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Information-Extreme Machine Learning of Wrist Prosthesis Control System Based on the Sparse Training Matrix

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Abstract. The article considers the problem of machine learning of a wrist prosthesis control system with a non-invasive biosignal reading system. The task is solved within the framework of information-extreme intelligent data analysis technology, which is based on maximizing the system's information productivity in machine learning. The idea of information-extreme machine learning of the control system for recognition of electromyographic biosignals, as in artificial neural networks, consists in adapting the input information description to the maximum total probability of making correct classification decisions. However, unlike neuro-like structures, the proposed method was developed within a functional approach to modeling the cognitive processes of the natural intelligence of forming and making classification decisions. As a result, the proposed method acquires the properties of adaptability to the intersection of classes in the space of recognition features and flexibility when retraining the system due to the recognition class alphabet expansion. In addition, the decision rules constructed within the framework of the geometric approach are practically invariant to the multidimensionality of the space of recognition features. The difference between the developed method and the well-known methods of information-extreme machine learning is the use of a sparse training matrix, which allows for reducing the degree of intersection of recognition classes significantly. The optimization parameter of the input information description, the training dataset, is the quantization level of electromyographic biosignals. As an optimization criterion is considered the modified Kullback information measure. The proposed machine learning algorithm results are shown in the example of recognition of six finger movements and wrist.

Keywords: information-extreme intelligent technology, machine learning, process innovation, sparse training matrix, prosthesis control system, information criterion, electromyographic sensor, biosignal.

1 Introduction

Despite a significant number of studies on improving the interaction of a person with a disability with a limb prosthesis, the convenience, functionality, and prevalence of active prostheses in everyday life remain low. For the user, the accuracy of movement selection, the intuitiveness of control, and the system's reaction time are essential properties of prosthesis control. The main direction of the development of hand prostheses is provided based on electromyography as a method of analyzing the natural control impulses of the nervous system. The most advanced are limb prostheses with an invasive biosignal reading system. But their main drawback is a very high cost on the world market. In addition, the use of invasive biosignal reading systems requires prior surgical intervention. This makes it possible to increase the "biosignal/interference" ratio, which significantly affects the accuracy of performing cognitive commands but creates additional inconveniences for people with disabilities. Non-invasive bionic prostheses controlled by signals from passive electromyographic sensors, as a rule, have a limited set of commands, and the corresponding cognitive commands are provided with insufficient accuracy. The reasons for this unsatisfactory state are the high noise of biosignals, mainly due to the unstable contact of the electromyographic sensor.

The primary trend of increasing the functional efficiency of non-invasive hand prostheses is the application of intelligent information technologies of data analysis based on machine learning and pattern recognition. The complexity of the information synthesis of the intelligent prosthesis control system lies in need to solve scientific and methodological problems caused by the arbitrary initial conditions of the operation of the prosthesis control system and the intersection in the space of features of recognition classes that characterize the possible permissible movements of the prosthesis.

The article deals with the issue of increasing the functional efficiency of the machine learning system for controlling a wrist prosthesis with a non-invasive electromyographic system for reading biosignals by using the so-called sparse training matrix.

2 Literature Review

Papers [1, 2] consider hand prostheses with an invasive system for reading biosignals, which require surgical intervention and have a high cost, being considered. Works [3, 4] describe prostheses endowed with a tactile function capable of recognizing and feeling the surface of an object. In addition, work [5] proposed to increase the accuracy of cognitive command execution using an additional eye movement optical tracking system. Still, this approach significantly increases the prosthesis's cost and complicates its use conditions. As for existing non-invasive prostheses controlled by signals from passive electromyographic sensors, achieving high accuracy depends on the reliability of recognizing electromyographic biosignals by the prosthesis control system. This is especially relevant when recognizing electromyographic biosignals of cognitive commands for the movement of individual fingers, even with undamaged muscle tissue. The unsatisfactory state of recognition of biosignals of the relevant cognitive commands is due to the shortcomings of modern intelligent information technologies of data analysis. There are well-known machine learning algorithms for establishing correspondence between biosignals and cognitive commands based on neural networks [6–8] and the method of support vectors [9, 10]. But the main disadvantages of these methods are sensitivity to the multidimensionality of the dictionary of recognition features and the alphabet of recognition classes, which occurs when recognizing biosignals of cognitive commands. In works [11, 12], it is proposed to use input data extractors built on artificial neural networks, which do not exclude the loss of information. The paper [13] considers the possibility of using fuzzy neural networks for signal recognition, but at the same time, there is also a problem of multidimensionality.

