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Hierarchical Information-Extreme Machine Learning of Hand Prosthesis Control System Based on Decursive Data Structure

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Abstract. The article considers the machine learning method for a hand prosthesis control system that recognizes electromyographic signals with a non-invasive recording system. The method was developed within the information-extreme intelligent data analysis technology framework to maximize the system's information capacity during machine learning. The method is based on adapting the input information description to maximize the probability of correct classification decisions, similar to artificial neural networks. However, unlike neural-like structures, the proposed method was developed within a functional approach to modeling cognitive processes of natural intelligence formation and decision-making. This approach allowed the recognition system to adapt to arbitrary initial conditions of electromyogram formation and flexibility when retraining the system by expanding the alphabet of recognition classes. The decision rules formed by the results of information-extreme machine learning were characterized by high efficiency as an essential indicator of an intelligent prosthesis. The distinctiveness of the developed method from known machine learning methods was in applying a hierarchical data structure as a decursive binary tree, which allowed for transitioning from multi-class machine learning to two-class learning for each stratum of the decursive tree. The modified Kullback–Leibler information measure was the optimization criterion for machine learning parameters. The proposed hierarchical information-extreme machine learning method was implemented using electromyographic biosignals of cognitive commands for six finger and hand movements as an example.

Keywords: information-extreme intelligent technology, hierarchical machine learning, decursive binary tree, prosthesis control system, process innovation, information criterion, EMG sensor, biosignal.

1 Introduction

For a person with a disability, essential indicators of interaction with a hand prosthesis of varying degrees of impairment are the accuracy of movement selection, intuitive control, and the speed of executing cognitive commands [1]. All these indicators depend on the accuracy of the control system's recognition of electromyographic (EMG) signals, which arise in the muscles when muscle fibers are excited by the corresponding cognitive commands. Therefore, the article's topic is relevant as it is dedicated to improving the functional efficiency of the machine learning control system for a hand prosthesis to recognize EMG signals. One way to increase the accuracy of the cognitive command execution of the corresponding movement is to use a prosthesis with an invasive EMG signal reading system. At the same time, to achieve this goal, it is necessary to solve two main tasks: to form a relevant input mathematical description of the EMG signal recognition system and to develop a machine learning method with high functional efficiency.

The main disadvantages of invasive prostheses compared to non-invasive ones are their very high cost on the global market and the necessity of preliminary surgical intervention [2]. In turn, non-invasive bionic prostheses are characterized by high noise levels in biosignals due to the unstable contact of the EMG sensor. Furthermore, in developing a machine learning method for a non-invasive prosthesis with high functional efficiency, it is necessary to overcome scientific and methodological challenges caused by arbitrary initial conditions of the prosthesis control system's operation, intersection of feature spaces of recognition classes that characterize permissible movements of the prosthesis, and multidimensionality of the feature dictionary and the recognition class alphabet.

The article examines the information synthesis based on hierarchical information-extreme machine learning for the recognition system of electromyographic (EMG) signals of cognitive commands for controlling a hand prosthesis.

2 Literature Review

In recent years, there has been a trend towards an increasing number of publications on using intelligent information technologies to improve the functional efficiency of hand prostheses. For example, papers [3–5] detail prostheses equipped with tactile functions capable of perceiving the surface characteristics of an object. These researches mainly emphasize the use of intelligent sensors. At the same time, the accuracy and speed of executing cognitive commands depend on the reliability of their recognition. Research [6, 7] proposes improving the accuracy of executing cognitive commands through an auxiliary optical eye-tracking system. This enhancement significantly increases the cost of the prosthesis and complicates its usage conditions. The main problem in improving the functional efficiency of non-invasive prostheses remains the low overall probability of correctly recognizing electromyographic biosignals [8]. Artificial neural networks are widely used to establish correspondence between EMG signals and cognitive commands [9–11].

The main drawbacks of neural-like structures include sensitivity to the multidimensional nature of the recognition feature space and inflexibility during retraining due to the expansion of the recognition class alphabet. At the same time, forming a representative training matrix requires a large volume of samples, which is associated with generally fuzzy partitioning of the feature space into recognition classes. A significant drawback of artificial neural networks is the dependence of machine learning time on the power of the feature dictionary and the recognition class alphabet. To reduce the impact of the multidimensionality of the recognition feature space, papers [12, 13] propose using neural-like extractors designed to compress input data. In this case, there is usually a risk of information loss.

