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An Original Algorithm for Classifying Premotor Potentials in Electroencephalogram Signal for Neurorehabilitation Using a Closed-Loop Brain–Computer Interface

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Abstract—Over the past decades, brain–computer interfaces (BCIs) have been rapidly evolving. A BCI is a system that records brain activity signals using electrophysiological methods and then processes these signals to generate control commands. The most challenging aspect of BCIs is the nonstationary nature of brain signals, which makes it difficult to achieve stable and accurate decoding. Therefore, developing robust methods for processing and classifying EEG signals to extract control commands is a critical research area. A related challenge is the low signal-to-noise ratio in EEG data, especially when target patterns are weak or the data is labeled inaccurately. This paper presents the results of an evaluation of an approach combining feature extraction and data augmentation techniques to address the aforementioned challenges applied to the classification of premotor potentials. The approach is based on the application of linear discriminant analysis (LDA) to sequentially extract informative components in the frequency and time domains For the first time, the applicability of this algorithm to EEG containing premotor patterns of real movements is demonstrated. Features of different nature (spectral power, Hjorth parameters, interchannel correlations) were tested and compared with each other and a traditional approach based on common spatial patterns and a linear classifier. It is shown that transformations in the frequency domain alone improve accuracy from 63.9% in the traditional approach to 77.5% on a dataset of 16 experiments on different subjects. With additional transformation in the time domain, accuracy increases to 98.8%. On average, across different model configurations, a segment length of 500 ms is the most optimal. Two approaches were developed and tested to achieve algorithm universality across subjects: universal transformations in frequency domain trained on data from all subjects and without this step at all. It is shown that accuracies of up to 98.3% can be achieved with such approaches. A discussion of optimal frequency bands, segment lengths, and features is provided. Thus, data from different subjects can be effectively classified by a common model, which is rare in global research and is usually accompanied by a number of assumptions, cumbersome models, and inferior accuracy. Thus, in addition to the achieved accuracy enhancement, the proposed algorithm exhibits robustness to transient noise and artifacts through signal segmentation into short epochs. It also effectively addresses the critical task of extracting informative signal components in scenarios with potentially imprecise expert annotations. Finally, it can be adapted to mitigate the need for subject-specific calibration. These attributes render the proposed algorithm suitable for real-time applications, including closed-loop BCIs for addressing the pressing challenge of neurorehabilitation.

Keywords: EEG, brain–computer interface, premovement potentials, motor imagery, machine learning

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1. INTRODUCTION

In recent decades, advancements in neurophysiology and psychophysiology, coupled with rapid progress in computational capabilities, have led to the emergence and rapid development of brain–computer interfaces (BCIs) [1–3]. BCIs are sophisticated software and hardware systems designed to facilitate direct communication between the human brain and electronic devices. They have found extensive applications in neurocontrol, particularly in the context of restoring lost motor functions [4].

There exists a wide range of applications and methods for forming control commands in such systems, often without overt physical manifestations. For instance, BCIs based on inner speech

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[5, 6] and motor imagery [7–9] are most commonly encountered. However, such cognitive activity is far from being fully understood [10, 11], and the experimental results associated with its study are poorly reproducible [12]. This lack of reliable knowledge regarding the electrophysiological correlates of cognitive control underlies the primary challenge of ideomotor and inner-speech-based BCIs. From a technical standpoint, this leads to the problem of extracting informative features from brain bioelectrical activity signals, particularly electroencephalography (EEG). The latter is most frequently used due to its accessibility, temporal resolution, and noninvasive nature.

On the other hand, there is the issue of EEG nonstationarity. Moreover, despite the existing knowledge of EEG patterns and characteristics during various sensory, motor, and cognitive activities, their specific forms are highly dependent on the subject and their current psychophysiological and functional state [13]. In the context of motor activity, the following conditions are crucial: (a) which body part will be involved in the movement, (b) whether it will be executed physically or imagined, and (c) whether the execution is voluntary or ballistic. The complex task of extracting discriminative patterns of cognitive activity is further complicated by the influence of the current state in various modalities: fatigue level, emotional state, monotony, etc. This is another major problem of ideomotor BCIs related to the need for adaptive methods that are robust to the natural nonstationarity and uncertainty of EEG [14, 15]. This problem can also be attributed to the shortcomings of experimental protocols where stimulus-instructions create an evoked potential that overlaps or even completely obscures the target EEG patterns [16]. Nevertheless, there are examples of systems based on classical and deep learning models that achieve sufficiently high accuracy in recognizing neurocontrol commands for practical use [1, 3, 15, 17, 18]. However, they have their drawbacks: limited set of control commands, computational resource consumption, universality across subjects, and requirements for a large amount of labeled data.

