Hierarchical Clustering Approach for Information-Extreme Machine Learning of Hand Brush Prosthesis

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Abstract

The article discusses a machine learning method for a control system for a hand limb prosthesis with a non-invasive biosignal reading system, which operates in the mode of agglomerative hierarchical clustering of electromyographic data. The method was developed within the framework of information-extreme intelligent data analysis technology, which is based on maximizing the information capacity of the system in the process of machine learning. In contrast to the existing methods of data mining, the method of information-extreme machine learning is developed as part of a functional approach to modeling cognitive processes inherent in human formation and decision-making. This approach makes it possible to endow the prosthesis control system with the properties of adaptability to arbitrary conditions for the formation of input signals and flexibility in retraining the system due to the expansion of the alphabet of recognition classes. In addition, the decision rules based on the geometric parameters of the hyperspherical containers of the recognition classes obtained in the process of machine learning are invariant to the multidimensionality in the feature space. Based on the proposed categorical model, a machine learning algorithm using an agglomerative hierarchical data structure has been developed. As a criterion for optimizing the parameters of machine learning, a modification of the Kullback information measure is used, which is a functional of the exact characteristics of classification decisions. The results of physical modeling confirm the high functional efficiency for the proposed hierarchical information-extreme machine learning method of the hand with a non-invasive system for reading biosignals prosthesis control system.

Keywords 1

information-extreme intellectual technology, hierarchial clustering, machine learning, information criterion, control system, prosthesis, electromyographic sensor

1. Introduction

In recent decades, research interest in intelligent prostheses has grown significantly. Prosthetics is currently considered not only as a visual masking of damaged limbs, but as an opportunity to effectively compensate lost limb functions. Thus, in addition to performing movements, modern prostheses are able to respond to the force of muscle compression and provide feedback to the muscles about the movements performed [1,2]. In addition, predictions of movements are a popular trend in the development of intelligent prostheses: according to the signatures of signals from the muscles, the prosthesis will determine the necessary force and perform finger movements to implement the gesture in real time [3-6].

High-quality signal recognition is required for prosthesis control programs, but in human-computer interfaces there is often a trade-off between stability and variety of gestures. Increasing the alphabet of classes complicates recognition primarily by increasing the intersection in the space of recognition

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classes features. In [7], a solution to the problem of classes intersection by proposing complex movements as a combination of several simple movements is proposed.

However, studies [8,9] point out that multidimensionality increases the set of features and this causes errors in the recognition of movements from one muscle or muscles belonging to one local group. Thus, in a machine learning experiment of a system with 50 classes of different gestures, a significant increase in the size of the alphabet of classes reduced the quality of recognition to values less than 2%[10]. The explanation for this problem is that the increase in sets of recognition features makes it difficult to recognize signals from known discrete patterns. Hence the problem of neural networks regarding false positive recognition [11,12].

As an alternative solution to the problem of multidimensionality, consider the so-called information-extreme intelligent data analysis technology, which is based on a geometric approach to the construction of class containers [13,14]. The information-extreme approach to the formation of decision rules[15,16] is characterized by the adaptation of the input mathematical description of the system to maximize the reliability of system recognition and, in contrast to neurosimilar systems, invariance to the multidimensionality of the dictionary.

In order to reduce the influence of the classes intersection in the recognition features space, according to the idea of clustering signals [17–20], the space of features is decomposed into smaller subspaces, forming an agglomerative hierarchical structure [21–23].

The article deals with information-extremal machine learning of a control system for a hand prosthesis with a non-invasive biosignal reading system with optimization of a hierarchical data structure.

2. Methods

The basis of machine learning methods in the framework of IEI-technology as well as neural networks methods is built on the same paradigm, which leads to adapting the input mathematical description of the recognition system and maximizing full probability of making the correct classification decisions. In contrast to neura-similar methods, information-extreme machine learning technology is formed within the framework of a functional approach of modeling the cognitive processes of natural intelligence in the processes of formation and adoption of classification decisions. This approach allows recognition system to get the properties of adaptability to initial conditions of signal formation and flexibility in retraining the system through the expansion data sets of the alphabet of recognition classes.

