine learning process, to construct decisive rules.

At the same time, the following restrictions are set for the machine learning parameters:

– the range of values of the radius of the hyperspherical container of the recognition class d_m, is given by the inequality $d_m < d(x_m \oplus x_c)$, where $d(x_m \oplus x_c)$ is the inter-center coding distance between the reference implementation of class x_m of class X_m^o and the reference implementation of x_c neighboring class X_c^o nearest to it; $\oplus$ – symbol of the logical operation of adding by module 2;

– the region of values of parameter δ is given by inequality $\delta < \delta_H / 2$, where δ_H is the normalized tolerance field on the recognition signs.

In the functioning of the on-board system in the exam mode, it is necessary to confirm the high functional efficiency of the machine learning onboard recognition system.

3 Categorical models of machine learning

The categorical model of on-board computer training includes an input mathematical description of the on-board vehicle recognition system in terrain, which has the form

$$\Delta_B = < T, G, \Omega, Z, K, Y, X; \Phi_1, \Phi_2 >,$$

where T is the set of moments of the time of obtaining information; G is the space of the functional states of the recognized object; Ω – the space of signs of recognition; Z – space of functional states of the recognition system; K – the set of frames of the electronic map of the area; Y is a sample set that forms the input training matrix; X – working binary training matrix; $\Phi_1 : G \times T \times \Omega \times Z \to Y$ – the operator of the formation of matrix Y; $\Phi_2 : Y \to X$ – s an operator for transforming the input training matrix Y into a binary matrix X.

Fig. 1 shows a categorical model of information-extreme learning of recognition system with optimization of geometric parameters of containers of recognition classes and system of control tolerances on recognition signs.

$$
\begin{tikzcd}
V \arrow[dd, "U"'] & & & & \\
& \boldsymbol{D} \arrow[d, "\delta_2"'] & & \boldsymbol{E} \arrow[ll, "\delta_1"'] \arrow[ulll, "\nu"'] \arrow[d, "r"'] & \Im^{|q|} \arrow[l, "\varphi"'] \\
\boldsymbol{T}\times\boldsymbol{G}\times\Omega\times\boldsymbol{Z}\times\boldsymbol{K} \arrow[r, "\Phi_1"] & \boldsymbol{Y} \arrow[r, "\Phi_2"] & X \arrow[r, "\xi"] & \tilde{\Re}^{|M|} \arrow[r, "\psi"] & I^{|S|} \arrow[u, "\gamma"']
\end{tikzcd}
$$

Fig. 1. Categorical model of machine learning

In Fig. 1 operator $\xi : X \rightarrow \tilde{\Re}^{|M|}$ displays the vectors of the implementation of recognition classes on the fuzzy partition of the $\tilde{\Re}^{|M|}$ binary traits of spaces, and the classification operator Ψ checks the basic statistical hypothesis of the validity of the class X_m^o mplementation and thus forms the set of hypotheses $I^{|l|}$, where l – is the number of statistical hypotheses. The operator γ, by evaluating the hypotheses received, forms the set of exact characteristics $\Im^{|q|}$ |, where $q = l^2$, and operator ϕ calculates the set of values of the information criterion E, which is a function of the exact characteristics. The contour of the model, which is closed by the operator r, restores, at each step of the machine learning, the recognition class containers that are built in the radial basis of the feature space. In this case, the iterative process of optimizing the geometric parameters of the partition $\tilde{\Re}^{|M|}$ is carried out by finding the global maximum of the information criterion in the working (admissible) region of its function definition. In fig. 1 contour of optimization of control tolerances for recognition signs is closed through set D – the system of control tolerances for recognition signs and allows in the training process to change the value of the working binary training matrix X, adapting it to the maximum functional efficiency of the classifier. Shown in Fig. 1 categorical model implies, in accordance with the principle of deferred deci sions, the transition to other types of radial-basic decision rules. For this purpose, its outer contour contains a set of V types of decisive rules, which are built using more complex radial-basic separation functions. The training process is regulated by the operator $U : V \rightarrow G \times T \times \Omega \times Z \times K$.