The use of ideas and methods of the so-called information-extreme intelligent technology (IEIT) of data analysis, which is based on maximizing the system's information capacity in the process of machine learning [14, 15], should be considered as a perspective direction. The central paradigm of information-extreme machine learning, as well as in neuro-like structures, is adapting the system's input information description to the maximum reliability of pattern recognition. But in contrast to neuro-like structures, the decision-making rules constructed within the framework of the geometric approach are practically invariant to the multidimensionality of the space of recognition features. The paper [16] considered the information-extreme machine learning system for controlling a wrist prosthesis for three gestures.

This article aims to increase the functional efficiency of the information-extreme machine learning of the hand bone prosthesis control system by optimizing the quantization of biosignals at the output of the electromyographic sensor. This approach makes it possible to form the so-called sparse training matrix, which reduces the influence of the power of the alphabet of recognition classes on the probability of making the correct classification decisions.

3 Research Methodology

3.1 Statement of the research task

Let the alphabet of recognition classes $\{X_m^o \mid m=\overline{1,M}\}$ and proper training matrix of the "object-property" type be formed $\| y_{m,i}^{(j)} \mid i=\overline{1,N};\ j=\overline{1,J_{\max}} \|$, where N, J_{max} – the number of signs of recognition features and pattern realizations, respectively.

According to the concept of IEIT a structured vector of functioning parameters of the system, trained to reconise class X_m^o realisations, is given in the binary space of Hamming recognition features:

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

where x_m – averaged binary feature vector of the recognition class X_m^o; d_m – the radius of the hyperspherical container of the recognition class X_m^o, which in the process of machine learning is restored in the radial basis of the space of recognition features; δ – parameter of the field of control tolerances on recognition features;

h – quantization step by electromyographic biosignal level.

The parameter δ is equal to half of the symmetrical field of control tolerances on recognition features as shown in Figure 1.

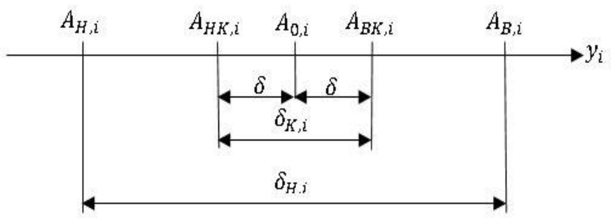


Figure 1 – Tolerance fields for the recognition feature

The following notations are used in Figure 1: $A_{0,i}$ – the nominal value of the feature y_i; $A_{H,i}$ – lower normalized (operational) tolerance; $A_{B,i}$ – upper normalized tolerance; $A_{HK,i}$ – lower control tolerance; $A_{BK,i}$ – upper control tolerance; $\delta_{K,i}$ – field of control tolerances; $\delta_{H,i}$ – field of normalized tolerances.

The parameters of the system functioning, which will be called parameters of machine learning, are imposed by the following restrictions:

- the value range of recognition features is set by the maximum battery current of 100 mA
- the inequality gives the range of values of the radius of the recognition class container

$$d_m < d(x_m \oplus x_c),$$

where $d(x_m \oplus x_c)$ – intercenter distance between the averaged feature vector x_m and analogous vector x_c nearest neighbor class X_c^o;

- the parameter δ value range is given by inequality

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

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

- the value of the parameter h is determined by the number of biosignal quantization steps in the range [0...100 mA].

It is necessary for the process of information-extreme machine learning of the hand prosthesis management system to:

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

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

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

2) decide whether the recognized realization belongs to one of the classes of the given alphabet at the exam stage to check the functional effectiveness of machine learning.