Within the IEI-technology framework [24], the solution to the information synthesis problem of the control system for a hand limb prosthesis is to maximize the information capacity of the system, which determines the reliability of classification decisions. Consider a formalized formulation of the information synthesis problem of a learning-capable prosthesis control system. Let each recognition class characterize the biosignal that is registered by the electromyographic sensor when executing the appropriate cognitive command. Hierarchical structure of the alphabet of recognition classes, which has the form $\{X^0_{h,s,m} \mid h = \overline{1,H},\ s = \overline{1,S}, m = \overline{1,M}\}$, represented by three-dimensional learning matrices $||y^{(j)}_{h,s,m,i}||, i = \overline{1,N}, j = \overline{1,n}||$, formed from UCI Machine Learning Repository database signals [25,26].

Since the controlled process is poorly formalized due to arbitrary conditions of image formation, the categorical model of information-extreme learning of the control system [27] will be considered in the form of a generalized oriented graph in which the edge characterizes the mapping operator. The input mathematical description is given in the form of a structure

$$I_B = < G, T, \Omega, Z, H, Y, X, f_1, f_2 >.$$

Fig. 1 shows a categorical model of information-extreme machine learning of the prosthesis control system of the limb with hierarchical structure optimization of the recognition classes alphabet.

$$
\begin{tikzcd}
 & & \boldsymbol{E} \arrow[ddll, rounded corners, to path={-| (\tikztotarget)}, "u"'] \arrow[dl, "h_1"'] \arrow[d, "\xi"'] & \mathfrak{I}^{|Q|} \arrow[l, "\varphi"'] \\
 & P \arrow[dl, "h_2"'] & \tilde{\mathfrak{R}}^{|M|} \arrow[d, "\theta"'] & \\
\mathbf{G \times T \times \Omega \times Z \times H} \arrow[r, "f_1"] & \mathbf{Y} \arrow[r, "f_2"] & X \arrow[r, "\psi"] & I^{|L|} \arrow[uu, "\gamma"]
\end{tikzcd}
$$

Figure 1: Categorical machine learning model

In fig. 1 Cartesian product $G \times T \times \Omega \times Z \times H$ specifies the test universe, which is the source of information. The term set E of the values of the information criterion for optimizing the parameters of machine learning is common to all optimization circuits. The operator ξ at each step of machine learning restores in the radial basis of the feature space containers of recognition classes, which in the general case form a fuzzy partition $\tilde{\mathfrak{R}}^{|M|}$. The operator θ projects the constructed partition $\tilde{\mathfrak{R}}^{|M|}$ on the distribution of binary feature vectors of the binary training matrix X, and the operator ψ tests the basic statistical hypothesis about the belonging of feature vectors to the corresponding recognition class. According to the results of hypotheses statistical testing, a statistical hypotheses set $I^{|L|}$ is formed, and the operator γ forms a set of accuracy characteristics $\mathfrak{I}^{|Q|}$, where $Q = L^2$. The operator φ calculates the set E of the information criterion values for optimizing the parameters of machine learning. In the categorical model, the contour of optimization of control tolerances for recognition features is closed through the term set D – a system of control tolerances, which are used as levels of quantization of recognition features in the formation of a working binary training matrix. The presence of a binary training matrix allows by quantizing the level of recognition features to adapt the input mathematical description to the maximum reliability of classification solutions. In addition, the categorical model has an additional optimization loop for the hierarchical data structure P, the vertices of which contain the attributes of the recognition classes from a given alphabet as seen from their training matrices.

According to the categorical model (Fig. 1), the machine learning algorithm of the prosthesis control system with optimization of the structure will be presented in the form of a procedure

$$P^* = \arg\max_{G_P}\{\max_{G_{R\cap\{s\}}} \bar{E}_s\}\}, \tag{1}$$

Consider the main stages of realization of the algorithm for optimizing the agglomerative hierarchical structure of data in the process of machine learning.

1. Resetting the counter of hierarchical structures variants (learning steps): $r := 0$.
2. Initialization the counter of hierarchical structures variants: $r := r + 1$.
3. Resetting the tier counter of the data structure: $h := 0$.
4. Initialization the tier counter of the data structure: $h := h + 1$.
5. Resetting the tier counter: $s := 0$.
6. Initialization the tier stratum counter: $s := s + 1$.
7. For each s-th stratum of the h-th tier of the r-th hierarchical structure the basic algorithm of information-extreme machine learning is implemented, which implements the categorical model right contour operators (Fig. 1). In order to optimize the geometric parameters all final strata of information criterion $\bar{E}^*_{r,h,s}$.
8. According to the formed parameters of containers the intercenter distances $D(X_1^0, X_2^0)$ are calculated. The matrix of distances $\acute{D}$ is formed.
9. If $s \le S_h$, then paragraph 6, is fulfilled, otherwise – paragraph 10.
10. If $h \le h_{\max}$, where $h_{\max}$ is the number of tiers of the r-th data structure, then paragraph 4 is fulfilled, otherwise – paragraph 11.
11. For the closest pair of classes $\min D(X_i^0, X_j^0)$ a metacluster is formed, which implements the logic of a new container of class (Fig. 2). The metaclass receives the realizations of both

classes as its own, the center of the metaclass becomes the average value of the centers of its inner classes.