Regarding specific challenges in studying motor and ideomotor activity, the first one is the uncertainty of the temporal boundaries of a motor imagery pattern or premotor potential. The increase in the amplitude of the electromyography (EMG) signal can only approximate the right boundary of the premotor potential, as it is physiologically lagged. It is also known that preparation for a real movement does not take more than 500 ms [19, 20], which again provides only a rough estimate of the left boundary of the premotor potential. Consequently, event-related potentials (ERP) methodology fails due to the poor synchronization. Using longer segments in turn can increase the proportion of uninformative signal in the sample. The latter can make a key negative contribution to the feature extraction process, as the target patterns are weakly expressed in amplitude [21] and can be lost in the background noise. Nevertheless, there are adaptive approaches that, to a certain extent, address this problem. For example, in the work [22], by prefiltering the EEG signal in the presumed frequency band of the expected pattern, it is possible to correctly determine the its temporal boundaries and improve the classification accuracy. It has also been shown that, with different signal-to-noise ratios and small sample sizes, high ideomotor classification accuracy can be obtained by refining informative segments [23].

In our previous work [24], we proposed a motor imagery patterns classification algorithm. The algorithm naturally incorporates adaptability through differences between directly adjacent windows of target and background signals. It also leverages the advantages of classical machine learning models to find short informative epochs of the signal. It was shown that the algorithm is capable of nearly perfectly distinguishing between motor imagery of the left and right hands even on a dataset of different subjects. Segment length of 750 ms was found to be optimal. However, it is impossible to verify that a motor imagery was executed, as they are not accompanied by external manifestations. To address this issue, computational experiments were conducted to test the algorithm that includes original feature extraction and data augmentation. This time, an EEG dataset with execution of real movements was used. The fact of movement execution is easily verified by the EMG signal, so the task is reduced to analyzing segments preceding the increase in EMG amplitude. To determine the lateralization of a real movement, 250–300 ms is sufficient [26]. In this work, in addition to the optimal segment length of 750 ms for motor imagery and shorter lengths of 500 and 250 ms were investigated.

Developing algorithms for reliable recognition of premotor patterns is one of the most demanded applications of BCIs, particularly for individuals who have suffered a stroke or lost motor function for other reasons [2, 7, 9, 27]. In this case, the key goal is to induce neuroplasticity, which is best achieved in closed-loop BCIs. In such BCIs, the successful formation and recognition of the target command is explicitly signaled to the subject, creating feedback [28, 29]. The feedback also allows the system to adapt to the subject's current state, which helps classify low-amplitude target patterns in nonstationary EEG. For such purposes, the algorithm needs to be implemented in real time. This, in turn, requires, high speed and algorithm's adaptability to different subjects, i.e., the absence of excessive individual tuning. The algorithm proposed in this work meets the former criteria, and to solve the latter problem, two approaches to achieve algorithm's universality were developed and tested. The approaches, respectively, imply either models for transformations in the frequency domain tuned on the dataset of all subjects or complete absence of such models.

Further in the article, in the section Materials and Methods, brief information is provided about the dataset and the main steps of the proposed algorithm. Subsequently, the results of the computational experiments are presented and analyzed in the section Results and Discussion, while the section Conclusions provides a brief summary of the obtained results, their significance, and the authors' plans for the further development and application of the algorithm.

2. MATERIALS AND METHODS

2.1. Dataset and Subjects

During the experimental session, subjects ($n = 16$, both male and female, age 21.5 ± 3.5 years) performed real movements with their right and left hands and feet. The moments of movement execution were not cued with any sensory stimuli. Instead, the subjects were continuously looking at the clock face on the display and executed movements when the clock hand was pointing at initially marked ticks. Movement execution for 2 s alternated with a resting state of 5–10 s, with EEG being recorded continuously. hands movements implied fist clenching, while feet movements meant flexing both feet vertically. Approximately 70 movement executions were recorded for each subject. A more detailed description of the experimental protocol can be found in our previous work based on the same dataset [24].

2.2. EEG and EMG Recording

EEG was recorded relative to ear reference electrodes using an Encephalan-131-03 electroencephalograph (Medikom MTD, Taganrog, Rostov oblast) from 17 standard leads (F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2). EEG signal preprocessing consisted of cleaning it from eye blink artifacts using a cross-correlation method with the electrooculogram (EOG) signal [25].