Thus, the task of information synthesis of an intelligent wrist prosthesis control system consists of optimizing machine learning parameters (1) by approximating the global maximum of the information criterion (2) to its maximum limit value.

3.2 Functional categorical model of machine learning

The categorical model of information-extreme learning of the prosthesis control system is considered in the form of an oriented graph, the edges of which are characterized by set mapping operators. At the same time, the input mathematical description has the following structure

$$I = < G, T, \Sigma, Z, Y, X;\ f_1,\ f_2 >,$$

where G – a set of biosignals registered by the system; T – a set of data registration time moments; Σ – a dictionary of recognition features; Z – the space of possible functional states of the controlled process; Y – set of vectors of realizations of recognition classes, which forms an input training matrix; X – binary training matrix; f_1 – the operator of the input training matrix Y formation; f_2 - binary training matrix formation operator X.

Figure 2 shows the functional categorical model of information-extreme machine learning of the prosthesis control system with optimization of control tolerances on recognition features and quantization levels of biosignals at the output of the electromyographic sensor.

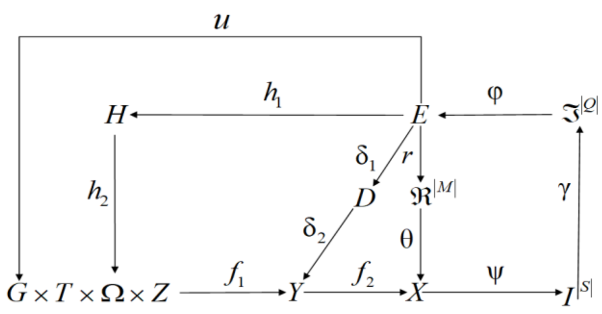


Figure 2 – Functional categorical model of information-extreme machine learning of the prosthesis control system

In Figure 2, the term set E, the elements calculated at each step of machine learning according to formula (2), is common to all optimization contours of vector parameters (1). The operator $r: E \to \tilde{\Re}^{|M|}$, in the process of machine learning, restores the containers of recognition classes in the radial basis of the binary feature space, which generally forms a fuzzy partition $\tilde{\Re}^{|M|}$. The operator θ reflects the partitioning $\tilde{\Re}^{|M|}$ into a fuzzy distribution of a priori classified binary feature vectors of recognition classes. The next operator is $\psi: X \to I^{|S|}$, where $I^{|S|}$ – the set of hypotheses that checks the main statistical hypothesis $\gamma_1: x_m^{(j)} \in X_m^o$. The operator γ defines a set of accuracy characteristics $\Im^{|Q|}$, where $Q = S^2$, and operator φ calculates a set of values of information optimization criterion E that is a function of accuracy characteristics.

The categorical model contains the contour of optimization of control tolerances on recognition features, which is closed through the term set D of permissible values of control tolerances. At the same time, the operator δ_1 changes the control field at each step of machine learning, and the operator δ_2 evaluates the dependence of recognition features on the given control field of tolerances. In addition, the categorical model contains a circuit for optimizing the quantization levels of electromyographic biosignals, which includes the term set H of admissible values of quantization levels. In this circuit, at each step of machine learning, the operator h_1 changes the quantization level, and the operator h_2 changes the dictionary of recognition features Σ. The operator u regulates the process of machine learning.

3.3 Description of the machine learning algorithm

According to the categorical model (Fig. 2), the information-extreme machine learning algorithm of the prosthesis control system is presented in the form of a three-cycle iterative procedure for finding the global maximum of the information optimization criterion (2) in the working area of determining its function:

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

where $\overline{E}^{(k)}_{\delta,h}$ – the average value of the information criterion, calculated according to formula (2) at the k-th step of machine learning; G_h – the range of permissible values of quantization levels of biosignals; G_δ – the area of permissible values of control tolerances on recognition features.

The implementation of the machine learning algorithm of the prosthesis control system according to procedure (3) was carried out with the parallel optimization of control tolerances on recognition features, in which all tolerances for recognition features change simultaneously by a given value.

The input information for the machine learning algorithm is the array of the training matrix $\{y^{(j)}_{m,i}\}$ and the system of fields of normalized tolerances $\{\delta_{H,i}\}$ for recognition features, which sets the range of values of the corresponding control tolerances.