12. The maximum value of the information criterion of optimization averaged over the final strata $\bar{E}^{*}_{r,h}$ is calculated.
13. If $r \le r_{\max}$, where $r_{\max}$ is the number of hierarchical data structures, then paragraph 2 is fulfilled, otherwise – paragraph 12.
14. Determines the optimal hierarchical data structure according to procedure (1), shown in Figure 2.

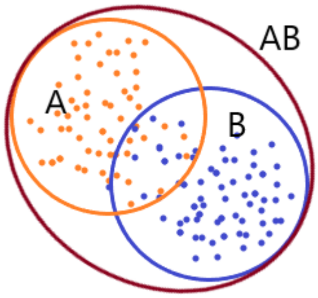


Figure 2: Schematic formation of a metacluster AB = AUB

Descriptions of the machine learning algorithm for realizing the logic of the message for the new hierarchical structures of the global maximum information criterion

$$\bar{E}_{\max} = \frac{1}{S_f} \sum_{s=1}^{Sf} E_{\max}^{(s)}. \qquad (2)$$

As an example of the realization of the above algorithm, consider machine learning control system of the limb prosthesis for the alphabet of six recognition classes: class X_1^0 – cylindrical grasp, class X_2^0 – hook grasp, class X_3^0 – lateral grasp, class X_4^0 – palmar grasp, class X_5^0 – spherical grasp, class X_6^0 – tip.

The structured vector-realization of one recognition class consisted of 3000 recognition features, which were equal to the discrete values of biosignals sequentially recorded from electromyographic sensors.

During the information-extreme machine learning of the prosthesis control system, the division of the feature space into subspaces was studied, according to the hierarchical structure of the classes. The closest greedy pair of classes formed a metacluster $X_7^0 = X_3^0 \cup X_4^0$, which will represent this pair in the future. This metacluster will be used as the inner class of a larger metacluster $X_9^0 = X_7^0 \cup X_6^0$. According to the logic of agglomerative hierarchical clustering, binary hierarchical structures were formed from the alphabet of classes, according to which the geometric parameters of pairs of recognition classes were optimized. In this case, the training matrix of the optimal recognition class was removed from the input training matrix. Then, the parameters of the recognition class pairs that remained in the alphabet were similarly optimized.

As a criterion for optimizing the parameters of machine learning of the prosthesis control system, a modified Kullback measure was used, which for two alternative a priori equally probable hypotheses has the form

$$E_{h,s,m}^{(k)}(d) = \frac{1}{n}\left\{n - \left[K_{1,h,s,m}^{(k)}(d) + K_{2,h,s,m}^{(k)}(d)\right]\right\} \log_2 \frac{2n - \left[K_{1,h,s,m}^{(k)}(d) + K_{2,h,s,m}^{(k)}(d)\right] + 10^{-s}}{\left[K_{1,h,s,m}^{(k)}(d) + K_{2,h,s,m}^{(k)}(d)\right] + 10^{-s}}, \qquad (3)$$

where $K_{1,h,s,m}^{(k)}(d)$ – amount of events when realizations of recognition class $X_{h,s,m}^0$ do not belong to its class; $K_{2,h,s,m}^{(k)}(d)$– amount of events when "foreign" realizations wrong belonged to recognition class $X_{h,s,m}^0$; d – the radius of the hyperspherical container of the recognition class $X_{h,s,m}^0$; n– the volume of a representative training sample; 10^{-s} – a small enough number to avoid division by zero ($1 < s \leq 3$).

Criterion (3) was calculated at a training sample size of n = 3000 and p = 2. At these values, the maximum value of the criterion is 4,39.

The scheme of partitioning the recognition classes is explained by the agglomerative data structure for a given alphabet, shown in Fig. 3.