Fig. 2 shows a categorical model of the functioning of the on-board recognition system in the mode of examination, which tests the functional efficiency of machine-based learning.

$$
\begin{tikzcd}
\boldsymbol{T}\times\boldsymbol{G}\times\Omega\times Z\times\boldsymbol{K} \arrow[r, "f_1"] & y \arrow[r, "f_2"] & x \arrow[r, "P"] & \Re^{*} \arrow[r, "\psi_1"] & \boldsymbol{F} \arrow[r, "\psi_2"] & \boldsymbol{I}^{|M+l|} \arrow[lllll, bend right, "U_E"']
\end{tikzcd}
$$

Fig. 2. Category model of functioning of on-board recognition system in the exam mode

In the categorical model (Fig. 2), the operator f_1 forms an incoming implementation of the recognizable object. Operator f_2, obtained on the learning stage, obtains optimal control tolerances for recognition attributes, converts incoming readmissions into binary realization x, and operator ξ reflects the implementation of the recognizable object on the optimal breakdown of $\Re^*$ recognition classes built at the stage of machine learning. The operator ψ_1 for each vector-realization calculates the values of constructed at the learning stage of the deciding rules and forms the term-set F, and the operator ψ_2 by the maximum value of the deciding rule, assigns implementation to one of the classes of a given alphabet $\{X_m^o\}$. The purpose of the operator U_E is the regulation of the exam.

4 Machine learning

The idea of information-extreme machine learning of the pattern recognition system, as in neural networks in accordance with the work, is to adapt the input mathematical description to the maximum reliability of classification decisions. In this case, the transformation of the input a priori fuzzy distribution of image implementations in the clear is carried out in the process of optimization according to the information criterion of the learning parameters that affect the exact characteristics of the classification decisions. Based on the results obtained in the process of machine learning, the optimal geometric parameters of containers of recognition classes are based on decisive rules that allow the exam to take promptly reliable classification decisions.

Optimization of the parameters of the vector (1) is carried out by searching at each step the purposeful change of the radiuses of containers of the classes of recognition of the global maximum of the alphabet of the classes of recognition of the information criterion

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

where $E_m(d)$ – information criterion for optimizing the parameters of the training system to recognize the implementation of class X_m^o; d – distance measure of radiuses of hyperspherical containers of recognition classes; G_E – working (admissible) area of determining the function of information criterion optimization of machine learning parameters; G_d is the permissible range for changing the radiuses of the recognition class containers.

As criteria of optimization of machine learning parameters in the methods of IEI-technology, modifications of the Kullback information measure and Shannon's entropy measure are mainly used. For example, the modified Kullback information measure for two alternatives to the a priori equivalence hypothesis has the form

$$E_m(d) = \left[1 - (\alpha_m(d) + \beta_m(d))\right] \log_2 \left(\frac{2 - (\alpha_m(d) + \beta_m(d))}{\alpha_m(d) + \beta_m(d)} \right), \tag{3}$$

where $\alpha_m(d)$ is a mistake of the first kind of acceptance of a classification decision at every step of machine learning; $\beta_m(d)$ is a mistake of the second kind.

On practice, when calculating the information criterion (3), when representing the amount of the training sample, it is necessary to use the estimates of the exact characteristics

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

where $K_{1,m}(d)$ is the number of events that indicate the inappropriateness of "their" implementations of the recognition class X_m^o; $K_{2,m}(d)$ – the number of events that indicate the belonging of "alien" implementations of class X_m^o, $n_{\min}$ – the minimum amount of representative sample of study.

The working modification of the Kullback criterion after the corresponding substitution of the estimates (4) in expression (3) takes the form

$$E_m^{(k)}(d) = \frac{1}{n}\{n-[K_1(d)+K_2(d)]\}\log_2\left\{\frac{2n+10^{-r}-\left[K_1^{(k)}(d)+K_2^{(k)}(d)\right]}{\left[K_1^{(k)}(d)+K_2^{(k)}(d)\right]+10^{-r}}\right\}, \tag{5}$$

where 10^{-r} is a sufficiently small number which is entered to avoid division into zero and in practice it is chosen in the interval $1 < r \le 3$.