EMG was recorded in the area of the superficial muscles that flex the forearm at the elbow joint (m. brachioradialis), the superficial flexors of the fingers (m. flexor digitorum superficialis), and the dorsiflexors of the feet (m. tibialis anterior). To label the data, the EMG signal was filtered in the 0.1–4 Hz range, after which the onset of real movement execution was stated when the amplitude exceeded 10 μV (approximate right boundary of the premotor pattern).

2.3. Informative Features for Premotor Patterns Classification Task

Nine biologically significant EEG frequency bands were used: δ(1–3 Hz), θ(3–7 Hz), α(7–10 Hz), μ(10–13 Hz), $\beta1$(13–25 Hz), $\beta2-\gamma1$(25–45 Hz), $\gamma2$(55–70 Hz), $\gamma3$(70–90 Hz), and $\gamma4$(90–110 Hz). Power spectral density (PSD) for these bands was calculated using Welch's method (Hanning window, 50% overlap of successive windows) [30]. After calculating the PSD, it was log-transformed and converted into a feature vector by summing the amplitudes of frequencies falling within the frequency boundaries of each band.

Additionally, Hjorth parameters [31] were used as features. This feature combination is traditionally considered quite complete for describing any functional state based on an EEG signal: activity, mobility, and complexity. The first represents the simple variance of the EEG signal, the second is interpreted as the dominant frequency of amplitude changes in the signal, and the third is the similarity of the signal to a perfect sinusoid. Given a time series $y(t)$, the parameters are calculated as follows:

$$\mathrm{activity}(y(t)) = \mathrm{variance}(y(t)),$$

$$\mathrm{mobility}(y(t)) = \sqrt{\frac{\mathrm{activity}(y'(t))}{\mathrm{activity}(y(t))}},$$

$$\mathrm{complexity}(y(t)) = \frac{\mathrm{mobility}(y'(t))}{\mathrm{mobility}(y(t))}.$$

Finally, the third group of features was interchannel correlations, which were calculated as the Pearson correlation coefficient between series of signals from all unique pairs of channels (136 pairs in the case of 17 channels).

2.4. Frequency Filtering

Frequency filtering was performed using the fourth order Butterworth filter with infinite impulse response.

2.5. Transformations in Frequency and Time Domains

A detailed description of these transformations can be found in our previous work [24], therefore only a concise description is provided here.

The extraction of informative parts from the frequency domain involves the sequential consideration of samples of each type of movement and the background signal. For each such a binary sample, a complete set of PSD features is calculated. Afterwards, a 1-component linear discriminant analysis (LDA) model is trained and saved. As a result, there are as many 1-component LDA models as the number of considered types of movements. Each model compresses information from the frequency domain in the most optimal way to separate patterns of its movement type from the background signal. When using Hjorth parameters or correlations as features for final classification, the frequency corresponding to the weight with the largest absolute value is extracted from each model. Then the EEG signal undergoes multiband filtering in the obtained frequency ranges. One of the approaches aimed at intersubject universality implies performing the described procedure using the sample of all 16 subjects. It is supposed to provide universal set of the models for frequency domain transformations.

For additional extraction of the most informative segments in the time domain, for each two-second signal preceding real movement, a sample of two-class examples created. One class was the considered movement and the second one was the background signal. The feature vector consisted of differences between the feature vectors of all combinations of short segments (250, 500, or 750 ms with a 100 ms shift) within the 2-second original signals of rest and movement. If PSD features were used, the obtained frequency domain LDA models were simply applied to the feature vector of each short segment. Otherwise, the multiband filtering approach described in the previous paragraph was applied to each short segment. A 2-component LDA model was trained on the obtained sample of two classes (differences in features of the background-movement and background-background segments pairs) based on one motor act. In this case, the columns of the sample correspond to the same short segments of the signal, i.e., they encode the time dimension. Hence, the obtained model optimally compresses information not only in the frequency but also in the time domain to discern the pattern of this movement and background. After independently processing all 2-second premotor EEG signals in this manner, they form a sample to be further classified.

2.6. Classification

Classification and accuracy evaluation were performed based on a logistic regression model with L2 penalty, L-BFGS optimization, and a stopping criterion of 0.0001. The regularization parameter C of the logistic regression was optimized on a grid of values: 0.001, 0.01, 0.1, 1, 10. Two-fold cross-validation was used to evaluate the classification accuracy.