Let's consider the main stages of information-extreme machine learning:

1) Definition for a given alphabet of the basic class of recognition, in relation to which the control tolerances on the features of the averaged vector are determined. For this purpose, the internal cycle of procedure (3) is implemented, the main functions of which are the calculation of the information optimization criterion (2) at each machine learning step and the search for its global maximum, which determines the optimal radii of hyperspherical containers of recognition classes. At the same time, this procedure is carried out for all classes of recognition, which are considered consistently basic. The scheme of the algorithm, for example, in the case of the base class, X^o_m looks like this:

a) the averaged feature vector $y_m \in X^o_m$ is determined;

b) the input training matrix is transformed into a working binary training matrix, the elements of which are determined by the rule

$$x^{(j)}_{m,i} = \begin{cases} 1, & \text{if } y_{m,i} - \delta \le y^{(j)}_{1,i} \le y_{m,i} + \delta; \\ 0, & \text{if else;} \end{cases}$$

c) an array of averaged binary realization vectors is formed $\{x_{m,i} | m = \overline{1,M}, i = \overline{1,N}\}$, it's elements are formed by the rule

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

where ρ_m – the selection level of binary vector coordinates $x_m \in X^o_m$, which is set by default ρ_m=0,5;

d) division of the set of averaged feature vectors $\{x_m\}$ into pairs of nearest "neighbors": $\Re^{|2|}_m = <x_m, x_l>$, where x_l – the averaged feature vector of the neighboring class X^o_l;

e) optimization of the code distance d_m according to the iterative procedure of finding the global maximum of the information criterion for machine learning parameters optimization in the working area of its function determining:

$$d^*_m = \arg \max_{G_E \cap \{k\}} E^{(k)}_m$$

when fulfilling the restriction on the value of the radius d_m of the container of the recognition class X^o_m, it gain the form

$$d_m < d(x_m \oplus x_l).$$

As a result of sorting through all the recognition classes, the class with the maximum value of the optimization criterion (2) is taken as the basic. Then, for a given alphabet with a defined basic recognition class, procedure (3) is implemented in full, and optimal lower $A^*_{H,i}$ and upper $A^*_{B,i}$ control tolerances on recognition features are determined, respectively, according to the rules

$$A^*_{H,i} = y_{m,i} - \delta^*; \quad A^*_{B,i} = y_{m,i} + \delta^*;$$

Thus, for hyperspherical containers of recognition classes, the optimal parameters of information-extreme machine learning are the averaged vectors of recognition features $\{x^*_m\}$ for a given alphabet $\{X^o_m\}$, the radii of containers $\{d^*_m\}$of recognition classes and the system of control tolerances $\{A^*_{H,i}\}$ and $\{A^*_{B,i}\}$ on recognition features.

As a criterion for the optimization of machine learning parameters, we will use the modified information criterion of Kullbak, the working formula of which in case of equally probable two alternative hypotheses has the form

$$E_m^{(k)} = \frac{\left[n - (K_{1,m}^{(k)} + K_{2,m}^{(k)})\right]}{n} * \log_2 \left\{ \frac{2n + 10^{-p} - \left[K_{1,m}^{(k)} + K_{2,m}^{(k)}\right]}{\left[K_{1,m}^{(k)} + K_{2,m}^{(k)}\right] + 10^{-p}} \right\}, \quad (4)$$

where $K_{1,m}^{(k)}$ – the amount of events that mean the non-belonging of "own" feature vectors to the recognition class X_m^o; $K_{2,m}^{(k)}$ – the number of events that mean belonging to "foreign" feature vectors of the recognition class X_m^o; 10^{-p} – is a sufficiently small number that is entered to avoid division by zero; p – a number that is recommended in practice to choose from the interval $1 < p \leq 3$.

The normalized modification of criterion (5) is given in the form [2]

$$E = \frac{E_m^{(k)}}{E_{\max}}, \quad (5)$$

where $E_{\max}$ – the value of the information criterion at the maximum values of the first and second reliabilities and zero errors of the first and second kind.