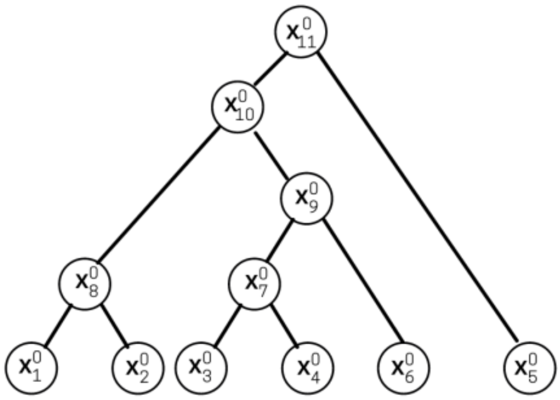


Figure 3: Diagram of the division of recognition classes in a hierarchical structure

According to the optimal geometric parameters of training obtained in the process of machine learning, decision rules for making classification decisions in the operation of the control system directly in the operating mode are constructed. For hyperspherical containers of recognition classes, the decision rules have the form

$$\left(\forall X_m^0 \in \Re^{|M|}\right)\left(\mathrm{x}^{(j)} \in \Re^{|M|}\right)[\text{if } (\mu_m > 0)\&(\mu_m > \mu_c) \text{ then } \mathrm{x}^{(j)} \in X_m^0], \qquad (4)$$

where $\mathrm{x}^{(j)}$ is a recognizable realization vector; μ_m, μ_c the functions of belonging of the recognized realization to the containers of the nearest recognition classes X_m^0 and X_c^0 respectively.

In expression (4), the corresponding membership functions for hyperspherical containers are determined by formulas

$$\mu_m = 1 - \frac{d(x^{(j)} \oplus x_m)}{d_m^*}; \quad \mu_c = 1 - \frac{d(x^{(j)} \oplus x_c)}{d_c^*}, \qquad (5)$$

where x_c is the averaged vector-realization of the recognition class X_c^0; d_c^* – obtained in the process of machine learning the optimal radius of the container of the recognition class X_c^0.

Thus, the control tolerances system optimization for recognition features is to organize the search in the process of machine learning of the information criterion global maximum (3) in the working area of determining its function.

3. Results

Table 1 shows the machine learning results of the control system for the hand prosthesis with the optimization of the class containers radii for a given alphabet of six recognition classes.

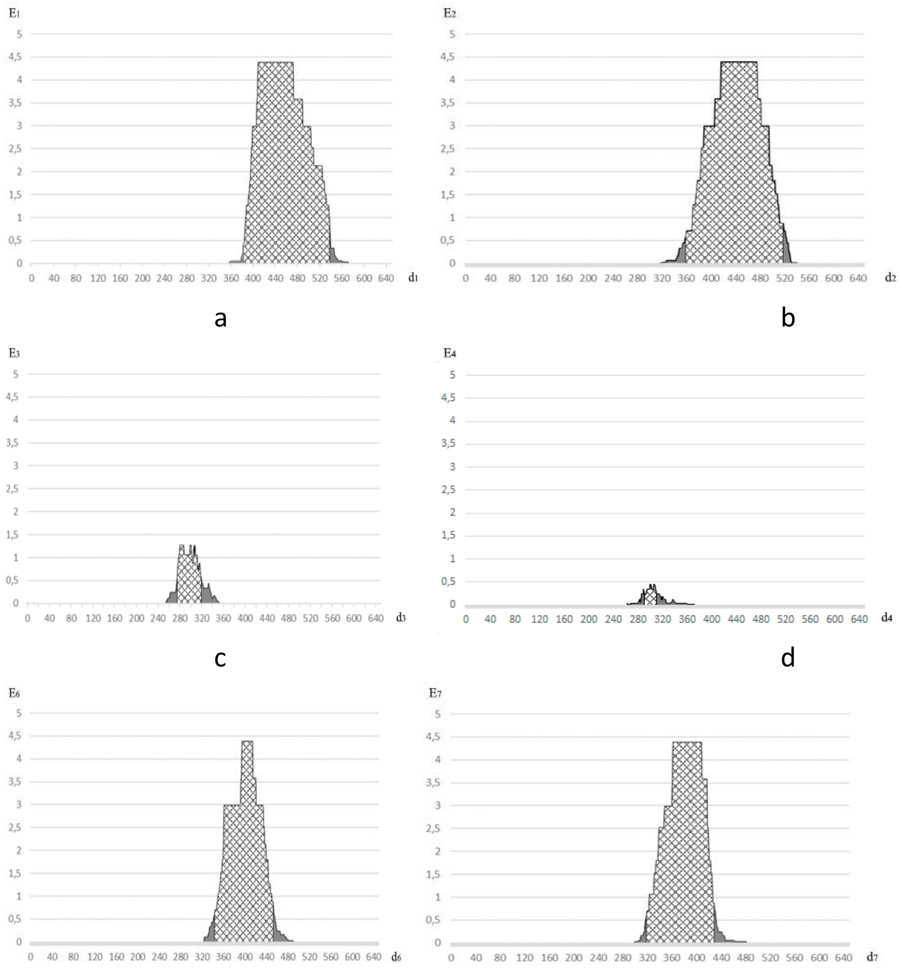
The following denotations are used in Table 1: $\overline{E^*}$ – the value of the information criterion averaged over the alphabet of recognition classes (3); $\overline{D_1}$ – the first reliability averaged over the alphabet of recognition classes; $\overline{\beta}$ – second type error averaged over the alphabet of recognition classes; $\overline{P}_1$ – average probability of correct decision making averaged over the alphabet of recognition classes.