A viable strategy for advancing the functional efficiency of machine learning is the construction of decision rules within a geometric approach. One such example is the support vector method [14, 15]. Challenges arise in implementing this method when there is a significant overlap between recognition classes in the feature space, which is typical in EMG signal recognition. Therefore, despite numerous research efforts aimed at enhancing intelligent prostheses, their functional efficiency remains relatively low due to the complexities of a scientific and methodological nature. These complexities are primarily attributed to arbitrary initial conditions in forming EMG signals, substantial intersections in the feature space of recognition classes, and the multidimensionality of the feature space and the recognition class alphabet.

A promising avenue for enhancing the functional efficiency of intelligent prostheses is the utilization of ideas and methods from the information-extreme intelligence (IEI) data analysis technology. This approach maximizes the system's information capacity during machine learning [16]. The primary set of theories of information-extreme machine learning, akin to neural-like structures, involves adapting the system's input information description to boost the probability of correct classification decisions. However, unlike neural-like structures, the decision rules derived from optimal geometric parameters of radial basis separation functions obtained during machine learning are practically unaffected by the multidimensional nature of the recognition feature space regarding information understanding.

In the paper [17], information-extreme machine learning of the hand prosthesis control system was considered for a limited number of movements. Simultaneously, the research revealed that the accuracy of machine learning with a linear data structure significantly decreases as the number of recognition classes increases. This phenomenon is attributed to the growth in the number of recognition classes leading to an increase in their intersection degree in the feature space with its unchanged dimension.

The article aims to enhance the functional efficiency of an intelligent, non-invasive hand prosthesis by using information-extreme machine learning for an EMG signal recognition system, employing a hierarchical data arrangement organized as a decursive binary tree.

3 Research Methodology

3.1 Statement of the research task

Let there be given an alphabet $\{X_m^o | m = \overline{1, M}\}$ of recognition classes, which characterize EMG signals of permissible movements of the prosthesis, and the corresponding training matrix of the 'object-property' type $\| y_{m,i}^{(j)} \mid j = \overline{1, J_{\max}}; i = \overline{1, N} \|$, where J_{max} is the number of structured feature vectors (hereinafter referred to as the realization) of recognition classes; N is the number of recognition features.

In the process of machine learning for the control system of a non-invasive prosthesis for EMG signal recognition within an information-extreme framework, it is necessary to do the following:

1) construct a decursive binary tree-based hierarchical data structure for the provided set of recognition classes:

$$\{X_{m_s,s,h}^o | m_s = \overline{1,2}; s = \overline{1, S_h}, h = \overline{1, h_{max}},$$

where $X_{m_s,s,h}^o$ represents the m_s recognition class of the s-th layer of the h-th level of the decursive tree; S_h is the number of layers in the h-th level.

2) the optimization of machine learning parameters in the Hamming feature space should be carried out according to the concept of IEI technology. Therefore, let's assume, for example, that the machine learning parameters for the recognition class $X^o_{m_s,s,h}$ are represented as a structured vector:

$$g_{s,h} =< x_{m_s,s,h}: d_{m_s,s,h};, \delta_{s,h} >, \qquad (1)$$

where $x_{m_s,s,h}$ is the mean realization of the recognition class $X^o_{m_s,s,h}$; $d_{m_s,s,h}$ is the radius of the hyperspherical container encompassing the recognition class $X^o_{m_s,s,h}$, restored throughout machine learning in the Hamming space radial basis; $\delta_{s,h}$ is a parameter with a value that equals half the symmetric field of control tolerance boundaries for recognition features.

Definition 1. A control field of tolerance is defined as a field in which the i-th feature of the base recognition class is found with a probability of $0 < p_i < 1$.

The number of optimization parameters in expression (1) defines the second level of depth in information-extreme machine learning as a vector $x_{m_s,s,h}$ that depends on the parameter $\delta_{s,h}$ of the control tolerance field.

The machine learning parameters are subject to the following constraints:

a) $d_{h,s,m_s} \in [0; d(x_{m_s,s,h} \oplus x_{c,s,h})]$, $d(x_{m_s,s,h} \oplus x_{c,s,h})$ is the midcenter distance of the mean feature vector $x_{m_s,s,h}$ and a similar vector $x_{c,s,h}$ of the nearest neighboring class $X^o_{c,,s,h}$;

b) $\delta_{s,h} \in [0; \delta_H/2]$, where δ_H is the normalized tolerance range for recognition features, setting the range of control tolerance values.