Feature values were z-standardized, and the entire dataset was randomly shuffled. The described classification procedure was applied separately to the datasets of each subject (unless explicitly stated otherwise), and the final estimate was calculated as the average of the estimates of all subjects.

As in our previous work [24], a combination of common spatial patterns (CSP; the number of filters from 1 to 9 was optimized through cross-validation) and logistic regression as a final classifier applied to samples from full 2-second premotor signals was used as a baseline.

3. RESULTS AND DISCUSSION

The baseline approach demonstrated modest results in the premotor potentials classification: on average 53.7% when considering only hand movements and 63.9% when considering also leg movements (Table 1).

3.1. Evaluation of the Algorithm Performance Using Premotor Potentials Data in the Intra-Subject Manner

When applying frequency domain transformations individually to the data of each subject and using all 2 s of the signal before each movement, PSD features perform best. This result is due to the frequency domain transformations themselves being optimized for PSD features: 67.5% when classifying 3 movements and 77.5% for the two hand movements (Table 1). Features based on Hjorth parameters and correlations are significantly inferior at this stage (by more than 10%). Interestingly, the LDA models for transformations in the frequency domain are trained on binary samples of each movement type versus background, but ultimately improve the classification of premotor patterns among themselves. This suggests the good effectiveness of this step in highlighting effects that are truly specific to each type of movement in the frequency spectrum.

Finally, in an individual approach to the data of each subject, additional extraction of informative short segments within 2-s signals of each premotor act was considered. The obtained results demonstrate a slight advantage of using 500 ms segments,

Table 1. Accuracy (%) of 2 or 3 types premovement potentials classification averaged across subjects in different approaches

		Individual transformations in frequency domain		Universal transformations in frequency domain		No transformations in frequency domain	
Approach	Features	3 movements	2 movements	3 movements	2 movements	3 movements	2 movements
CSP+LR	CSP-filters	53.7	63.9	53.7	63.9	53.7	63.9
Frequency domain manipulations	PSD	67.5	77.5	50.3	68.8	58.2	74.1
	Hjorth params	54.7	66.5	57.0	69.9	64.9	75.2
	Correlations	52.5	63.8	54.6	65.2	58.3	65.9
Frequency + time domain (750 ms) manipulations	PSD	56.8	72.5	38.7	45.5	40.0	48.1
	Hjorth params	68.5	89.4	71.1	88.9	69.3	94.9
	Correlations	72.1	98.8	69.4	89.9	69.9	98.3
Frequency + time domain (500 ms) manipulations	PSD	61.6	72.5	37.7	48.5	40.1	48.2
	Hjorth params	68.7	98.4	71.1	95.6	69.4	93.8
	Correlations	71.6	98.8	68.6	92.6	67.9	95.5
Frequency + time domain (250 ms) manipulations	PSD	64.2	78.7	38.7	48.6	40.9	51.8
	Hjorth params	62.6	83.5	64.7	87.0	61.6	80.1
	Correlations	64.7	89.6	68.5	96.0	64.3	88.3

while for motor imagery, the optimal length was 750 ms. At the same time, almost perfect separation of hand movements was again obtained: 98.8% and 98.4% using features of interchannel EEG signal correlations and Hjorth parameters, respectively, after multiband filtering (Table 1). At the same time, the results obtained based on PSD features do not show noticeable improvements compared to the previous step. this effect is most likely due to the decrease in the quality of Welch's periodograms calculated on such short segments.

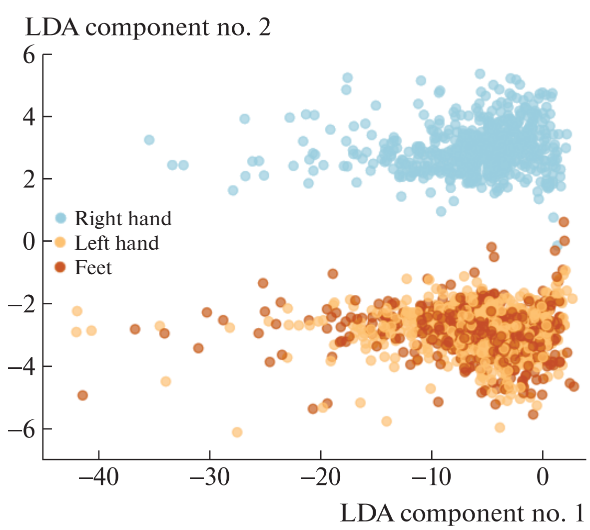

Fig. 1. All 16 subjects' data clustering after time domain transformations (interchannel correlations features, 500 ms segments).