Decision rules were formed according to the optimal geometric parameters of the recognition class containers obtained in the process of machine learning. These rules may be presented in production form

$$(\forall X_m^o \in \tilde{\Re}^{|M|})\Big(if\ [(\mu_m > 0)\,\&\,(\mu_m = \max_{\{m\}}\{\mu_m\})]$$
$$then\ x^{(j)} \in X_m^o\ \ else\ x^{(j)} \notin X_m^o \Big), \quad (6)$$

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

In expression (6), the membership function for the hyperspherical container of the recognition class X_m^o is determined by the formula

$$\mu_m = 1 - \frac{d(x_m^* \oplus x^{(j)})}{d_m^*}, \quad (7)$$

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

Since the decision rules (7) are built within the framework of a geometric approach, they are practically invariant to the multidimensionality of the dictionary of recognition features and are characterized by high efficiency, which is an important indicator of the functional efficiency of the prosthesis control system in the working mode.

4 Results

The implementation of the machine learning algorithm considered above was carried out according to a fuzzy classified three-dimensional input learning matrix, obtained by processing electromyographic biosignals for seven movements of the wrist and fingers:

a) squeezing the thumb and middle fingers into a ring (class X_1^o);

b) pinch little finger and thumb (class X_2^o);

c) squeezing the thumb and forefinger into a ring (class X_3^o);

d) palm flexion (class X_4^o);

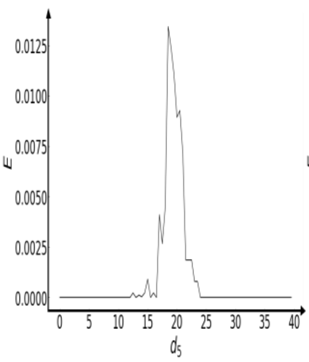
e) clenching the palm into a fist (class X_5^o);

f) palm extension (class X_6^o);

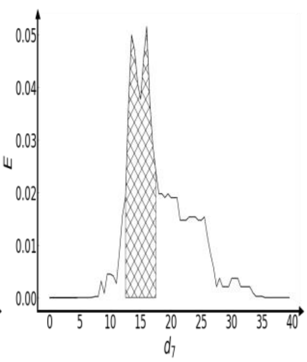
i) pinching the thumb and ring finger into a ring (class X_7^o).

Based on the electromyographic biosignals given in [17], an input training matrix was formed for each of the specified recognition classes. The formation of structured vectors of features of the corresponding classes of recognition was carried out by time quantization of a biosignal with a period of 10 ms at a given time interval of 2 s. That is, each vector consisted of 200 recognition features, and the number of vectors for each recognition class was equal to $n = 40$. At the same time, in order to filter the noise, the quantization of the biosignal began when its amplitude reached the threshold value of 30 *mV*.

The recognition class X_4^o (palm flexion) was chosen as the basic one, for which the maximum average value of the normalized criterion (5) was obtained. Then, machine learning of the prosthesis control system was implemented according to the procedure (3). At the same time, the quantization level was changed by 20 *mV* at each step of machine learning. Figure 3 shows graphs of the dependence of criterion (5) on the radii of the recognition class containers at the initial quantization level $h = 30mV$.