Definition 2. A normalized field of tolerance is defined as a field in which the i-th feature of the base recognition class is found with a probability of $p_i = 1$ or $p_i = 0$.

3) optimize the parameters of vector (1) by searching for the global maximum of the information criterion averaged over the alphabet of recognition classes of the s-th stratum of the h-th level in the working range of its function definition:

$$\overline{E}_{s,h,} = \frac{1}{2}\sum_{m_s=1}^{2} \max_{G_E \cap G_d} E_{m_s,s,h}(d), \qquad (2)$$

where $E_{m_s,s,h}(d)$ is the value of the information criterion calculated for the current radius d of the recognition class container $X^o_{m_s,s,h}$; G_E is the working domain of the information criterion; G_d is the permissible set of values for the radii of the recognition class containers.

4) construct highly reliable decision rules based on the optimal (hereinafter referred to in the informational sense) geometric parameters of the recognition class containers obtained during the machine learning.

5) validate the efficiency and performance metrics of the machine learning and decide on the membership of the recognized EMG signal to one of the recognition classes of the recognition classes set $\{X^o_m\}$ at the examination stage.

Thus, the synthesizing information task for a learning-capable hand prosthesis control system involves adjusting the machine learning parameters for optimal performance (1) by approximating the global peak value of the evaluation metric (2) to its highest boundary value.

3.2 The functional categorical model of machine learning

The functional categorical model (FCM) of information-extremal learning of the recognition system is represented as a directed graph, with the edges being operators mapping sets involved in the machine learning process. At the same time, the mathematical formulation for FCM input is depicted as a structure:

$$I =< W, T, \Omega, Z, Y^{|M|}, H, \{Y^{|2|}_{s,h}\}, \{X^{|2|}_{s,h}\}; f_1, f_2, f_3, f_4 >,$$

where W is the set of factors influencing the EM biosignal recognition system; T is the set of time moments for information acquisition; Ω is the feature space of recognition; Z is the alphabet of recognition classes; $Y^{|M|}$ is input (Euclidean) training matrix; H is a hierarchical arrangement in the shape of a recursive binary tree; $\{Y^{|2|}_{s,h}\}$ is a set of input training matrices of recognition classes of the s-th layer of the h-th level of the decursive tree; $\{X^{|2|}_{s,h}\}$ is the binary training matrix of the s-th layer of the h-th level of the decursive tree; f_1 is the operator for forming the input training matrix $Y^{|M|}$; f_2 is the operator for constructing the decursive binary tree; f_3 is the operator for forming the set of input training matrices $\{Y^{|2|}_{s,h}\}$; f_4 is the operator for forming the set of binary training matrices $\{X^{|2|}_{s,h}\}$.

The functional categorical model of information-extremal machine learning for the hand prosthesis control system, based on the hierarchical data structure in the form of a recursive binary tree, is shown in Figure 1.

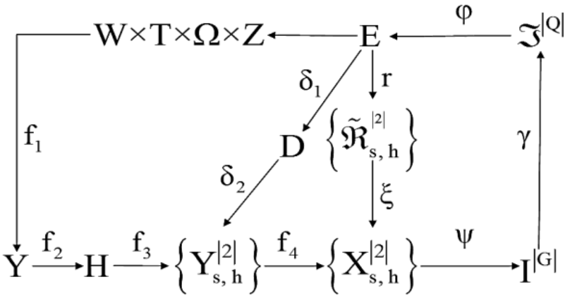

Figure 1 – The functional categorical model of hierarchical information-extremal machine learning for the EMG signal recognition system

In Figure 1, the following notations are used: E is the set of values of the information criterion applied to optimize machine learning parameters; r is the operator for constructing the generally fuzzy partition of the recognition classes $\{\tilde{\Re}^{|2|}_{s,h}\}$ in the s-th stratum of the h-th level of the decursive tree; ξ is the operator for mapping the partition $\{\tilde{\Re}^{|2|}_{s,h}\}$ to the distribution of binary vector realizations of the training matrices $\{X_{s,h}^{|2|}\}$; ψ is the classification operator that tests the main statistical assumption about the classification of realizations into their respective recognition classes and forms the set of statistical hypotheses $I^{|G|}$, where G is the number of statistical hypotheses; γ is the operator for forming the set of accuracy characteristics $\mathfrak{I}^{|Q|}$, where $Q = G^2$; ϕ is the operator for calculating the information criterion E.