Table 1
Machine learning results

Class ID	$\bar{E}^{*}$	$\bar{D}_1$	$\bar{\beta}$	$\bar{P}_t$
1	4.39	1.00	0.00	1.00
2	4.39	1.00	0.00	1.00
3	1.27	0.65	0.15	0.54
4	0.44	0.75	0.35	0.39
5	4.39	1.00	0.00	1.00
6	4.39	1.00	0.00	1.00
7	4.39	1.00	0.00	1.00
8	2.98	0.90	0.05	0.79
9	0.87	0.85	0.30	0.47
10	4.39	1.00	0.00	1.00

Analysis of the table 1 shows that the pairs of classes X_1^0 and X_2^0, X_5^0, metaclass X_{10}^0, X_6^0 and metaclass X_7^0 formed the optimal classifiers and their information measure reached the maximum value for this set of features. However, the classes X_3^0 and X_4^0 showed rather low values of the Kullback test, as did the metaclasses X_8^0 and X_9^0.

Fig. 4 shows the dependence graphs of the information optimization criterion (4) on the radii of the recognition classes containers.



a b

c d

e f

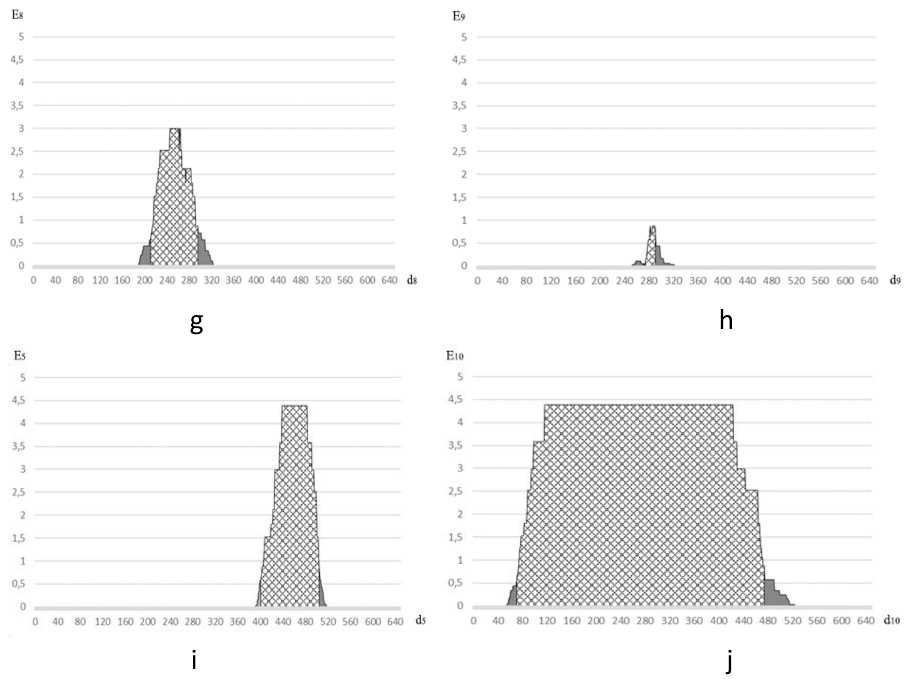


Figure 4: Graphs of dependence of the criterion on the radii of the recognition classes containers: a – class X_1^0; b – class X_2^0; c – class X_3^0; d – class X_4^0; e – class X_6^0; f – metaclass X_7^0; g – metaclass X_8^0; h – metaclass X_9^0; i – class X_5^0; j – metaclass X_{10}^0.