a



b

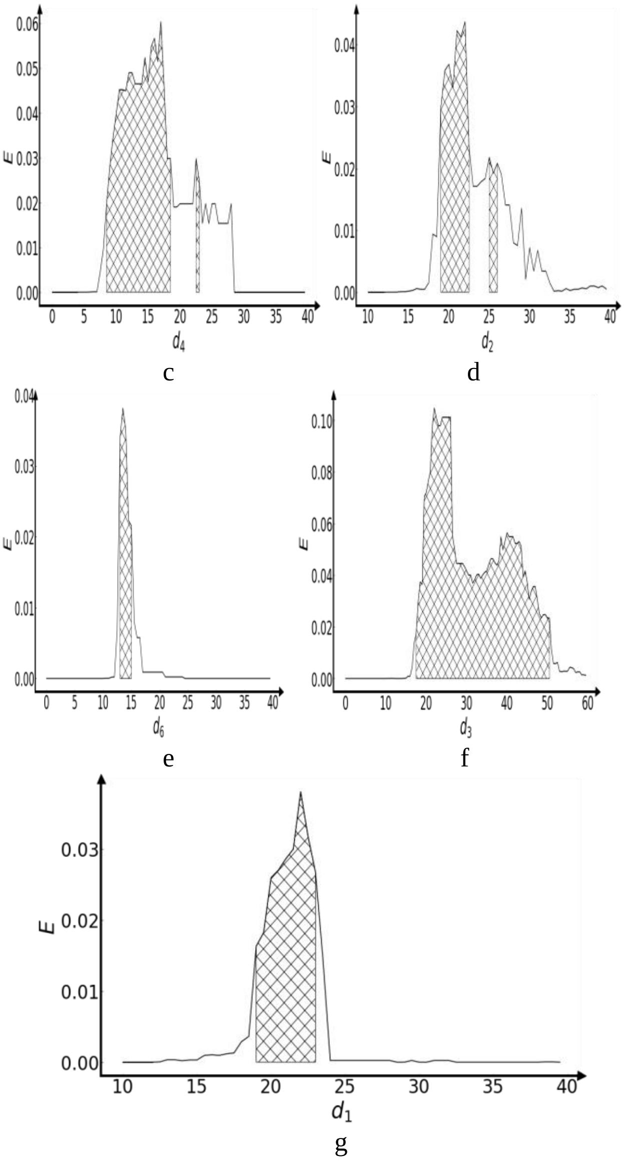


Figure 3 – Graphs of the dependence of the optimization criterion (5) on the radii of the recognition class containers: *a* – class X_1^o ; *b* – class X_2^o ; *c* – class X_3^o ; *d* – class X_4^o ; *e* – class X_5^o ; *f* – class X_6^o ; *g* – class X_7^o

In Figure 3, the working (allowable) area of the definition of the function of the information criterion (4) is indicated by double hatching, in which, with two alternative solutions, the first and second reliability is more, respectively, errors of the first and second kind.

The analysis of this figure shows that at the initial quantization level of biosignals ($h = 30mV$), the average value of the normalized information optimization criterion (5) is equal to $\overline{E} = 0{,}04$. At the same time, the recognition class X_1^o was not classified since there is no working area of the defining function of the information criterion. In the process of machine learning, the level of quantization of biosignals $h^* = 70mV$ is considered optimal, because the average value of criterion (5) is equal to $\overline{E} = 0{,}18$, i.e. increased more than four times.

Figure 4 shows graphs of the dependence of the normalized information criterion (5) on the radii of the recognition class containers at the optimal quantization level.