The optimization loop for control tolerances on recognition features includes the term set D of control tolerance values for recognition features. Meanwhile, the operator δ_1 changes the parameter $\delta_{s,h}$ of the control tolerance field for recognition features for each stratum and the operator δ_2 forms the control tolerance field for recognition features of the training matrices $\{Y_{s,h}^{|2|}\}$. The operator u regulates the machine learning process.

The considered functional categorical model has two optimization loops, which respectively determine the second level of depth in the information-extreme machine learning. Suppose there is a need to increase the depth level. In that case, the functional categorical model will have additional optimization loops for the respective machine learning parameters, provided that the term set E, according to the principle of complete composition, is inherent to all iterative optimization procedures.

3.3 Description of the algorithm

Based on the functional categorical model (Figure 1), the scheme for a hierarchical framework for machine learning of the EMG signal recognition system using a recursive binary data structure is presented as a two-cyclic iterative process for fine-tuning the parameter $\delta_{s,h}$ of the control tolerance field for recognition features by searching for the ultimate peak of the performance metric (2) within the working range of its function:

$$\delta_{s,h}^{*} = arg \max_{G_\delta} \left[\frac{1}{2}\sum_{m_s=1}^{2} \max_{G_E \cap \{d\}} E_{m_s,s,h}(d)\right], \qquad (3)$$

where $E_{m_s,s,h}(d)$ is the value of the optimization information criterion computed at the current radius of the recognition class container $X_{m_s,s,h}^{o}$; G_δ is the domain of permissible values for the parameter of the control tolerance field for recognition features; G_E is the working domain for the information criterion function (2); $\{d\}$ is the ordered set of values for the radii of the recognition class containers. Consider the algorithm scheme for information-extreme machine learning of the EMG signal recognition system according to procedure (3) with parallel optimization of control tolerances for recognition features, where the parameter $\delta_{s,h}$ of the control tolerance field changes simultaneously for all features. At the same time, the input data are a three-dimensional array of the input training matrix $\{y_{m_s,s,h;j,i}\}$ for the given alphabet $\{X_{m_s,s,h}^{o}\}$ of recognition classes and the normalized field δ_H of control tolerances for recognition features.

The main stages of hierarchical information-extreme machine learning are the formation of an ordered variational series of recognition classes, construction of a hierarchical arrangement in the shape of a recursive binary tree, optimization of the machine learning parameters of a given depth level using the two-cycle procedure (3) for each stratum of the decursive tree, construction of decision rules for each stratum of the decursive tree relying on best-fit geometric parameters of the recognition class containers acquired during machine learning, functional testing to verify the error-free performance of the decision rules using the training sample, and verification of the functional efficiency of machine learning in the examination mode.

The algorithm for forming a variation series of recognition classes has the following stages:

1) for any recognition class X_m^o in the Euclidean feature space, find the nearest neighboring recognition class X_c^o;

2) remove recognition class X_m^o from the alphabet, and for recognition class X_c^o from the residual alphabet, find the nearest neighbor;

3) remove recognition class X_c^o from the alphabet, and continue the process to determine all nearest neighbors from the specified alphabet of recognition classes.

Thus, the variation series is formed in increasing order relative to the chosen recognition class by interclass distance for the given alphabet.

The construction of the decursive binary tree is carried out according to the following scheme:

1) the alphabet $\{X_m^o | m = \overline{1,M}\}$ of ordered recognition classes is divided into two groups, which respectively determine the two branches of the decursive binary tree;

2) as attributes of the vertices of the upper (first according to the dendrographic classification) tier of the decursive binary tree, the training matrices of the boundary recognition classes of each group are chosen;

3) the attributes of the stratum of the upper tier are transferred to the vertices of the corresponding strata of the lower tier;

4) the strata of the lower tiers of each branch of the tree contain, in addition to the training matrix transported from the upper tier, the training matrix of the nearest neighboring recognition class within its group;

5) the construction of the tree continues until the final strata are formed, which contain the training matrices of all recognition classes.