Thus, it has been confirmed that the algorithm previously proposed for motor imagery can be applied to premotor patterns without loss of accuracy. The clustering of data using correlation features and a segment length of 500 ms is shown in Fig. 1. However, the individual approach used has a significant drawback in the need to train models separately for each subject. That is, in the BCI paradigm, such an approach would require a long calibration in a controlled experimental session for each new subject. In this work, we tested two approaches to solve this problem: (a) the use of a universal set of LDA models for transformations in the frequency domain and (b) elimination of this step. Option (a) involves training LDA models on samples of each movement and background, composed of data from all subjects. Option (b) consists in using only transformations in the time domain. In the latter case, the feature space of each short segment is calculated based on the raw EEG signal without filtering when using Hjorth parameters and correlations. In the case of PSD

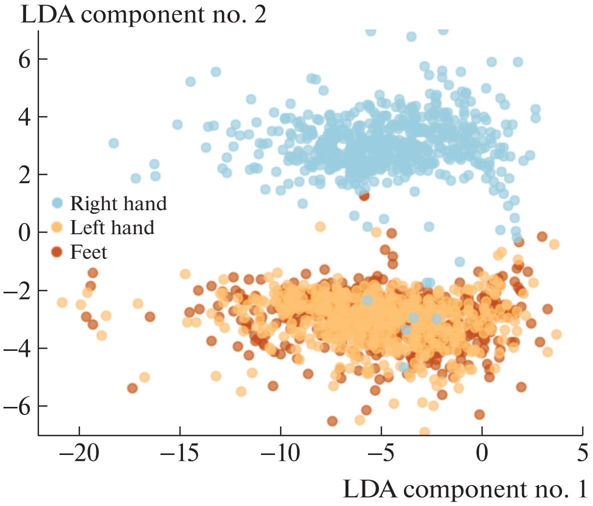

Fig. 2. All 16 subjects' data clustering after time domain transformations in the approach with universal models for frequency domain transformations (Hjorth parameters, 500 ms segments).

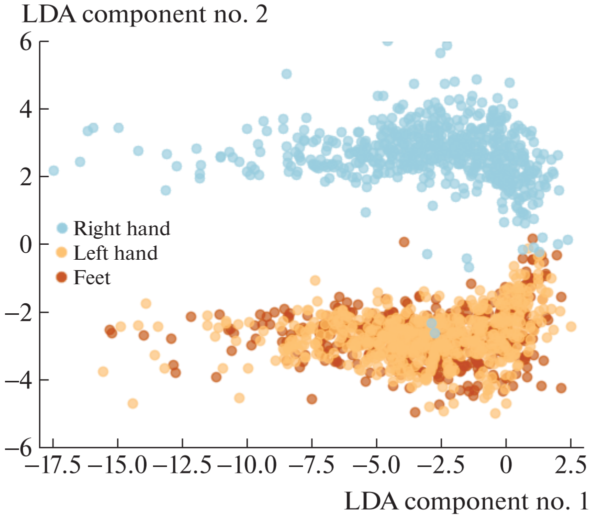

Fig. 3. All 16 subjects data clustering after time domain transformations in the universal approach without models for frequency domain transformations (interchannel correlations features, 750 ms segments).

features, it just means no feature space compression for each short segment.

3.2. Evaluation of the Approach Based on Universal Models for Frequency Domain Transformations

When using the universal approach with training a set of LDA models for transformations in the frequency domain that is common to all subjects, the accuracy obtained for PSD features decreased as expected (Table 1). At the same time, the accuracy when using Hjorth parameters paradoxically increased by 2–4% (Table 1). The latter effect can be explained by a more accurate definition of frequency ranges for filtering when training on a large dataset of all subjects simultaneously. However, obtained improvements in accuracy when using Hjorth parameters and correlations do not reach the values obtained in the individual approach using PSD features adn transformations in the frequency domain.

Regarding the further extraction of informative segments, in this approach, the optimal segment length, according to the average assessment of different features, was also 500 ms. When using Hjorth parameters, 71.1% and 95.6% (Fig. 2), respectively, when considering all 3 movements or only hands; for correlation features—68.6% and 92.6%, respectively (Table 1). However, when using correlation features and 250 ms segments, a slightly higher accuracy of 96% was obtained, while for Hjorth parameters with this segment length, it dropped to 87% (Table 1).