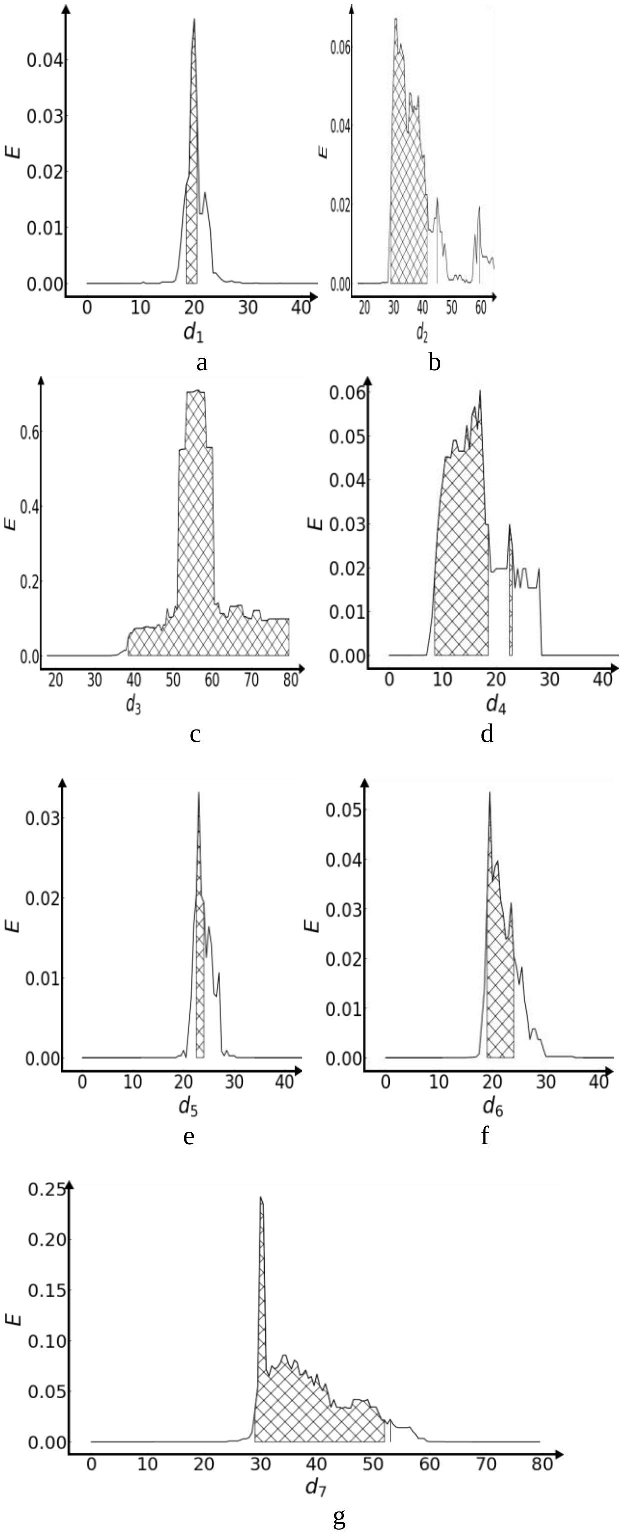


Figure 4 – Graphs of the dependence of the optimization criterion (5) on the radii of the recognition class containers at optimal level of quantization of biosignals: *a* – class X_1^o ; *b* – class X_2^o ; *c* – class X_3^o ; *d* – class X_4^o ; *e* – class X_5^o ; *f* – class X_6^o ; *g* – class X_7^o

In Figure 4, all recognition classes have working areas for determining the function of the optimization criterion, which means they are all informationally separated. To construct the decision rules (6), knowledge of the optimal geometric parameters of the recognition class containers obtained in machine learning is required. The analysis of Figure 4 shows that the optimal radii of the containers of the recognition classes are equal to: $d_1^* = 20$ (the Hamming distance in code units is still used here) for the class X_1^o, $d_2^* = 31$ for the class X_2^o, $d_3^* = 59$ for the class X_3^o, $d_4^* = 19$ for the class X_4^o, $d_5^* = 23$ for the class X_5^o, $d_6^* = 19$ for the class X_6^o i $d_7^* = 29$ for the class X_7^o.

The relatively low value of the criterion for optimizing machine learning parameters indicates the existence of a significant intersection of recognition classes in the space of Hamming features.

Conclusions

The information-extreme machine learning algorithm of the prosthesis control system is proposed for the recognition of electromyographic biosignals of cognitive commands for seven wrist and finger movements. The depth of machine learning was equal to the third level, at which the geometric parameters of the recognition class containers, the system of control tolerances for recognition features, and the levels of quantization of biosignals from the output of the electromyographic sensor were optimized.

This level of depth of information-extreme machine learning made it possible to obtain the information separability of all classes of recognition from the given alphabet. In addition, optimizing the quantization level of biosignals made it possible to significantly increase the functional efficiency of machine learning due to the formation of a sparse learning matrix. The use of a sparse matrix reduces the degree of intersection of recognition classes in the feature space, which makes it possible to increase the reliability of classification cracks. Based on the optimal geometric parameters of the recognition class containers obtained in machine learning, decisive rules are built that are characterized by high efficiency.

A promising direction for increasing the functional efficiency of the proposed method of information-extreme machine learning is to increase its level of depth by optimizing additional parameters, including input data processing parameters. In addition, when increasing the power of the alphabet of recognition classes, it is advisable to use hierarchical information-extreme machine learning.

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