Thus, the decursive binary tree constructed according to the above scheme divides the given alphabet of recognition classes into strata, each containing two nearest neighboring classes. This allows for applying a linear algorithm of information-extreme two-class machine learning to each final stratum. Suppose the constructed decision rules do not ensure error-free recognition of the realizations from the training matrix. In that case, it is necessary to advance the complexity of machine learning by fine-tuning supplementary parameters of the recognition system's functioning according to the deferred decision principle. The machine learning algorithm according to procedure (3) is implemented as follows:

1) the recognition class counter is reset: $m_s := 0$;

2) the recognition class counter is initialized: $m_s := m_s + 1$;

3) the counter for the steps to change the tolerance field parameter is reset: $\delta_{s,h} := 0$;

4) $\delta_{s,h} := \delta_{s,h} + 1$;

5) the counter for the steps to change the container radii of the recognition classes is reset: $d_{m_s,s,h} := 0$;

6) $d_{m_s,s,h} := d_{m_s,s,h} + 1$;

7) for the array $\{y_{m_s,s,h;j,i}\}$, the averaged feature vector of recognition $\overline{y}_{m_s}$ is determined;

8) for each i-th feature of the vector $\overline{y}_{m_s}$, the lower $A_{HK,i}$ and upper $A_{BK,i}$ tolerance limits are calculated using the following formulas:

$$A_{HK,i} = \overline{y}_{m_s,i} - \delta;\ A_{BK,i} = \overline{y}_{m_s,i} + \delta, \qquad (4)$$

where $\overline{y}_{m_s,i}$ is the value of the i-th parameter of the mean vector $\overline{y}_{m_s}$ of the recognition class $X^o_{m_s,s,h}$;

9) a three-dimensional array of the binary training matrix $\{x_{m_s,s,h;j,i}\}$ is formed, the elements of which are calculated by the rule:

$$x_{m_s,j,i} = \begin{cases} 1, if A_{HK,i} < y_{m_s,j,i} < A_{BK,i}; \\ 0, if else; \end{cases}$$

10) for the array $\{x_{m_s,s,h;j,i}\}$, the averaged vector $\overline{x}_{m_s}$ is determined;

11) the information criterion (2) for optimizing the machine learning parameters is calculated for the training matrices of the recognition classes of the s-th stratum of the h-th level of the decursive tree with the identification of the working domain of its function definition;

12) if $d_{s,h} < d(\overline{x}_{m_s} \oplus \overline{x}_{m_c})$, then step 6 is performed, otherwise, step 11;

13) if $m_s \leq 2$, then step 2 is performed, otherwise, step 12;

14) in the working domain G_E of the criterion function (2), its maximum value, and, accordingly, the optimal values of the parameter $\delta^*_{s,h}$ and the container radii of the recognition classes of the s-th stratum of the h-th level of the decursive tree are calculated;

15) according to the formula (4), the optimal lower $A^*_{HK,i}$ and upper $A^*_{BK,i}$ tolerance limits for the recognition features are calculated;

16) Stop.

As the criterion for optimization of the machine learning parameters, the modified Kullback-Leibler information measure will be considered in the form:

$$E_{m_s,s,h}(d) = \frac{1}{n_{\min}}\{K_{1,m_s,s,h}(d) - K_{2,m_s,s,h}(d)\} \times \\ \times \log_2\left\{\frac{n_{\min} + K_{1,m_s,s,h}(d) - K_{2,m_s,s,h}(d) + 10^{-\lambda}}{n_{\min} - K_{1,m_s,s,h}(d) + K_{2,m_s,s,h}(d) + 10^{-\lambda}}\right\}, \qquad (5)$$

where $K_{1,m_s,s,h}(d)$ is the number of realizations of the recognition class $X^o_{m_s,s,h}$ correctly classified at the current container radius; $K_{2,m_s,s,h}(d)$ is the number of realizations of the nearest neighbor class erroneously classified as the recognition class $X^o_{m_s,s,h}$; $n_{\min}$ is the minimum volume of the representative training sample.

The normalized form of the information criterion is represented as the ratio of criterion (5) to its maximum value, which it takes at the values of $K_{1,m_s,s,h}(d) = n_{min}$ and $K_{2,m_s,s,h}(d) = 0$.

Based on the optimal geometric dimensions of the recognition class enclosures obtained during machine learning, decision rules are constructed to recognize EMG signals in functional testing and examination modes. If the results of the tests confirm the high reliability and efficiency of the decision rules, they are stored in the control system's memory and used in operational mode.