According to the categorical model (Fig. 1), the algorithm of ORS informational and emergency machine learning with optimization of the system of control tolerances can be represented as a two-cycle procedure for finding the global maximum of the information criterion (2)

$$\delta_K^* = \arg\{\max_{G_\delta}\{\max_{G_E \cap G_d} \overline{E}(d)\}\}, \tag{6}$$

Let's consider the main stages of implementing the algorithm (5) of information-extreme machine learning ORS. The input data is the array of the input learning matrix for a given alphabet of recognition classes and parameter:

1. zeroing the count of the recognition classes: $m := 0$;
2. increment of the count of recognition classes: $m := m+1$;
3. zeroing the counter of the steps of changing the tolerance field parameter: $k := 0$;
4. $k := k+1$;
5. zeroing the counter of steps to change the radius of the container of the recognition class: $d := 0$;
6. $d := d+1$;
7. calculation of the lower $A_{KH,i}[k]$ and upper $A_{KB,i}[k]$ control tolerances for all signs, respectively, according to the formulas

$$A_{KH,i}[k] = y_{1,i} - \delta[k]; \quad A_{KB,i}[k] = y_{1,i} + \delta[k]; \tag{7}$$

8. formation of the binary training matrix $\left\| x_{m,i}^{(j)} \right\|$ by the rule

$$x_{m,i}^{(j)} = \begin{cases} 1, & \text{if} \quad A_{KH,i} \le y_{m,i}^{(j)} \le A_{KB,i}; \\ 0, & \text{if} \quad \text{else}. \end{cases}$$

9. calculation for class X_m^o binary averaging vector x_m according to the rule

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

where ρ_m is the level of selection of the coordinates of the averaged binary vector of the recognition class X_m^o, which by default is equal to $\rho_m = 0,5$;

10. pairwise decomposition of the set of averaged vectors of recognition classes by the method of closest neighbors;
11. formation for the breakdown of $\Re_m^{|2|} =< x_m , x_c >$ educational matrix;
12. calculation of the information criterion for optimizing the parameters of machine learning GIS, for example, in the form of modification of the information measure of Kullback (2.5);
13. if $d < d(x_m \oplus x_c)$, then paragraph 6 is executed, otherwise, paragraph 14;
14. if $k < \delta_H / 2$, then paragraph 4, is executed, otherwise, paragraph 15;
15. if $m \le M$, then paragraph 2 is executed, otherwise, paragraph 16;
16. calculation of averaged alphabet classes recognition information criterion (6) optimization of machine learning parameters;
17. determining the optimal value of parameter δ by the formula (5);
18. calculation of the formula (7) of the optimal lower and upper control tolerances for the diagnostic signs, respectively;
19. STOP.

Based on the results obtained in the process of machine learning, the optimal geometric parameters of the classes of recognition containers are based on decisive rules, which, when the recognition system operates directly in the operating mode, verifies the functional efficiency of machine learning. For hyperspherical containers of recognition classes, decisive rules have the form

$$(\forall X_m^o \in \Re^{|M|})(x^{(j)} \in \Re^{|M|})[\mathit{if}\ (\mu_m > 0) \,\&\, (\mu_m = \max\{\mu_m\})\ \mathit{then}\ x^{(j)} \in X_m^o], \quad (8)$$

where $x^{(j)}$ is an implementation that is recognized; the function of ownership of the container of the recognition class X_m^o.

In expression (8), the membership function for hyperspherical containers is determined by the formula [10]

$$\mu_m = 1 - \frac{d(x^{(j)} \oplus x_m)}{d_m^*} ; \quad (9)$$

where d_m^* – obtained in the process of machine learning the optimal radius of the container of the recognition class X_m^o.