Nevertheless, the effectiveness of small segment lengths becomes clear if we consider that in the resulting universal frequency domain transformation models for hand movements. The optimal frequency ranges were determined to be 7–10 and 25–49 Hz. These ranges are quite high-frequency, so it is easier to catch specific effects in them at shorter segment lengths. The accuracy when using PSD features drops to almost chance level, which is associated with a combination of factors of short segments and the absence of individual frequency tuning (Table 1).

Thus, it was shown that the approach based on training the models for frequency domain transformations on all subjects' data leads to negligible decrease in classification accuracy (less than 3%). This makes the approach applicable in practice, as it is very likely to successfully work while being fed with a new subject data.

3.3. Evaluation of the Approach without Models for Frequency Domain Transformations

In another universal approach without a set of LDA models for frequency domain transformations, the accuracy when using PSD features decreased by less than 4% when considering hand movements. But for all 3 movements, the decrease was almost 10% (Table 1). This is likely explained by the fact that in this case, without compression in the frequency domain, the number of features is quite large for the available number of examples. Therefore, even despite the most complete representation of the frequency domain, the classification model struggles to achieve high accuracy on a relatively small sample of each individual subject. At the same time, the accuracy when using Hjorth parameters further increased almost to the values obtained in the individual approach using PSD features at the stage of frequency domain transformations—64.9% (3 movements) and 75.2% (hand movements) (Table 1). Apparently, this is due to the fact that in the raw unfiltered EEG signal, all complex frequency effects are most fully represented. Those effects can be quite effectively captured by the mobility (∼ dominant frequency) and complexity (∼ similarity to an ideal sinusoid)—two of the three Hjorth parameters.

When further extracting informative temporal segments in this approach, the most optimal segment length, according to the average assessment of different features, was 750 ms. When using Hjorth parameters, 69.3% and 94.9%, respectively, when considering all 2 movements or hands movements only; for correlation features—69.9% and 98.3% (Fig. 3), respectively (Table 1). This result can be explained by the fact that, in the absence of specificity in the frequency domain, it is more advantageous to use a slightly longer and therefore more diverse segment of the signal. However, a further increase in accuracy by increasing the segment length to 1000 ms is unlikely, since the maximum previously obtained accuracy has already been practically achieved.

Similarly to the previous universal approach, the accuracy when using PSD features drops to almost chance level (Table 1).

4. CONCLUSIONS

In this paper, we demonstrated the applicability of an algorithm we previously developed for the classification of motor imagery EEG patterns to premotor EEG patterns. In an individual approach with sequential feature extraction in the frequency domain and data augmentation within each individual segment of the signal prior to a movement, similar accuracies of up to 98.8% were achieved when considering only movements of the left and right hands.

Further refinement of the algorithm to achieve its robustness to intersubject variability was also tested. Recall that the algorithm, in terms of time domain transformations, achieves robustness to variability in functional states by calculating the differences between neighboring segments of the background and target signals. Two options for achieving universality were proposed: with a universal set of frequency domain transformers and without frequency domain transformations at all. It is shown that both of them work, with loss of accuracy being quite negligible compared to the subject-specific approach. The approach without frequency domain transformations using correlations almost completely repeats (98.3%) the best result in the subject-specific approach (98.8%) when considering hand movements. Indeed, correlations take into account important spatial effects, and the relatively short length of the segments limits the set of frequencies affecting the results.

An analysis of the results of both universal approaches was conducted to understand how the information from the frequency domain was utilized. For instance, the optimality of short segment lengths in universally trained frequency domain transformation models can be explained by the relatively high-frequency ranges determined as optimal in these models. Hjorth parameters, among other things, indirectly characterize frequency effects, so it is not surprising that they allowed achieving high accuracies even without frequency domain transformations using the raw EEG signal.

As a further validation of the obtained results, it is planned to examine in detail the patterns in different subjects in the frequency ranges from universally trained frequency domain transformation models. In approaches to achieving universality across subjects, before practical applications, it is necessary to conduct computational experiments in a "leave-one-out" paradigm. The latter implies that training is performed on data from all subjects except one, and then the trained model is tested on the data of the excluded subject. After these checks, it should become clearer which of the universal approaches is more suitable for practice, since in this work very minor differences were obtained between them. At the same time, in the context of feature extraction, it would probably make sense to combine Hjorth parameters and correlations, since they alternately show the best results in different approaches. The obtained results will be converted into the final version of the algorithm, ready for real-time operation, in particular, within a closed-loop BCI for neurorehabilitation tasks.

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CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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