For the hyperspherical classifier, the production decision rules may be described as:

$$(\forall X^o_{m_s,s,h} \in \Re^{|2|}_{s,h})(\forall x_e \in \Re^{|2|}_{s,h}) \begin{bmatrix} if\,[(\mu_m > 0)\,\& \\ \&\,(\mu_{m_s,s,h} = \max_{\{m_s\}}\{\mu_{m_s s,h}\})]\; then \\ x_e \in X^o_{m_s,s,h}\; else\; x_e \notin X^o_{m_s,s,h} \end{bmatrix}, \qquad (6)$$

where x_e is the examination realization being recognized; $\mu_{m_s,s,h}$ is the membership function of realization x_e to recognition class $X^o_{m_s,s,h}$.

For the hyperspherical classifier, the membership function $\mu_{m_s,s,h}$ is defined as follows:

$$\mu_{m_s,s,h} = 1 - \frac{d(x_e \oplus x^*_{m_s,s,h})}{d^*_{m_s,s,h}}, \qquad (7)$$

where $d(x_e \oplus x_{m_s,s,h})$ is the Hamming distance between realization x_e and the optimal averaged realization $x^*_{m_s,s,h}$ of recognition class $X^o_{m_s,s,h}$; $d^*_{m_s,s,h}$ is the most effective radius for the recognition class $X^o_{m_s,s,h}$.

4 Results

The application of the process described above was carried out using machine learning for recognizing cognitive command EMG signals for performing seven hand movements. An alphabet of recognition classes was formed to characterize the following stages:

1) fist flexion (recognition class X^o_1);

2) radiocarpal joint's flexion (recognition class X^o_2);

3) radiocarpal joint's extension (recognition class X^o_3);

4) pinch of the index and thumb (recognition class X^o_4);

5) middle and thumb pinch (recognition class X^o_5);

6) pinch of the ring and thumb (recognition class X^o_6);

7) little finger and thumb pinch (recognition class X^o_7).

For the given alphabet of recognition classes, a variation series is formed by increasing the intercentroid distance from the recognition class X^o_1:

$$< X^o_1, X^o_4, X^o_6, X^o_5, X^o_7, X^o_3, X^o_2 >. \qquad (8)$$

For the variation series (8), a decursive binary tree is constructed using the above algorithm (Figure 2).

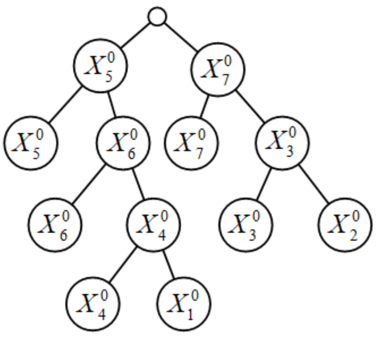

Figure 2 – Decursive binary tree

For each layer of the decursive tree, a two-class informational-extremal machine learning with optimization of control tolerances on recognition features is implemented according to procedure (3).

Figure 3 shows graphs of the normalized information criterion (5) dependence on the parameter of the field of control tolerances $\delta_{s,h}$ on features of recognition classes for layers of the decursive tree. At the same time, the numbering of the tree levels is carried out according to the dendrographic classification from top to bottom. The graphs indicate the working (admissible) domain of determination of the information criterion function, in which the reliabilities for the 1st and 2nd two-alternative decisions exceed the respective 1st and 2nd-type errors.