The algorithm of functioning of the ORS in the mode of examination has the following input data:

1. $\{x_m^* \mid m = \overline{1,M}\}$ is an array of reference binary vector-image implementations that determine the geometric centers of the corresponding optimal containers of recognition classes constructed at the stage of machine learning;
2. $\{d_m^*\}$ is an array of optimal radiuses constructed at the stage of training of the corresponding containers;
3. $\{x_s^{(j)} \mid s = \overline{1,SMAX}; j = \overline{1,n}\}$ is an array of binary vectors-implementations of identified frames, where $SMAX$ is the number of frames of a reconstructed terrain;
4. $\{\delta_{k,i}^* \mid i = \overline{1,N}\}$ is the optimal system of control tolerances for recognition signs, determined at the stage of training.

According to the categorical model (Fig. 2), the algorithm of the exam within the framework of the IEI-technology is based on the analysis of the values of the decisive rules formed at the stage of learning (8). If for all classes of recognition the maximum values of the function (9) are negative, then according to the deciding rules (8) the object is not identified;

The analysis of decisive rules (8) shows that they differ from other methods for recognizing low computational complexity, which allows BSC to take classification decisions in real time.

5 Results of physical modeling

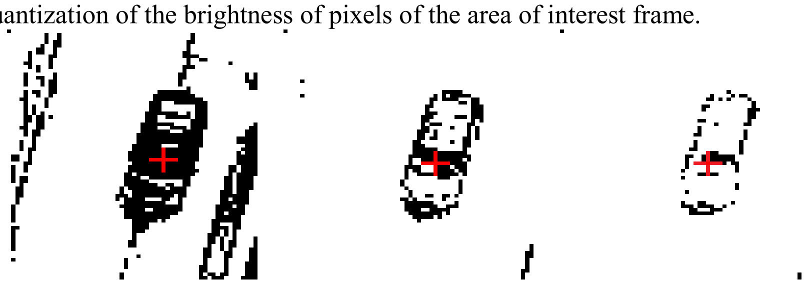
Approbation of the proposed algorithm for information-extreme machine learning was carried out on the example of the recognition of three cars that were moving along the highway (Fig. 3). At the same time, in order to check the functional efficiency of machine learning ORS cars specially selected monotonous and with approximately the same contours.

a *b* *c*

Fig. 3. Picture of cars of class X_1^o (*a*); class X_2^o (*b*); class X_3^o (*c*)

The formation of the input training matrix was carried out by processing images of cars in the polar coordinate system, which allowed to ensure the invariance of the decision of the rules to the arbitrary position of the object of recognition in the frame of the zone of interest. As a sign of recognition, the average value of the brightness of the pixels of the reading range, built around the center of the polar coordinate system, was taken. At the same time, the definition of the center of the polar coordinate system on the car was carried out by the class SelectedObject, which, moreover, handles the image of the object in the polar coordinate system and forms the input training matrix ORS.

Fig. 4 shows a screenshot of the result of the Class SelectedObject program, which shows the center of the polar system on a class X_3^o (Fig. 3*c*) at different levels of quantization of the brightness of pixels of the area of interest frame.



a *b* *c*

Fig. 4. Results of the centering of the car at the levels of quantization of brightness (in brightness gradations): $a - \eta = 25; b - \eta = 50; c - \eta = 75$

To form the implementation of the input training matrix, all pixels of the frame of the interest zone, which was accepted as the first quadrant of the Cartesian coordinate system, was numbered. This allowed us to determine polarization centers of cars as average arithmetic numbers of pixels whose brightness exceeded the corresponding quantization level. Then the center of the Cartesian coordinate system was transferred to the found center of the polar system, around which the area of the given radius was asked. In the given region, the coordinates of the pixels were converted to polar and formed arrays of pixels with the same radiuses. For each RGB-component image of the car for recognition, the average brightness value of the pixels of the corresponding array was taken.