Graphs in Fig. 4 shows the distribution of information measure (4) for pairs of hierarchical structure clusters. The graphs show that the distribution of values has areas of the "plateau" type, for which the determination of the optimal radii of the recognition classes containers was carried out by the values of the fuzzy compactness coefficients (6).

The optimal radii of the recognition classes containers determined according to expression (5) were respectively: for pairs of classes X_1^0 – d_1^*= 409 (hereinafter in the code units of the Hamming binary space) and X_2^0– d_2^*= 417, classes X_3^0 – d_3^*= 293 and X_4^0 – d_4^*= 307, class X_6^0 – d_6^*= 394 and for metaclass X_7^0 – d_7^*= 408, metaclasses pairs X_8^0 – d_8^*= 261 and X_9^0 – d_9^*= 282, class X_5^0 – d_5^*= 467 and metaclass X_{10}^0 – d_{10}^*= 421.

Implementing the stage of the exam, signals from the UCI Machine Learning Repository database were used, which were the movements followed by the trained system. The examination realizations were not used in the training matrices. The step-by-step control system determined the belonging of the new realization to one of the classes in the subspace of the hierarchical tree clusters features. In the case when the realization was not classified according to the formed decision rules (5), ie it did not belong to the recognition classes from a given alphabet, it was noticed as unknown. Thus, to recognize the motion of hook grasp, the values of the membership function (6) were equal: μ_5= -0,07 and μ_{10}=0,92, which meant that the metaclass X_{10}^0 ; μ_8=0,83 and μ_9=0,32 – belonging to the metaclass X_8^0; μ_1= -0,42 and μ_2=0,76 – recognized motion hook grasp of class X_2^0. The value of the average total probability of correct gesture recognition for a given alphabet of six recognition classes was equal to $\bar{P}_t$ = 0,82.

4. Discussions

According to the results of machine learning of the prosthesis control system, given in table. 1 shows that the agglomerative hierarchical structure of classes provided a high marginal probability of correct recognition of cognitive commands. However, the maximum probability of correct recognition could not be achieved. That is, it can be argued that the division of the feature space into pairs of clusters allowed to build highly reliable, but not infallible decision rules.

The functional efficiency of machine learning should be considered high, because the value of the total probability of correct recognition of cognitive commands is close to one. This probability value was obtained during the operation of the prosthesis control system in the examination mode, when the vectors of gesture signs from the signal base, which did not belong to the training matrices, were recognized. The average total probability of correct recognition of cognitive commands for a given alphabet of recognition classes obtained by the results of the exam was equal to $\bar{P}_t$ = 0,82. This figure is quite high because it is at the level of prostheses with an invasive system of reading biosignals. However, it should be noted that the system did not show a high probability of recognizing classes X_3^0 (lateral grasp) and X_4^0 (palmar grasp). This is due to the significant similarity of movements. To solve this problem, it is necessary to consider the optimization of the control tolerances system for recognition features and additional methods of processing biosignals. It is clear that in this case the system will form a different hierarchical structure.

5. Conclusions

The method of information-extreme machine learning with agglomerative hierarchical clustering of classes, which is practically invariant to the multidimensionality of the features dictionary, is considered in the work. The system based on information-extreme intelligent technology is resistant to increasing the alphabet of recognition classes and flexible to retraining the control system. In addition, based on the results of machine learning in the geometric approach, the decision rules allow to make highly reliable classification decisions and, very importantly, with high efficiency, close to the speed of cognitive commands. The application of the obtained scientific results for machine learning of a prosthetic arm with a greater degree of freedom is associated with the need to increase the set of features by recording biosignals in different parts of the muscular system, which are used to perform appropriate gestures and their combinations. In this case, it is necessary to consider the impact of increasing the depth of machine learning, including by optimizing the control tolerances on the recognition features and additional parameters of the control system. In this case, changing the set of classes will affect the spatial division of classes, and hence the final form of the hierarchical structure. In addition, in the future it is necessary to pay attention to the parameters of biosignals processing, the influence of biosignal noise levels and consider the signs informativeness assessment.

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