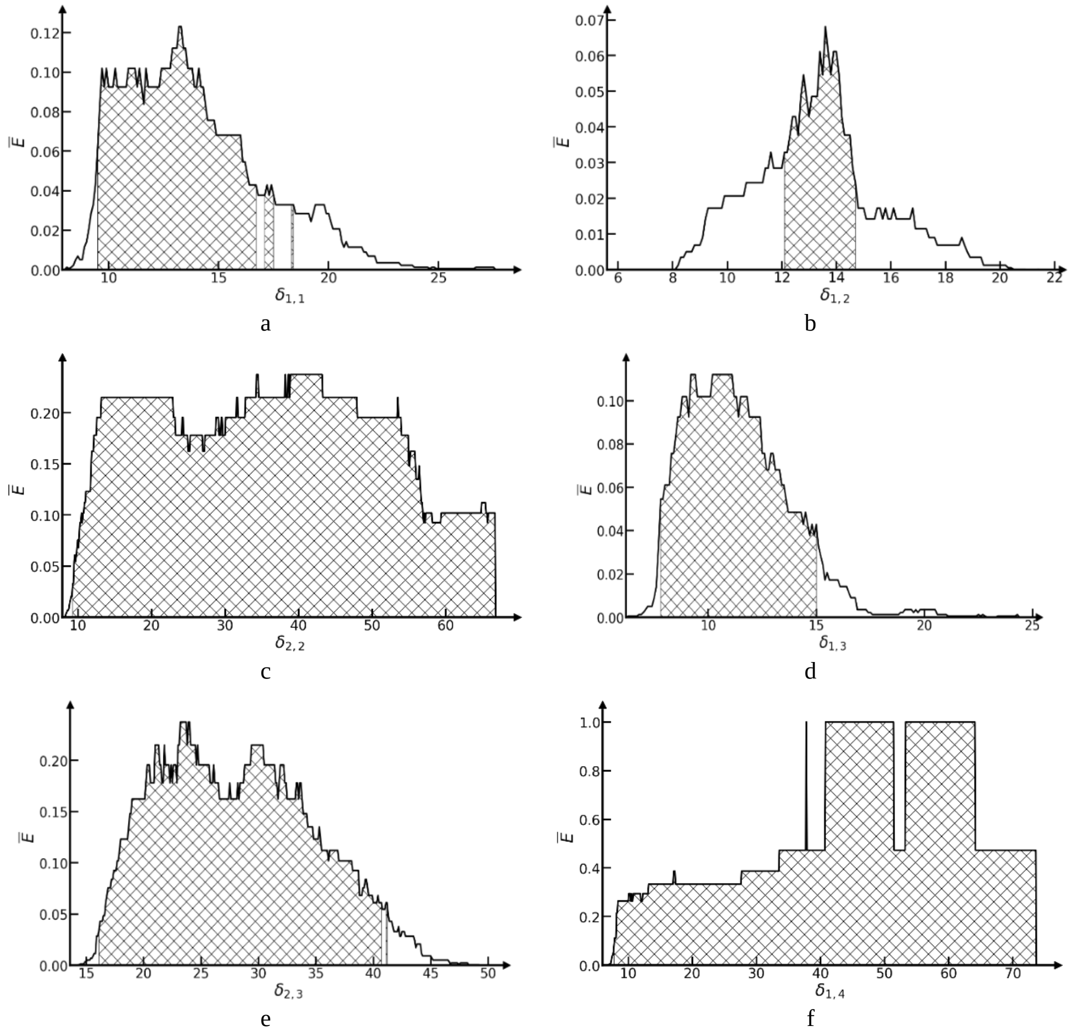

Figure 3 – The effect of the control tolerance field parameter on criterion (5) for the recognition feature:
a – 1st-layer stratum; b – 1st stratum of the 2nd layer; c – 2nd stratum of the 2nd layer;
d – 1st stratum of the 3rd layer; e – 2nd stratum of the 3rd layer; f – 4th layer stratum

On graphs 3c and 3f, the maximum values of the criterion are located on segments of the graph of the "plateau" type. In this case, to determine the optimal parameter, the minimal-distance coefficient is used:

$$MDK = \frac{d_m}{d(x_m \oplus x_c)}, \qquad (9)$$

where $d(x_m \oplus x_c)$ is the code distance between the geometric centers of the nearest neighboring recognition classes X_m^o and X_c^o, respectively.

Given the minimum value of the coefficient (9), the optimal parameters of the control tolerance field for recognition features are equal to $\delta_{1,1}^* = 14$ (hereinafter considered value in mV), $\delta_{1,2}^{*} = 13$, $\delta_{2,2}^{*} = 39$, $\delta_{1,3}^{*} = 10$, $\delta_{2,3}^{*} = 24$ and $\delta_{1,4}^{*} = 43$.

To form the decision rules (6), it is vital to ascertain the best-fit geometry of the recognition class containers.

Figure 4 shows graphs depicting the correlation between the normalized informational criterion (5) and the radii of the containers for the recognition classes of the first stratum of the first tier.