Fig. 5 shows the graph of the dependence of the information criterion recognition (5) alpha of the information criterion recognition classes (5) on parameter δ, obtained during the machine learning process in accordance with the procedure (6) at the quantization level of brightness $\eta = 50$. In this case, parallel optimization was carried out, at which, at each step of machine learning, control tolerances changed simultaneously for all signs of recognition. When calculating the information criterion (5) parameters $n = 40$ and $r = 2$ were taken.

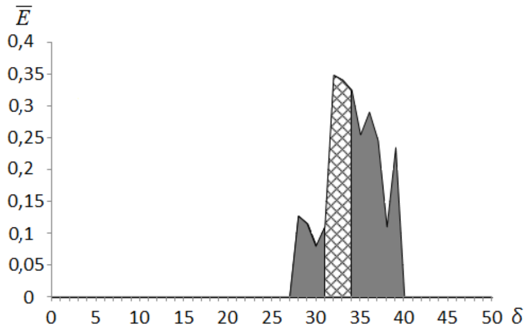
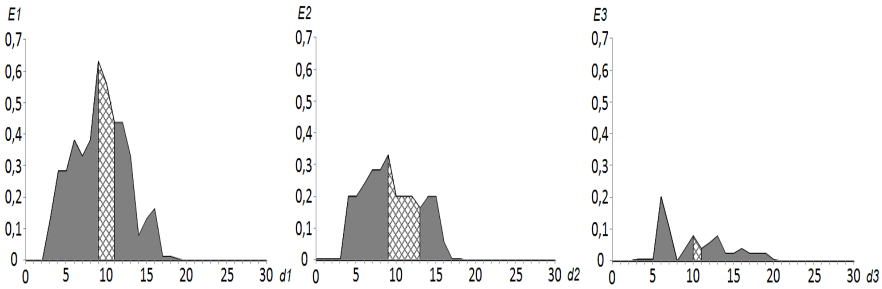


Fig. 5. The graph of the dependence of the information criterion (5) on the parameter of the field of control tolerances on the signs of recognition

Fig. 5 shows and then the double hatching indicates the working (admissible) area of definition of function (5), in which the value of errors of the first and second kind is less than the first and second reliability, respectively. Analysis of Fig. 5 shows that the maximum value of the informational criterion (5) in the work area for determining its function is equal to $\overline{E}^* = 0,35$. In this case, the optimal value of the parameter field of control tolerances on the recognition signs is equal to $\delta^* = 32$ brightness gradations.

To construct the decisive rules (7), it is necessary to know the optimal geometric parameters of the classes of recognition containers. Fig. 6 shows the graphs of the information criterion (5) dependence on the radiuses of the recognition class containers, obtained in the process of optimizing the control tolerances for recognition attributes.



a *b* *c*

Fig. 6. Graphs of the dependence of the information criterion on the radiuses of containers of recognition classes: *a* – class X_1^o; *b* – class X_2; *c* – class X_3^o

Analysis of Fig 6 shows that the optimal value of the radius of the container of the recognition class X_1^o is $d_1^* = 10$ (here and below in the code units), for class X_2 – $d_2^* = 9$ and for class X_3^o – $d_3^* = 11$.

The results of the physical simulation of the on-board recognition system in the exam mode showed that the full probability of correct recognition of the vector-realization of class X_1 is $P_t = 0,84$, class X_2 – $P_t = 0,80$ and class X_3 – $P_t = 0,78$.

6 Conclusion

The method of information-extreme machine learning of the ORS ground vehicle with optimization of the system of control tolerances on recognition signs is proposed. The formation of the input mathematical description was carried out on the basis of the results of processing images of vehicles in the polar coordinate system, which ensured the invariance of the deciding rules to the arbitrary position of the object of recognition in the frame of the interest zone. The results of machine learning were not allowed to construct non-error-based educational matrix deciding rules due to the high degree of intersection of classes of recognition in the space of signs. Therefore, in order to increase the functional efficiency of the ORS, it is necessary to increase the depth of machine learning by optimizing other learning parameters, including the parameters of image processing of terrestrial objects.

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