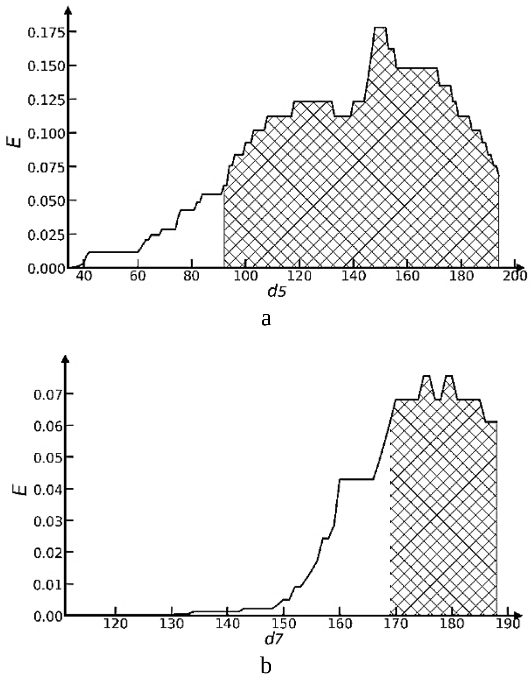

Figure 4 – Graphs displaying the effect of the radii of the containers on the criterion (5): a – recognition class X_5^o; b – recognition class X_7^o

In the process of information-extreme machine learning, the following optimal radii of containers of recognition classes were obtained: $d_5^* = 152$ (hereinafter in code units) for the recognition class X_5^o; $d_7^* = 175$ for the recognition class X_7^o; $d_6^* = 18$ for the recognition class X_6^o; $d_3^* = 204$ for the recognition class X_3^o; $d_4^* = 50$ for the recognition class X_4^o; $d_2^* = 175$ for recognition class X_2^o and $d_1^* = 159$ for recognition class X_1^o.

During functional testing according to the received decisive rules, the total probability of correct decision-making was equal to $P_t = 0.76$. Thus, according to the modern classification of the accuracy of machine learning, it can be considered an acceptable result.

5 Discussion

An analysis of Figure 3 demonstrates that all recognition classes exhibit operational regions, indicating their distinguishability within the feature space of recognition. Simultaneously, the evaluation metric's comparatively low value suggests some overlap among classification categories within feature space. Notably, the recognition classes of the fourth stratum (Figure 3f) achieve complete separability. This is evidenced by the normalized information criterion reaching its maximum boundary value at the optimal parameter of control bounds.

When determining the optimal container radii, it is crucial to consider that recognition class parameters, excluding extreme values in the variation series, undergo optimization twice with different neighbors. Therefore, according to the minimum-distance principle of pattern recognition theory, the minimum optimal code value for the radius of the hyperspherical container should be selected for decision rules. Additionally, when extreme radius values fall within plateau-like areas, the minimal radius value is also optimally chosen according to the same principle.

To enhance the accuracy of machine learning, increasing its depth through the optimization of additional parameters of the EMG signal recognition system is imperative. These optimization parameters may include the formation parameters of the system's input mathematical description. For example, in the study [18], a method of information-extreme machine learning with optimization of the level of EMG signal quantization was discussed. Such an approach enables the formation of a "sparse" training matrix, thereby augmenting the average interclass distance for a priori fuzzy classification of recognition classes. The ultimate objective of further refining the outlined procedure of hierarchical information-extreme machine learning for EMG signal recognition systems is to construct error-free decision rules independent of the implementations of the training matrix.

The practical aspect of implementing the research results lies in personalizing the input data for the EMG signal recognition system, considering both the anthropological and psychosomatic characteristics of individuals with disabilities. A promising approach to achieving this involves creating a mobile application that enables individuals with disabilities to configure input data by capturing biosignals from an EMG sensor located on their unaffected arm. To verify the consistency of this input with actual EMG signals from sensors on the affected arm, a proportionality coefficient will be calculated based on the discrete values of biosignals analyzed by the recognition system from both sources.

6 Conclusions

A functional categorical model for extreme information machine learning is proposed to recognize EMG signals, utilizing a hierarchical data structure known as a decursive binary tree. This model's construction scheme allows for partitioning a large-capacity recognition class alphabet into pairs of nearest neighbors. This facilitates a transition from multi-class to two-class machine learning for each layer of the decursive binary tree, thereby improving machine learning accuracy.

Based on this functional model, an algorithm for hierarchical extreme information machine learning of EMG signal recognition systems has been developed and implemented. The algorithm targets seven hand-bone movements with a depth level of two. Computer modeling results demonstrate that fuzzy separability has been achieved for all recognition classes within the feature space at the specified depth level. However, it is noted that the constructed decision rules may not be error-free due to the averaged values of the information criterion across the tree's layers not reaching their maximum boundary value.

To enhance the accuracy of machine learning, further research is needed to increase the depth of the model by optimizing additional parameters of the recognition system's operation.

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